A DIGITAL IMAGING MODEL FOR PLANT STRESS DETECTION

Amos Chege Kirongo

A thesis submitted in partial fulfillment of the requirements for the award of the Degree of Doctor of Philosophy in Information Technology of Masinde Muliro University of Science and Technology.

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DECLARATION

This thesis is my original work prepared with no other than the indicated sources and support and has not been presented elsewhere for a degree or any other award.

Signature   Date…….7TH **AUGUST 2020**……….

Amos Chege Kirongo

SIT/H/14-57870/2016

CERTIFICATION

The undersigned certify that they have read and hereby recommend for acceptance of Masinde Muliro University of Science and Technology, a thesis entitled "A Digital Imaging Model for Plant Stress Detection."

Signature…………………….   Date……7TH **AUGUST 2020**….

Dr. Kelvin Kabeti Omieno

Department of Information Technology & Informatics

School of Computing & Information Technology

Kaimosi Friends University College

Signature…………………….   Date………………….

Dr. Stephen Makau Mutua

Department of Computer Science

School of Computing and Informatics

Meru University of Science and Technology

Signature…………………….   Date………………….

Dr. Vitalis Ogemah

Department of Agro-Industrial Technology

School of Agriculture, Veterinary Science and Technology

Masinde Muliro University of Science and Technology

DEDICATION

This thesis is dedicated to my darling wife Dorothy and my beloved daughter Abigail for being a pillar of courage, perseverance, tolerance, determination, resilience, consideration and love. I also dedicate this thesis to my father Mr. Abel Kirongo retired Agriculture Extension Officer and my mother Mrs. Salome Kirongo retired Agriculture and Biology teacher for exposing me to Agriculture and Extension Services and motivating me to execute this research.

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ABSTRACT

Detection of stress in plants has been one of the many difficulties faced by the farming industry in the developing world. This difficulty has been attributed to a variety of factors, namely; reduced food production and consequent food insecurity, and limited access to computing technologies that result to technological evolution challenges among Kenyan farmers. With respect to the cause of these difficulties, research indicates the need to experiment with a diversity of image processing techniques, and formulation of algorithmic models that would tackle the challenge in plant stress. These stresses require technological advances in image processing and algorithms that can be used by local farmers in detection of plant stresses. Digital image processing approaches based on relevant algorithms allows for precision farming through detection and remedying of foreseen stress before it causes destruction on the plants in the farmers' fields. To achieve this, the general objective of this study was to develop a digital imaging model for detection of plant stress for enhanced productivity of crops and food security. In order to realize the general objective, the study was guided by the following specific objectives; to analyze existing image-based plant stress detection approaches; to establish the physical features of stress in plants; to map the physical features into digital imaging signature characterizing stress in plants; to develop a digital imaging model for plant stress detection and to validate the digital imaging model for detection of plant stress. This study was guided by positivism research philosophy, and explored existing models, algorithms and image processing techniques for detection of plant stress, and studied the growth of mobile telephony with relation to the need for food security. An experimental research design was employed through embracing the Convolution Neural Networks. The study resulted to a model that was developed and implemented in a mobile application and web interface to enhance food security through detection and monitoring of tomato pests and disease stress. The images were captured using mobile phone cameras, acquired input images were preprocessed through resizing and rescaling of images, whereas Gaussian blur, thresholding and dilating were used in feature extraction. SoftMax was used for classification and optimization carried out using the Adam Optimizer. Validation for accuracy of the model was based on training steps, sets and epochs and TensorBoard was used in bid to validate the model. The results of the study proved the reliability of the model in detection of stress using the digital imaging model to be more efficient over traditional approaches of plant stress detection. The findings of this study if adopted will contribute to increasing food production and enhance food security, contribute to the body of knowledge on digital imaging technology, and inform academic researchers, computer scientists, policy makers in education, and all stakeholders in farming and agriculture, on the implementation of new and emerging deep leaning technologies in improving existing work.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

AI: Artificial Intelligence

AMD: Advanced Micro Devices, Inc.

ANN: Artificial Neural Networks

API: Application Programming Interface

BRB: Bottleneck Residual Block

ChlF: Chlorophyll Flourescence

CNN: Convolution Neural Networks

CNTK: Cognitive Toolkit

Dbh: Diameter at the base

DBMs: Deep Boltzmann Machines

DBNs: Deep Belief Networks

DL: Deep Learning

DNN: Deep Neural Network

FFT: Fast Fourier TRansform

FPGAs: Field PRogrammable Gate Array

GLCM: Grey Level Co-occurence Matrix

GNN: Generative Adversarial Networks

GPS: Geographic Processing Unit

GPU: Graphics Processing Unit

GSMA: Global System for Mobile Communications Association

HOG: Histogram of Oriented Gradients

HSV: Hue Saturation Value

ICT: Information Communication Technologies

ITU: International Telecommunication Union

KNN: k-Nearest Neighbor

LAI: Leaf Area Index

ML: Machine Learning

MMUST: Masinde Muliro University of Science and Technology

NACOSTI: National Commision for Science Technology and Innovation

NGOs: Non-Governmental Organizations

NPK: Nitrogen Phosphorus and Potassium

OAU: Organization of African Unity

OBIA: Object Based Imabe Analysis

PCA: Principal Component Analysis

ReLUs: Rectifier Linear Units

RGB: Red-Green-Blue

RL: Reinformcement Learning

RMSProp: Root MEan Square Propagation

RNN: Recurrent Neural Networks

SDE: Stacked Autoencoders

SDGs: Sustanable Development Goals

SIFT: Scale-Invariant Feature Transform

SMS: Short Message Service

STI: Science Technology & Innovation

STISA: Science Technology and Innovation Strategy for Africa

SVM: Support Vector Machines

TPUs: Tensor Processing Units

UAV: Unmanned Aerial Vehicles

UNCSTD: United Nations Conference on Science and Technology Development

UPCA: Unfold Principal Component Analysis

VFSR: Very Fine Spatial Resolution

OPERATIONAL DEFINITION OF TERMS

Digital Imaging: Digital imaging is the art of acquisition of digital images that are digitally encoded representations of the visual characteristics of an object depicting the physical sceneries or the interior structure of an object.

Homeostasis: is a meta-stable steady-state maintained by a plant. Any change in the surrounding environment modulates homeostasis resulting to biological stress.

Plant Stress: 'Stress' in plants can be defined as any external factor that negatively influences plant growth, productivity, reproductive capacity or survival(Smirnoff, 2014). It is the adverse effect on the physiology of a plant induced as a result of transition from some optimum environmental conditions where homeostasis is maintained to some suboptimal condition which disrupts the initial homeostatic state.

Abiotic stress: is a physical (e.g., light, temperature) or chemical insult that the environment may impose on a plant.

Biotic stress: is a biological insult, (e.g., insects, disease) to which a plant may be exposed during its lifetime.

Artificial Intelligence: AI is short for artificial intelligence, a term coined by John McCarthy in 1955 at Dartmouth College. It is related to the work of Alan Turing, who in 1950 developed the Turing test, which evaluates a machine's ability to exhibit behavior equivalent to, or indistinguishable from, a human. The scientific study of AI aims to develop computer hardware and software which emulates processes of the human brain, including the processing of photographic images and human languages.

Image Processing: Image processing involves the manipulation or analysis of images by a digital device, usually a computer. Most techniques involve handling the image as a two-dimensional signal but then applying one-dimensional processing routines.(University of tartu, 2014).

Algorithm: Derived from the name of Al-Khwārizmī (Elaine, 2013) a corruption of his name. An algorithm is a solution to a problem that meets the following criteria; a list of instructions, procedures, or formula that solves a problem, can be proven, and Something that always finishes some given work. The image processing procedure entails the following:

> **Input** - The input portion refers to uploading an image to a hard drive, either from a digital camera, the Web, or physical image via scanner;
>
> **Processing** - The image is usually enhanced, compressed or analyzed scientifically to find patterns;
>
> **Output** - The output portion means to print the image or save it for later use.

Machine Learning: The ML concept originates from artificial intelligence which focused on development of computing systems that can accomplish tasks without explicit instructions. Instead of being told step-by-step and case-by-case how to do something, ML systems "learn" by repeatedly processing "training data" (representative sets of example information), the results of the processing are graded by how close they are to a desired result(Samuel, 2000).

Neural Network: A neural network simulates intelligence based on how a human brain receives and processes information. It is sometimes referred to as connectionist architecture, neuromorphic systems, or ANN (Artificial Neural Network). Because neural networks rely on parallel processing, standard computers are incapable of performing the tasks needed for neural networks and require special hardware or processors.

Classification: Image classification analyzes the numerical properties of various image features and organizes data into categories.

Deep Learning: Deep learning which is also known as deep structured learning or hierarchical learning creates computational models (LeCun, Bengio, & Hinton, 2015) made up of several processing layers that characterizes data in diverse abstraction levels. It is part of a broader family of machine learning methods based on artificial neural networks. Learning can be supervised, semi-supervised or unsupervised(Schmidhuber, 2015).

Image Pre-Processing: Operations on images at the lowest level of abstraction (Miljkovi´c, 2009).

Feature Extraction: Features are the variables that are specifically used as input to an algorithm. Features are selected or extracted as raw values from input data, or as values derived from that data. The right features ensure accurate feedback from the algorithm in real-world problems which generate data with inherent noise and variation.

Plant: a living organism of the kind exemplified by trees, shrubs, herbs, grasses, ferns, and mosses, typically growing in a permanent site, absorbing water and inorganic substances through its roots, and synthesizing nutrients in its leaves by photosynthesis using the green pigment chlorophyll.

CHAPTER ONE

INTRODUCTION

1.0 Overview

This chapter discusses global, regional and local food security indices, with relation to plant stress due to abiotic and biotic stress and how digital imaging techniques contributes to timely detection and accurate diagnosis of pests and diseases. This chapter also presents the background study; problem statement; main objectives and specific objectives; justification, significance, scope and assumptions of the study and thesis structure.

1.1 Background to the Study

Global food security assessment conducted by the Economist Intelligence Unit cuts across three internationally established dimensions; affordability, availability, quality and safety. The Global Food Security Index (GFSI) report of 2019 alludes that 88% of countries in the index report enough available food supply in the country, yet more than a third of countries in the index, 10% of the population is under malnourished (The Economist Intelligence Unit, 2018). Africa's socio-economic and political aspirations projected to the year 2063 is enshrined in Agenda 2063. This blueprint envisages a prosperous, sustainably-developing Africa that is integrated, politically united and respectful of human rights, the rule of law, justice, good governance and democracy. In addition, it envisions a peaceful and secure continent, with strong cultural values, ethics and heritage, and one whose people-driven development influences global partners (African Union Commission, 2015). The plan also predicts that Africa would embrace modernized agriculture for increased production, productivity and value addition, which contribute to farmer and national prosperity for food security. According to this stratagem, Science Technology and Innovation would impel African countries to be among the best performers in global quality of life measures by 2025 (DeGhetto, Gray, & Kiggundu, 2016).

The African Agenda 2063 aims at consolidating the modernization of agriculture and agronomy businesses through scaling up for value addition and productivity. Once this is done, the blueprint envisages that by year 2063, hunger and food insecurity will be completely eliminated, and food imports reduced by raising intra-Africa trade in agriculture and food by 50% (DeGhetto et al., 2016) of the total formal food and agriculture trade. Further, the agenda outlines the intention to expand modern agricultural systems, technologies, practices and training; including the banishment of the hand-hoe. The Agenda 2063 states that there is an intention of developing and implementing affirmative policies and advocacy that ensures increased access to land and farm inputs by making sure that 30% and above of agricultural financing are accessible by women and youth in support of economic empowerment (African Union Commision, 2014), by way of enhancing access to financial resources for investment in the agricultural sector. Arguably, this would be achievable through embracing ICT technologies (African Union Commission, 2015; Masheleni, 2018). The Science, Technology and Innovation Strategy for Africa (STISA) Priority number one is to eradicate hunger and achieve food security by paying special attention to Agriculture through integration of Information and Communication Technologies (ICT) (African Union Commision, 2014). This study describes Information Communication Technologies (ICT) as a fundamental enabler of timely detection and accurate diagnosis of plant stress through digital imaging.

Further, this study has been informed by Africa Regional Initiatives 2018-2021. The initiative focuses on building digital economies in Africa so as to foster innovation;

promoting emerging broadband technologies; building trust and security in the use of telecommunications/information and communication technology; strengthening human and institutional capacity building; and management and monitoring of radio-frequency spectrum for transition to digital broadcasting platform (Biotech, Yi, & Ying, 2013). The expected results of 2018-2021 Africa Regional Initiatives include: enhancing adoption of e-applications geared towards sustainable development in various aspects of African economies; promoting adoption and implementation of disruptive digital innovations; and fostering development and operationalization of frameworks for manufacturing of ICT goods in Africa. The initiative anticipates that innovative works would accelerate realization of these objectives. According to the initiative, digital services will fast-track the attainment of food security and Sustainable Development Goals in the African Region. The initiative, therefore, supports digital solutions and innovations for agriculture at national level, and implementation of the same as a national priority, with the hope that the solutions would contribute to food security, improving nutrition, and promote sustainable agriculture by building capacities for generation of African digital leaders in the transformation of the agricultural sector, using ICT technology (Biotech et al., 2013).

According to the International Telecommunication Union (ITU) in the last two decades, Africa has experienced growth in mobile phone penetration and internet connectivity, and has continued to close the digital divide by having a presence in the global knowledge economy(African, Policy, & Network, 2010). In the year nineteen ninety-six, the African Information Society Initiative (AISI) (African et al., 2010) was launched to act as the regional ICT-for-development framework. AISI was meant to be a reference point for an African digital vision and agenda in a globalized world. Considering the social nature of African people, numerous African countries have embraced the capabilities of mobile phone technologies in diverse areas. For instance, automation of Mobile Money transfer, and subsequent mobile banking pivots on the penetration of mobile phone technologies. Through the M-PESA, (Swahili for 'Mobile Money'), Kenya provides a good example of mobile money transfer. Softwares like the USHAHIDI.com (Swahili for testimony) web interface which was initially developed as a tool for mapping and reporting violence in 2008 Kenya via Short Message Service (SMS), are prototype cases of how mobile phone technologies can be tapped for development. Such mobile phone applications which combine crisis information, citizen-generated reports, media reports, Non-Governmental Organizations (NGOs) reports, as well as geographical mapping tools are currently being used globally to accurately and in a timely manner track unrest in crisis areas like Lebanon, Afghanistan and Mexico.

The Third Medium Term Plan 2018-2022 of the Republic of Kenyan focuses on transforming the lives of the Kenya citizens through advancement of socio-economic development through the "Big Four" (Republic of Kenya, 2018). The Big Four is comprised of initiatives aimed at enhancing Industrialization, Manufacturing and Agro-processing; Affordable Housing; Food Security; and Universal Health Coverage. The focus on initiatives aimed at enhancement of Food Security and Nutrition is the second most important Pillar by the Republic of Kenya. The Food Security and Nutrition pillar indicates that Agriculture accounts for 31.5 percent contributes to the country's GDP, 75% of Labor force and over 50% revenue from exports (Republic of Kenya, 2018). The Global Food Security Index 2019 based on affordability, availability, quality and safety of food (Agriscience, 2019) indicated that Kenya is food insecure and was ranked at number 86 out of 113 countries. Hence the need for adoption of low cost service delivery model that leverage on ICT digital imaging techniques in collection and dissemination of information, along with proper policy and strategic interventions with a view to mitigate the timely and accurate detection and diagnosis of plant stress challenges the Agriculture sector faces to enhance food security.

The success of USHAHIDI.com and M-PESA ICT initiatives in the Kenyan market has informed the development of the digital imaging model for timely and accurate detection and diagnosis of plant stress, web interface and mobile application interface for the farming communities in Kenya, which this study discusses, with the aim of scaling up farming to global standards.

Continued food insecurity directly affects 239 million Africans; with 30% to 40% of children under the age of 5 years suffering from chronic under-nutrition (African Union Commision, 2014). Massive loss of crops results from drought, pests and diseases, inappropriate agricultural practices and cost of production. Food and Agriculture Organization (FAO) indicates that in Kenya, Agriculture contributes to 26% GDP, employs 40% of total population and 70% of rural population(Food and Agriculture Organization of the United Nations, 2018). Timely and accurate detection and diagnosis of pest and diseases in plants still remains an open challenge due to inaccessibility of remote areas by agronomist and agriculture extension officers leading to delayed timely and accurate diagnosis of pests and diseases.

This study aimed at achieving the timely and accurate plant stress detection and diagnosis priority in digital imaging. This was achieved through digitizing diagnosis techniques that lead to increased detection accuracy of plant stress and thus timely response. Timely and accurate detection of pests and diseases in both open environment and controlled environments is key to the enhancement of food security.

Notifications to farmers were enabled through creation of a technological smartphone application capable of detecting and diagnosing pests' infestation and prevalence of diseases, and later provide recommendations to farmers on certified pesticides and herbicides to be applied on the detected stress. The smartphone application is branded as 'Tunza Leaf' which has been proven through validation using the similarity rate of correct comparison criterion (SRCC) (Chabrier et al., 2008) and testing among farmers through collection and sharing of knowledge, synergies and experiences. SRCC involves the comparison of the study versus human expert opinion.

There exists efforts made towards e-agriculture models (Aasha Nandhini, Hemalatha, Radha, & Indumathi, 2018; Kumba, 2019). The existing e-agriculture models apply artificial intelligence in agricultural robots, crop and soil monitoring and predictive analytics, weed control, crop harvesting, solid diagnosis and crop health monitoring, weather prediction and crop sustainability. Through emerging Artificial Intelligence (AI) and aerial technologies, the developed digital imaging model improved efficiency and addressed challenges facing the agriculture industry. The cost if implementation of existing robotic AI approaches was found more affordable through automation of the digital imaging model for plant stress detection, and diagnosis of plants pests and diseases, thought implementation of the model on a mobile smartphone and validation using the Similarity Rate of Correct Comparison (SRCC) criterion comparing expert farmers experience and the web based interface in enhancement of food security.

Timely and accurate detection of pests and diseases is pertinent to the reduction of hunger and enhancement of food security, through embracing digital imaging solutions leveraged by modelling artificial intelligence approaches for timely and accurate detection of pests and diseases in plants. There has been a limited focus on assessing how research efforts in ICT are contributing to solving the needs in provision of agriculture extension services (United Nations, 2017), for enhanced food security through timely detection and accurate diagnosis of plant stress.

All around the World, most farmers grow a variety of plants in order to harvest it as food, feed, fiber or for aesthetic value. Plants are vulnerable to stressors due to their physiological formation. Stress is categorized as either biotic or abiotic(Fujita et al., 2006). Abiotic stress is a physical or chemical insult that the environment may impose on a plant. Abiotic stress includes water, pollution, light, nutrient, salt, heavy metal, low temperature and high temperature. Biotic stress is a biological insult to which a plant may be exposed during its lifetime. Some biotic stresses include insects and disease infestation among others; which are the focus in this study. Plants respond to stresses either by resistance, susceptibility or avoidance (Nejat & Mantri, 2017). Resistance results into acclimatization, growth and survival. Susceptibility results into senescence and finally death, whereas avoidance results into survival. Plants are vulnerable to abiotic stress due to their exposure. Plants are immobile; hence they need to be protected. They contain molecular cues that enable them to endure different stresses exposed to them. In order to avoid stress factors, plants adjust their gene compositions, metabolism, growth and development characteristics so as to endure harsh stressors. In their quest to tolerate stress, some plants have better tolerance (Innocenti et al., 2016), resistance, protective and acclimatization survival mechanisms,(Bhargava & Sawant, 2013) while others do not. Visual detection of these plant stresses has been based on physical observation of the abiotic stress which affects the growth and physiology of the plants. Plant growth response affects germination, growth, maturity and productivity. Physiological plant response affects water uptake, transpiration rate, photosynthesis, respiration, and nitrogen assimilation.

To address the biotic stress factors, this study has applied knowledge generated through image recognition artificial intelligence techniques through deep learning and neural networks, on users' smartphone camera and investigation of strategies that address the problem of timely and accurate detection and diagnosis of stress in plants at an early stage. This study utilized convolution neural networks (Nachtigall, Araujo, & Nachtigall, 2017; Shen, Zhou, Li, Jian, & Jayas, 2018) that employ algorithms calibrated on smartphone application (Newzoo, 2017) by capturing images of plants in an open field and a controlled environment in a greenhouses. The smartphone application as well gives timely and accurate feedback to the user with the type of stress detected, information on the diagnosis and the recommended possible remedial solutions to the farmer. This strategy has been modeled through a digital imaging interface that apply deep learning (Arnal Barbedo, 2019), and which has timeliness and accuracy benefits. This is as opposed to the traditional approach where farmers conduct scouting by physically visiting the farms and identify stresses using the human eye and contact agricultural extension officer for advice.

There are numerous benefits of this strategy, namely; timeliness, accuracy, collaboration, active farmer participation, interaction between farmers, agronomist and agrochemical stores. Other benefits include; interaction with developers, remote mapping of affected regions, accurate and timely prediction of pests and diseases, accurate and timely feedback to farmers on the viability of their products to markets, and prediction of harvest time. This study developed the digital imaging model for plant stress detection, to enhance food security through timely detection and accurate diagnosis of plant stress. Smartphone mobile based solution in accessing plants grown in remote areas through ensuring timely detection, and accurate diagnosis of pests and diseases. This was achieved thorough digitizing diagnosis techniques leading to increased detection accuracy of pests and diseases and thus timely response to the impending stress, while giving recommendations on the actions to be taken in cases of the onset of an impending stress on the plants.

1.2 Problem Statement

Agriculture forms the base of economic growth and food security of most African countries (Mutanga, Dube, & Galal, 2017a), 239 million Africans (African Union Commision, 2014) are affected by hunger resulting to food insecurity. In Kenya, Agriculture contributes to 26% GDP and 70% employment to the rural population. However, most farmers have to fight off with different pests and diseases (Food and Agriculture Organization of the United Nations, 2018). This not only increases the cost of food production, but also often leads to massive loss of crops leading to hunger and food insecurity (Adhikari, Nejadhashemi, & Woznicki, 2015). To overcome this, timely and accurate detection and diagnosis of pests and diseases is pertinent. However, inaccessibility of remote areas by agronomists and agriculture extension officers delays timely detection and possible accurate diagnosis. Additionally, a number of pests and diseases bear closely related symptoms which lead to misdiagnosis by the agronomist as well. Consequently, the use of information and communication technologies have been considered as potential remedy.

Therefore, to better detect and categorize different pests and diseases, this study hypothesizes that there is need to integrate open field and controlled environments. This will not only provide a deeper understanding of image signatures but also enable the utilization of multiple inputs in predictive models for various pests and diseases.

Thus, this study proposes a digital imaging model for plant stress detection. The work is based on an experimental approach in which tomato images were captured in both open field and controlled environments to form the dataset. Digitizing detection and diagnosis techniques can enhance timely detection and accurate diagnosis of plant stress. Timely detection and accurate diagnosis of pests and diseases in open and controlled environments is key to enhancement of food security. Hence the need for a digital imaging model from plant stress detection.

1.3 Objectives

1.3.1 General Objective

The general objective of this study was to develop a digital imaging model for plant stress detection in enhancement of food security.

1.3.2 Specific Objectives

The following specific objectives guided the study;

(i) To analyze the existing image-based plant stress detection approaches

(ii) To establish the physical features of stress in plants

(iii) To map the physical features into digital imaging signatures characterizing stress in plants

(iv) To develop a digital imaging model for plant stress detection

(v) To validate the digital imaging model for detection of plant stress

1.4 Research Questions

(i) What are the existing plant stress detection approaches?

(ii) How does stress manifest itself physically on plants?

(iii) How can the physical features be mapped into digital signatures?

(iv) How can a digital imaging model be designed for plant stress detection?

(v) To what extent is the imaging model valid in the detection of plant stress?

1.5 Justification of the Study

Adoption of Smartphones has been facilitated by the entry of affordable devices that help drive strong data traffic growth across Sub Saharan region (Naik et al., 2017a). Smartphone technologies have contributed to Sustainable Development Goals (SDG) 2 and SDG 12, which contribute to Zero Hunger, and Responsible consumption and production respectively (United Nations, 2018). The SDGs are applicable among smallholder farmers struggling to sell their produce in urban areas, where issues with storage, transportation or intermediaries mean that city dwellers end up being overcharged for farm produce.

The Internet World Statistics Report of 30th June 2019, on internet usage among populations of the world indicates that Africa has a 39.8% internet penetration rate, against the rest of the world that stands at 60.9%. In the same report Kenya is the leading in Africa at 83% internet penetration among its population. Kenya is also the third leading country with the highest number of internet users with 43 million internet users, after Nigeria with 119 million users and Egypt with 49 million users. (Internet World Statistics, 2019). Kenya mobile phone connectivity by January 2020 increased by 4.2 million (+8.7%) between January 2019 and January 2020 (Kemp, 2020). This study was motivated by Internet World Statistics Report which put Kenya's internet penetration at 83%; Kenyan internet usage at 89%; and the Smartphone usage at over 60% as of year 2017, with massive movement of Kenyans from Cyber Cafés to Smartphones (Kaigwa, 2016).

As of September 2018, Kenya had a total of 42.2 million mobile phone subscribers on fixed data/internet; where Wananchi companies Kenya Limited was the leading with a market share of 39.2 % followed by Safaricom PLC with a market share of 27.6% and Jamii Telecommunications Limited with a market share percentage of 13.1% (Authority-Kenya, 2016). Kenya leads globally in technology for innovation in mobile and internet technology (Kimutai, Kimutai, & Mzee, 2010). Few Kenyans have (McCurdy, Perry Simone, Herrera, Heckathorne, & Perry, 2018) harnessed the existing services offered through Smartphone functionalities hence this study utilized the ability of Smartphones in the detection of stress in crops through modeling of Convolution Neural Networks (CNNs) by providing agricultural solutions for modern ICT enabled farming for timely detection and accurate diagnosis of plant pest and disease stress.

The study found out that farmers, in their geographical locations have access to minimal information on best practices in addressing timeliness in detection and accuracy in diagnosing stress posed by pests and diseases. The study also found out that farmers in their locations also lack authentic farming information with regards to the accurate diagnostic remedies to apply to their plants; as a solution to timely detection of the pest and diseases facing their crops. The farmers conducted manual traditional processes of crop monitoring when the effect of the pest and diseases has been noted. The farmers also face challenges of fetching best prices for their farm produce, and in accessing the market due to exploitation by middlemen due to their inability to access the best markets for the farm produce, which is not in the scope of this study. Tomato *(Lycopersicon esculentum)* is a key crop among farming population affected by pests and diseases but lacks artificial intelligence enabled digital imaging mechanisms for timely detection and accurate diagnosis of pest and disease stress.

1.6 Significance of the Study

Agriculture forms the base of economic growth and food security of most African countries (Waha et al., 2018). With this in mind, the digital imaging model was developed for mapping physical features to digital signatures. This was able to cushion farmers, agricultural stakeholders including suppliers and consumers of agricultural produce by enabling timely detect and accurate diagnosis of plant stress, and get feedback through a mobile based Smartphone application. For any feedback to be desirable, it must uphold integrity by being timely, relevant and accurate. With an automated digital imaging model, this was achieved and validated among farmers in their farms.

The findings of this study have generated interest among academia for further research on the dynamic area of image processing in farming. It is vital in the academic arena since it can be reviewed by other researchers. It has broadened understanding of the policy makers in the farming sector on the main benefits of digital imaging and computer vision in timely detection and accurate diagnosis of plant stress. The findings of this study have benefited agricultural consultants who endeavor to provide advice to various farming institutions on timely detection and accurate diagnosis of plant stress. The findings have made stakeholders at these institutions have a better understanding of the benefit of geographically mapping locations affected by pests and diseases so as to enhance food security through timely detection and accurate diagnosis of plant stress thus enhanced farmer access to digital agronomists.

1.7 Scope of the Study

Plants face numerous stresses during their germination both biotic and abiotic(A. Singh, Ganapathysubramanian, Singh, & Sarkar, 2016). These stresses result to losses and eventually food insecurity (Deng, Wang, Han, & Yu, 2018). Different plants are susceptible to diverse stresses. This study was done on the Tomato *(Lycopersicon esculentum)* plants by applying digital imaging techniques for timely detection and accurate diagnosis of pest and disease stress (Indriani, Kusuma, Sari, Rachmawanto, & Setiadi, 2018; Indriani, Kusuma, Sari, Rachmawanto, Setiadi, et al., 2018; Ireri, Belal, Okinda, Makange, & Ji, 2019; Jos & Venkatesh, 2020; Upender, Surendiran, & Reddy, 2018). Timely detection and accurate diagnosis by the farmers is achieved through harnessing Smartphone camera technology and recommendations through the digital imaging model implemented on the mobile phone application and validated through the web interface.

There are digital imaging approaches available for identification, classification, and quantification of biotic and abiotic stresses in plants with a variety of deep machine learning vision frameworks able to identify and classify stresses in plants (Christian Rose, Paulus, & Kuhlmann, 2015; Ghosal et al., 2018a; Margulies et al., 2006). A pre-trained deep learning algorithm was used for identification and classification of plant diseases (Arnal Barbedo, 2019; Coulibaly, Kamsu-Foguem, Kamissoko, & Traore, 2019a; Ferentinos, 2018; Omran;, 2017; Too, Yujian, Njuki, & Yingchun, 2019a; Verman, Shradha; Singh, Amit; Chug, Anuradha; Sharma, Shubham; Rajvanshi, 2019) including leaf curling (Mokhtar, Ali, Hassanien, & Hefny, 2015), early blight and late blight (El Massi, Es-Saady, El Yassa, Mammass, & Benazoun, 2016; Es-Saady, El Massi, El Yassa, Mammass, & Benazoun, 2016; Wang, Zhang, Zhu, & Geng, 2008); and plant pests (A. Fuentes, Yoon, Kim, & Park, 2017a; Mukhtar, 2010; Picon et al., 2019, 2019; Verman, Shradha; Singh, Amit; Chug, Anuradha; Sharma, Shubham; Rajvanshi, 2019) affecting Tomato (L. Zhang, Jia, Li, Gao, & Wang, 2019) including Tuta Absoluta (Desneux, Luna, Guillemaud, &

Urbaneja, 2011; El Massi et al., 2016; Es-Saady et al., 2016; Guimapi et al., 2016; Massi, Saady, Yassa, Mammass, & Benazoun, 2016; Venkatramanan et al., 2018), leaf miner (El Massi et al., 2016; Es-Saady et al., 2016; Massi et al., 2016), whiteflies (Huddar, Gowri, K., S, & Rupanagudi, 2012; Y. Li, Xia, & Lee, 2015; Xia, Chon, Ren, & Lee, 2015) and aphids (Xia et al., 2015) pest. Images were captured in an open field and controlled environment.

The algorithm was modeled and made available and usable through Smartphone application. The Smartphone application was integrated with a web-based interface that resided on an Alienware Graphics Processing Unit (GPU) computer server that receives the images and Geographical Positioning System (GPS) locations of where the detected stresses were identified by the farmers. The Smartphone application was configured with stress characteristics of major plants based on the findings from the farmers. They were created with an ability to send diagnosis messages to farmers, through their mobile phones, for preventive action to take and information concerning any other farm related information with linkages to suppliers of the farm inputs, digital agronomist assistance and approved agrochemical manufacturers and suppliers. The Smartphone application interface was tested and validated in the open field and in controlled environment by the farmers for timely detection and accurate diagnosis of tomato pests and disease stress.

1.8 Assumptions of the Study

This study assumed that the changes in the plants surface structure, reflectance, and transpiration patterns are expressions of its internal physiological changes; and assumed that color features in the visible spectrum provide additional image characteristics over the traditional grey-level representation. This study also assumed that farmers have access to affordable Smartphones with cameras and internet and that the farmers can grow tomato plants in their farms and that plant stress characteristics would be the same for all tomato plants. This study further assumed that users would be able to learn and adopt to the new system, and that the digital imaging model, web interface and mobile phone application interface would operate optimally without failure.

1.9 Thesis Structure

This thesis seeks to extend knowledge in Agriculture, more precisely by integrating deep learning in timely detection and accurate diagnosis plant stress in both open field and controlled environments. To achieve this, the work has been divided into six chapters as outlined;

Chapter One discusses Information Communication Technologies as an enabler in modernization of agriculture from an international, regional and local level, defines plant stress, outlines the causes of plant stress, highlights existing approaches of plant stress detection, and the importance of timely detection and accurate diagnosis of plant stress, while exposing challenges with relation to the existing approaches. This section further goes ahead to state the problem in the study, the general and specific objectives, the research questions, justification of the study, significance of this study, the scope and assumptions of this study, and the thesis structure.

Chapter Two reviews literature related to this study. In this chapter, a review of plant stress concepts is discussed, with a focus on abiotic and biotic plant stress detection. Image based stress detection in plants is also reviewed for both analog and digital image-based analysis. Traditional plant stress classification approaches are reviewed with a focus on its limitations. Emerging technologies and their importance on agriculture are also discussed with a review on mobile technology, deep learning and food security. An overview of the deep learning approaches in plant stress reviewed, deep Convolution Neural Networks pests stress classification is discussed, focusing on digital plant imaging stress signatures and image processing techniques. Digital plant image stress signatures are reviewed with a focus in height ration, leaf area index and biomass. Image processing techniques are also reviewed with a focus on preprocessing, feature extraction, classification and grey level co-occurrence matrix. Finally, the theoretical frameworks related to the model designed is reviewed. Generally, this chapter addresses the concerns of objective one of this study.

Chapter Three highlights the methodology that was used in the study. The chapter highlights the research philosophy, research design, the location of the research, the study population, the sampling procedure and sample design and size, the data collection procedure, data analysis techniques, validity and reliability, the research instruments used include Smartphone cameras, farmer interview schedules, and participatory observation, validity and reliability of the research instruments used and ethical considerations for the study then a summary of the chapter. This chapter responds to objective five.

Chapter Four discusses plant stress signatures. It outlines the demographic information, physical features of stress in plants, and maps them with the digital imaging signatures characterizing stress in plants. The image preprocessing, resizing, rescaling and horizontal flip are discussed. Feature extraction processes including Gaussian blur, thresholding, eroding, dilating and histograms are discussed. Predictions using the trained model for tomato pests and diseases, and prediction are discussed on this chapter. This chapter responds to objectives two and three of this study.

Chapter Five derives the digital imaging model that responds to the fourth and fifth objectives, as well as answering fourth and fifth research questions. This chapter entails the description of the digital imaging model for plant stress detection, the digital imaging model summary, SoftMax activation function, and optimization with the Adam Optimizer, Similarity Rate of Correct Comparison (SRCC), confusion matrix and web interface for validation, and graphical plots for the result of the model. It also includes several graphs that provide the accuracy measures based on the training steps, training sets and the training epochs. The chapter goes ahead to visualize the details of the digital imaging model for plant stress based on the Tensor Board. The details of the model are discussed based on the tensor attributes, inputs and outputs that relate to identity, lambda, merger, optimizer, production, training, module and tensors. The graphs relating to the model are also discussed as per the scalar, distribution and histogram.

Chapter Six concludes by mapping the objectives to their respective sections attained outlining its importance to policy, while spelling out recommendations for adoption and usage of the developed tools, and outlines the direction for future research based on the gaps that were realized in the course of the study.

CHAPTER TWO

LITERATURE REVIEW

2.0 Overview

This chapter provides a detailed review of literature related to this study. Further, the chapter explores the concept of plant stress with reference to physical image-based stress detection, the biotic and abiotic stress characterization are also discussed. In addition, the chapter reviews the status of mobile phone technology penetration and prevalence, deep learning and food security. Further, imaging processing techniques are reviewed with a focus on preprocessing, feature extraction and classification. Finally, the digital imaging signatures, analog and digital based detection approaches are surveyed while presenting a theoretical framework.

2.1 Concepts of Plant Stress

Stress is an altered physical condition resulting from either biotic or abiotic factors that disrupt the equilibrium in plants. Plant stress initiates modification of the leaf structure so as to adjust light reflection on the leaf surface, which affects the color of the leaf surface and the texture of the leaf (Ghosal et al., 2018a; Naik et al., 2017b). Plant stress may result from excessive supply of water to plants in the field resulting to water logging and clogging and is important for plants that require excessive water quantities for growth and production (T. Zhao, Stark, Chen, Ray, & Doll, 2017). Plant stress may also be caused by minimum or no supply of water to plants during the period of growth and is important for crops during the harvest time of mature crops (Alter et al., 2015; Duarte-Galvan et al., 2014). Plant stress resulting from weeds is caused by growth of unwanted crops among crops planted for human consumption or economic purposes. Weeds compete for nutrients and water. However, weeds have various benefits. For instance, they play a critical role in facilitating cross pollination, and can serve as feeds for animal consumption or for aesthetic value (Jan Behmann, Mahlein, Rumpf, Ro, & Plu, 2015). Plant stress resulting from nutritional deficiency is caused by deficiency of ingredients necessary for plant growth (Nachtigall et al., 2017), while plant stress resulting from disease is caused by microorganisms that affect growth and yield of crops. Plant disease stress is important for regulating the quantity of yields. Plant pest stress is caused by attacks on the physical composition of plants and their seeds by flying and crawling pests and insects and it is important as food for birds and biodegradation which result into enrichment of soil fertility (Herala, Vanhala, Porras, & Krri, 2016; Jige, 2017; Tichkule, 2016). These categories of stress in plant can be seen as either abiotic stress or biotic stress.

2.1.1 Biotic Plant Stress

Biotic stress is a part of the ecosystem which impacts production of plants affecting food security. Biotic stress relates to living factors affecting crops including fungi, but not limited to bacteria, virus, weeds, parasites, insects and pathogens (Dhingra, Kumar, & Joshi, 2018; Kumba, 2019; A. Singh et al., 2016). Plants have unique ways of responding (Czedik-Eysenberg et al., 2018; Joshi et al., 2016; J.-M. Kim, Sasaki, Ueda, Sako, & Seki, 2015; Koryachko et al., 2015) to stress as a mechanism to enable them survive the threat of the stresses they face. To ensure that the plant cells are protected from the effects of stress, the plant defense reactions can be at molecular level (Virlet, Sabermanesh, Sadeghi-Tehran, & Hawkesford, 2016) or cellular level (Guimapi et al., 2016). Biotic stress in plant results to less leaf area due to plant senescence, leaf curling and wilting resulting to lower harvest weight, plant diameter, height and less leaves (Omran, 2016; Saakre et al., 2017) .

2.1.2 Abiotic Plant Stress

Abiotic stress (Ghosal et al., 2018a; Lowe, Harrison, & French, 2017) majorly focus on plant growth and metabolism, controlling pathogens and systemic tolerance (Saakre et al., 2017). Abiotic stress relates to non-living factors such as drought, flood, nutrient deficiency, and other environmental factors. Biotic stress (Nejat & Mantri, 2017) is concerned with deficiencies of water and nutrients, insect infestation in vegetation, which result to cell structures that impedes photosynthesis and transpiration in affected tissue or plant (Virlet et al., 2016).

Drought stress arises from deficiency of sufficient water for use or consumption by the crops in the field (B. Singh, Bohra, Mishra, Joshi, & Pandey, 2015). The weakness of this approach is that it requires the farmer to be physically present in the farm so as to identify the effect. Additionally, the effect must have been inflicted on the plant for it to be physically noticed by the farmer(B. Singh et al., 2015). The advantage of this approach, however, is that the farmer is able to notice whether the dryness of the plant is as a result of maturity for harvest or as a result of water deficiency. Most crops in Kenya have suffered from drought stress (Huho & Mugalavai, 2016), (Adhikari et al., 2015), (Opiyo, Wasonga, Nyangito, Schilling, & Munang, 2015) as a result of climate change, poor and inadequate rainfall and unavailability of irrigation mechanisms due to their associated cost.

2.1.3 Biotic Plant Stress Detection

Inducible immunity is one way of plants response to pathogens (Nejat & Mantri, 2017). In this approach plants detect the pathogen attack and transmit this information through a signaling network within cells and distance tissues; resulting to the initiation of a defense response. However, pathogens have been known to attack the signaling network. Plants and animals detect the presence or absence of potential pathogens through the perception of conserved microbial patterns by cell surface receptors. Potato, pepper and tomato being salacious plants detect flgII-28 which is a region of bacterial (Hind et al., 2016) flagellin that is distinct from that perceived by flagellin sensing 2 receptor(Hind et al., 2016). Tomato contains flagellin sensing 3 receptor that binds flgII-28 and enhances immune responses leading to a reduction in bacterial colonization of leaf tissues (Hind et al., 2016). Recent research show that histones(J.-M. Kim et al., 2015) found in nucleosomes when modified play an important role in plant stress memory in response to effects of chromatin in plant stress.

2.1.4 Abiotic Plant Stress Detection

The conventional approaches that exist in abiotic plant stress detection are based on the various classifications of stresses. Abiotic stresses that affect plants include weeds (Ip, Ang, Seng, Broster, & Pratley, 2018; Khanna et al., 2019; Tamouridou et al., 2018), nutritional stress (Memeu, Kirongo, & Boiyo, 2017), disease stress (Rançon, Bombrun, Keresztes, & Germain, 2019; Wahabzada et al., 2015), pests stress (A. Fuentes, Yoon, Kim, & Park, 2017b), water stress (Cheruiyot, Midega, Van den Berg, Pickett, & Khan, 2018; Katsoulas et al., 2016; Mazare, Ionescu, Visan, Lita, & Serban, 2018) and drought stress (Gente, Born, Balzer, & Koch, 2016; Kirongo, 2016a; Saakre et al., 2017). Nutritional stress (Contreras-Medina et al., 2012; Nachtigall et al., 2017) is always detected by the farmers once they notice changes in coloration of the leaves of the plants. Disease effects of crops always show after the impact has been felt (Coulibaly et al., 2019a). Weed stress is generally detected by the human eye after planted crops have sprouted. After watering, plants that were not initially grown by the farmer appears on the ground. Such plants are usually considered as weeds and appropriate farming mechanisms are taken (Jan Behmann, Mahlein, Rumpf, et al., 2015). Water stress emanates from excessive downpour or floods which come about when excessive water is supplied to the field (Massi et al., 2016). In addition, drought stress results from deficiency of water for use or consumption by the crops in the field (Picon et al., 2019)[41]. The resulting effect of this stress chiefly includes food insecurity due to the inability of food production in dry soil.

2.2 Image Based Plant Stress Detection

Image based plant stress detection has been utilized in the recent past in plant stress detection. They range from use of sensors technology, static scanning technologies, fisher discrimination analysis and three-dimensional modelling. Sensing technologies like magnetic resonance, soft x-ray imaging, and ultrasound, have been used to detect phenotypic reactions (Simko, Jimenez-Berni, & Sirault, 2016) during plant-pathogen interaction. Static scanning technologies have also been used to collect images of crops and work on parameters using RGB mean value function and using the hierarchical identification of NPK deficiencies, using the region pop function in MATLAB. Fisher discrimination analysis has been used to build a diagnostic model in validation and accurate identification of Nitrogen (N) Phosphorus (P) and Potassium (K) deficiencies (Khanna et al., 2019), the findings from this study based on rice can also be applicable and developed in similar plant family.

Field Programmable Gate array (FPGAs) based Smart Sensor (Basnet & Bang, 2018; Negrete, 2018) for Drought Stress Detection in Tomato plant have also been used (Fan et al., 2018) to monitor primary variables in plants to detect and monitor drought stress in normal plant growth conditions. Deficiency of moisture causes leaf color changes due to decreased chlorophyll content that arise from chloroplast oxygen. Additionally, thermal based imaging has been used to detect water deficiency in plants (Bhugra, Chaudhury, & Lall, 2016), (Blumenthal, Megherbi, & Lussier, 2014; Raza, Prince, Clarkson, & Rajpoot, 2015). Plant phenolic analysis (Lorigooini, Jamshidi-kia, & Hosseini, 2020; Yuming Sun et al., 2020) demands a variety of sensors be used to measure physical characteristics of plant surface and to estimate the plant biomass. Studies that focus on plant 3D Modeling methods are made up of three steps which include image quality improvement, plant segmentation, and 3D construction (Jan Behmann et al., 2016). Chlorophyll fluorescence (ChlF) (Simko et al., 2016) in plant response to stressors over time, has been identified as a vital tool to detect plant stress. Timely detection and accurate diagnosis of plant stress is imperative in enablement of farmer access to digital agronomists for enhanced food security.

2.2.1 Analog Image Based Analysis

An analog image analysis signal is a signal that is amplitude modulated between two limiting levels, the maximum black level and the maximum white level corresponding respectively to black elements and white elements of the image (Britton, 1985). It is an invention that applies a self-adaptive, all-or-nothing converter of an analog image analysis signal, that related to all-or-nothing converters for analog image analysis signals captured from a document interpreted as image analysis signals. The transmitters in this invention were used in devices installed with the capability of transmitting facsimile signals. Images detected by photo diodes as analog signals compared both the white level and the black level through an analog process.

The analog signal required to be compared with a threshold that existed in between the modulation limits of the white and the black levels, where the decision threshold of white is set to a value almost to the level of white. When the image to be analyzed is greyscale or colored, the analog analysis signal is compared with a constant decision threshold, that enables the conversion of an analog image onto a two-valued signal. Image analysis is aimed at localization and identification of image structures, the measurement of single parts of the image and the investigation of the whole image as regards its density and structure (Ulf R. Meinel, 1990). Images are analyzed to keep errors low in a simple and practical approach for correct interpretation and reproduction. A wrongly used method may result to improper interpretation. Therefore analysis of the relationship between the problem, object, method and result is very vital (Ulf R. Meinel, 1990).

There exists three groups of analog image analysis which include optical-photometric procedures; photographic procedures, and color coding and color mazing (Deepak & Adams, 1983). Analog image analysis is applied in taking images with standard format cameras for accuracy in solar aureole radiance measurement. Photography data reduction techniques in analogue image analysis include photometry relations, densitometry, sensitometry, photogrammetry and off-axis illumination distribution. (Deepak & Adams, 1983) describes procedures for setting up a photographic analog imaging system for sky and quantitative spectral radiance measurement for ease of use with Nikon and Hasselblad camera, which are suitable for capturing images both on land and on the stratosphere. (Corrêa Alegria & Cruz Serra, 2000) utilizes image analysis algorithms to automate system calibration computer vision techniques for measuring instruments that lack a digital interface. Originally analog cameras did not have a digital interface that could interpret the images. This study relied on the approach by (Corrêa Alegria & Cruz Serra, 2000) in the calibration of cameras by generating a software application interface with a user-friendly interface that enables users with minimal training to perform the calibration procedure of capturing and interpreting the images of plants. The use of analog image-based analysis approach creates a deeper understanding of how repeatability and systems can be enhanced for accuracy in calibration of automated measurement instruments in computer vision.

2.2.2 Digital Image Based Analysis

Digital image based analysis can be traced back to the year 1954 when (Kirsch, Cahn, Ray, & Urban, 1954) describes a research experiment that would allow complex investigation of pictorial information by suggesting that computers be programmed to process such information with ease as per how humans process visual information. (Kirsch et al., 1954) proposes development of automatic techniques for the recognition of visual patterns, and suggests automation of those techniques. Later on in 1966 (Pfaltz, 1966) automated the technique through programed code, after IBM wrote and tested a program in FAP symbolic assembly language, which later became a FORTRAN subroutine that accepts a digital picture on magnetic tape as input.

Each row of picture element had a value from 0 to 2^6-1, and each row had up to 2000 elements. Image classification has evolved overtime as a complex process that is (D. Lu & Weng, 2007) based on practices, problems and prospects of image classification. Modern advances in digital image classification approaches and techniques improve (Barbedo, Koenigkan, & Santos, 2016; Ghyar & Birajdar, 2018) classification accuracy and classification performance. Existing literature suggest that the design of a suitable digital imaging image-processing procedure, should result to successful classification performance. Multiple features (El Massi et al., 2016) can be considered for effective selection and classification of multiple features for improved classification accuracy.

Existing work operates with data classification from multiple sources (D. Lu & Weng, 2007) has considered non-parametric classifiers (D. Lu & Weng, 2007; M.

Kacira, P. P. Ling, & T. H. Short, 2013; Yong et al., 2016) like decision trees, knowledge based classifiers and Neural Network classifiers (El Massi et al., 2016; Golhani, Balasundram, Vadamalai, & Pradhan, 2018a; D. Lu & Weng, 2007; R. & Park, 2018) which is the main focus of classifier in this study. Modern research has embraced remote sensing of digital images from multiple data sources, integrated with (D. Lu & Weng, 2007) Geographical Information Systems (GIS), and recommender systems (T. Li, Zhao, Liu, & Huang, 2017). This study has applied the deep learning while identifying and reducing the errors that originate from the image-processing chain by improving on the classification accuracy.

Image segmentation is an important aspect in the detection of physical characteristics of plant leaves. This is achieved using genetic algorithms (Samuel, 2000). The color of plant leaves is closely correlated with nitrogen (N) status and can be easily quantified with a digital still color camera coupled with image processing software. Image color indices and N status under natural light is vital for plant monitoring and N diagnosis in the field (Tan, Yuan, & Wang, 2003). (M. Lee, Yoe, Lee, & Yoe, 2015) discusses an Analysis of environmental stress factors using Artificial Growth System and plant fitness optimization. Image segmentation (Sandler, Howard, Zhu, Zhmoginov, & Chen, 2018a) involves a system made up of IoT sensors which monitor plant growth status which sense (Sayad, Mousannif, & Le Page, 2015) electrical conductivity, pH, temperature, humidity, CO_2, and light based on collected information through the sensors designed to remotely collect plant information(Khanna et al., 2019) and communicate over the internet by handling information collected remotely in a cloud database and can be accessed remotely by the users. Plant growth is analyzed based on historical information regarding sowing, (Nejat & Mantri, 2017) plant growth conditions, and harvest. Thereafter, appropriate growth conditions are then defined based on the plant analysis (Katsoulas et al., 2016)approach selected.

Physical traits of the plant surface have become an interesting area in recent research work that is aimed at the 3D plant modeling(Lewis, 2007; Liang, Zia, Zhou, & Sirault, 2013; Omasa, Hosoi, & Konishi, 2007). Concepts include building of 3D plant models based on digital imaging techniques of acquiring hyperspectral images(Lowe et al., 2017) through hyperspectral image captured in a controlled lab environment. This approach is based on the 3D mesh processing algorithmic (Furbank et al., 2011)technique for 3D plant analysis which is used as an imaging based, automated, non-invasive, and non-destructive high-throughput plant phenotyping platform for acquiring and recording raw data calibrated, reconstructed, and analyzed in the development of sophisticated image understanding and quantification algorithms (Lewis, 2007).

This approach has proved to be beneficial in the generation of 3D plant models in the machine learning based plant segmentation (U. Lee, Chang, Putra, Kim, & Kim, 2018; V. Singh & Misra, 2017) of the plant image from its background based on K-mean clustering algorithm for segmentation and Neural Network for classification (Anand, Veni, & Aravinth, 2016). Recent developments in hardware and software have resulted from the increased performance of hardware and the advent of powerful graphical processing units (GPUs) (Abadi et al., 2016; Bridge, 2005) applied in scientific computing. Image annotation based on user generated images on Facebook, Instagram and Twitter as well as online search (Bridge, 2005) engines through application of Convolution Neural Networks in face recognition (Koo, Cho, Baek, Kim, & Park, 2018). CNN has been applied for training of images in the recognition of account users and further applied in timely plant stress detection and accurate diagnosis of plant stress.

Besides training data being one limiting factor for visual monitoring at a certain level of quality, there are several other and equally important challenges from the (N. Zhang, Donahue, Girshick, & Darrell, 2014) computer vision and machine learning perspective. These includes: the number of plant species to be distinguished with relation to their stressors, generic classifiers that learn feature representations of data by extending existing systems for analyzing and optimizing for monitoring different plant classes; fine-grained recognition that identifies relevant visual parts of images to allow for reliable classification for visually similar species; detection of the unexpected species (Krause & Jin, 2015) unknown to the ML classifier or wrongly assigned to a class; and anomaly detection, keeping the human in the loop in detection of partially visible plant in the images for reliable statistical feedback from the machine to the farmer, and feedback from the farmer to the machine for refinement and optimization of the digital image processing system (Aghaei, Leva, & Grimaccia, 2016).

2.2.3 Sensor Technologies

A variety of sensors applied for plant noninvasive investigations (Rose et al., 2016) in different scales and modalities include magnetic resonance imaging (Simko et al., 2016), positron emission tomography (Simko et al., 2016), hyperspectral imaging for rich pixel information on plant properties, and optical imaging (L. Li, Zhang, & Huang, 2014). Challenges in measuring plant visible properties include shape, size and other structural traits of plant organs and population. Plants are self-changing and not static systems. Plants have complex shapes and appearances which keep changing over time. Algorithms are expected to deal with the highlighted complexities (Minervini, Scharr, & Tsaftaris, 2015). Wireless sensor networks (Aqeel-ur-Rehman, Abbasi, Islam, & Shaikh, 2014; Dahiya, Shamim, & Kumar, 2015) have been broadly employed in the detection and remote transmission of images and features of detected images in the drought stress experimental setup (Berger, Parent, & Tester, 2010).

2.3 Traditional Plant Stress Classification Approaches

The past decade has witnessed an upsurge in remote sensors by a variety of Earth observations platforms, including but not limited to aerial systems, Unmanned Aerial Vehicles (UAV), and satellite devices (H. Kim, Ben-Othman, & Mokdad, 2017). Such technologies have continued to contribute daily to the growth of availability of very fine spatial resolution (VFSR) images (C. Zhang et al., 2019). VFSR images avail unique spatial details, for practical application in many areas including precision agriculture (Ozdarici-Ok, Ok, & Schindler, 2015), and land-cover and land-use classification (Ghulam, 2014). Land-cover classification is complex because of its heterogeneity due to illumination conditions among other conditions, whereas land-use classification is challenging due to the indirect relationship between the physical Earth surface characteristics and being a function of human activities cannot be interpreted using texture, tone, or shape of image features (M. Li, Stein, & Bijker, 2016).

The classification of land-cover and land-use remotely sensed images is still an open unresolved area in the research on remote sensing, hence the need for alternative plant stress detection approaches. The past decades have seen tremendous efforts made in the development of automated plant stress classification methods using remotely sensed digital imagery. Traditional classification approaches for land-cover can be broadly classified into either per-object or per-pixel depending on the basic processing unit.

Per-object method is built upon the homogenous objects of pixel values across the image in the identification of land cover by observing physical properties such as shape, texture and spectra of ground components in classifications using methods like VFSR imagery. The method that has dominated the identification of land cover is the approach known as object-based image analysis (OBIA) (Sandler, Howard, Zhu, Zhmoginov, & Chen, 2018b). OBIA framework has been used in the classification of land use based on spatial context both within-object information like texture, spectral and shape; and between-object information including direction within adjacent objects, contiguity, connectivity and distances. It has a major challenge of selection of segmentation scales to obtain an object corresponding to a given land cover (Blaschke, Lang, & Hay, 2008).

Pixel-based methods are widely used in the classification of individual pixels in to specified land cover categories based on spectral reflectance. Hence this method is limited in classification performance due to the increased inter-class variance resulting to pixel-based approaches that rely on post-classification (Hester, Cakir, Nelson, & Khorram, 2013). Precision agriculture focused on plant stress detection requires a more focused approach to the leaves, stem and fruits. Stress is an altered physical condition resulting from factors that disrupt the equilibrium in plants and is categorized to either biotic or abiotic (Jan Behmann, Mahlein, & Plümer, 2015; Lin, Chen, Si, & Wu, 2013b).

Plant stress resulting from weeds is caused by growth of unwanted crops among crops planted for human consumption or economic purposes. Weeds compete for nutrients and water. However, they are important as animal feeds, food and aesthetic value for humans and facilitate cross pollination among other benefits (Jan Behmann, Mahlein, Rumpf, et al., 2015). Plant nutritional stress is caused by deficiency of ingredients necessary for plant growth (Nachtigall et al., 2017), while plant disease stress (Golhani, Balasundram, Vadamalai, & Pradhan, 2018b) is caused by microorganisms that affect growth and yield of crops and it is important for regulating the quantity of yields.

Pests stress is caused by attacks on the physical composition of plants and their seeds by flying and crawling pests and insects and is important as food for humans, animals, birds and biodegradation resulting into enrichment of manure (Huddar et al., 2012). Water stress is caused by excessive supply of water to plants in the field resulting to water logging and clogging and is important for plants that require excessive water quantities for growth and production (T. Zhao et al., 2017). Drought stress is caused by minimum or no supply of water to plants during the period of growth and is important for crops during the harvest time of mature crops (Alter et al., 2015; Duarte-Galvan et al., 2014).

2.4 Limitations of Traditional Plant Stress Classification Approaches

Most of the traditional methods of classification for plant stress are manually hand-engineered in feature design, and classification on their architecture involves two complementary steps, namely; feature extraction and classification (Zhu et al., 2017). Feature extraction is done by specified operators on local portions of the image (e.g. objects, image regions, image patches, or pixels) to transform the original spectral feature space to an abstract representation ready for supervised classification (Yanbiao Sun, Zhao, Huang, Yan, & Dissanayake, 2014) so as to recognize the content of the input imagery (Y. Chen, Jiang, Li, Jia, & Ghamisi, 2016). Hand-engineering features is a tedious trial-and-error process for feature extraction and selection (Zhu et al., 2017). It is a tedious process because the features are task specific. Use of low-level features are not sufficient to mine underlying semantic functions due to the lack of higher-level feature representations (Yuan-Yuan, Lin-Lin, Yue-Yong, & He, 2017) hence limited classification performance has been achieved to-date which apply very fine spectral images that are structurally and spectrally complicated.

2.5 Emerging Technologies and Importance in Agriculture

Artificial Intelligence (AI), Machine Learning (ML) (Dosovitskiy & Koltun, 2016) and Deep Learning (DL) technologies have greatly influenced this study. The term 'AI' was coined by John McCarthy, in the year 1956 during the Dartmouth Conference when he stated that AI is "The science and engineering of making intelligent machines, especially intelligent computer programs" (Buchanan, 2005). Recent advances in big data has led to the growth of AI through combination of large amounts of data sets with intelligent algorithms, allowing AI Softwares to automatically learn from the patterns or features in the large amounts of datasets. AI has been adopted in various areas including self-driving cars, real-time face recognition in airports just to name a few. Deep Neural Networks (DNN) leads in the Gartner's list of Hype Cycle Emerging Technologies of year 2018 (Gartner, 2018). Artificial Neural Network (Genç, 2019) and Deep Neural Network Technology are illustrated in Figure 2.1. and Figure 2.2.

ML is a subset of AI, and is made up of sophisticated techniques and models that enable computers to deduce meaning out of data and result to AI application. ML is the science of getting computers to act without explicit programming.

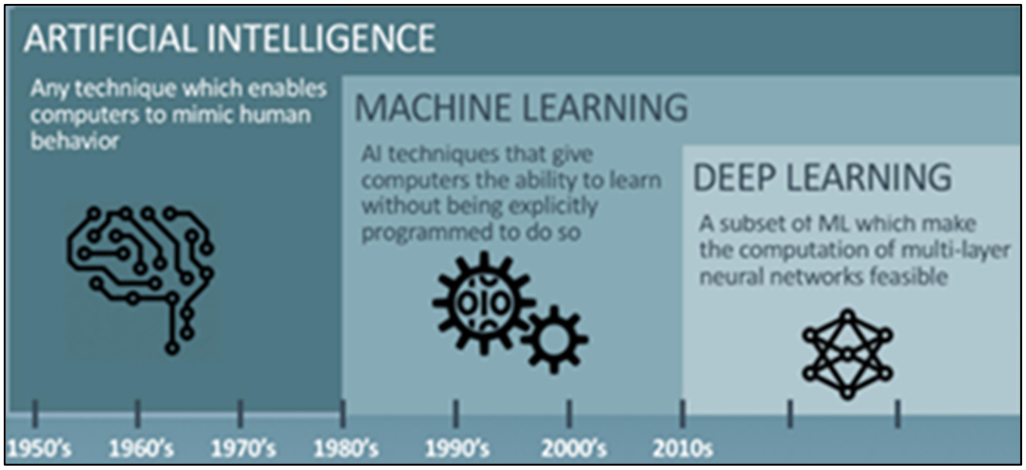


Figure 2.1: Artificial Neural Network Evolution

(Source: Genç, 2019)

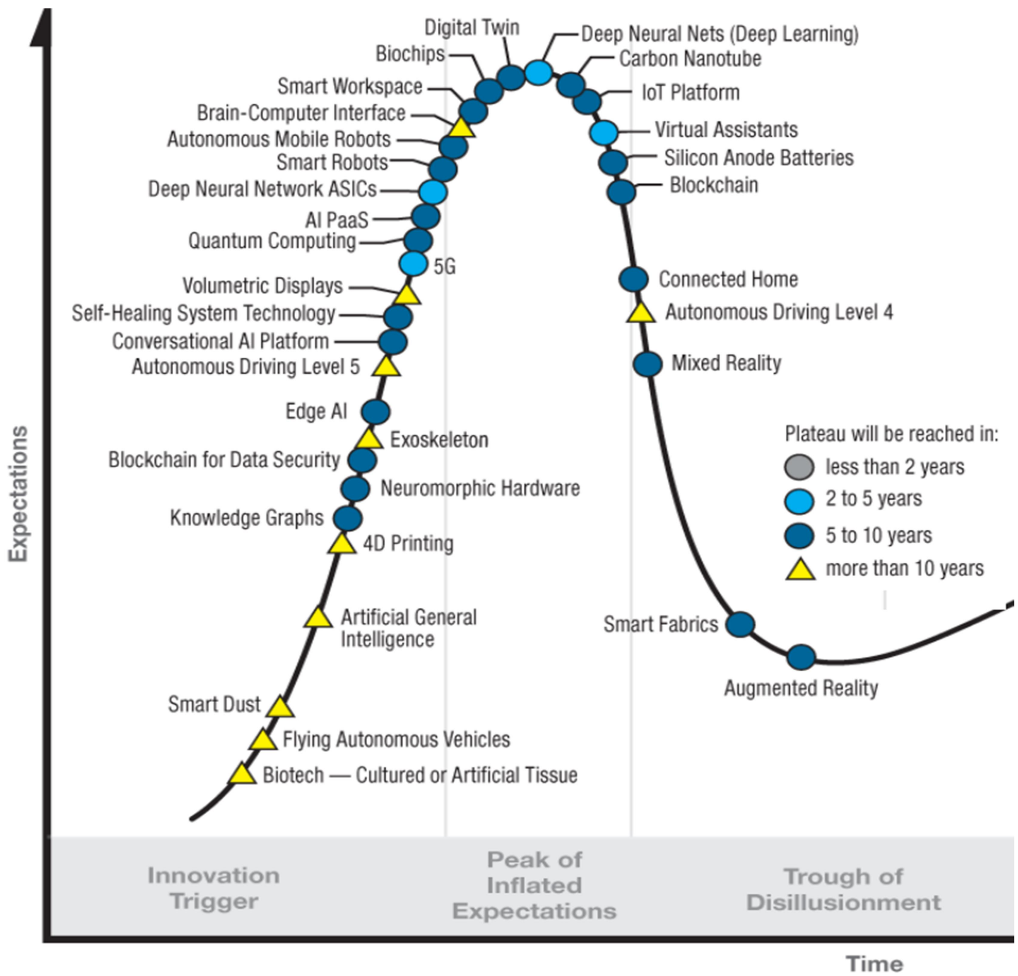


Figure 2.2: Deep Neural Network Technology

(Source: Gartner, 2018)

Machine Learning (ML) (Udompetaikul, Slaughter, Lampinen, & Shackel, 2011) communities developed data mining techniques which are increasingly being used for a variety of environmental applications, and have shown a potential for plant stress monitoring. Data mining approaches in ML involve tools and techniques that incorporate ML Methodologies of pattern recognition, statistics and visualization designed to identify complex patterns related to variables. The ML approach is flexible in handling different categories of data types, that are un-normalized, and hierarchically related among variables to model an output.

ML (Fielding, 1999) has been applied in a computer vision study method for prediction of cherry tomato volume and mass based on machine learning algorithms has been done (Nyalala et al., 2019) where tomato mass and volume was established as M = 1.312V 0.9551, and was used to estimate mass on a test dataset at an R2 of 0.9824 and RMSE of 15.84g. The depth of tomato images at different orientations were acquired and features extracted by image processing techniques and five regression prediction models based on 2D and 3D image features were developed. The RBF-SVM outperformed all explored models with an accuracy of 0.9706 (only 2D features) and 0.9694 (all features) in mass and volume estimation respectively. The model predicted mass or volume can then be applied to the established mass-volume power function. This system can be applied as a non-destructive, accurate and consistent technique in sorting and grading of cherry tomatoes based on mass, volume or density. AI, machine learning and deep learning technologies have been illustrated in Figure 2.3.

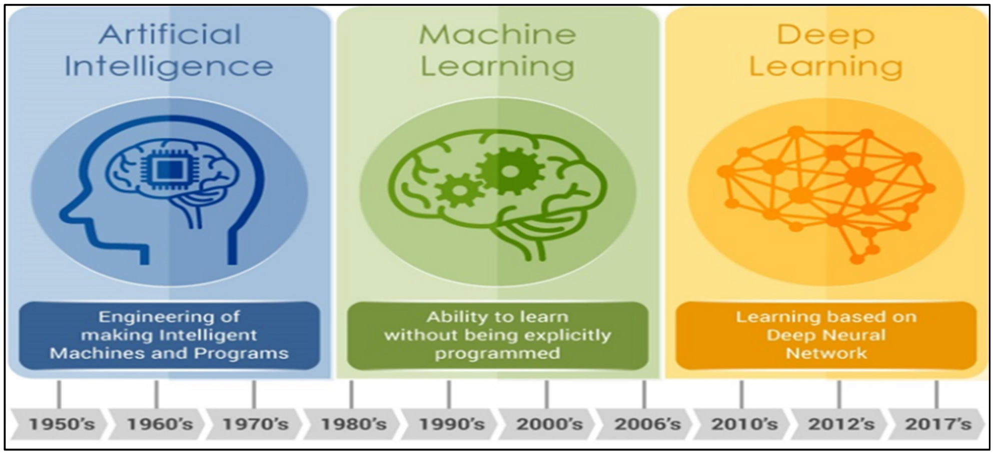


Figure 2.3: Artificial Intelligence, Machine and Deep Learning Technologies

(Source: Genç, 2019)

Machine Learning is made up of different models that fall into three different categories namely; Supervised, Unsupervised and Reinforcement Learning (Hoo-Chang Member et al., 2016; Rehman, Mahmud, Chang, Jin, & Shin, 2019; Schmidhuber, 2015). Supervised learning entails association of output labels with dataset instances. The outputs can either be discrete, categorical or real-valued. Real valued output involves a supervisor that is more knowledgeable than the neural network itself. It involves training of algorithms (Hill, 2016) for a number of times with the input data set that is tagged with the classification so as to aid the ML in learning the characteristics of the subject. ML requires data labeled with direct feedback to predict the outcome(Fielding, 1999), and works well with techniques such as linear or logistic regression and decision tree classification. regression applies in problems where we are required to predict and forecast for continuous-response values when provided with datasets and an algorithm that predicts the outcome based on a fitting function.

Classification is where certain observations in a group require categorization. Unsupervised Learning is an unaided type of learning when handling data sets (De Mauro, Greco, & Grimaldi, 2015) with known answers but search is focused on a hidden pattern that employs clustering and association. Clustering entails grouping of similar things together while association entails discovering of exact rules that describe large portions of data. Reinforcement Learning (RL) (J. Li et al., 2016) entails systems that are trained by receiving virtual "rewards" or "punishments", essentially RL is learning by trial and error. The algorithm applicable in reinforcement learning adjusts its weights to make better decisions in subsequent times. Reinforcement Learning (RL) is applied popularly in Deep Learning based on a number of hidden nodes according to the algorithm applied.

Deep Learning (DL) (Yoshua Bengio, Goodfellow, & Courville, 2015) is a statistical learning method that extracts features from raw datasets. DL does this by utilizing multi-layered artificial neural networks with hidden layers stacked one after another. DL has sophisticated algorithms and requires powerful computational resources. DL is made up of three popular models. These models include Recurrent Neural Networks (RNN) (Oord, Kalchbrenner, & Kavukcuoglu, 2016; S. Zheng et al., 2015), Generative Adversarial Networks (GNN) (Gan, 2017; Radford, Metz, & Chintala, 2015), and Convolution Neural Networks (CNN) (Sandler, Howard, Zhu, Zhmoginov, & Chen, 2018c)(Vedaldi & Lenc, 2014). Deep Learning (DL) (Radford et al., 2015)employs multi-layered artificial neural networks (ANN) (Sakuta & Kudoh, 2018) to deliver high accuracy in tasks like detection of objects (L.-C. Chen, Papandreou, Kokkinos, Murphy, & Yuille, 2018), translation of language, recognition of speech (W.-L. Zheng, Liu, Lu, Lu, & Cichocki, 2019) and plant disease diagnosis (A. F. Fuentes, Yoon, Lee, & Park, 2018; Saurkar & Watane, 2012),(Petrellis, 2017), as well as in measuring plant stress and other biotic and abiotic conditions that affect plants. ANN is modeled using layers of artificial neurons to receive input and apply an activation function along with a human set threshold. The comparison between biological neurons and artificial neural network is illustrated in Figure 2.4.

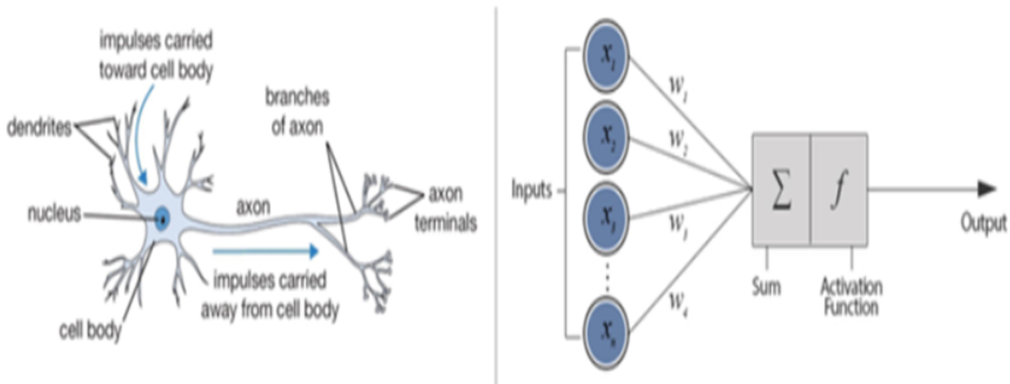


Figure 2.4: Biological Neuron versus Artificial Neural Network
(Source: Genç, 2019)

The basic feed forward neural network is made up of five main components of artificial neurons. They include input nodes, connections, weighted sum, transfer or activation function and output node. Input node is associated with a numerical value, which normally a real number. Connections are associated with weights (*w*) and can be any real number. Weighted sum receives as input the values and weights from the input nodes of the connections. The output from the weighted sum will be used as input in the transfer or activation function. The artificial neuron, just like the biological neuron (Genç, 2019), will only fire when the input exceeds a threshold. The output node results from associating the function of the weighted sum of the input node. Deep-learning networks are notable due to the number of hidden node layers known as depth, for optimization during training, testing and running the

ANNs. Simple Neural Network versus Deep Learning Neural Network with input layer, hidden layer and output layer is illustrated in Figure 2.5.

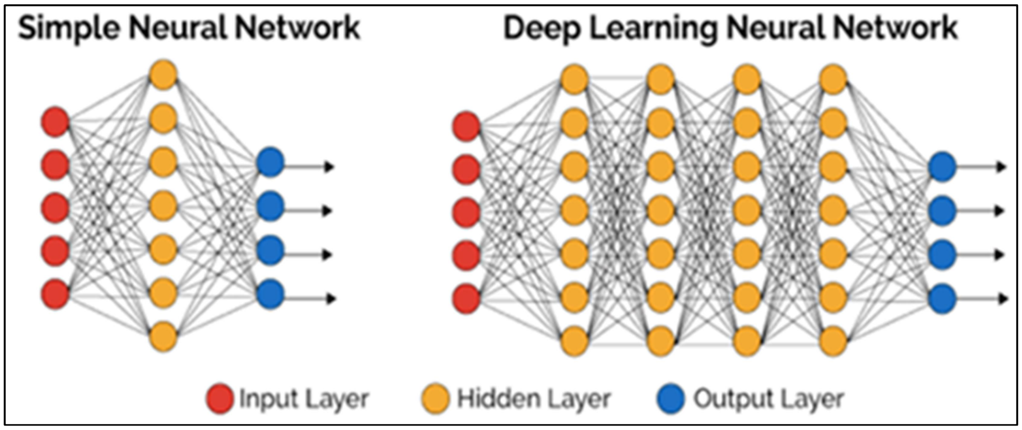


Figure 2.5: Simple Neural Network Versus Deep Learning Neural Network

CNNs are popularly applied in DL for image processing or computer vision application. CNNs are deep artificial neural networks applied in image classification, clustering, and in performing image recognition within scenes. These algorithms have been applied in face recognition and plant flower recognition, CNNs algorithm sees images in pixel format by considering the width, height and depth that makes up the three dimensional Red-Green-Blue (RGB) values for color coding. Depending on the success of the prediction a loss function is calculated and the network updates its weights through a back pass, by adjusting weights through a method known as backpropagation.

The backward pass process done by the CNN model determines the weight that contributes the most to the loss and finds ways to readjust the weights such that the loss reduces after several passes. In the onset the loss calculation is expected to be high and is also expected to decrease to a minimum value after several times of forward and backward passes; resulting to a well-trained network with correctly tuned weights of the layers. When testing is done to see whether the CNN model works, different sets of images and labels should be passed through the CNN, then the output is compared to the testing set to find out whether the network works as expected. CNN like algorithms are applied in Facebook, Google and Pinterest in automatic tagging photo searching and home feed personalization. RNN and GNN are not applied in this study.

This study applies CNNs for timely detection and accurate diagnosis of pests and disease stress in plants. Timely detection is vital to avert effects that result into reduced crop yield, both qualitatively and quantitatively; so as to enhance food security. Pre-symptomatic digital imaging techniques has been used in real-time, objective, detection systems for the identification and quantification of plant stress (Jan Behmann, Mahlein, & Plümer, 2015).

2.6 Deep Learning Techniques in Plant Stress

Deep learning comes with diverse outlooks on feature learning and representations, where diverse, abstract and invariant features are learnt end-to-end, hierarchically, in form of raw data like image pixels, to semantic labels, which is a major advantage compared to previous state of the art methods (Nogueira, Penatti, & dos Santos, 2017). A couple of deep learning-based methods have been proposed. These includes stacked autoencoders (SDE) (Ca, Edu, Lajoie, Ca, & Ca, 2010), deep belief networks (DBNs)(H. Chen, Wang, Tang, Xiao, & Li, 2017), deep convolution neural networks (CNNs) (P. Jiang, Chen, Liu, He, & Liang, 2019), and deep Boltzmann machines (DBMs) (Y. Bengio, 2009). Among the methods, CNN model represents the most established method, with impressive performance and great success in the field of computer vision and pattern recognition, intended for visual recognition, image retrieval and annotation.

Deep learning is growing in the field of remote sensing and plant stress detection. Existing publications since year 2015 show huge potential and practical utility in several remote sensing tasks including precision agriculture from object detection (S. Zhao, Zhang, & Philip Chen, 2019), semantic segmentation (Sandler et al., 2018b), yield prediction (Kızıl, Genç, İnalpulat, Şapolyo, & Mirik, 2012), Chlorophyll and Nitrogen estimation (Patane & Vibhute, 2014) and pest and disease detection (Massi et al., 2016) and classifications for plant stress phenotyping (Khanna et al., 2019).

Figure 2.6 summarizes the published papers over a period of five years starting from year twenty fifteen until year twenty nineteen outlining the papers with relations to topics of study. The figure clearly shows the increase in interest in the remote sensing areas of plant stress remote sensing detection, where the trend increases sequentially from 51 publications in 2015 to 62 in 2016, 84 in 2017, 152 in 2018 and 92 in July 2019. It is predicted that these publications will double by 2019 Table 2.1 and Figure 2.6 Illustrates the number of papers published since 2015.

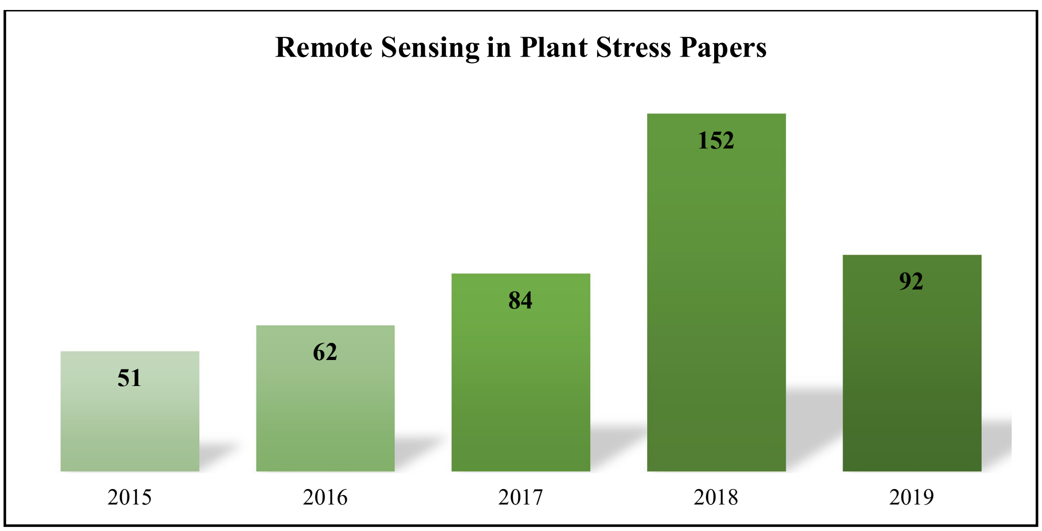


Figure 2.6: Publications in deep learning and remote sensing in plant stress

A review of plant stress detection, with regard to object detection, semantic segmentation, yield prediction and estimation, Chlorophyll estimation, nitrogen estimation and image processing and precision agriculture, pests classification, disease classification, yield prediction, and plant stress was conducted. Table 2.1 illustrates a summary of remote sensing tasks with regards to precision agriculture.

Table 2.1: Deep Learning and Remote Sensing in Plants

No table of figures entries found.	2015	2016	2017	2018	2019	No of Papers
Object Detection	3	6	7	9	11	36
Semantic Segmentation	1	2	4	7	7	21
Yield Prediction and Estimation	1	2	1	4	6	14
Chlorophyll Estimation	7	8	3	3	4	25
Nitrogen Estimation	1	2	2	5	8	18
Image Processing	8	10	22	24	10	74
Precision Agriculture	5	4	1	22	10	42
Pests Classification	2	1	6	23	6	38
Disease Classification	9	10	22	24	10	75
Yield Prediction	8	8	3	16	13	48
Plant Stress	6	9	13	15	7	50
Number of Papers	51	62	84	152	92	441

A systematic review of eleven types of major applications in the remote sensing domain targeting object detection, semantic segmentation, yield prediction and estimation, Chlorophyll estimation, nitrogen estimation and image processing and precision agriculture, pests classification, disease classification, yield prediction, and plant stress detection was conducted. These remote sensing domains are drawn from published academic papers. The previous works in Table 2.2 represent the focus of research that is viable and relevant to deep learning in the remote sensing domain. It is vital to note that as much as this section covers literature on research contributions to deep learning; it does not provide a comprehensive review of deep learning in plant stress remote sensing. Table 2.2 illustrates the eleven remote sensing tasks categorized according to applications, the pest's classification (75 papers), image processing (74 papers) and plant stress (50 papers) which constitute the majority cases. However, the others are not as much researched.

Table 2.2: Remote Sensing papers published 2015 to 2019

Remote Sensing Tasks	No of Papers	Sources
Object Detection	36	(He, Zhang, Ren, & Sun, 2016; Howard et al., 2017a; Lecun, Bengio, & Hinton, 2015; Sandler et al., 2018b)
Semantic Segmentation	21	(L.-C. Chen et al., 2018; L.-C. Chen, Papandreou, Schroff, & Adam, 2017; L. C. Chen, Zhu, Papandreou, Schroff, & Adam, 2018; Sandler et al., 2018b)
Yield Prediction and Estimation	14	(Jimenez-Berni et al., 2018; MacDonald, Staid, Staid, & Cooper, 2016; Mahlein, 2015; Saakre et al., 2017)
Chlorophyll Estimation	25	(Cheruiyot et al., 2018; Garriga et al., 2017; Vergara-Diaz, Kefauver, Elazab, Nieto-Taladriz, & Araus, 2015; Y. R. Zhao, Li, Yu, Cheng, & He, 2016)
Nitrogen Estimation	18	(Barillot, Chambon, & Andrieu, 2016; Khanna et al., 2019; Kiani & Mamedov, 2017; Pandey, Ge, Stoerger, & Schnable, 2017; Yong et al., 2016)
Image Processing	74	(Aygun & Gunes, 2016; Kamilaris & Prenafeta-Boldú, 2018; Khanna et al., 2019; Y. Li et al., 2015; Naik et al., 2017b)
Precision Agriculture	42	(Mahlein, 2015; Shen et al., 2018; Y. Zheng, Wu, Zhang, & Zeng, 2016)
Pests Classification	38	(Ding & Taylor, 2016; Y. Li et al., 2015; Xia et al., 2015)(Deng et al., 2018; Ebrahimi, Khoshtaghaza, Minaei, & Jamshidi, 2017; Verman, Shradha; Singh, Amit; Chug, Anuradha; Sharma, Shubham; Rajvanshi, 2019)
Disease Classification	75	(Arnal Barbedo, 2019; Coulibaly et al., 2019a; Mohanty, Hughes, & Salathé, 2016a; Thomas, Wahabzada, Kuska, Rascher, & Mahlein, 2017; Vergara-Diaz et al., 2015; Verman, Shradha; Singh, Amit; Chug, Anuradha; Sharma, Shubham; Rajvanshi, 2019; Wallelign, Polceanu, & Buche, 2018)
Yield Prediction	48	(Cheruiyot et al., 2018; Das Choudhury, Samal, & Awada, 2019; MacDonald et al., 2016; Mahlein, 2015; Saakre et al., 2017)
Plant Stress	50	(Khanna et al., 2019; J.-M. Kim et al., 2015; Kirongo, 2016b; Naik et al., 2017a; A. K. Singh, Ganapathysubramanian, Sarkar, & Singh, 2018)

However, this study provides a concise overview of deep learning methods for classifying plant pests and disease stress using Smartphone camera remotely captured digital images. The study focuses on deep convolution neural networks (CNN), being the most typical and well-established deep learning method that has been adopted in the remote digital imagery domain for timely detection and accurate diagnosis of plant pest and disease stress.

Deep CNNs are a variant of multilayer neural networks that are specifically designed to process large-scale images or sensory data in the form of multiple arrays by considering local and global stationary properties (C. Zhang et al., 2019). CNNs have a translational invariance characteristic, provided through a patch-based procedure, where a higher-level object can be recognized even if the image pixels are distorted or shifted. Deep CNNs were designed originally for solving image categorization tasks so as to assign the entire image into a semantic class such as digital (Lecun et al., 2015; Lecun, Eon Bottou, Bengio, & Haaner, 1998) or an object category. In the case of remotely sensed images, the aim is to solve problem existent in the remotely sensed plant images through classification, by categorizing image patches to either healthy or stressed with pests or diseases of diverse categories.

These sorts of plant disease and pests classifications tasks are closely related to object detection (Howard et al., 2017a) and localization (L.-C. Chen et al., 2018; Howard et al., 2017b; Thomas et al., 2017), where translational invariance (B. P. Singh et al., 2015) genomics is the key advantage of the CNN to detect the plant as an object with higher order features, such as plant pest or disease infested area of the image. However, the characteristic becomes a major weakness in plant stress images of pests and diseases classification for pixel-level differentiation, from which blurred boundaries are produced between the ground surface and the plant leaf or fruit. Here, we review the classification of both pest and diseases using CNNs to elaborate these challenges in detail in bid to identify the research gap.

2.6.1 Deep CNN for Pests and Disease Stress Classification

Deep Convolution Neural Networks (CNN) have been applied on Computer -Aided Detection of dataset characteristics, face verification, and visual saliency detection which is based on multi-scale deep CNN features (J. C. Chen, Patel, & Chellappa, 2016; Hoo-Chang Member et al., 2016; G. Li & Yu, 2016). Plant pests classification from remotely captured digital images using CNN models has been undertaken in form of plant pests classification, with the aim of assigning a label to an image according to the insect pests affecting a region of a plant stem fruit or leaf(Abdullahi, Sheriff, & Mahieddine, 2017; Y. Chen et al., 2016; Nieuwenhuizen & Hemming, 2018; Seung-Jin Kim; Yoe, 2018). Recent research has shifted the focus on patch-based CNN for classification of land cover in designing pixel-level architecture (also known as pixel labelling) for remotely sensed imagery (Volpi & Tuia, 2017).

Principally, the fully convolutional networks (FCN) and their extensions (A. Fuentes et al., 2017b)(S. Zhao et al., 2019) were proposed for the task of semantic segmentation (L.-C. Chen et al., 2018) to classify a set of low-level plant disease image semantics. These FCN-based methods involve convolution and down-sampling together with pixel-wise semantic segmentation. Convolution utilizes the neighborhood information as context. Further, there is a trade-off between strong down-sampling and sequent up-sampling to maintain the resolution of output map to be the same as the original input image, where the class likelihoods for an entire image were produced for pixel-wise semantic segmentation (Yong et al., 2016). Consequently, the FCN models still face challenges in pixel-wise dense labelling.

2.7 Digital Plant Image Stress Signatures

Digital image signatures for plant pest and disease stress used in earlier studies include Gaussian blur, color transformation for HSI (hue, saturation and intensity), masking green pixels and segmentation (Y. Chen et al., 2016; Dhingra et al., 2018; Ter Braak & Prentice, 1988).

A number of digital image stress signatures have been proposed over time. These stress signatures include, among others, height ratio, leaf area index, laser induced fluorescence imaging and biomass using tools like SmartRoot (Lobet, Pagès, & Draye, 2011).

2.7.1 Height Ratio

Plant height can vary as a result of plant morphology due to propagation in different seasons. Plant height can be measured using image processing approaches in estimation of canopies through oblique images (Usha & Singh, 2013). Popular sensors applicable in plant stress include thermal and stereo visible light, remote sensing, Kinetic RGB depth images, visible and thermal image, hyperspectral images, fluorescence imaging spectroscopy, UAV-based RGB images and multispectral images, RGB images, aircraft based sensors, scanned images, hyperspectral reflectance, fusion of RGB and multispectral image, and spectral reflectance (J. Behmann, Schmitter, Steinrücken, & Plümer, 2014; Kaundal, Kapoor, & Raghava, 2006; Kersting et al., 2012).

Existing literature (Wakawa, 2016) applies random sampling techniques in selection of the study field location where the plant to be analyzed are located, as per a number of parameter measurements. The parameters include the data on the plant growth parameters including: *Dbh*; diameter at the base, middle and top of plant; plant total height measured with *Dbh* greater than or equal to ten centimeters within the sampled plots. The measurements are carried out using diameter tape and Spiegel Relaskop. The basal area of each plant was computed based on the different sample plots considered in equation one which shows how Basal Area (*BA*) (Scott, 2016) in square feet is arrived at by multiplying pi with diameter breast height. Mathematically *Basal area (square feet) = pi × ((DBH)^2/4).*

$$BA = \frac{\pi Db\ ^2}{4} \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Where BA is the basal area (m^2); and π = constant (3.1429) and *Dbh* is the diameter breast height, representing the diameter at the base.

The plant height ratio (McDowell et al., 2002) can be modelled through development of a regression equation at individual plant tree level. The Hight-diameter models for height ratio based on linear, logarithmic, polynomial, power and exponential are represented as presented in the equations respectively;

$$H = b_0 + b_1 Dbh \ldots \text{ linear} \ldots\ldots\ldots\ldots \quad (2)$$

$$H = b_0 + b_1 lnDbh \ldots \text{logarithmic} \ldots\ldots\ldots\ldots \quad (3)$$

$$H = b_0 + b_1 Dbh + b_2 Dbh \ldots \text{ polynomial} \ldots\ldots\ldots\ldots \quad (4)$$

$$H = bBbh^{b_1} \ldots\ldots\ldots\ldots \text{power} \ldots\ldots\ldots\ldots \quad (5)$$

$$H = b_0 e^{b_1 Dbk} \ldots\ldots\ldots\ldots \text{ Exponential} \ldots\ldots\ldots\ldots \quad (6)$$

Where *H* is the plant total height (m); *Dbh* is the diameter at breast height (cm);; and *ln* is the natural logarithm *(log$_e$); b_0, b_1* and b_2 = regression parameters.

2.7.2 Leaf Area Index (LAI)

Leaf Area Index (LAI) (Xiao, Wang, Liang, & Sun, 2016) is a quantity of plant canopy dimensionless characterization defined according to a one-sided green leaf area per unit ground surface area;

LAI = (*leaf area / ground area,* m^2/m^2) . . . . (7)

LAI is concerned with the measurement of the total leaf area per unit ground area with relation to the light intensity intercepted by a plant. It is a vital variable applicable in the prediction of production, evapotranspiration and also used as a tool referenced in the process of growth of a plant. LAI is very vital in the productivity of any plant. The inverse exponential relationship between the intercepted light and the LAI is proportionate linearly to the primary rate of production (Weseni, Watson, & Anteneh, 2015). The primary rate of production function can be arrived at as follows;

$$P = P_{max}(1 - e^{-C \cdot LAI}) \quad (8)$$

Where P_{max} *denotes the maximum primary production, c denotes a plant-specific growth coefficient*.

LAI ranges from the bare ground (0) to dense conifer forest of over (10). LAI can be calculated by taking into consideration the statistical significant samples of the plant canopy foliage (López-López, Calderón, González-Dugo, Zarco-Tejada, & Fereres, 2016) the leaf area measurement per sample plot divided by the plot land surface area or indirectly measuring the canopy geometry (Chelle & Andrieu, 2007; Ruiz-Ramos & Mínguez, 2007) or extinction of light by relating it to the LAI.

Global warming, climate change and climate modeling problems have necessitated the need for long term and high quality global Leaf Area Index (LAI) (Xiao, Liang, Wang, & Jiang, 2016). Retrieval algorithm (Xiao, Liang, et al., 2016) was adopted for LAI retrieval, to enable spatial and temporal consistencies. Values retrieved from different satellite observations, the Leaf Area Index, and the fraction of light absorbed through photosynthesis, as well as active radiation informed LAI in digital imaging.

2.7.3 Biomass

Standing Biomass is a standard operating procedure for plant biomass determination. This standard describes the method used for the determination of biomass (Jimenez-Berni et al., 2018; A. . Lee & Nikraz, 2015; Salas Fernandez, Bao, Tang, & Schnable, 2017; Tilly, Aasen, & Bareth, 2015) of plant tissues based on;

Water Content=Fresh Weight – Dry Weight. . . . . (9)

Standing Biomass = (Dry Weight of above ground tissue ÷ Plot area). . . . . (10)

Where the water content is determined by subtracting the dry weight form the fresh weight. The standing biomass is determined by dividing the dry weight of above the ground tissues by the plot area.

Plant Biomass is an important parameter for crop management and yield estimation. However, since biomass cannot be determined non-destructively, other plant parameters are used for estimation. Previous studies (Cabrera-Bosquet et al., 2016; Liang et al., 2013) which show that plant height and hyperspectral data can be used to estimate biomass with bivariate and multivariate models, to estimate yield improvements. When used together with LAI and 3D (Tilly et al., 2015) spatial and spectral measurements, it can improve on estimation of biomass nondestructively.

2.8 Image Processing Techniques

Image processing entails a number of stages such as preprocessing, feature extraction, and selection and finally classification. They are discussed in detailed in subsequent subsections.

2.8.1 Preprocessing in Plant Stress

Preprocessing of image data is a very important step in deployment of ML methods. The careful choice of a preprocessing significantly improves the performance of ML preprocessing varies from cropping, contrast enhancement, and removal of background to more sophisticated operations such as clustering, and dimensionality reduction using principal component analysis (PCA). Principal Component Analysis (PCA) is a procedure that statistically uses an orthogonal transformation to convert observations of correlated variables into a set of linearly uncorrelated variables called principal components. Unfold Principal Component Analysis (UPCA) is a tool aimed at detection of plant and/or plant stress conditions, in order to help farmers to curb in a timely manner or so as to prevent or minimize damage caused by stress on plants.

PCA is a dimensionality reduction method applied in data pre-processing. This can aid in the detection of data streams that can be supported by automatic analysis using novelty and anomaly detection methods hence as clustering in the sense of reduction of human efforts to the most important parts of data streams (Bridge, 2005). Preprocessing relies on concentration of information for the improvement of the signal-to-noise ratio, for enhancement of the ML model to easily recognize useful patterns and trends so as to classify data into appropriate classes. Preprocessing contributes to the domain knowledge in the identification of relevant image features that are vital for model training. This includes background removal of tags, dirt and soil from the fore ground image of either leaf or fruits so as to identify the image.

There exist image processing tools for conversion of raw datasets into more relevant datasets with the extracted features. Preprocessing operations applicable include: image segmentation; enhancement of contrast; image thresholding to binary data; image conversion from one form to another [RGB to greyscale; RGB to hue saturation value (HSV)]; de-noising images using filters [band-pass, low-pass, fast Fourier transform (FFT)]; feature extraction at different scales using image transforms (FFT, wavelet transforms, Hough transform, Harr transforms, Radon transforms); pixel-based classification; image clustering into classes; and dimensionality reduction of images. Some of the ML tools discussed are applicable to these preprocessing stages (Khan, Nisar, Ng, & Lo, 2016). The mentioned preprocessing steps have been applied in image segmentation in weed management with (Vala & Baxi, 2013) Otsu's thresholding method being used in the differentiation of sunflowers, maize and wheat from weeds, in weed management.

Plant growth data from Smartphone cameras provide various detailed parameters, such as plant stress, diseases, pests, growth level and water deficiency in terms of draught stress, on both leaves and fruits(A. Singh et al., 2016). Although the leaf and fruit surface characteristics are associated with processing biotic and abiotic stresses, it can easily be affected by pests and diseases and environmental luminance. This observation informed the choice of deep learning (Sujata, 2019) in this study.

There exist numerous deep learning frameworks. This study applied the python deep learning library framework known as Keras (Sujata, 2019). It employed a high-level Application Program Interface known as Keras which is a neural network API able to run on top of TensorFlow, and Microsoft Cognitive Toolkit (CNTK) used for experimentation. It supports fast prototyping and convolutional networks and recurrent networks while running on CPU and GPU. Keras is user friendly, modular easily extensible and works well with Python.

The choice of this framework is due to its ability to prioritize developers experience, its broad adoption in the industry and the research community and efficiency inn turning models in to products. It's got support for multiple backend engines as a result of its support for different deep learning backend.

The supported backend includes; TensorFlow backend from Google, CNTK backend from Microsoft, Theano backend and Amazons MXNet backend. This makes it trainable on multiple hardware platforms. The hardware processing unit platforms supported includes; Central Processing Units (CPUs), NVIDIA Graphics Processing Units (GPUs), Google Tensor Processing Units (TPUs) with TensorFlow backend, Google Cloud and OpenCL enabled GPUs from AMD via the PlainML Keras backend. Keras has a strong Multi-GPU support and distributed training support, due to its usage by Horovod from Uber having been trained on TensorFlow Estimators and cluster GPUs for Google Cloud. Its utilization as backend support by key companies in the deep learning ecosystem include Google, Microsoft, NVIDIA and Amazon Web Services (AWS).

Based on the observation that the changes in the leaf and fruit surface response to the different biotic and abiotic stress, the images were resized, and denoised using Image Data Generator in Keras for preprocessing (Sujata, 2019). This is arrived at through the generation of tensor image data batches with real-time data augmentation.

Earlier preprocessing approaches applied a plant detection method to localize the plant leaf regions in the captured image. The (Pethybridge & Nelson, 2015) study focused on plant pests and disease, through the use of visible-light image for plant detection method; hence, obtains the localized plant leaf images as shown in (Mutka & Bart, 2015). With this input image, this study applied the method by training two CNN models to extract the image features for visible-light images. CNN as a learning-based (Too, Yujian, Njuki, & Yingchun, 2019b) method for image classification has been used in various applications (Y. Lu, Yi, Zeng, Liu, & Zhang, 2017). Using the CNN method, the extracted features from the visible-light images is analyzed, and the stress is detected using Support Vector Machine (SVM) (Farhat, 2002).

In this study, the preprocessing of images for timely detection and accurate diagnosis of tomato pests and diseases involved image resizing. The images were resized (Bhange & Hingoliwala, 2015) to the dimension of 224 by 224 pixels so that they can to get to equal dimensions. Rescaling (Bréda, 2003) was also conducted on the leaf images based on the RGB coefficients. Rotation (Das Choudhury et al., 2019; Deng et al., 2018; Desaeger & Rao, 1999; Rusydi, Sasaki, & Ito, 2014; W. P. Yang et al., 2009) of the images was also done in accordance to the range, and then flip. While reversing columns and rows of pixels, images were flipped to fifteen degrees before processing.

2.8.2 Feature Extraction and Selection in Plant Stress

In Computer Vision, the growth of Artificial Intelligence tries to bridge the gap between human capabilities and machine capabilities so as to enable machines to view the world as human beings. Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP) feature extractors (Dalal & Triggs, 2005) have been applied in previous studies on plant stress detection for classifiers such as Adaptive Bosting (AdaBoost) (Schapire, Labs, Avenue, Room, & Park, 1999) and Support Vector Machines (SVM) (Farhat, 2002).

The limitation of these previously used approaches is that the same feature extractor is used at all locations in the image despite texture differences between locations. Further, the feature extractors are designed in a manner that they capture a number of problem features. For example, the LBP method (Blaanco et al., 2016) is designed to count the number of uniform and non-uniform image texture features in an image. This approach of image feature extraction has fixed parameters even though it is applied in various types of images with different textures. The extracted image features are weak and the consequent recognition result is limited. To overcome this problem, we propose the use of CNN, that happens to be a learning-based method (Shen et al., 2018)(Mohanty, Hughes, & Salathé, 2016b)(Sladojevic, Arsenovic, Anderla, Culibrk, & Stefanovic, 2016), for feature extraction Gaussian blur, thresholding, eroding and dilating have been applied in chapter four.

The overall architecture of our CNN is based on the MobileNetV2 (Sandler, Howard, Zhu, Zhmoginov, & Chen, 2018d) building block. MobileNetV2 is applicable on Mobile application devices. MobileNetV2 as part of TensorFlow-Slim Image Classification Library is applicable on Mobile Vision applications by improving the art of mobile visual recognition in object detection, classification, and semantic segmentation. The MobileNetV2 architecture is illustrated in Figure 2.7.

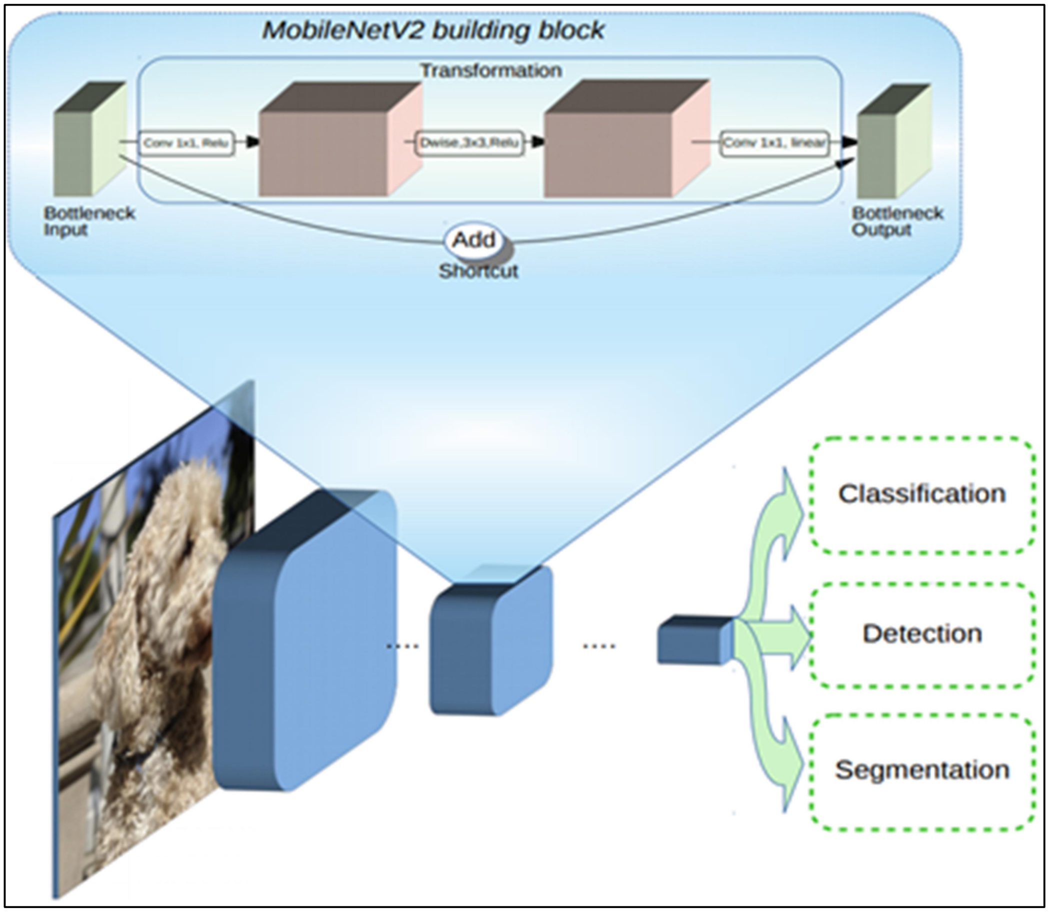


Figure 2.7: MobileNetV2 Architecture

Source: (Mohanty et al., 2016b)

MobileNetV2 uses depth-wise separable convolution through linear bottlenecks between layers and shortcut connections between bottlenecks. The bottlenecks encode the model's intermediate inputs and outputs while the inner layer encapsulates the model's ability to transform from lower concepts such as pixels to higher level descriptors such as image categories with the shortcuts enabling for accuracy while applying Depth-wise Separable Convolutions.

Depth-wise Separable Convolutions is a lightweight building layer in CNN (L. C. Chen et al., 2018) used in the construction of the neural network architecture. The convolutional operator is replaced with a factorized version that splits the convolution into two separate layers. the first layer performs lightweight filtering by filtering each convolutional filter per channel; while the second layer is a 1×1 pointwise convolution for building new features through computing linear combinations of the input channels(Sandler et al., 2018c). The depth-wise convolution applies one filter per channel, reducing the number of computation and parameters (Fan et al., 2018). The depth-wise convolution is illustrated in Figure 2.8.

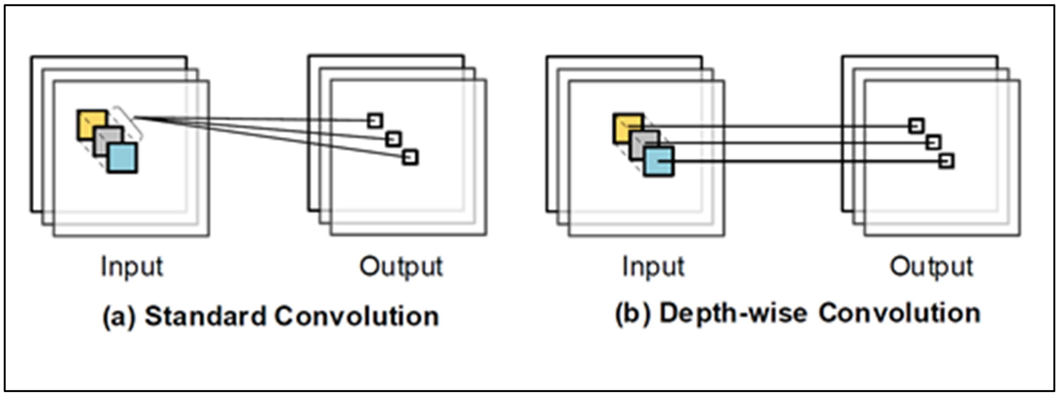


Figure 2.8: Standard and Depth-wise Convolution

Source: (Fan et al., 2018)

Depth-wise convolution is more efficient as compared to standard convolution. Due to its ability to filter input channels, an additional layer is required to compute a linear combination of the output depth-wise convolution via 1 × 1 convolution to generate new features because it cannot combine input channels to create a new feature which results to depth-wise separable convolution.

The main design of a CNN is convolutional layers followed by the Rectified Linear Units (ReLUs) and Pooling Layers (Ding & Taylor, 2016; Lecun et al., 2015; Nguyen et al., 2017). CNN method has previously been used in earlier studies on computer vision and has resulted to impressive results as opposed to traditional methods. The following areas have applied CNN; Human recognition in surveillance environments (Koo et al., 2018), real-time detection of tomato plant disease (A. Fuentes et al., 2017b), detection of stored-grain insects (Shen et al., 2018), recognition of plant diseases (Sladojevic et al., 2016), sketch recognition on Smartphones (Boyaci & Sert, 2017), hyperspectral palmprint recognition (S. Zhao et al., 2019), deep cross-layer activation for visual recognition (Papadopoulos, Machairidou, & Daras, 2016), spatial features for audio tagging (Xu, Kong, Huang, Wang, & Plumbley, 2017), gender recognition for human-body images (Nguyen et al., 2017), soybean plant disease identification (Wallelign et al., 2018), detection and analysis of wheat spikes(Hasan, Chopin, Laga, & Miklavcic, 2018), and Fine-grained category detection (N. Zhang et al., 2014).

2.8.3 Grey level Co-occurrence Matrix (GLCM)

Grey Level Co-Occurrence Matrix (GLCM) has been evaluated by (Marceau, Howarth, Dubois, & Gratton, 1990) in measuring texture representations that can be measured in spatial properties extracted from digital images. This is the relationship between existing grey levels in neighboring pixels that contribute to the overall appearance of an image. The GLCM matrix contains the relative frequencies with which two neighboring pixels (separated by distance d and angle a) occur on the image, one with grey tone I and the other with grey tone j. GLCM can be used to measure statistical measures like homogeneity, contrast, and entropy, to describe specific textural characteristics of the image, to create a new texture image or band which can be incorporated in spectral feature space for classification purposes (Marceau et al., 1990).

GLCM method relies on making decisions that rely on variables related to spatial resolution, spectral and, quantization level of image, size of moving window, inter-pixel distance and angle during co-occurrence computation and statistics used as texture measures. Less attempts have been made to clarify the relationships between these variables and classification results. (Ondimu & Murase, 2008) compared the detection of stress as a result of water as seen in GLCM for the plant known as Sunagoke Moss. GLCM can be combined with Principle Component Analysis (PCA) and Nearest Neighbor Classifier (KNN) that were used for detection of diseases in cotton with a 95% accuracy (Tichkule, 2016). These classifiers can be extended in hand held devices in timely detection, classification of plant stress signatures, and accurate diagnosis of pest and disease stress in tomato.

2.8.4 Classification

In the recent past, Convolution Neural Networks in object recognition and image classification has gained popularity in the classification of plant diseases (Mohanty et al., 2016b), pests(Deng et al., 2018; Y. Li et al., 2015; Mutanga, Dube, & Galal, 2017b; Verman, Shradha; Singh, Amit; Chug, Anuradha; Sharma, Shubham; Rajvanshi, 2019) and insects (Shen et al., 2018) as seen in deep convolution neural network in tomato (A. Fuentes et al., 2017a). Earlier approaches for detection of diseases and pests in Tomato relied on predefined environmental features such as controlled environments and open environments. For effective performance of the earlier approaches on image classification techniques and approaches like non-contracting techniques for high-throughput phenotyping (Y. Yang, Ling, Fleisher, Timlin, & Reddy, 2008), thermal infrared imaging for plant canopies (Jones et al., 2009), are applied by diagnosing the entire plant through a three dimensional camera (Chéné et al., 2012), and infra-red thermography for field phenotyping (Prashar & Jones, 2014) in controlled environment.

In instances where datasets associated with the subject of study keeps changing, feature engineering needs to be reconsidered and studied for a simpler and cost-effective approach. This is a problem majorly associated with traditional plant disease detection through the intervention of computing devices that employ vision, and the overreliance on hand-held engineering features (Mohanty et al., 2016b), image enhancement and noise removal methods (Reza, Nuzhat, Mahsa, & Ali, 2016).

The learning rate for the training setup can be increased by dividing and executing a running average of the magnitudes of recent gradients for that weight. The running average (Arpad, 2020; Kumar, Sarkar, & Pradhan, 2020) is calculated in terms of mean square, as shown in Equation 11, while Equation 12 shows parameter updating.

$$v(w,t) := \gamma v(w,t-1) + (1-\gamma)(\nabla Q_i(w))^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots (11)$$

where, γ is the forgetting factor and the parameters are updated as

$$w := w - \frac{n}{\sqrt{V(w,t)}} \nabla Q_i(w) \quad \ldots\ldots\ldots\ldots\ldots\ldots (12)$$

RMSProp has shown excellent adaptation of learning rate in different applications and can be generalized with mini-batches. The RMSProp Optimizer was used in (Chéné et al., 2012) and (Kumar et al., 2020), with decay set at 0.99 and momentum set at 0.0. batches were normalized after each layer and standard weight decay set at 0.00005. An initial learning rate of 0.055, and a decay rate of 0.99 per epoch based on MobileNetV2 setup was used using an 8 GPU and a batch size of 98 as shown in Figure 2.9.

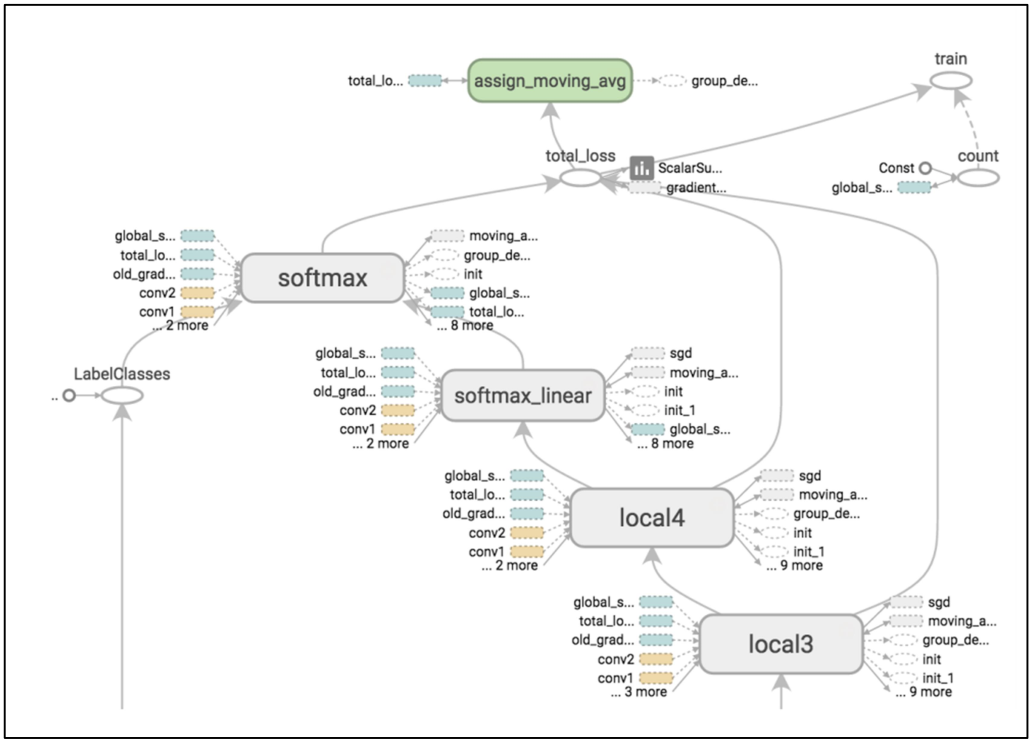


Figure 2.9: TensorBoard graph visualization of a CNN model

Source (Abadi et al., 2016)

Convolution Neural Networks in object recognition and image classification has grown in recent years, as seen in the classification of plant diseases (Mohanty et al., 2016b), pests and insects (Shen et al., 2018); through deep convolution neural network in tomato (A. Fuentes et al., 2017a). Earlier approaches for detection of diseases and pests in tomato relied on predefined environmental features, including controlled environments and open environments for effective performance of the earlier approaches of image classification techniques and approaches like non-contracting techniques for high-throughput phenotyping (Y. Yang et al., 2008), thermal infrared imaging for plant canopies and infra-red thermography for field phenotyping (Prashar & Jones, 2014) in controlled environment. In instances where datasets associated with the subject of study keeps changing, feature engineering needs to be reconsidered and studied for a simpler and cost-effective approach. This is a problem that is majorly associated with traditional plant disease detection with the intervention of computing devices that employ vision, due to the overreliance on hand-held engineering features(Mohanty et al., 2016b), image enhancement and noise removal methods (Reza et al., 2016).

Artificial Neural Networks (ANN) studies have been based on the hope of achieving human like performance in the area of image recognition (Lippmann, 1987). Traditionally neural networks classifiers have been used to represent unknown input patterns, mostly grey scale of pixels of pictures to represent different objects. An algorithm is applied to equate the relationship between the input and the output with assumptions made based on underlying elements. Parameters are estimated using a training data using Multivariate Gaussian distributions to compute scores that are made using an algorithm coded into symbolic representations which is passed to a classifier. At this stage the parameters are decided and the class with maximum score is selected, and a symbol that represents that class is sent out to complete the classification task (Lecun et al., 2015). Vector quantizers are used on imaging systems to compress the amount of data that must be processed without losing important information. Figure 2.10 illustrates some neural network classifiers that can be used for fixed pattern.

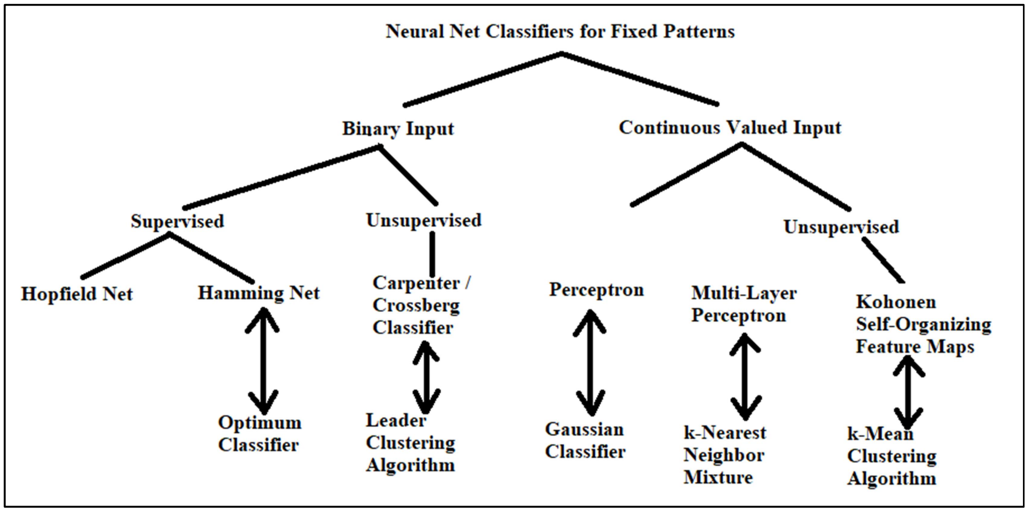


Figure 2.10: Neural Networks Classifiers for Fixed Patterns

Source: (Fine & Parks, 1990)

2.9 Digital Image Model Related Work

Convolution Neural Network (CNN) Model structure choice is dependent on a couple of factors. Modelling of Neural Networks is based on; selection of Input and Output Variables, Building the Neural Network Model, Cluster training, testing and data validation, training the neural network model with training data set and Validation of the neural network model (Din & Marnerides, 2017) using Similarity Rate of Correct Comparison (SRCC).

The design process of a neural network involves a very important aspect of selection of inputs. In this study we considered images captured through Smartphone cameras of stressed and healthy tomato plants data as input. The images captured made up a collection of data sets for training and testing. The data sets require normalization to accommodate the selection and application of activation functions. In order to normalize the load, the following formula is applied as seen in Equation 13.

$$Normalizedload = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (13)$$

Where x is the actual data value, whereas x_{max} and x_{min} representing maximum and minimum data values. Neurons and hidden layers are selected randomly for building the neural network model, then datasets are categorized into testing sets, training sets and validation sets. These datasets will be used by comparing the obtained results with the actual data. The training of the neural network involves determination of the network weights with minimum error. Once the training process is complete, validation of the network is necessary.

As recently applied in monitoring mammals in Portugal, designing of an algorithmic model based on automated visual monitoring life-long learning cycle is vital (Rillig et al., 2015). This can be done by applying initial, generic classifier (Lecun et al., 2015), active learning to reduce costly annotation effort by experts (Freytag, Rodner, & Denzler, 2014; Käding, Freytag, Rodner, Bodesheim, & Denzler, 2015), fine-grained recognition (to differentiate visually very similar species) (Simon & Rodner, n.d.), and efficient incremental update of the classifier’s model over time (Rodner, Freytag, Bodesheim, Fröhlich, & Denzler, 2017). For most of these challenges, initial solutions exist.

Building first visual monitoring systems, possibly for a restricted area or set of species, will definitely help to improve all parts over time, if biodiversity and computer vision researchers are working closely together. “PhenoCam” and Drone Deploy which uses networked digital cameras – webcams – and Drones for phenological monitoring in a range of ecosystems across the North American continent; where images are captured every 30 minutes, uploaded to the PhenoCam server for display in real-time, and processed to yield quantitative measures of vegetation “greenness” (Bridge, 2005). The model results in a formation that applies real time monitoring of tomato pests and diseases by detecting and monitoring plant stress with regards to biotic stress. The model meets the need for better documentation of biological responses to a changing world, and improved phonological monitoring. Imaging has emerged as a novel technique for real-time and non-invasive stress diagnosis in plants. The research however never captured the inclusion of Smartphone cameras in the capturing of the images. These were applied in this research, to extend the existing knowledge.

Imaging techniques have been applied in controlled environments with the aim of inventing better ways for detection of plant stresses (Lin, Chen, Si, & Wu, 2013a) in earlier related studies. However, the techniques in greenhouse environments employed costly tools. This research entailed harnessing the abilities in the Smartphone cameras, and transmitted images to a server for processing where a threshold value was used to determine water stress levels (M. Kacira et al., 2013). Other related studies however, (Kurata & Yan, 1996) lack the concept of real-time monitoring and dissemination of images to a machine learning environment using mobile phone solution. The approaches used are not calibrated with knowledge derived from exiting agricultural extension officer data gathered in regards to plant stress. Textural features for image classification were discussed (Haralick & Shanmugam, 1973).

Texture was identified in this study as one area that is important in identifying regions of interest in an image. (Revathy & Roselin, 2015) describes easily computable features based on grey tone spatial dependencies and illustrates their application on category identification tasks by dividing the data into a training set and a test set by applying grey-tone spatial dependency metric. (Marceau et al., 1990) evaluated Grey-Level Co-occurrence Matrix method for Land-Cover classification using SPOT Imagery using four texture indices, seven window sizes, and two quantization levels;

supervised classification and factor analysis was employed to optimize the discrimination of each vegetation cover type. However, this study failed to evaluate the relationship between spectral and spatial resolutions of the images and texture information that can be extracted in the identification of the best combination of spectral and textural data in feature space in order to maximize the class separability. (Lippmann, 1987) introduced Computing with Neural Nets by introducing tin to the field of artificial neural networks (ANN) by reviewing six important neural network models that can be used for pattern classification while exploring how existing classification and clustering algorithms can be performed using simple-neuron like components using a three-layer feed forward network (Lippmann, 1987).

Digital imaging for plant stress follows the approach for image acquisition, preprocessing through filtering and size rescaling is applicable in pre-trained classification of diseases, pests and drought stress. Timely detection and accurate diagnosis of plant pests and disease stress is applied in this study. Images are acquired using Smartphone cameras, and implemented on a mobile application. Preprocessing and classification is executed according to pest and disease stress categories. Image preprocessing techniques are applied on the images for filtering, rescaling and classification of the diverse stresses, whether pests, or disease. Results are later validated and relayed through the web interface. The digital imaging for Plant Stress is illustrated in Figure 2.11.

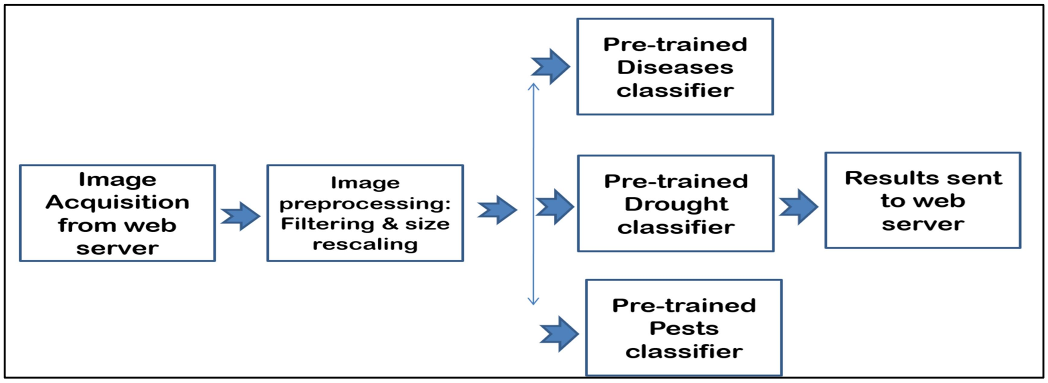


Figure 2.11: Digital Imaging for Plant Stress

The relayed data and the images were stored in a cloud to create an open cloud dataset for further use in research by any researchers interested in the application of the developed model for the detection of the diverse stresses faced by crops, and employ data capturing techniques by harnessing the possibilities provisioned by Smartphone mobile technologies by embracing image acquisition through Smartphone cameras.

This research extends the concept of the collective research network done by (Mohanty et al., 2016a) which suggests that future work be aimed at Smartphone-assisted crop disease diagnosis. This work addresses the limitation of accuracy, and operation in different conditions by classifying images of diseases as they present themselves on the plant in different environmental conditions as in (Ghosal et al., 2018a; Sandler et al., 2018a) (Ghosal et al., 2018a; Mohanty et al., 2016b; Sandler et al., 2018d). This limitation is addressed through timely detection, and accurate diagnosis of pest and disease stress by the use of a digital imaging model for plant stress detection implemented on a mobile application software running on a Smartphone device.

2.10 Gaps Identified in Literature

A number of gaps were identified after conducting an in-depth survey of literature. The identified gaps are highlighted in the Table 2.3.

Table 2.3: Identified Gaps

Gap Type	Gap Description
Existing Image based plant stress detection approaches	Existing Imaging models have untimely lower accuracy visual estimate levels in detection of pest and disease stress in plants. Several have difficulty in interpretation dark-adaptation measurements in agricultural field, and are affected by Sensitivity to environmental variations; cloud cover, solar orientation, difficulty to separate soil background and crop canopies, and require a large amount of disk space and computing power for storage and analysis and are applicable in laboratory environment.
Existing Model Performance	Existing models applied in classification of plants perform poorly on plant physical signature to digital mapping, timely detection and model accuracy.
Existing Imaging Tools	A couple of tools exist, however, they can't enable accessibility to remote areas by agronomists and lacks indigenous datasets, digitized GPS Location, diagnosis techniques for enhanced timely detection and increased diagnosis accuracy of plant stress.

2.11 Theoretical Framework

The theory of induced innovation in agricultural development was conceptualized in the year 1971 as a result of the increased demand for agricultural products, due to the population growth and growth in income among the population (Yujiro Hayami, 1971) and increase in prices of farm inputs, affecting the farm produce output.

The reliance of the farm produce necessitated the technical innovations that were aimed at saving the factors that characterized the supply and demand of farm produce and supplies, with an aim of ensuring more profitability among agricultural producers. This made farmers to look for technical alternatives that saved them from the increasingly scarce factors of production.

The research institutions and perceptive scientists went ahead to respond by availing new technical possibilities coupled with new farm inputs that enabled the farmers to opt for more profitable substitute inputs that resulted to increased productivity with lower costs (Juers & Fishel, 1972).

This study is informed by the theory stated in (Yujiro Hayami, 1971) that ”Any attempt to develop a model of agriculture development in which technical change is treated as endogenous to the development process rather than as an exogenous factor that operates independently of other development processes must start with the recognition that there are multiple paths to technological development”.

In this study we extend the theory of “induced innovation” by adopting deep convolution neural network modelling in computer vision in agriculture research. It includes the process of utilization of Deep Learning for timely detection and accurate diagnosis of plant pest and disease stress. The digital imaging model is implemented on a smartphone mobile application, and validated through web interface, so as to adopt and diffuse digital imaging technology, that is supportive to agricultural development, for enhanced food security, by lessening the constraints experienced by farmers in digitization of extension services for timely detection and accurate diagnosis of plant stresses in their crops, through digital imaging technology.

Historically many revolutions have occurred which changed the livelihood of humans. In the field of agriculture, the Green Revolution (Evenson & Gollin, 2003) drastically changed global productivity, in the mid-20th century. During this period chemical fertilizers, synthetic pesticides and herbicides were created, increasing the yields. The chemicals created were able to kill or deter insects, control weeds, prevent diseases hence higher farm produce. High yield crops were also developed and multiple cropping was introduced.

Although the green revolution had myriad of benefits, the chemical and herbicides developed resulted to human and environmental effects including erosion and pollution. Nevertheless, digital imaging has become more sophisticated in the recent past and is aimed at aiding in prediction of stresses in crops.

Agriculture has historically played a leading role in sustainable development for food security and human nutrition (HLPE, 2016), through diversification of food production and utilization. This however aims at leveraging the ability of enhancing this by utilization of computer vision and digital imaging in deep learning to enable prediction of stresses in the crops at an early stage for food security.

2.12 Summary

This chapter reviewed literature and examined the concept of plant stress by discussing the causes and importance of a variety of plant stress. Generic detection approaches were also discussed outlining their strengths and weaknesses.

Image-based plant stress detection was also discussed while highlighting their strengths and weaknesses. Image-processing classifier approaches were also discussed with a view of establishing how they are used for classification. Existing e-agriculture models were also analyzed. The research gap identified and the Theoretical Framework was discussed. However, for timely detection and accurate diagnosis of stress in plants, there is a need for the development of a digital imaging model for plant stress detection. The research methodology applied in this study is discussed in the third chapter.

CHAPTER THREE

RESEARCH METHODOLOGY

3.0 Overview

This chapter outlines the research philosophy, research design, location of the study, study population and sampling technique and sample size. Data collection procedure and data analysis techniques are also discussed, with a view of ensuring validity and reliability through quality control. Research instruments utilized in this and their validity are also highlighted and ethical considerations outlined.

3.1 Research Philosophy

Research philosophy (Scotland, 2012) refers to the set of beliefs concerning the nature of the reality being investigated and. The choice of the type of research philosophy applied in an area of research study depends on the knowledge being investigated. Ontological philosophy is concerned with the nature of reality and outlines the difference between reality, our perception about reality and how this influences everything around us (Abidi, 2011). The positivism ontological framework informed this research. Positivism creates a body of research that can be replicated by other researchers to generate the same result. This study borrowed from epistemology philosophy (Krauss & Putra, 2005) and applies the axiology branch of philosophy in attempting to clarify the prediction of the behaviour of crops in an environment that has been infested by pests and diseases. Positivism research philosophy is also applied in searching the cause of the phenomenon affecting plants in a systematic way (Collis & Hussey, 2009).

This study is highly structured, entails multiple and large quantitative samples, and its data source is based on measurements (Krauss & Putra, 2005). As a result, it embraces the positivism research philosophy. In positivism philosophy, the object of study is independent of researcher's knowledge and has to be discovered, verified through direct observations or the phenomenon measured; before facts are established by taking a part of the phenomenon to examine its component parts (Krauss & Putra, 2005).

This study was guided by positivism research philosophy, that applied the mixed method, that follows the experimental and survey strategy in quantitative research, in a longitudinal time horizon (Tosey, 2013). The positivism research philosophy is a scientific method employed for testing theories based on highly structured data that is measurable. The mixed methodological approach was employed through combining both the qualitative and quantitative data collection technique. It involves large samples of quantitative data to confirm a theory based on the findings.

3.2 Research Design

Research design refers to the overall approach that were used to integrate the various study components in a comprehensive and logical way in order to appropriately address the research problem (McNabb, 2009). Experimental research is a scientific procedure focused on a relatively smaller sample whose data is collected through reading of experimental data. Survey research is divided in to qualitative research and quantitative research. Survey research is used on descriptive research with large samples of data collected through observation, interviews and case studies. Quantitative research can be directly analyzed and it deals with numbers. The longitudinal time horizon was used to answer research questions to address the research problem through gathering and analyzing data over an extended period of time. Experimental design with pre-test post-test design is applicable in checking the difference in groups prior to effecting manipulation. In order to address the research problem at hand, this study adopted the (Gribbons & Herman, 1997). Experimental pre-test post-test non-equivalent group design was used. The selected design was applied on images acquired from the open field and controlled greenhouse environments and used to train the model. The design is appropriate for open field and controlled greenhouse environments for the experiments on the farms when experimental and control groups of the farmers were assembled with relation to the images acquired. Table 3.1 highlights the design of the study based on the experimental Pre-test Post-test Non-equivalent Group design.

Table 3. 1: Experimental Pre-test Post-test Non-equivalent Group design

Group	**Pre-Test**	**Treatment**	**Post-Test**
A	C_1	Y	C_3
B	C_2		C_4

As seen in Table 3.1, two image groups were acquired for internal validity; the Experimental Group (A) in the open field and the Control Group (B) in the Controlled Environment for this case the Greenhouse. Both groups received pre-test (C_1 and C_3) to ascertain whether the two groups under study had comparable characteristics, homogeneity and with similar image characteristics. Group A was exposed to the experiment (use of Smartphone cameras to capture the images of the plants before and after design of the Smartphone application) while group B used conventional methods for detection of stresses in plants. Both groups applied the post-test experimental approach. To avoid interaction of images from different fields, two sets of images were captured in each field forming the experimental images and control images from each field. Two plots from each field were used in the study to acquire images based on the tomato crop grown in each region to ensure each field was represented in the study. Twelve different plots in each field were used in the study. Figure 3.1 shows the operationalization of the research design.

Target Population

↓

Stratified sampling, purposive sampling and simple random sampling

↓

Treatment Group

↓

Control Group

↓

Pre Test

↓

Treatment Group (Crop images captured under stressful conditions)

↓

Control Group (crop images under conventional farming methods)

↓

Post Test

↓

Data Analysis

Figure 3. 1: Operationalization of the research design

Cross-sectional design, was applied while measuring the response of plants to pest and disease stress at given stages of growth. This methodology draws from the research onion in the formulation of the methodology and definition of the approach and strategy adopted in data collection.

3.3 Location of Study

The study area was conducted in Buuri, Imenti North and Tigania West Sub Counties of Meru County, Kenya, as shown in Appendix V. Meru County lies to the East of Mount Kenya whose peak cuts through the southern boundary of the county. It straddles the equator lying within 0° 3′ North and about 0° 1′ South, and latitudes 37° West and 38° East. The county has a total area of 6,936.2 Km^2 out of which 1,776.1 Km^2 is gazetted forest. It shares borders with Isiolo County to the North East, Laikipia County to the North West, Nyeri County to the South West, and Kirinyaga

County, Embu County and Tharaka Nithi County to the South as per Appendix IV. The county is agricultural in nature with Major Towns being Meru, Kiirua, Ruiri, Maua, Igoji, Nkubu, Mitunguu, Mikinduri, Kangeta and Laare.

The County's vision is to be a green united prosperous model county, with a mission of sustainable development and wealth creation in the County through commerce, technological innovations and industrialization that leverages on creativity and ingenuity, by seeking innovations and ideas that can bring a positive change to the basin and with the value of creativity that is focused, data-driven, result-oriented, and continuously-improving. Buuri, Imenti North and Tigania West Sub Counties were selected due to their popularity in the production of tomatoes, pests and diseases stresses notwithstanding. At the time of the study there was no documented statistics that would show the prevalence of pests and diseases in the selected Sub Counties with regards to the Tomato Plant. It could be inferred that accurate farming information on Tomato in the selected regions was lacking. The study strove to find out how far the developed model implemented in the mobile phone application named "Tunza Leaf" (Appendix III) would be able to timely detect pest and disease and accurately give recommendation for plant diagnosis in open and controlled environment to enhance food security to the farmer using the mobile phone application in their Smartphone.

3.4 Study Population

Data was collected from the fields and from the controlled environment. In this regard, test plants were tomatoes of the Libra F1 and Cal JVF varieties. These represent the major vegetables in Kenya (Asfaw, Mithöfer, & Waibel, 2009). For each plant, the experiments were carried out both in greenhouse under controlled conditions on the farmers' fields, and open field owned by the farmers. Each experimental setup was conducted by farmers in the named locations. Treatments were replicated three times. The plants occupied 6 plots each measuring $4m^2$ in the field and 6 plots in greenhouse. Standard agronomic practices were used in terms of spacing and timing planting. The experiments were conducted in split plot design. Field work carried out include; growing the plant, capturing the images, storing them and analyzing the data. All the 8745 images captured from the farmers' plots, in both open field and controlled environment, formed the target population.

3.5 Sampling Technique and Sample Size

This section outlines the sampling technique employed during the study in settling at the sample size for use in the study.

3.5.1 Sampling Procedure

The three Sub Counties were stratified in to existing Major towns herein referred to as Fields: namely, Ruiri, Tutua, Rwarera, Motonyi, and Maili Saba in Buuri Sub County, and Nchiru area of Meru University farm, in Tigania West Sub County. In each of those selected fields, simple random sampling was used to select farmers to participate in the study. The locations were selected due to their proximity to the researcher. The areas were also selected due to their popularity in growing tomato for commercial purposes within Meru County (Stanley Mbagathi, 2009). This technique was appropriate because it ensured that all farmers and plots in the fields had equal chances of being included in the study sample. The experimental and control groups were drawn from different farmers and plots per field to minimize the chances of interaction and bias. Participatory research was carried out in the field, where the researcher distributed seedlings to farmers who planted plants for a period of four weeks during the first and second experiment. Data were collected at the onset of the study and repeatedly throughout the length of the study in a span of six months to measure the changes in the plant growth.

3.5.2 Sample Size

Twelve plots from the fields were used in the study. Six fields formed twelve plots where the experimental groups of six plots were selected where farmers were provided with Smartphones to capture images from their plots. The other six plots constituting the control group which was treated to conventional farming practices. The actual image sample size that were used in the study was 8745 images captured from tomato plants grown in twelve plots by a total of twelve farmers in the six fields. The image samples of tomato plants which were chosen for the study resulted from the sampled specific tomato plots. The images were selected from a set of images with the kind of features needed for the experiment. Essentially, larger samples improve external validity and accuracy of the results. Conclusions were confidently drawn since both the images from the controlled environment and the open field plots were many.

The fields correspond to the regions where Field 1 is Ruiri, Field 2 is Tutua, Field 3 is Rwarera, Field 4 is Motonyi, Field 5 is Maili Saba and Field 6 is Nchiru as seen in Appendix V. These subjects were used in their twelve intact plots that were randomly assigned to Experimental and Control Groups as shown in the Table 3.2: Image distribution by field.

Table 3. 2: Image Distribution by Field

Type of Field	Experimental Group (Plots)	Control Group (Plots)	Total Number of Images
Field 1	735	733	1468
Field 2	759	651	1410
Field 3	755	739	1494
Field 4	767	738	1505
Field 5	739	743	1482
Field 6	739	647	1386
Total	**4494**	**4251**	**8745**

3.6 Data Collection Procedure

An approval letter of proposal reference number MMU/COR: 509099 was obtained from the Directorate of Postgraduate Studies of Masinde Muliro University of Science and Technology (MMUST), with the authority for data collection (Appendix VIII). A research license permit number NACOSTI/P/18/58635/25690 (Appendix IX) and an authorization letter with the same reference number was obtained from the National Commission for Science, Technology and Innovation (NACOSTI) with authority to conduct the research experiment (Appendix X). Research authorization reference number: ED.12/VOL.III/62 from the Meru County Commissioners, Ministry of Interior and Coordination of National Government (Appendix XI) and research authorization reference number: MRU/C/EDU/11/1/215 (Appendix XII) was acquired from the Ministry of Education State Department of Early Learning and Basic Education from the Meru County Director of Education. These informed the ethical legality of engaging with the participants in the research during the field tests to acquire images and determine the adaptability of the developed model, through the developed Smartphone mobile application. Particular attention was paid on the capturing of images and pre-processing. The experiment was carried out with sensitivity to the laid-out regulations by NACOSTI, the University, County Commissioners Office, Ministry of Education and the Ministry of Agriculture. Images used in this study were collected from leaves and fruits of tomato plants from open field and controlled environment. The images were captured using digital Smartphone cameras. The digital cameras were configured to the Tunza Leaf Mobile application (Appendix III). Images collected were stored on a memory stick transferred to the web interface that was configured with the algorithm.

Unstructured interviews were administered for data collection at the beginning of the study. The interviews were conducted to ascertain their homogeneity. Images from the experimental setup and the control setup of the fields were captured using the Smartphone cameras and conventional methods. Observations were made on the images captured. As a non-participant observer in the far, the researcher watched and recorded notes without becoming involved in the image acquisition and interpretation process. By not actively participating in the dynamics of the image acquisition of the images, it made the farmers feel more comfortable with researcher presence in their farms. The focus was on how farmers used the mobile phone application in the interpretation of the different stresses affecting the plants. The purpose was to seek a deeper understanding and insight on the aspects that made the use of the mobile phone application different from conventional farm practices in the identification of plant stress signatures and interpreting it to a specific pest or disease affecting the plant. At the end of the four weeks, all the pests and diseases detected in the fields were completed in both the experimental and control groups. Images were captured using mobile phone cameras. The images were collected from both the experimental and control plots on the farms.

A web interface and mobile Smartphone application were developed for the agronomists and the farmers based on the unique specifications by farmers. The mobile phone application presented an interface that allowed the farmer to capture images from the farm. The images captured by the phone concerns the leaf area and the fruit of the tomato plant. Once a farmer scans the crop to the desired accuracy levels, the identified stress with its descriptions is given as feedback including the stress type and the recommended product and recommended contact person. The researcher recruited twelve (12) research assistants who were engaged in capturing of the images of tomato from the twelve different plots in both an open field and controlled environment for a duration of one month. The researcher further trained the farmers on how to capture images using the developed Smartphone mobile application. The researcher further trained the farmers on how to capture images using the developed Smartphone mobile application. During the training farmers were taught how to capture images and respond to the interview questions. The agronomists were also engaged in the training of the farmers and helping them in the interpretation of the recommendation generated by the mobile phone application. The training was conducted to farmers for a period of 2 weeks. The lead farmers were trained as trainer of trainees who were later engaged in training specific farmers. To master the use of the mobile phone application interface on tomatoes, the farmers were trained to capture and interpret images.

After training, each farmer in the experimental setup were provided with the mobile application software for installation on their phone. Farmers were expected to implement the use of the mobile phone applications to detect pests and diseases on tomato plants planted in their fields both on the open field and the controlled environment in the greenhouses. All the farmers were also informed about the ethical issues related to confidentiality, informed consent and acceptance. After the three-week practice, the researcher then embarked on administering the research instruments. A pre-test was done then after two weeks the post test was done. Several visits were made to the sample farms. During the first visit to each of the farms the researcher explained purpose of the study and discussed details of the study with the agronomists, and the lead farmers, and the selected farmers. In the second visit, the researcher trained the farmers and agronomists handling the selected farmers on how to use the Smartphone application in plant stress detection in readiness for their roles in the study. The farmers trained on how to use smartphone application for plant stress detection were given instructions on what was expected for them during this research study duration.

The training of the farmers involved in the experimental groups took two weeks. Thereafter, the trained farmers practised together in order to develop their confidence in the study. During the practice sessions, the researcher supervised, discussed and addressed any technical issues that arose. The reason for this thoroughness was to ensure uniform procedures are followed in the six experimental fields. The researcher then pre-tested the instruments in two fields in Buuri Sub-County and Tigania West Sub-County which were not used in the actual study. During the implementation stage, the researcher visited two groups of farmers for discussion on the progress and challenges faced in use of the mobile phone application for plant stress detection. The visits necessitated the harmonization of the implementation of the new technique of detection of plant stress in all the sample fields using the Smartphone mobile application. The farmers were taught how to use the mobile Smartphone application ad interpretation of the recommendation.

3.6.1 Data Analysis Techniques

Images were captured using a mobile phone camera, acquired images were resized and pre-processed, features extracted and classified and later subjected to the designed Model. Data cleaning was executed to remove noise from the collected images for good quality of image outputs. Data were analysed using Convolution Neural Networks. These were achieved by resizing (Figure 4.10), rescaling (Figure 4.11) and horizontal flip (Figure 4.12) the images captured to obtain images for prediction of plant disease and pest stresses. The purpose of resizing and rescaling was to aid in the determination of the leaf area. Data was presented through a designed mobile application after being pre-processed through the calibrated Model. The presentation of the results was done through the digital imaging model summary (Figure 5.12) and graphs of accuracy and loss against training steps, training set and training epochs (Figures 5.2, 5.3 and 5.4).

The neural network was visualized for debugging and optimization through the generation of a TensorBoard Graph as seen in Figure 5.5. The images were collected from both the experimental and control plots on the farms. Data pre-processing involves data cleaning, feature exploration and feature engineering and its impacts on model performance. The *numpy*, *pandas*, and *matploitlib phython* libraries were utilized. These approaches were applied in image resizing, rescaling and training. Preprocessing consisted of segmentation, and denoising. Three sub-images were planted from each captured image as follows; a sub-image each from both healthy and stressed sets and a reference image from a bare surface. Preprocessing of images were done by selecting a sample image and identifying image coordinates representing the three regions. The acquired images were taken through the pre-processing, feature extraction and Convolution Neural Networks (CNN). CNN was trained using acquired images to detect mean color intensities of the plants and relay messages back to farmers through calibrations done on the mobile based application, customized according to the developed Model.

The averaged image intensities from the two sets of images (healthy and stressed) were used in training and validation of a Convolution Neural Network (CNN) classifier. Validation using Similarity Rate of Correct Comparison (SRCC) and web interface was vital to ensure timely detection and accurate diagnosis of the detected pest and disease stress in the plants. The objective was to feed the CNN with the intensity features from either healthy or stressed sets of plant images and then get an output indicating whether the plant from which the input features were obtained is healthy or suffering stress. The classifier which recorded the best learning performance were used in the validation session using an independent set of features. Keras was used to create and train the CNN classifier. The training set comprised of a selected set of feature vectors from images captured and a series of 1's and 0's as the targets (desired outputs) corresponding to feature vectors from healthy and plant stress images respectively. A digital imaging Model was developed trained, validated and tested, for timely detection and accurate diagnosis of plant pest and disease stress. A prototype Android platform using Java programming language was developed. The mobile application prototype was developed based on the digital imaging Model. The Client-Server model were used where the server side were implemented using PHP and MySQL database. JSON was used as the format of data transfer between the Android client and the server. The prototype was validated using the acquired images to understand and expose design, implementation, use and adoption issues to ensure timely detection and accurate diagnosis of the detected pest and disease stress. Transfer Learning (Coulibaly, Kamsu-Foguem, Kamissoko, & Traore, 2019b) was employed in feature extraction and selection through the pre-trained Mobile Net Version Two model architecture (Sandler et al., 2018c).

The SoftMax activation function (S. Zhang, Huang, & Zhang, 2019) was used to determine which neurons should be activated. The model employed the Adaptive Momentum Estimation (Adam) Optimizer (Kingma & Ba, 2014) due to the speed at which its able to converge and learn. The process entails image acquisition, pre-processing, feature extraction, and classification by application of Convolution Neural Networks (CNN). The digital imaging model was used for timely detection and accurate diagnosis of pest and disease stress in plants and relay the diagnostic messages to the farmer.

3.7 Validity and Reliability

To ensure the desired quality of the work, validity of the captured data and its reliability were enforced using the methods as outlined in the following subsections.

3.7.1 Validity

Validity (Ernst et al., 2012) entails a number of things such as the timeliness and accuracy of the instruments, used in the study for timely detection and accurate diagnosis of pest and disease stress using Smartphone camera, in the open field and controlled environment for consistency. The validation approach of the model was based on the procedures that were automated in the developed Model, based on the experimental pre-test post-test research design. Validation of the Model was based on a Similarity Rate of Correct Comparison criterion (SRCC) (Chabrier et al., 2008) applied on the Tunza Leaf web interface (Appendix III). Participatory research was conducted where the researcher conducted content analysis, record inspection, observations, interview, listen and ask questions on the prototype while interacting with farmers while doing a walkthrough and think-aloud session with farmers being the participants.

3.7.2 Validity of the Research Instruments

To ensure that the research tools were relevant and valid, the instruments were given to experts for validation (agronomists, software developers and lead farmers). The instruments of research were tested for determination and establishment of both the face validity and for relevance, meaningfulness and content appropriateness to the farmer respondents. To measure content validity of the mobile phone application, a careful examination of the items included in the research instruments were considered. To further check the instruments validity, the two instruments were given to two agronomists, two software developers and four lead farmers with experience in the farming practices. The agronomist and the lead farmers were given the instrument to check on the validity in feedback related to the average rating which ranged from a score of 1 (extremely invalid), 2 (fairly valid), 3 (valid), 4 (highly valid), 5 (extremely valid). The overall average mean rating was 3.5 on a scale of 1 to 5 (Appendix II). The validation was done as shown in Table 3.3.

Table 3. 3: Validation of Research Instrument

Experts	Research Instruments	Face Validity	Content Validity	Average	Verdict
Agronomist 1	Digital Smartphone Camera App	4	3	3.5	Valid
	Farmers Interview	3	4	3.5	Valid
Agronomist 2	Digital Smartphone Camera App	3	5	4	Valid
	Farmers Interview	4	4	4	Valid
Farmer 1	Digital Smartphone Camera App	3	3	3	Valid
	Farmers Interview	2	5	3.5	Valid
Farmer 2	Digital Smartphone Camera App	3	4	3.5	Valid
	Farmers Interview	3	3	3	Valid
Farmer 3	Digital Smartphone Camera App	4	4	4	Valid
	Farmers Interview	3	4	3.5	Valid
Farmer 4	Digital Smartphone Camera App	4	3	3.5	Valid
	Farmers Interview	3	5	4	Valid
Developer 1	Digital Smartphone Camera App	3	4	3.5	Valid
	Farmers Interview	3	2	2.5	Valid
Developer 2	Digital Smartphone Camera App	4	3	3.5	Valid
	Farmers Interview	4	4	4	Valid

The expert validators found the instruments to be valid. The agronomists suggested the restructuring of modification of the classification of the recommended products to farmers to include insecticides, fungicides and fertilizers. The agronomists also recommended that the chemical recommendations be categorized in terms of trade name and the active ingredient. The modifications were implemented in the mobile phone application interface. The questionnaires addressed to the farmers were also modified by replacing the complex terminologies to simpler language that is understandable to the framers.

3.7.3 Reliability

The data was subjected to field tests and cross checking against traditional approaches of detection monitoring and response to biotic and abiotic stresses facing plants. Reliability (Hull, 2002) is dependent on validity (Dalton, Ballarin, & Brun, 2009) and therefore it can be enforced through methods such as repetition of experiments i.e. multi-thronged approach which compare the results. The essence of reliability is to ensure consistency and believability.

3.7.4 Reliability of the Research Instruments

The digital Smartphone camera app and the interview questions were tested for reliability using the Pearson Product Moment of Correlation statistic. The test-related technique was employed on four independent occasions within two weeks' period under similar conditions. The test data was correlated using the Pearson Product Moment of Correlation (r_{xy}) which were as follows .587 for interview questions and .780 for digital Smartphone camera app (see Appendix III). The results show a correlation of above 0.8 and between the first score and the second score implying the instruments were reliable. A reliability coefficient (r_{xy}) of 0.8 and above is considered in making inference based on the findings (Fraenkel, Wallen, & Hyun, 2019), (Plun, Rozenberg, Salomaa, Blass, & Gurevich, 2010).

It was observed that all the 6 experimental farms faced similar challenges with regards to pests and disease. Farmers faced similar challenges with regards to response to plant stress detected. The sampled farmers used android phones, version 8.1.0 and below. This provided a platform for the mobile application for plant stress detection. The farms were planted with tomato crops on both open field and control environment. The images of the crops were captured at specified intervals in the different points of growth of the plants to detect any of the stresses.

An experimental approach was used in this research. With a special focus on the pests and disease stresses, the tomato plants were scanned in both open and controlled environments so as to detect the various stresses affecting them. A model was developed and availed through a mobile phone application. The mobile phone application was calibrated to the major plants to aid in detection of plant stress. Pest and Disease stresses were tested on well-watered soil conditions of 90% soil capacity and stressed plants were in soil with moisture content of less than 60% on a decreasing drift. Images captured were correlated against plant pests and diseases stresses. The experiments were done both in a controlled environment and open environment.

The images were captured using a digital camera on a mobile Smartphone, at predefined intervals. Data were collected at the onset of the study and repeated throughout the length of the study in a span of six months to measure the changes in the plant growth. A total of 8745 raw images were captured to perform timely detection of plant stress and send accurate diagnostic messages to farmers through their mobile phones for preventive action for enhanced food security. The mobile application was calibrated with stress characteristics of the Tomato plant. The outcome of this research has helped farmers in detection of pests and diseases stresses and has resulted to alleviating effects caused by stresses through detection. It also aids farmers in connecting them with potential agronomists and suppliers of agronomical products. This aids in the remedying of the stress damage and thus substantially reducing yield losses and ensure food security.

An experimental research design was adopted for the selected plant variety. Since the researcher did not control all the confounding variables, that cause stress to plants, but only concentrate on pest and disease stress. The control experiment was set up in the university farm and nearby farms. Two sets of tomatoes plants were propagated, one in each set being used as a control experiment.

The different stresses detected on the planted crops at different intervals of growth were detected and features extracted. Changes experienced in the plants were captured using digital cameras on Smartphones. The captured images were stored in the memory and used to come up with an algorithm that inform the construction of the digital imaging Model for timely detection and accurate diagnosis of plant pest and disease stress.

3.8 Research Instruments

Research instruments used to collect data for this study include; Digital Smartphone Cameras, Unstructured Interviews & Questionnaires and Participatory Observations.

3.8.1 Digital Smartphone Camera App

The digital smartphone camera app user manual is in Appendix III. The manual highlights the use of the app in timely detection and accurate diagnosis of plant pest and disease stress. Appendix V shows the location where images in the farmers' fields were captured. Images were acquired using digital smartphone camera devices as source data, and the images used to create labelled dataset, and classified as either pest infested or disease infested. The discrete labels plant images result to a grid of numbers between [0,255] for example in this study each image has a $224 \times 224 \times 3$ where 3 represents the three channels of RGB. The viewpoint variations affect the pixels every time the camera moves the pixels change. Illuminations of images of plants are considered any time an image is captured at different light intensities against the image of the plant. Deformations of images affected by different formations due to the effect of the stress on the plant was considered. Occlusion was also considered in instances where the image was partially covered by surrounding vegetation like weeds or other plants.

Background clutter was also considered in moments where the image coloration was observed to be almost similar to the surrounding environment. Whereas interclass variations happened where images acquired had very close similarities with adjacent images of the plant, for this case image in focus was the tomato plant. Attempts have been made to find edges of the image in focus through a data driven approach in collection of the images from the fields using the Smartphone cameras. The Smartphone cameras were used to capture images at different resolutions distances and illuminations to bring forth the actual reality on the ground. Images were captured both in the open field and in a controlled environment.

3.8.2 Farmers Interviews

The theory of induced innovation in agriculture as per Section 2.11 recognizes the role of farmers in enhancing food security through utilization of digital imaging technologies in timely detection and accurate diagnosis of pests and disease stress in plants. In this study farmer interviews conducted consisted of fifteen structured items which measured the farmer's motivation toward using Smartphones in timely detection and accurate diagnosis of plant pest and disease stress. The fifteen items were divided in to four corresponding usability attributes of efficiency, effectiveness, learnability and errors covering. The interview responses were recorded in a 4-point Likert-type of tool from Strongly agree (SA) to Strongly disagree (SD). These statements and their related attributes are shown in Appendix I. Interview questions as seen in the Appendix I sought to establish the usability of the Mobile Application and Web interface among farmers with regards to installation input process and output process. With regard to learnability and effectiveness of the mobile application and web interface, the study went ahead to find out technical challenges encountered by the farmers. The application of the mobile system usability was measured based on 4 Likert scale type tool that sought to establish usability, accuracy, response time and reliability attributes of the mobile application among the farmers based on the ten statements.

Interview questions in the usability category measured the extent to which the interest of the farmer was captured and their curiosity to use Smartphone cameras for capturing images of plants to detect their stresses. The usability mentioned in this case referred to the interest displayed by the farmers in interpreting the stresses detected (Appendix I). Items in the reliability category served to measure the extent to which plant pest and disease stress can be timely detected and accurately diagnosed using the smartphone cameras owned by the farmer to meet the farmers' needs and goals in farming. Items related to response time evaluated the perception of farmers about whether they were able to succeed in detection of the plant stresses within a stipulated period of time. The confidence level of the digital imaging model for plant stress detection focused on establishing positive expectations for achieving successful detection of stresses in plants among the farmers. Finally, the items in the category of accuracy measured the extent to which farmers' accomplishments were reinforced as a result of accurate detection and recommendation of the stresses and their remedies. When the outcome of the farmers' efforts in detection of the plant pest or disease herein referred to as stress and successful recommendation of the remedial action to be taken, they will rely on the proposed model presented in the form of a mobile phone application. When the outcome of the farmers' effort is consistent with their expectation and they feel relatively good about those outcomes, they will rely on the technological solution provided. This motivation can be from a sense of achievement, or remedial action taken at an early stage (Appendix I).

3.8.3 Participatory Observation

Participatory observation was adopted to observe farmer interaction with the plants and their stresses prior to the introduction of the new technology as per the Technology Acceptance Model (TAM) (Legris, Ingham, & Collerette, 2003; Venkatesh & Davis, 2018). The purpose of this observation was to gather data on farmer interaction with the new mobile phone application developed for detection of plant stress. The researcher made a list of the various plant diseases, pests detected with their remedial measures.

3.9 Ethical Consideration

There were no human subjects directly involved in the research as the focus was plants. However, approvals were acquired as per Section 3.6.

3.10 Summary

This section discusses the research philosophy employed in the research, the research design, the location of the study, the study population, the sampling techniques, size and procedure used. The data collection and analysis procedures have also been discussed with an aim of showing their validity and reliability through approvals obtained to carrying out the study. Research instruments utilized have also been discussed showing how images were acquired through the digital smartphone cameras, interviews and observations, highlighting their validity and reliability; finally, the ethical considerations discussed.

CHAPTER FOUR

CLASSIFICATION OF DIGITAL IMAGING SIGNATURE FEATURES CHARACTERIZING STRESS IN PLANTS

4.0 Overview

This chapter presents plant stress signatures, interpretation and discussion. It is divided in to five sections namely; demographic information, physical features of stress in plants, mapping of the physical features into digital imaging signatures and predictions using the trained model. This is discussed in line with image preprocessing activities of rescaling, resizing and horizontal flip. Timely detection and accurate diagnosis for both pests and diseases are also discussed and summarized; aligned with details about objectives two and three and research questions two and three of the study. Data is presented, interpreted and discussed per objective. This Chapter was guided by the objectives; to establish the physical features of stress in plants and to map the physical features into digital imaging signatures characterizing stress in plants. Consequently, the study sought to answer the research questions; how does stress manifest itself physically in plants, and how can the physical features be mapped into digital signatures?

4.1 Demographic Information

This section gives an overview of the response rate per farm per plot. Also shows the type of field whether controlled environment or open field. The above categorizations informed the use of the developed mobile phone application in the capturing and interpretation of the crop images. The average response rate of the study was at 87.5 % this percentage is an adequate representation of the findings that can be generalized. Respondents from different farms and plots exhibited different response rates as shown in Table 4.1.

Table 4. 1: Response Rate in Percentage

Field	Experimental Group			Control Group		
	No. Issued	No. Returned	Response Rate (%)	No. Issued	No. Returned	Response Rate (%)
1	32	30	94	43	39	91
2	48	44	92	42	38	90
3	50	46	92	32	27	84
4	58	47	81	28	24	86
5	33	28	85	34	26	76
6	35	31	89	52	46	88
Total	256	226	89	231	200	86

From the results shown in Table 4.1, experimental group had the highest response rate at 89% while the control group had the lowest 86%. However, the different was insignificant. This can be attributed to the excitement in the use of smartphone camera app technology used among farmers in the experimental group.

4.2 Physical Features of Stress in Plants

Tomato plants are susceptible to a variety of disorders as a result of attacks necessitated by pests and diseases. The effects on the crops can be attributed to abiotic disorders (J. Jiang et al., 2017) as a result of environmental conditions, such as humidity, temperature, nutritional excesses due to under or over application of fertilizers, temperature, light and different plant species; and tomato pests (Verman, Shradha; Singh, Amit; Chug, Anuradha; Sharma, Shubham; Rajvanshi, 2019) that spread diseases from one plant to another plant. Further, the most common pests include whiteflies, tuta absoluta, aphids, leaf miners, bugs and worms. Consequently, the most common diseases (Y. Lu et al., 2017) include fungal, viral and bacterial diseases, early blight being one of the most common. Those pests and diseases affecting the tomato plant may present different physical signature characteristics, which include diverse shapes, colors, forms, among others. Therefore, owing to similar patterns, those variations are difficult to distinguish, further making it more challenging to recognize the stress. However, timely detection and accurate diagnosis can avoid severe loss in the whole plant lading to enhanced food security. Based on the physical features in plants, plant stress signature characteristics have been considered for analysis as highlighted in subsection 2.7 and 3.6.1.

Color and shape of the leaves was first considered with regard to pest stress physical features mapped to their digital imaging equivalent features, as seen in Figure 4.1 to 4.3. Depending on the pest or disease, the plant may show different colors or shapes at different infection stages, as the plant grows. Disease infestation signatures were also considered by analyzing the disease infection status as shown in Figure 4.4 to 4.6. A plant shows different patterns along with their infection's status according to the life cycle of the disease. The infection status can be seen on the physical features on the leafs. Infection status was analyzed as seen in Figure 4.1 and 4.4. Healthy Tomato Leaf is seen in Figures 4.7. The Patterns of the Leaf was also considered as a signature as shown in Figures 4.10 and Figure 4.11. Symptoms of the disease and pest shows visible variations either on the front side or the back side of the leaves. The other signature that was considered was the location of the pest or disease as shown by the Symptoms as seen in Figure 4.12 & 4.13; where the figures shows a representation of the diseases and pests under different conditions and variations as identified in this study.

4.3 Mapping of the Physical Features into Digital Imaging Signatures

In this study, the approach used in recognition of physical traits from the captured images was to label the images with both the disease information and the pests' information, the disease name being already included in the data containing the image from the original raw images captured from the field. Experts in this case being Agronomist were involved in the tagging of the images with the actual diseases. The disease stress and the pest stress detected were connected to the image with characteristics that related to the actual stress.

4.3.1 Mapping Physical Pest Stress Features to Digital Imaging Signatures

This study aims at mapping different identified signature characteristics of pest and disease stress that affect tomato plants to digital imaging signatures characterizing stress in plants. The process starts by loading an image to the model, convert the image to grayscale and passing a low frequency Gaussian Blur filter of size 11 by 11, later reducing the high frequency noise from the resulting grayscale image. For an 8-bit RGB color image, greyscale image, 0 represents black or 0x000000 and 255 represents white or 0xFFFFFF, and p is the pixel proportion whose greyscale level is greater than or equal to 200 and less than 200.

To get the region with white flies, we perform a thresholding as per Formula 14.

$$if(p \geq 200)\ set\ P = 255(white)\ and\ if(p < 200)\ \ set\ P = 0(black)\ .\ .\ .\ .\ .\ .\ . \quad (14)$$

After this operation, a binary image with some little noise is created by performing an erosion followed by dilation, removes the noise and makes the white flies clearer.

Figure 4.1 shows the Gaussian Blur, Thresholding, Eroding and Dilating feature extraction techniques applied on the image.

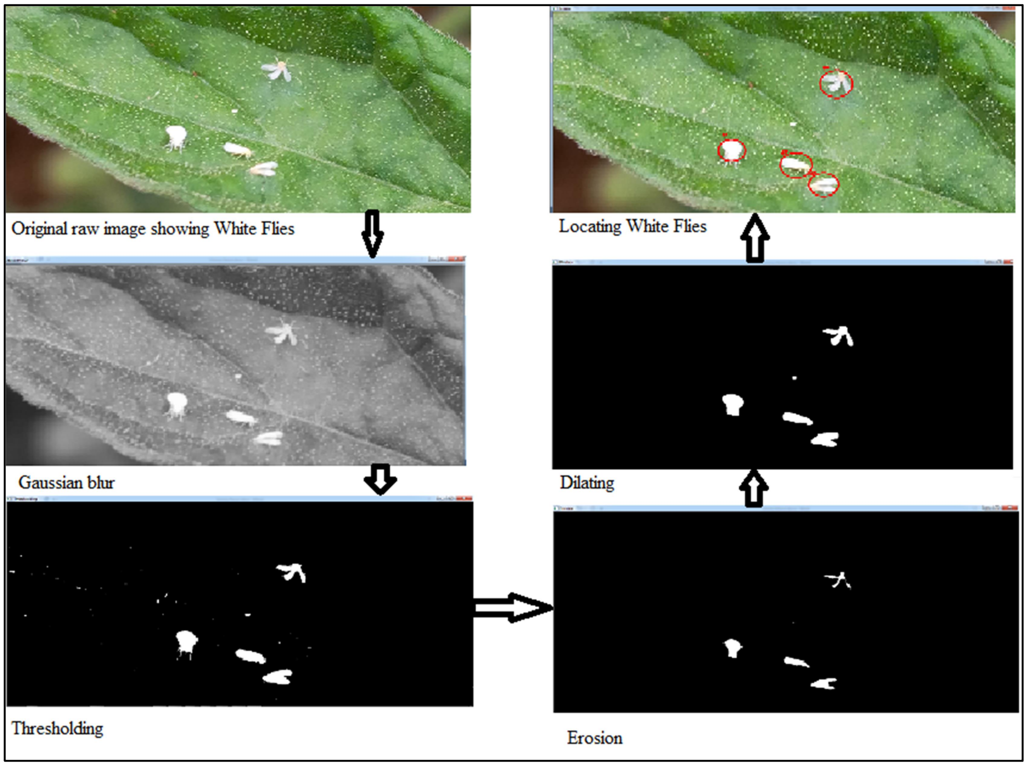


Figure 4. 1: Mapping physical pest stress features to digital imaging signature

In the eroding section of the process, the value of the output pixel is the minimum value of all pixels in the neighbourhood. Erosion removes islands and small objects so that only substantibe objects remain. In the binary image, a pixel is set to 0 if any of the neighboring pixels have the value 0.

Dilating occurs when the value of the output pixel is the maximum value of all pixels in the neighborhood. In a binary image, a pixel is set to 1 of any of the neighboring pixels have the value 1. Dilation makes objects more visible and fills the small holes in the objects. Figure 4.2 shows Histogram for Color Scale leaf image, with the x-axis showing the number of pixels, y-axis showing the color value (0-255); the red line representing the red color, green line representing green color and the blue line representing the blue color.

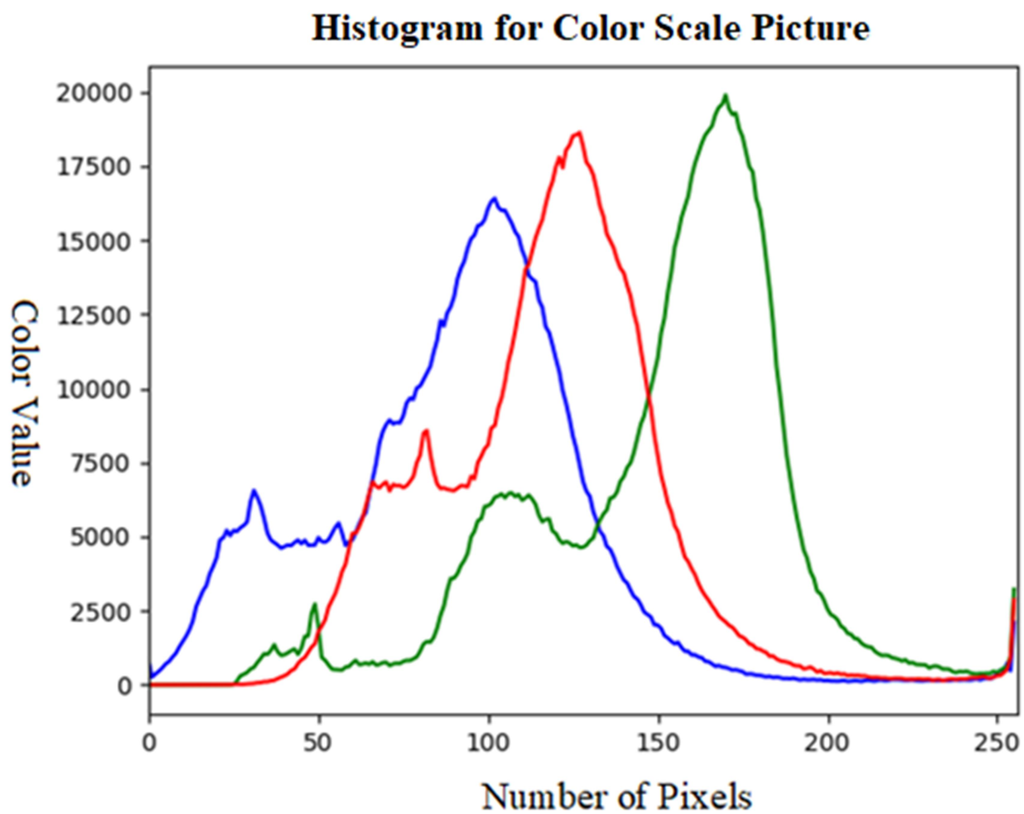


Figure 4. 2: Histogram for Color Scale for Leaf Image

Figure 4.3 shows the histogram of the dilated image showing the x-axis with the number of pixels, y-axis with the greyscale color values.

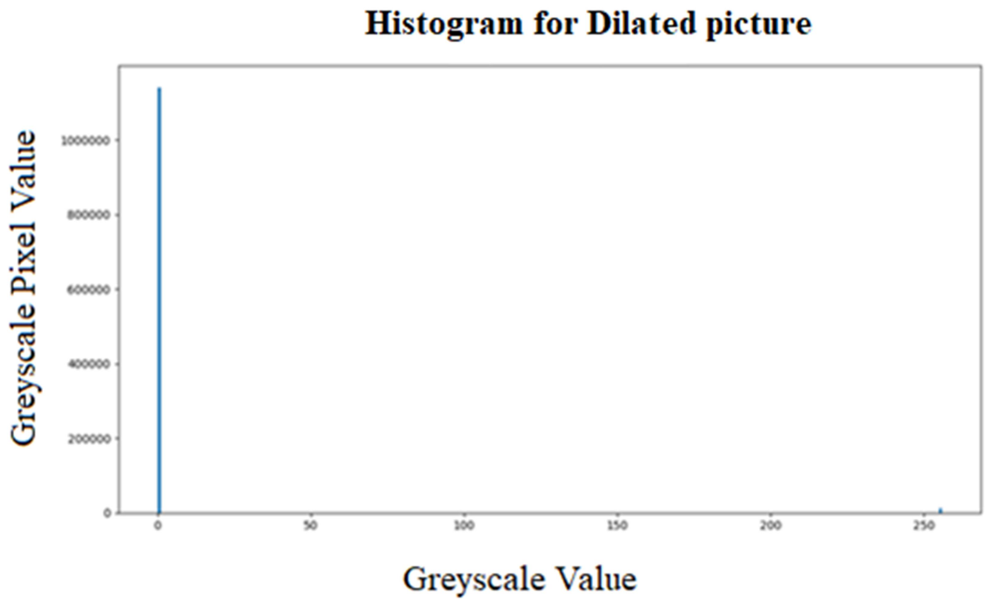


Figure 4. 3: Histogram of Image greyscale color values

4.3.2 Mapping Physical Disease Stress Features to Digital Imaging Signatures

The process of mapping disease physical features to digital imaging signatures involves color transformation and segmentation. In color transformation the HSI (hue, saturation, intensity) color model based on human perception is applied so as only the H (hue) component of HSI color space is taken into account since it provides the required information. Green color pixel performed is represented to show the healthy region of a leaf. Green pixels are masked based on the specified threshold values. Finally, segmentation is carried out to mark the infected portion of the leaf and extracted by segmenting the diseased part with other similar colored parts (say, a brown colored branch of a leaf that may look like the disease) which have been considered in the masked-out region of interest (ROI). Figure 4.4 shows the various color transformations masking green pixels and different segmentations occurring on a leaf infected with Early Blight.

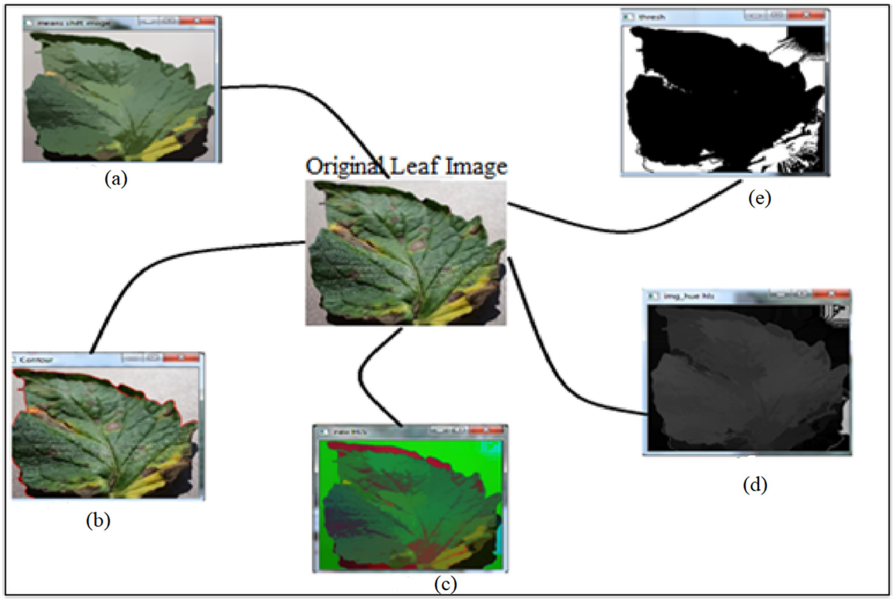


Figure 4. 4: Color Transformations of a leaf infected with Early Tomato Blight, with (a) means shift on the image, (b) contours on the edges of the image, (c) High Level Synthesis (HLS), (d) hue HLS and (d) Thresholding

Histogram of original healthy leaf shown in Figure 4.5. The Red, Green and Blue features of the original image are depicted by the color values with relation to the number of pixels.

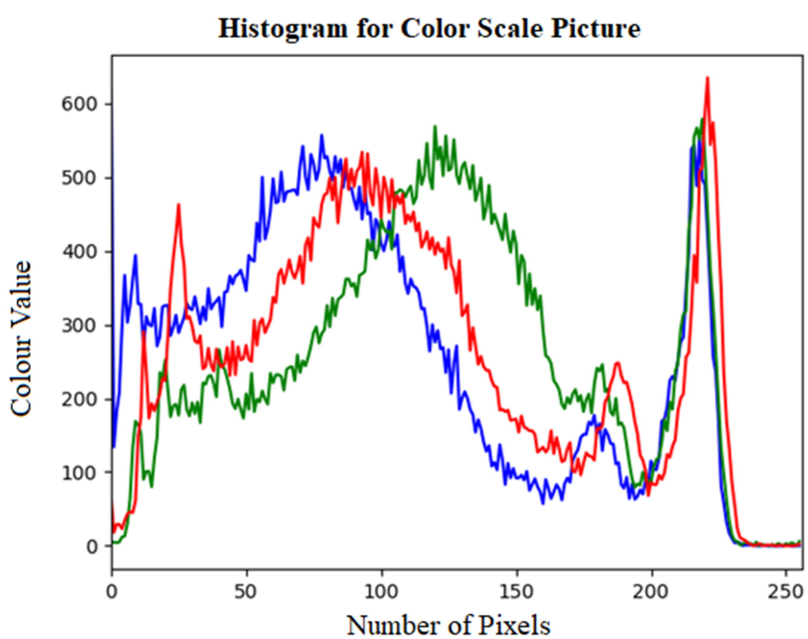


Figure 4. 5: Histogram color scale of the original leaf

Mapping of disease transformations shown in the histogram displayed in Figure 4.6. The x-axis shows the greyscale values and y-axis shows the greyscale pixel values. The greyscale value 0 has the highest pixel values whereas greyscale value 255 has lower greyscale pixel values.

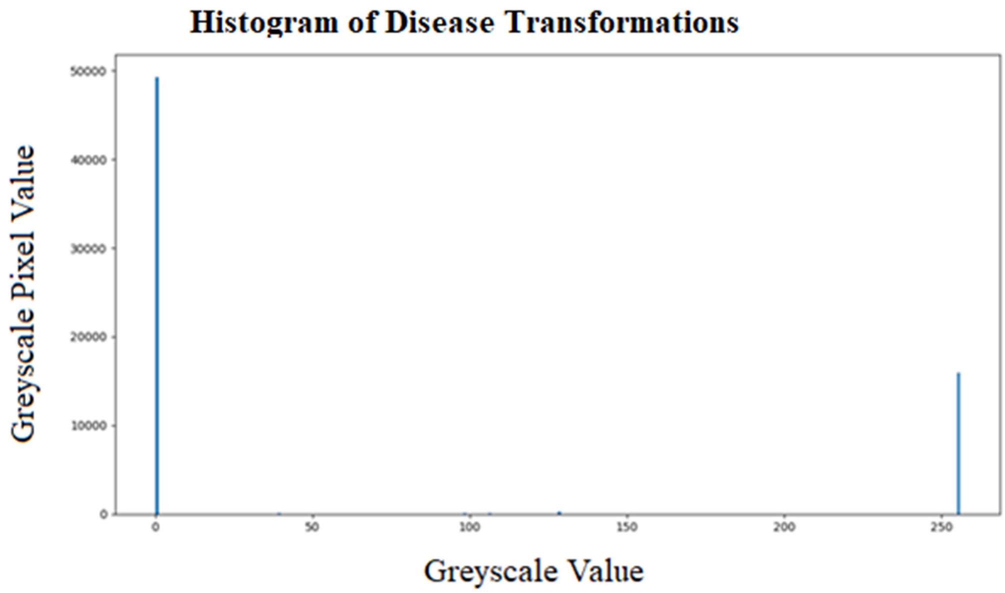


Figure 4. 6: Histogram of Mapped disease transformations

Images of Healthy Tomato leaf were subjected to meanshift as applied in clustering algorithm, to determine the number of clusters for the determination of features of healthy leaf. The digital imaging features of a healthy leaf are shown in Figure 4.7.

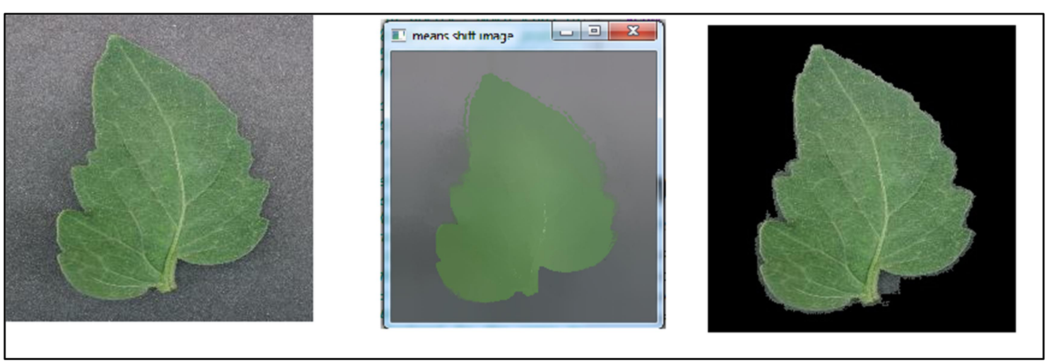


Figure 4. 7: Images of Healthy Tomato Leaf taken through mean shift to determine the digital imaging signature of a healthy leaf

The Histogram depicting the color scale original picture of a healthy leaf in Figure 4.8. A region of interest (either diseased or pest infested region) is not found in the healthy image and other operations are not performed on the image.

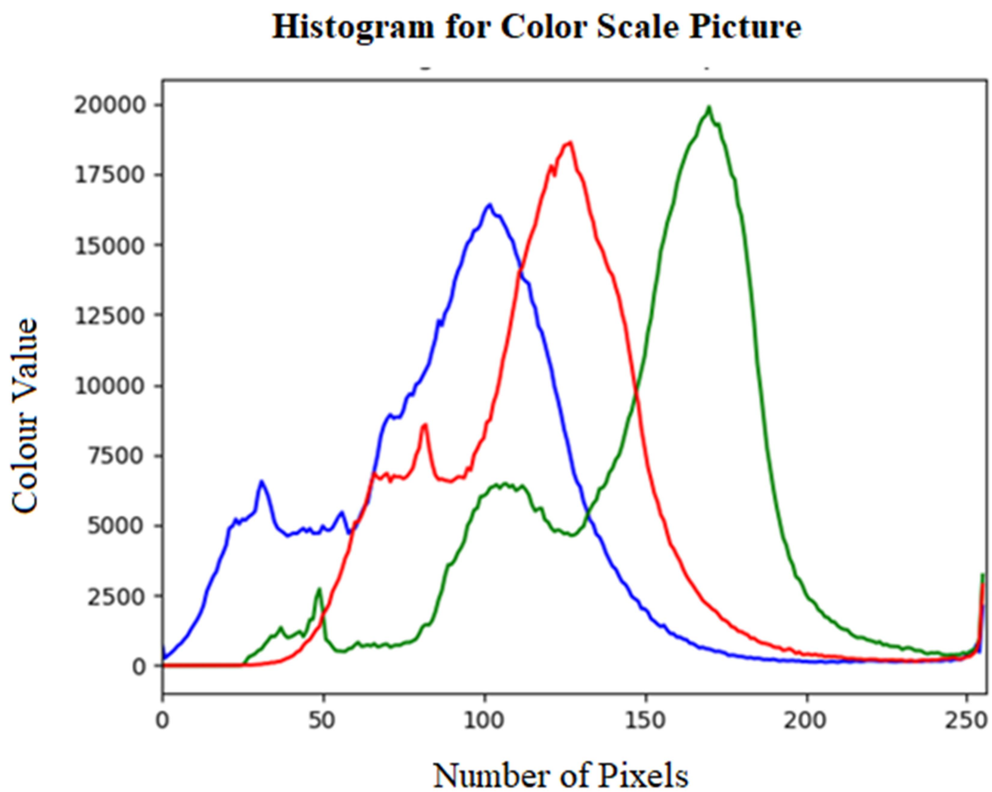


Figure 4. 8: Histogram with Color scale of healthy leaf

The bins representing the number of pixels range from 0 to 255 plotted on the x-axis. The y-axis contains the color values in each bin. The majority of color pixels are in the range of 75 to 125 for blue and red, and 125 -150 for green. In the range of 150 to 255 there are few pxels. The color scale picture of a healthy leaf under mean shift is indicated in Figure 4.9.

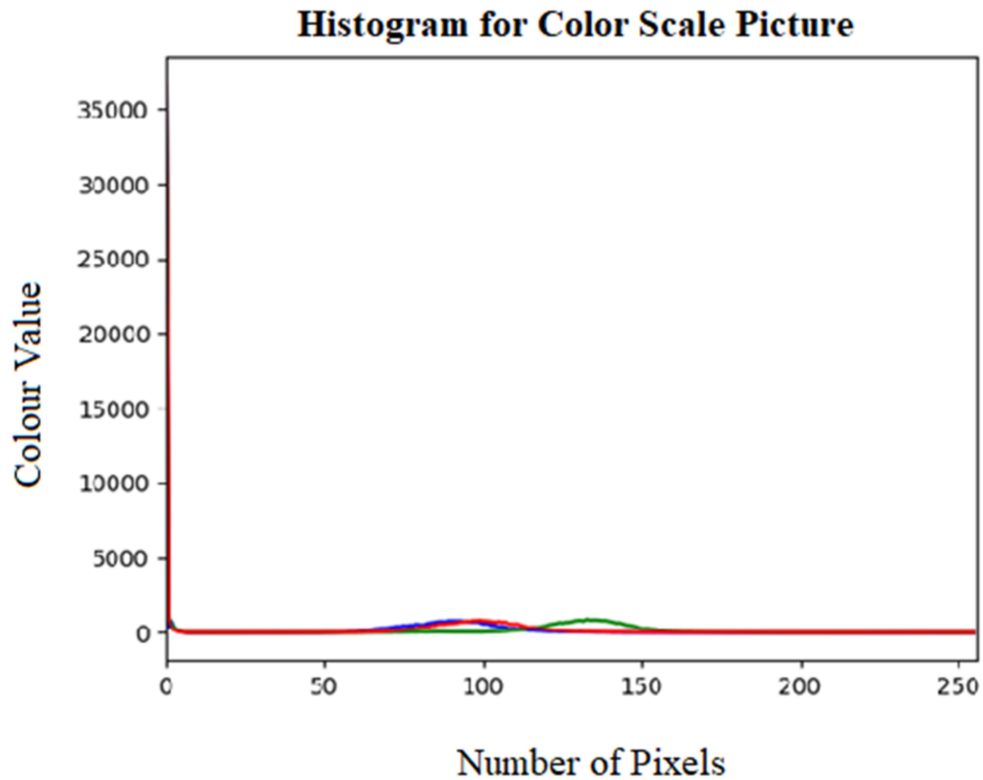


Figure 4. 9: Color scale picture of a healthy leaf under mean shift

The 8745 image datasets utilized in this study contained images of several diseases and pests in tomato plants. Using smartphone cameras, images were collected under diverse conditions and times depicting different illuminations, different humidity and temperature conditions, and places taken which included open environment and controlled environment including greenhouses. Data was collected using digital cameras installed on smartphones. This resulted to images with different resolutions; and different stages of infection status by diseases and infestation by pests from early medium and late time infected; images with different areas of plant infection including leaves, stem and fruits; different sizes of plants; and images with different background characteristics showing objects that were captured around the images.

The 8745 image datasets were further annotated manually, so as to identify areas of every image containing features that depicted disease or pest's infestation. Some diseases presented similar characteristics depending on the status of the infestation presented; in such cases, inorder to be able to identify the type of pest or disease was provided by the experts in this area. This helped in the visible identification of the different categorizations of images and affected areas on the infected plant.

The process of annotation was aimed at labeling the location of the infected areas in the image. The major output of this step was the coordinates of the different sizes of the images with their corresponding disease and pest classified, as visualized in the Figure 4.10 & 4.11. Figure 4.10 shows Images of Tomato with (a) Early Blight, Alternia solani; (b) Bacterial Speck, Pseudomonas syringae ; (c) Bacterial cancer, Clavibacter michiganensis; (d) Bacterial spot, Xathomonas campestris; (e) Tomato Leaf Curl ; (f) Bacterial wilt, Ralstonia Solana.

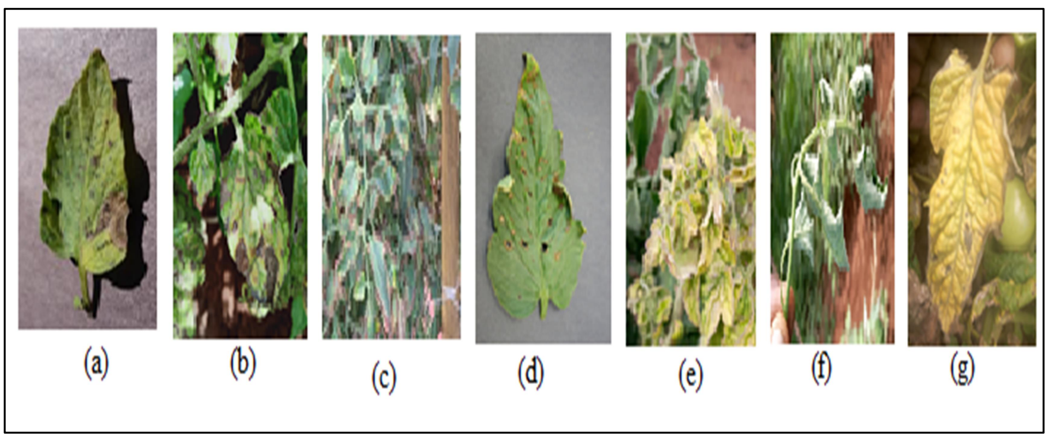


Figure 4. 10: Images of Tomato Diseases

Once the stresses have been predicted, recommendations are passed to the farmer to aid him in the process of correcting the predicted disease before the effect is felt on the crop. Figure 4.11 shows Multiple predictions of (a) Tomato Leaf Miner, (b)

Spidermite, (c) Tomato Leaf Hopper, (d) Tuta Absoluta, (e) White Flies and (f) Aphids on stressed Tomato plants.

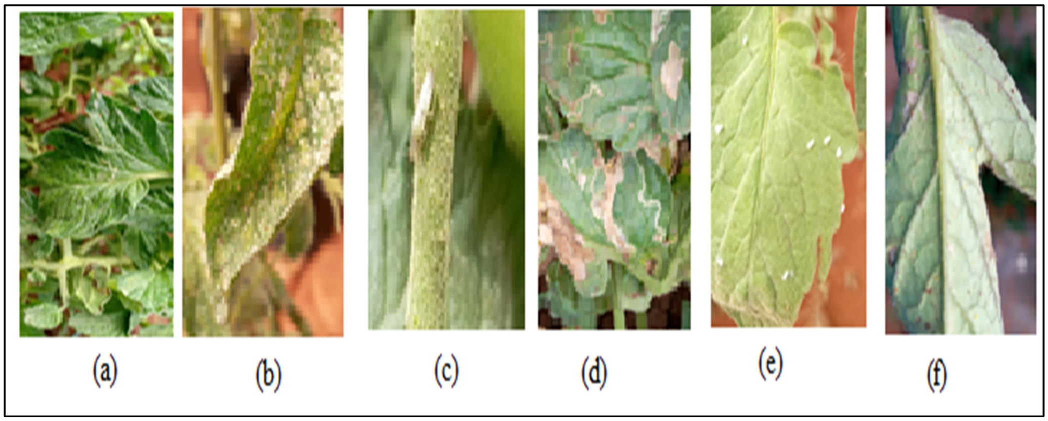
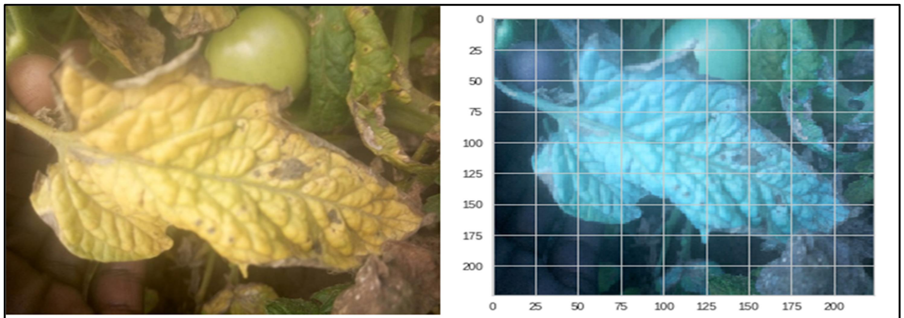


Figure 4. 11: Images of Tomato Pests

4.3.3 Image Preprocessing and Resizing

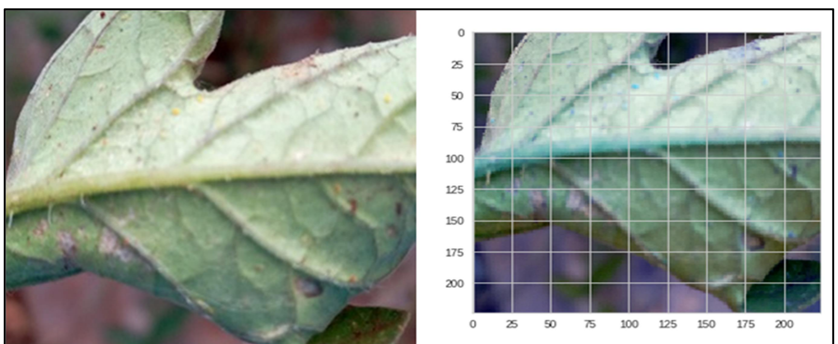
Images were captured from the open field and controlled environments and imported in to the web server. Images were preprocessed to predict pests and disease stresses detected as per the developed digital imaging model. The images were resized to a ratio of 224 by 224 pixels so as to be of equal dimensions. The values 224 by 224 were chosen as the MobileNetV2 accepts such dimensions. Images were resized, rescaled and flipped horizontally for extraction of best features for the training purposes. Figure 4.12 illustrates (a) Image Before Resizing and (b) Image After Resizing.



(a) Image Before Resizing (b) Image Aftee Resizing

Figure 4. 12: Image Resizing

The images have the RGB coefficient 0-255 which are too high for our model so the coefficients were lowered to between 0 and 1 by a factor of 1/255. Figure 4.13 illustrates (a) Image before rescaling and Image (b) Image After Rescaling.



(a) Image Before Rescaling (b) Image After Rescaling

Figure 4.13: Image Rescaling

4.3.4 Image Horizontal Flip

The horizontal flip argument was set to true to enable this. Image flipping is the rotation of an image end-over-end. This was done also to increase the accuracy of the trained model so as in any chance an image is flipped it can easily detect and classify that image without any difficulty. Figure 4.14 illustrates Tomato Leaf Image (a) Before and (b) After Horizontal Flip.

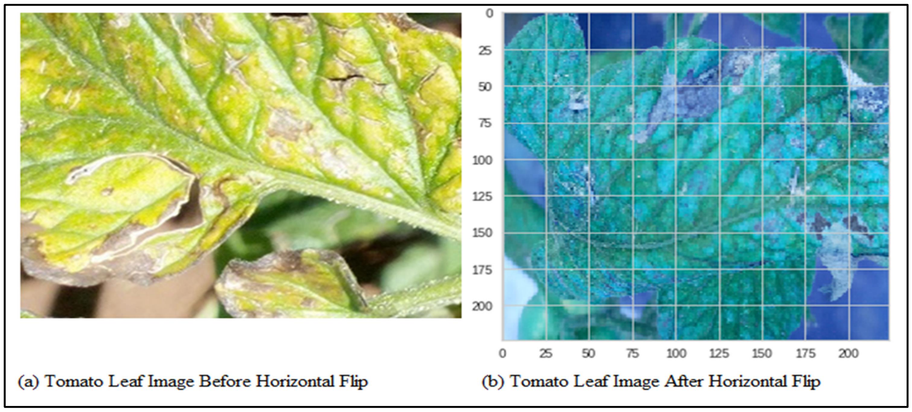


Figure 4.14: Horizontal Flip

4.4 Plant Stress Feature Extraction and Classification Approach

Image acquisition involved labelling of labeled source datasets obtained from images captured for classification of plant stresses. The CNN training network utilized the pre-trained model using large datasets for extraction of features. The already learned network was used to determine which pest or disease was detected to be utilized as classification input images. The output results represent the probability of the classes found. This approach is illustrated in Figure 4.15.

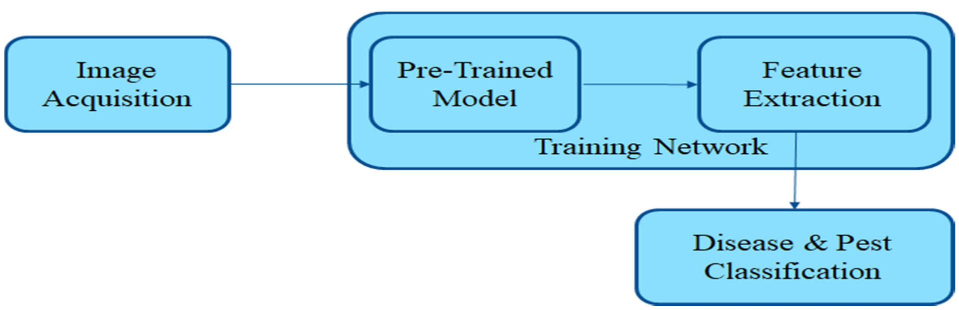


Figure 4.15: Plant Pest and Disease Classification

Convolution Neural Network Training entailed training the model on large datasets used to extract features. Disease and pest classification entailed the already learned network to determine presence or absence of pest and disease stress on input image classification for the input images, and outputting results representing probabilities of class found. The Faster R-CNN feature extractor was extended as used in (Shen et al., 2018) for object recognition to estimate the location of the disease or pest detected. For each image captured ROI pooling was performed on the images inorder to classify and used bounding-box (A. F. Fuentes et al., 2018) regression to estimate the target location of the stress detected.

The steps for feature extraction involved a number of steps as described below. The network parameters were initialized and all the weights of the pre-trained layers by freezing. This resulted to extension of the fully connected (FC) layers trained on the target data. This ended up resulting to outputs classifying pests and diseases, showing the presence or absence of stress. All the layers were trained on the new image and the final layer used SoftMax to make the binary classification. this approach is illustrated in Figure 4.16.

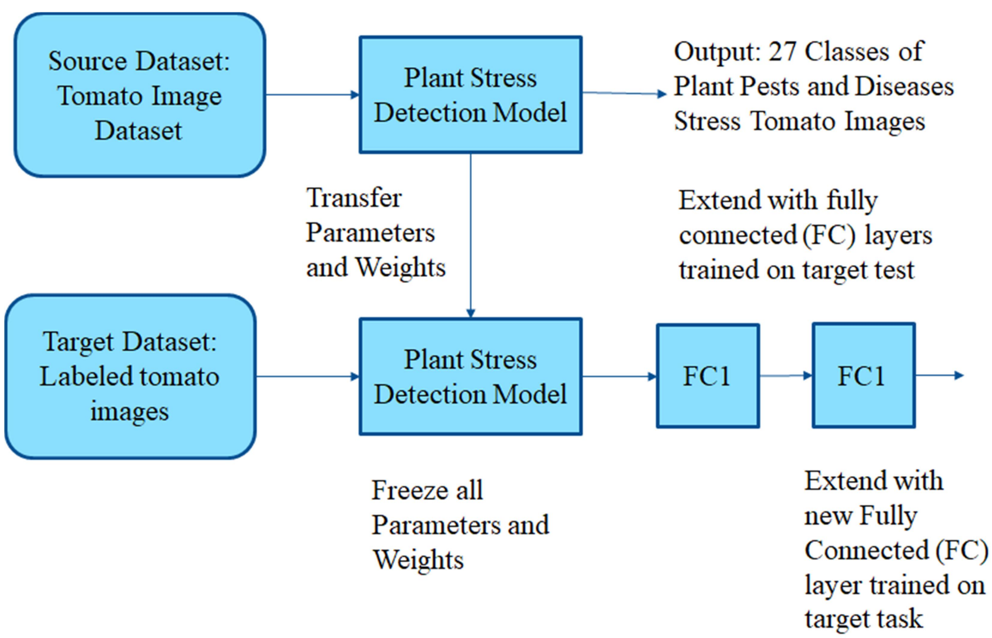


Figure 4. 16: Plant Stress Feature Extraction Approach

4.5 Feature Extraction and Classification Algorithm

The approach for feature extraction involved initialization of network parameters, freezing the weights of the pre-trained layers, then extending the load allocated for the two fully connected layers resulting to an output of the classifying presence or absence of pest and disease stress. All the layers are trained on the new image and the final layers uses the SoftMax sigmoid function for binary classification. The feature extraction and classification algorithm is as follows;

1. Resize each image to a size of 224 * 224.
2. Create two batched datasets i.e. training and validation set
3. For each image in the batch, apply the first convolution filter in the residual block with Relu6 activation.
4. Perform depthwise convolution on the output.
5. Apply the third convolution filter without non linearity.
6. Perform classification on the last prediction layer with SoftMax while updating the loss and accuracy.
7. Repeat the above processes using a backpropagation algorithm for N number of iterations.

Progressive image resizing (Blake Weyland, 2019) is a technique applied on the dataset during the training to build an image classifier using Keras. Specifically, this study uses progressive resizing on the dataset to build a CNN that learns to distinguish between 27 different kinds of tomato diseases and pests in what in this study is called Tunza Leaf Tomato Model Dataset. Progressive image resizing affects the accuracy, training, and transfer of learning within the convolution neural network.

In this study a total of 8,745 images were captured using smartphone cameras for visual recognition of the stresses in different environmental conditions which include open field and controlled environments. The images were captured over a period of 28 days and repeated in a period of six months. Prediction and validation of the performance with the Convolution Neural Network model calibrated in a Mobile phone application installed on android phones of farmers was done, hence the physical features were mapped to the digital signatures characterizing disease and pest stress in the tomato plant images.

4.5.1 Timely Detection of Tomato Diseases

Figure 4.10 contains images of tomato plants affected by a diverse range of diseases. Out of the 27 disease images predicted it correctly predicted 27 images as validated through the web interface. This is as a result of timely capturing of the images at an early stage during image acquisition. This was tested and validated in the system by installing the software on farmer phones and allowing them to scout their farms for diseases. This enabled the farmers to apply remedial measures recommended by the mobile application due to the calibration that were installed in their Smartphones. Diagnostic messages on the app enabled the developer to refine the calibration of the application installed on the farmer phone to timely detect the disease and recommend diagnosis.

The process starts when the farmer launches the application on the phone and points the camera of the phone to the section of the plant that he thinks its affected. Once the farmer captures the image of the portion of the plant using the camera, the developed model preprocesses the image based on the algorithm in the model, to respond with diagnostic recommendations to the farmer. The variety of recommendations include the agrochemicals to be applied, the agrovet shop where farmer can get the recommended agrochemicals, and the contact for the available Agricultural Extension officer for the farmer to call and get advice on where the agrovet is or any further instructing necessary. The farmer and the extension officer is also able to know the location on the farm where the stress has been detected based on the geographical positioning. Once the farmer detects the stress and applies the necessary remedy, the goal of this study will be achieved by enhancing food security through timely detection and accurate diagnosis of the detected disease.

4.5.2 Timely Detection of Tomato Pests

The figure 4.11 displays the different categories of pests detected and used for prediction of the multiple pests. The images of pests captured during data collection was used for training and testing before the physical features and signatures of the different plants. The different categories of pests are captured on either side of the leaf. Once captured the images are used for timely detection of the presence of absence of the pests based the trained model for accurate diagnosis of the detected pets. Once the stress is detected the model diagnoses the stress associated with the pest, and accurately recommends the remedial measure to be taken by the farmer. The farmer can go ahead and procure a pesticide from recommended agrovet or contact the resident agronomist in the region, so as to be able to be assisted with technical and agronomic assistance based on the detected pests.

The farmer is able to see the location that the pests are detected based on the geographical positioning and is able map the location that a pest is detected, and enable the farmer to be at a position to remedy the challenges as a result of the pests at an early stage before the effect of the pest is felt. This enables the farmer to be in a position to leverage the abilities provisioned by the power of the Smartphone application algorithm in the model to learn and detect the pest stresses in the crop at an early stage for accurate diagnosis at an early stage through timely detection of the effect likely to be felt and also recommend to the farmer the contacts to locations where to procure authentic pesticide for the tomatoes and instruction on how to apply. This achieves the aim of calibration of the model with the capability of timely detection and accurate diagnosis of the pests.

4.6 Summary

This section discussed the demographic information related to the study. The physical features of stress in plants are also discussed with mapping of the pests and disease physical features to the digital imaging signatures, and displayed on a histogram based on Gaussian blur, Thresholding, Eroding and Dilating. Image pre-processing approaches were also discussed highlighting the resizing and rescaling approaches involved including horizontal flip. Images categorised in broad categories of plant disease and pest with predictions employed on the images, feature extraction and classification algorithms was also discussed.

CHAPTER FIVE

DIGITAL IMAGING MODEL FOR DETECTION OF PLANT STRESS

5.0 Overview

This Chapter comprises of the implementation of the convolution neural network model, the structure of the convolution neural network, the datasets used, the activation function applied and the optimizers. The digital imaging model is also discussed with a focus on the dependencies imported, the data preprocessing techniques applied, transfer learning approach used, feature extraction, and classification. The training applied on the digital imaging model is discussed and the confusion matrix model discussed. The validity of the results of the model have also been discussed, with a focus on accuracy graphs that relate to training steps, training sets, and training epochs.

The digital imaging model for plant stress that has been visualized through the TensorBoard graph, is discussed describing the digital imaging model optimization. The Model is also outlined graphically highlighting the approach used in extraction of features for tomato diseases. This chapter presents the Digital Imaging Model under the themes derived from the fourth and fifth objectives of the study that include; to develop a digital imaging model for plant stress detection and to validate the digital imaging model for detection of plant stress.

5.1 Digital Imaging Neural Network Model

The digital Imaging Neural Network Model was developed using the TensorFlow deep learning platform (Rampasek & Goldenberg, 2016). This study has developed a digital imaging neural network model on a TensorFlow platform. The developed Model was further tested using a variety of activation functions and neurons.

Subsequent sections will present the model. Neurons and Layers are key in the modeling of neural network structures. For CNN the number of input and output neurons is predetermined based on the dimension of the training set and the prediction sets.

5.1.1 Algorithm of the Plant Stress Detection Model

Algorithms outline a systematic approach following steps leading to arrive at an expected solution to an existing problem. The algorithm designed for the digital imaging model for timely detection and accurate diagnosis of plant stress is shown in this section. The algorithm is informed by plant stress feature extraction and classification approach discussed in section 4.5 and illustrated in figure 4.15 and figure 4.16. Images acquired using a digital imaging device are represented by N-images form the labelled dataset. The CNN training network performs pre-training and feature extraction for classification of pest and disease stresses. The large dataset features are extracted by initializing the network parameters which include n-images, k-classes and i-preprocessing steps. Weights are freezed and features extracted from k-arrays to classify images either representing pest or disease infestation.

Features extracted from test datasets result to two batches of datasets which include training set and validation set. In the training module each image in the batch applies Convolution filters resulting to classification with SoftMax activation function. Weights are regulated while updating the loss and accuracy. This process is iterated using backpropagation algorithm, resulting to classification of 27 classes of pest and diseases stresses from acquired tomato images as output. The prediction module relies on the MobileNetV2 building blocks for depth wise separable convolution blocks to predict output values of pests and disease based on the extended fully connected layers Error measurement is attained through validation based or SRCC, web interface and Mobile app interface through transfer learning based on MobileNetV2. The algorithm of the digital imaging model for the plant stress detection is shown in Figure 5.1.

```
Input: N images
PreprocessAn: [];
Output: K classes
1.      Input the N images
2.      for i=1 to N do
3.              PreprocessImg [] ←  Pre_ProcessingImg (i);
        for j=1 to PreprocessImg [size]
                ExtractFeature [] ← ExtractFeature (PreprocessImg[j);

        for k-=1 to ExtractArr [size]
                classify [] ←  ClassifyFeatures (ExtractArr(k))

Pre_ProcessImg(img){
                for 1 to N do
                rotation
        Flip
        Rescaling
        }

ExtractFeature (img) {
        Gaussian Blur
        Thresholding
        Erosion Dilating
        }

ClassifyFeatures () {
        Optimization: Adam Optimizer
        Activation Function:SoftMax

VandateFeature () {
        Confusion Matrix
        Accuracy
        Precision
        Recall
        }
```

Figure 5. 1: Algorithm of the Digital Imaging Model

5.1.2 Structure of the Digital Imaging Model

The digital imaging model for detection of plant stress is discussed in this section. The proposed architectural model contains the data processing module, training module and prediction module of the Digital Imaging Model for plant stress detection. Acquired images are composed of plant images captured which are further taken through the annotation and augmentation stage in the data preprocessing module. This is followed by the testing, training and validation stage for the data.

The training and validation data used in the model are based on the 8745 images acquired in the study. Two thirds of the images equating to 80% of the images are used as validation data and training data having been validated by qualified agronomists, lead farmers and qualified software personnel, whereas a third of the images forming the remaining 20% used as test data. Testing is based on the test data which verifies the performance of the CNN prediction model before giving the final result. The trained data results to formation of the CNN model and activation functions selected.

Training of the model is done so as to enable the timely detection and accurate diagnosis of pest and disease stress in plants applied in the CNN prediction model, where prediction relates to the ability of the web interface and mobile application interface being able to provide diagnostic recommendations for the farmer based on the stress detected. Error measurement for detected errors are taken through the validation process in the web interface to ensure accurate diagnosis of detected pest and diseases. Figure 5.2 presents the system overview of the digital imaging model for timely detection and accurate diagnosis of tomato plant pest diseases.

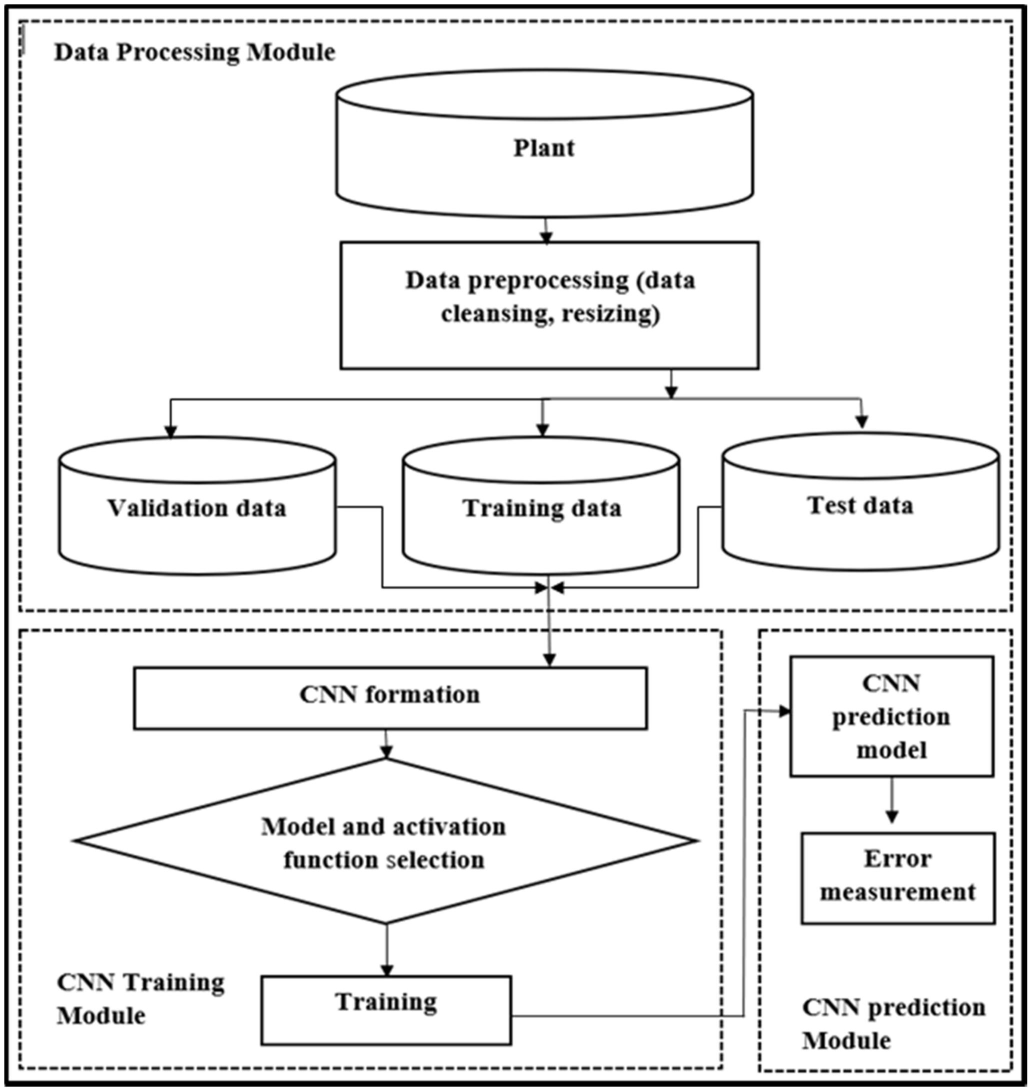


Figure 5. 2: Digital Imaging Model for Plant Stress Detection

5.1.3 Activation Function

An activation function is a deciding parameter used for evaluation and capturing the trends or feature patterns from within the data. If the output value originating for the activation function is zero, the feature is absent and if the value is one the feature is present in the data. In computational networks, the activation function of a node defines the output from that node given an input or a set of inputs. A standard computer chip circuit function of "on" and "off" corresponding to '1' and '0' depending on the input. This relates to how linear perceptron in neural networks operate. In artificial neural networks this function is also referred to as the transfer function. An activation function was used for the neural network to determine which neurons should be activated.

$$y = Activation(\sum (Weight \times Bias) + Bias) \ldots \quad (15)$$

In training of this neural network model, activation function plays a very important function in regulation of the weights. In this study, we have used a non-linear sigmoid SoftMax hidden layers in the model.

The standard SoftMax function σ: □$^{K} \longrightarrow$ □^{K} is defined by the formula in equation 16. The standard applies exponential function to each element z_j of the input vector z of K real numbers, consisting of K probabilities. The elements z_j of input vector z are normalized by division of the sum of all exponentials which are normalized to ensure that the summation of the component results to output vector $\sigma(z)$ resulting to 1 as defined by the formula in equation 16.

$$\sigma(z)_j = \frac{e^{zj}}{\sum_{k=1}^{K} e^{zk}} \ for \ j = 1, \ldots, K. \ldots$$

(16)

The activation function takes an input of vector z of K real numbers then normalized to a K probabilities of the input numbers. This activation function reduces the output of each class in this case to between 0 and 1 and divide by the sum of outputs therefore giving their probability.

5.1.4 Optimization with Adam Optimizer Algorithm

The Adam Optimizer Algorithm is a method for stochastic optimization (Kingma & Ba, 2014) in deep learning and it combines the advantage of two other stochastic gradient descents which are; Adaptive Gradient Algorithm (AdaGrad) and Root Mean

Square Propagation (RMSProp) to realize their benefits. Adam optimizer was applied due to its capability to work with large datasets and models efficiently ion solving practical deep learning problems. The model implemented this optimization because it converges fast and its learning speed is fast compared to the others.

The Adam optimizer algorithm was applied at the classification stage. An optimizer in a neural network reduce the loss function which in turn shows the optimizer if it is doing the right thing. It estimates the first and the second moment of the gradient to change the neural networks' weights. The n-th moment of a variable is expressed as:

$m_n = E[X^n]$ . . . . (17)

The variables m represents the moment; X represents a random variable and E represents the expected value respectively.

5.2 Digital Imaging Model Implementation

This section covers importation of dependencies, data preprocessing, transfer learning, classification, modelling, training the model, and performance of confusion matrix and Image rescaling and resizing that was conducted on the images.

5.2.1 Importing Dependencies

The model interface is based on *TensofFlow, Keras, Matploit, Numpy, Sklearn, Time, and Opencv*. *TensorFlow*, an open source platform that supports deep learning. The *Keras* high level application programming interface for *TensorFlow* was utilized in coding process. *Matplotlib* python package was used for plotting. *Numpy* python package was used for numerical processing. The *Time* package was used for time epochs. *Sklearn* package was used to construct the confusion matrix and also it was used to find the precision score and recall score. *Opencv* package was used for plotting the images.

5.2.2 Data Preprocessing

The training section is made up of Train_root and Test_root. Train_root points the path to the training of the images whereas Test_root points the path to the testing images. The next step was to create an instance of ImageDataGenerator using the train_image_generator. This resulted to rescaling of the image by 1/255, and rotation of the image by 15 degrees and flipping the image horizontally for the training data. This was followed by test_image_generator which rescaled the image by 1/255, rotated it by 15 degrees and finally flipped the image horizontally for the test data. Image training and testing through the image generator was followed by loading the images from the saved path and the resizing the images to 224 by 224, then later saving the images to variables train_image_data and test_image_data.

Rescaling was implemented through the Keras ImageDataGenerator. The original images are in the RGB format and such values are very high for processing. We have to target values between 0 and 1 so we rescale by a factor of 1/255 and resizing target size was set to (224 by 224). Having resized the images to 224 by 224 looping is done through the training images to ascertain the batch shape for the labels and images, using the method shape to determine batch shape. Image batch shaping is followed by test images which loops through the test images to ascertain the batch shape for the labels and images. We use the method shape to find the batch shape.

5.2.3 Transfer Learning

MobileNetV2 we was used for transfer learning (Coulibaly et al., 2019a; Kaya et al., 2019; Şeker, 2019). This was applied so as the deep learning neural network developed can be reused at a later time. Hence transfer learning is used to enable reusing of a model that has already been trained in a given predictive modeling problem. In this study transfer learning enabled the improvement of the performance of the deep CNN model developed. MobileNetV2 was applied through acquisition of images of tomato plants for timely detection and accurate diagnosis of pest and diseases stress, for enhanced food security. This was made possible through the application of transfer learning on CNN to the created dataset containing images of tomato plants.

5.2.4 Feature Extraction

The function called feature_extractor checks the expected image size and create the module. The module was later wrapped in to keras layers. Then later the variables were freezed in to the feature extractor. Image low level feature extraction algorithms were used. The gradient descent iterative optimization algorithm has been applied in feature extraction and improve on the learning rate. Feature Extraction is demonstrated in figure 4.16. Transformations using Gaussian blur, Thresholding, Eroding and Dilating as highlighted in Section 4.3 was found to be more effective in the scale-space detection on the tomato images, with key point localization, orientation assignment and key point description of the feature vector that is quantized in to visual words representing different stresses identified that relate to the tomato stress. The frequency of the existence of each feature is represented in histograms as shown in the Sections 4.3.1 and 4.3.2.

5.2.5 Classification

The step that followed was the creation of a sequential model in Keras. This was done through the provision of the feature extraction layer and the activation function which is SoftMax activation function. Later the TensorFlow hub was initialized. A single batch is later passed to the model to confirm the batch shape. Classification has been outlined in figure 4.15.

5.2.6 Compiling the Digital Imaging Model

An optimizer is provided which is the AdamOptimizer, then later provided a loss for the model which is the categorical_crossentropy and finally we provided a metric which is the accuracy. It creates and custom call back and it inherits from the class tf.keras.callbacks.Callback. The function on_batch_end provides the loss and accuracy values at the end of each batch. The function on_epoch_begin records time at the beginning of each epoch while the function on _epoch_end finds the time taken by each epoch. Steps to be taken per epoch in the model are later calculated. The samples were divided by the batch size to result to 36 steps that were needed per epoch. Early stopping was later implemented to prevent overfitting of the model and stop training when validation loss starts increasing.

5.2.7 Training the Digital Imaging Model

This digital imaging model summary was fitted. To fit the model five epochs were provided, the steps per epoch were thirty-six (36). Custom callbacks were also included and finally validation data were provided which were the test images. The model fitting was followed by plotting of the model summary for timely detection and accurate diagnosis of pest and disease stress in plants for enhanced food security as shown in Figure 5.3.

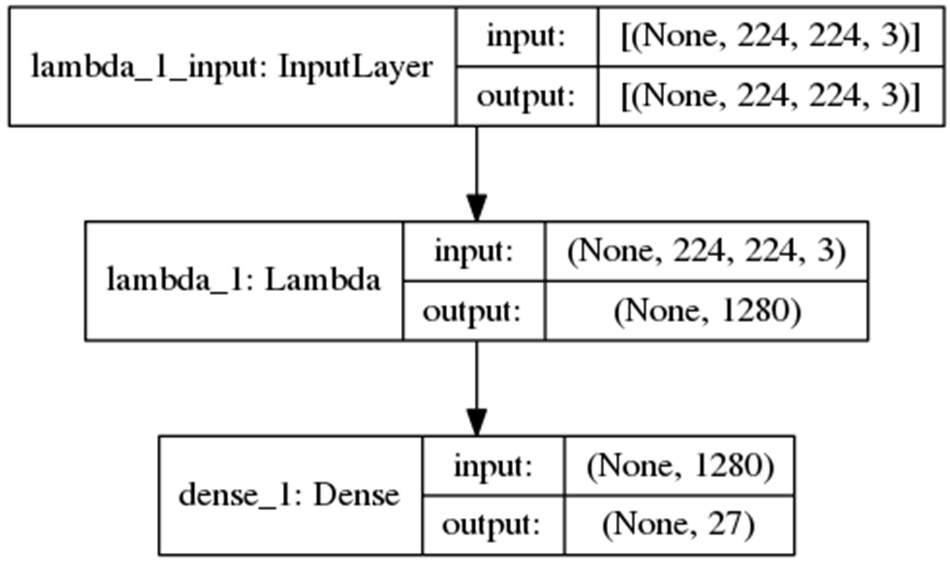


Figure 5. 3: Summary of the Digital Imaging Model

The input layer is a 4d tensor [batch, height, width, channels]. The Height is 224 pixels and the Width is 224 pixels, the channels are 3 representing the RGB and the image batch shape was tested testing. Then creating a prediction for the test images using the trained model and later the correct labels were stored.

The input layer lambda 1 input is made up of input images set to resolution of 224 by 224 and set to an RGB value of 3 where R represents Red with a digit 1 G represents Green with a digit 1 and B represents Blue set to a digit 1. The other layers for lambda 1 and dense 1 also have similar input as lambda 1 input. The output of layer one is input to layer two and subsequently the output of layer 2 is the input to layer three depicted as dense which generates an output of 27 different classes of images depicting different categories of stresses. To improve the feature extraction capability this study implemented transfer learning technique where it was used in the pre-trained model called MobileNetV2. The model type is sequential so as to allow the stacking of sequential layer.

5.2.8 The Model Confusion Matrix

The confusion matrix was later created by passing the predicted classes and the actual classes. The confusion matrix for the model contains higher values along the diagonal from top left to the bottom right pointing the model accuracy. The precision_score, the f1_score and recall_score was arrived at by passing in the actual and the predicted classes.

This study employed epochs for the extraction as all images that could not fit to the model at once. Epoch represents the number of times the dataset is passed through forward and backwards by the neural network. We used five epochs with thirty-six steps per run. The study further used the accuracy metric to test how good the model is for classification tasks.

$$Accuracy = \frac{TP+T}{TP+FP+FN+T} \ldots\ldots\ldots\ldots\ldots\ldots (18)$$

In True Positives (TP); the value of the actual class is a yes and that of the predicted class is also a yes. For True Negative (TN) the value of the actual class is a no and also that of the predicted class. In False Positive (FP) the value of the actual class is a no whereas the predicted class is a yes. In False Negative (FN) the value of the actual class is a yes whereas the predicted class is a no. Precision score this is fraction of relevant instance among the retrieved instances.

$$Precision = \frac{TP}{TP+FP} \ldots\ldots\ldots\ldots\ldots\ldots (19)$$

Recall is the percentage of the total relevant results classified by our algorithm.

$$Recall = \frac{TP}{TP+FN} \ldots\ldots\ldots\ldots\ldots\ldots (20)$$

F1 score this is a measure of test accuracy that considers both precision and recall so as to compute the score.

$$F1 = 2 \cdot \frac{precision \cdot recall}{preci} \quad (21)$$

The graphical presentation of the confusion matrix Figure 5.4 shows the accuracy levels of the model.

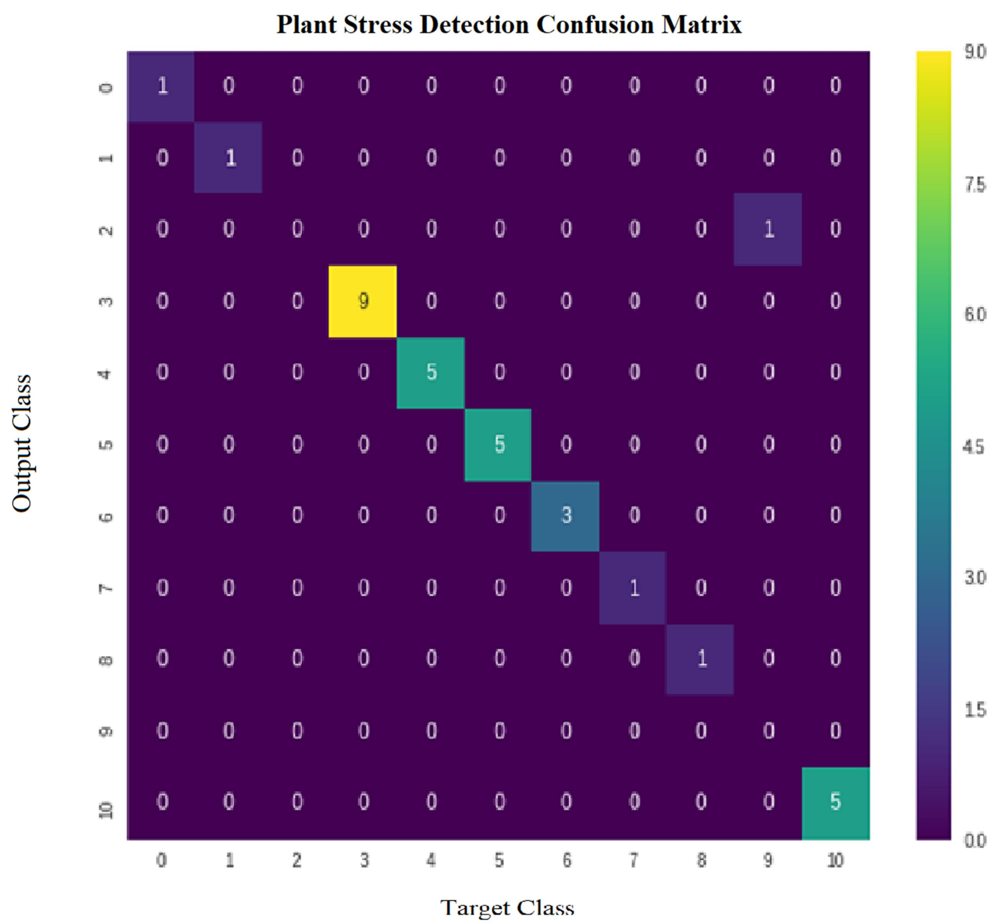


Figure 5.4: Confusion Matrix for the Model

5.3 Plotting the Results of the Model

The matplotlib graph plots the models' loss and accuracy against the training steps. We limit the y axis from 0 to 1 to represent percentage. As the training increases the accuracy of the model increases and its loss decreases as illustrated in figure 5.5.

5.3.1 Graph of Accuracy and Loss against Training Steps

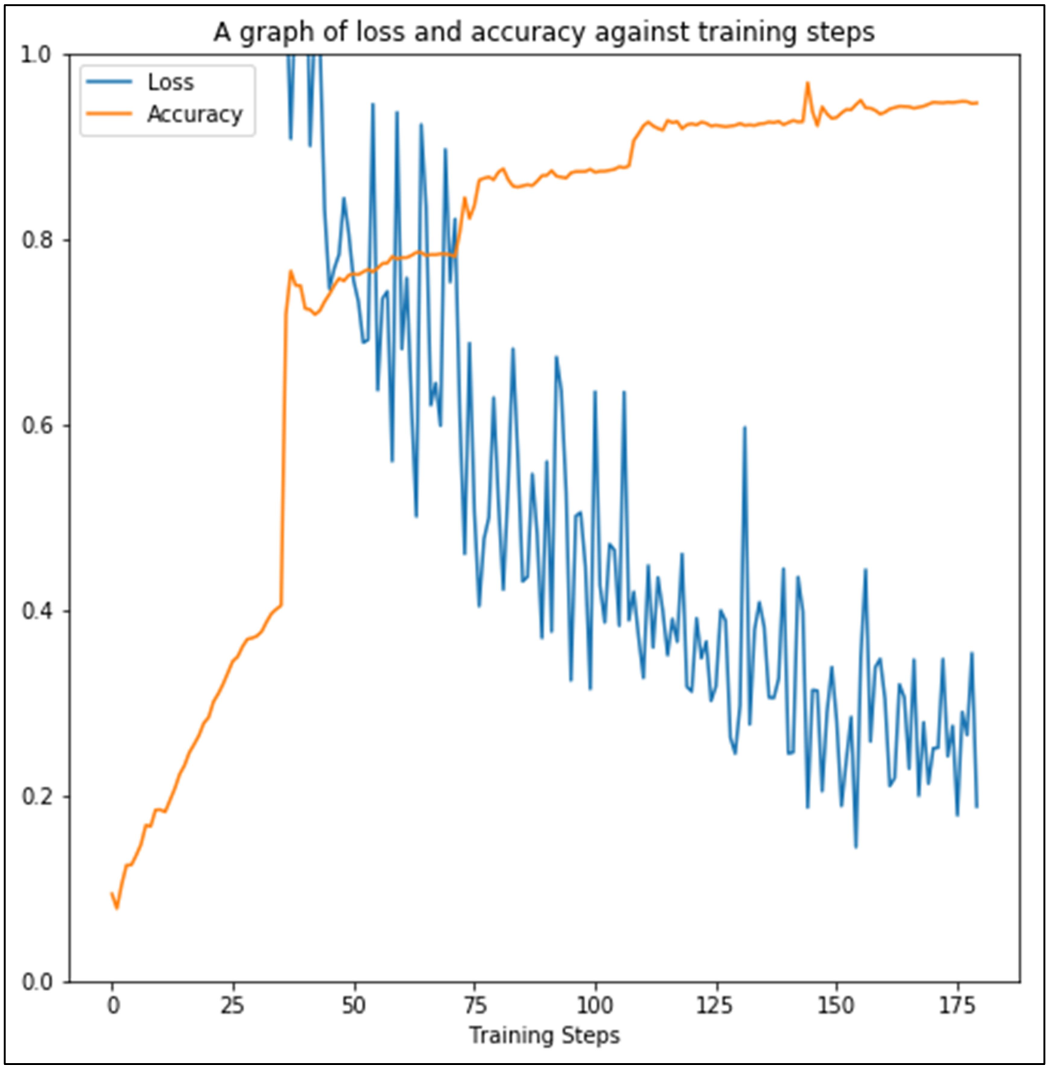


Figure 5.5: A graph of Loss and Accuracy against training steps

The graph of loss and accuracy against training steps shows that loss reduces as accuracy continues to increase. Loss is depicted in blue on the graph and as the training steps continue to increase the loss is very high at step 25 but as the accuracy continues to rise, the loss continues to reduce.

5.3.2 Graph of Accuracy Level against Training Set

The graph plots the models' accuracy against the training set. This is illustrated in the line graph in figure 5.6. The graph in the figure 5.6 shows that the accuracy level of the digital imaging model developed improves as the training sets keeps increasing.

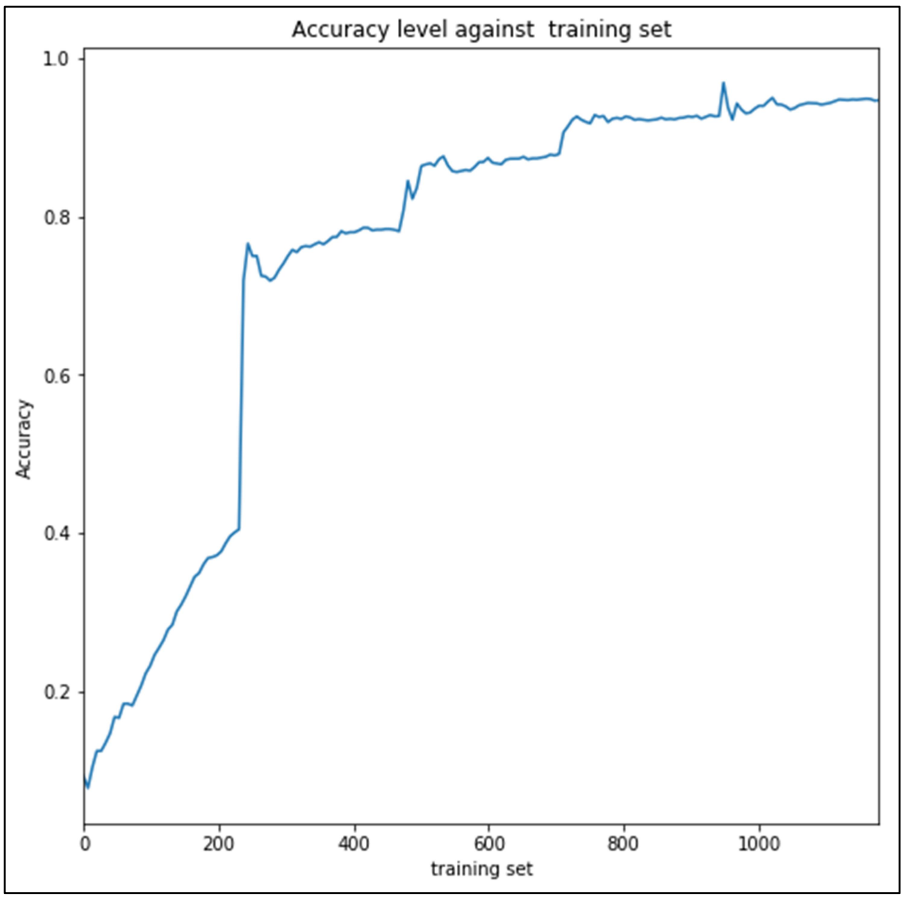


Figure 5. 6 Graph of Accuracy level against training set

The graph of accuracy level against training set shows the raise in the accuracy level of the training set. As the training set increased the accuracy level continues to increase. The accuracy level tends towards 100%.

5.3.3 Graph of Accuracy Level against Training Epochs

The graph created plots the models' accuracy against the training epochs. The accuracy level as per the graph in the Figure 5.7 increases as the number of epochs for both the test and train sets increases. Accuracy level for both training and testing sets are equal at 70% accuracy in the first epoch but as epochs increases, training set tends towards 99% accuracy while the testing set lowers. As the number of epochs increase, both the test and train accuracy of the model increases.

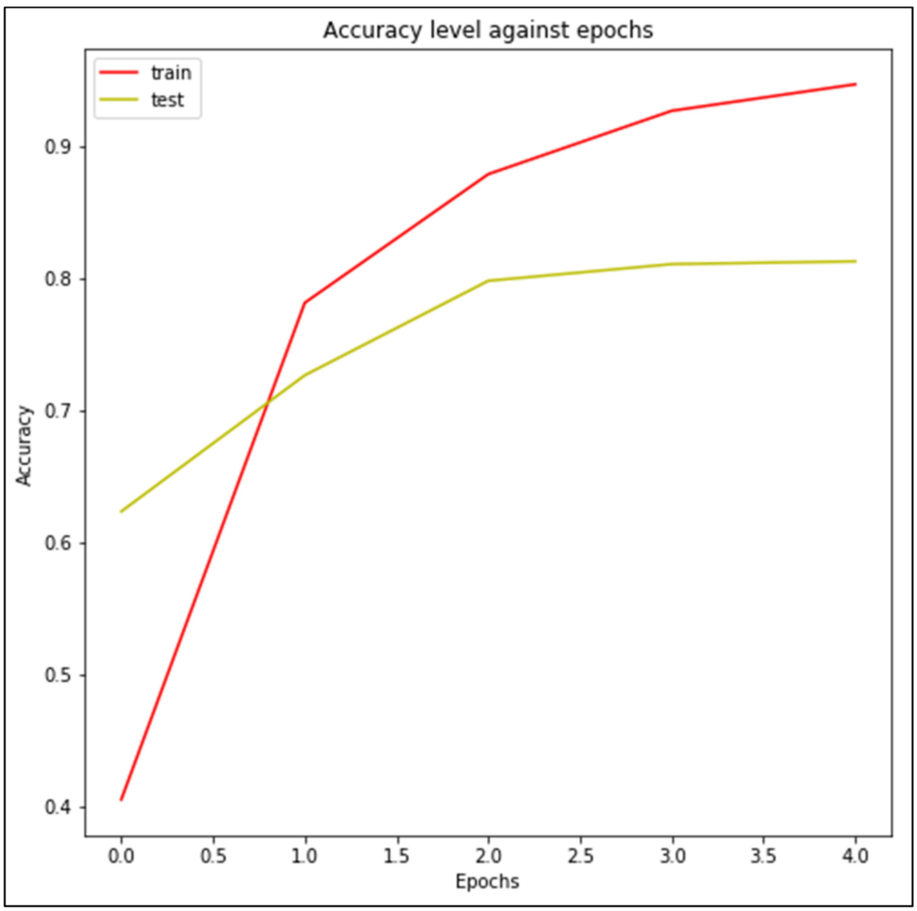


Figure 5.7: Graph of Accuracy level against epochs

5.4 The TensorBoard Visualization of the Digital Imaging Model

The developed digital imaging model for timely detection and accurate diagnosis of plant stress has been saved into the saved_models folder by writing the logs, used by TensorBorad for graph visualization on the TensorBoard. The legend key for the symbols used in the TensorBorad Graph for the Digital Imaging Model for timely detection and accurate diagnosis of Plant Stress are as illustrated below.


High-level node representing a name scope. Double-click to expand a high-level node.

Sequence of numbered nodes that are not connected to each other.

Sequence of numbered nodes that are connected to each other.


An individual operation node.


A constant.


A summary node.

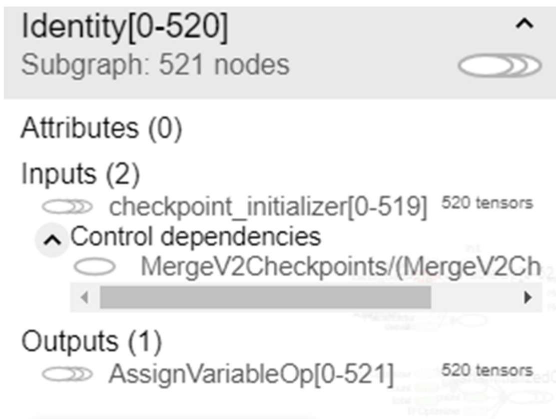

Edge showing the data flow between operations.


Edge showing the control dependency between operations.

— A reference edge showing that the outgoing operation node can mutate the incoming tensor.

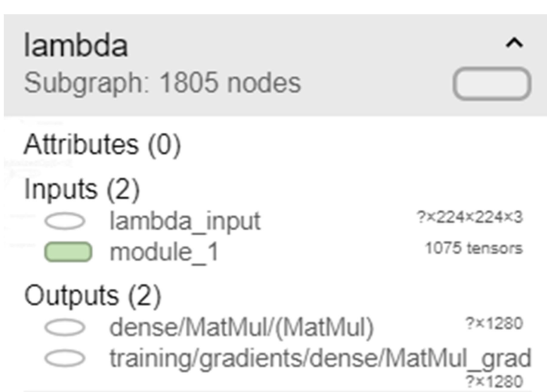
1. **Identity tensors, attributes, inputs and outputs**

- A tensor is a way to generalize matrices and vectors to a higher dimension. They are of base datatype.
- The identity tensor has no attributes.
- The input is a checkpoint initializer of 520 tensors.



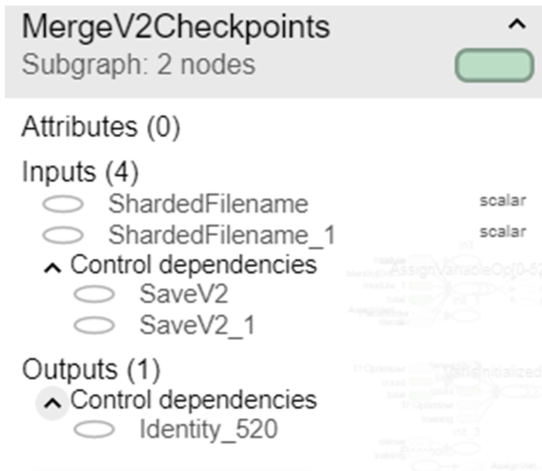
2. **Lambda tensors, attributes, inputs and outputs**

- Lambda enables arbitrary expressions as an object of type Layer. It enables the use of the functional API and the sequential one. They are saved through serialization of python code.
- The input takes a tensor of shape (224,224,3).
- The output is an operational node involving matrix multiplication.



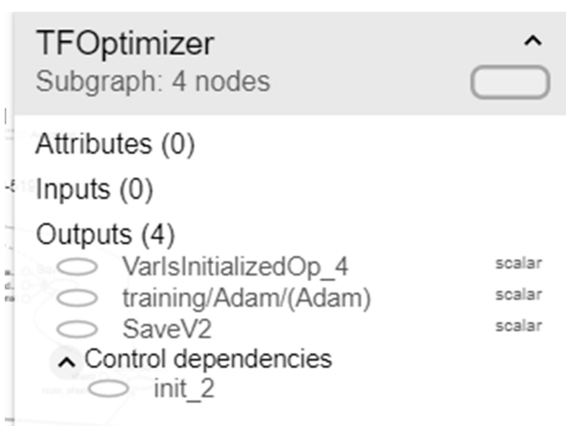
3. **Merge tensors, attributes, inputs and outputs**

- Merge tensors link different graphs together to become one.
- It has 0 attributes.
- Its’ inputs are the shared filenames.
- The control dependencies for the inputs are saveV2 and saveV2_1.



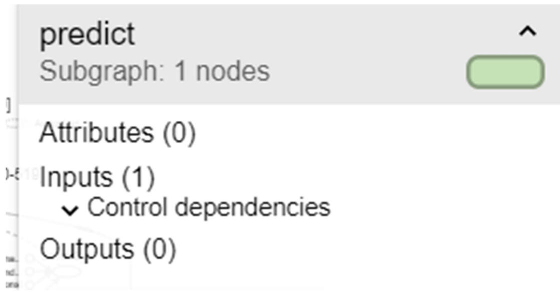
4. **Optimizers’ tensors, attributes, inputs and outputs**

- It has 0 attributes and inputs.
- The outputs are of type scalars.



5. **Predict tensors, attributes, inputs and outputs**

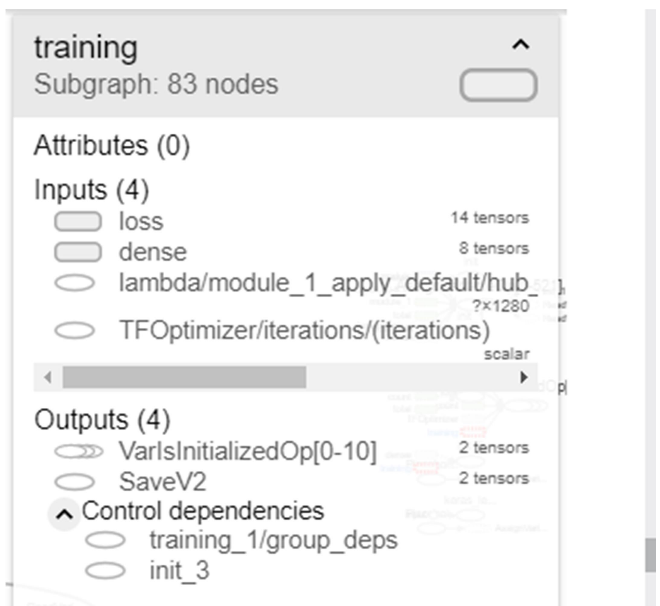
- It has 0 attributes, one control dependency



6. **Training tensors, attributes, inputs and outputs**

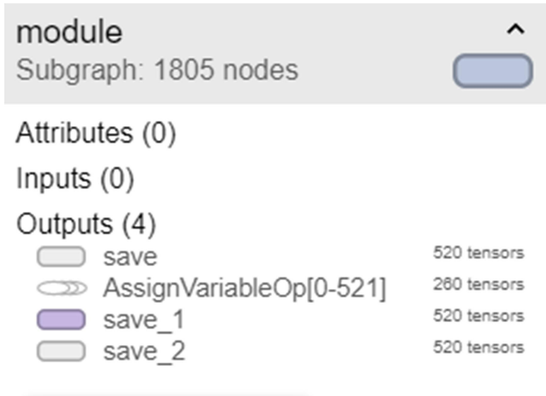
   It has four inputs:

- Loss with 14 tensors.
- Dense with eight tensors.
- The Adams' optimizer of type scalar.
- Lambda module of shape (1280)



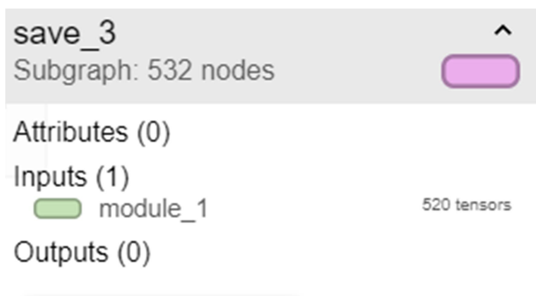
7. **Module tensors, attributes, inputs and outputs**

- It has 0 inputs and attributes.
- It has four outputs save, Assign VariableOp, save_1 and save_2

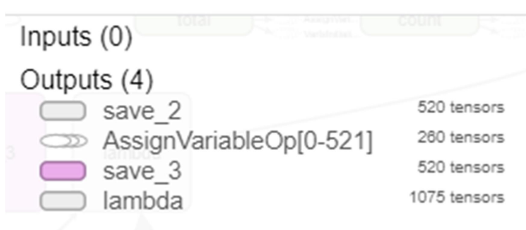


8. **Save tensors, attributes, inputs and outputs**

- It has 0 attributes and one input which is module_1.
- It has 0 outputs.



9. **module_1 tensors, attributes, inputs and outputs**



10. **save_1 inputs and outputs**

The TensorBoard graph for the Digital Imaging Model for timely detection and accurate diagnosis of plant stress is as illustrated in Figure 5.8.

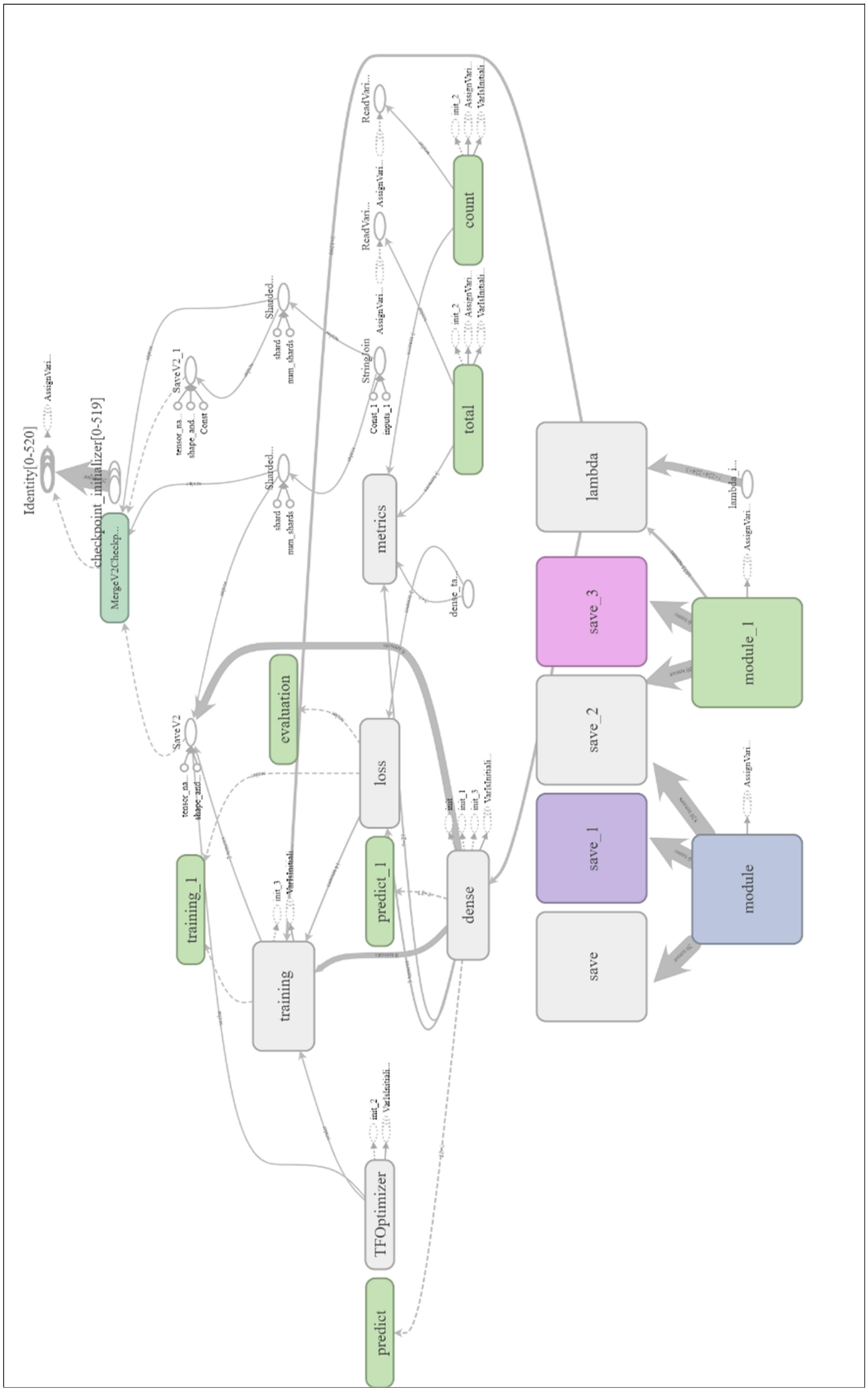


Figure 5. 8: TensorBoard Graph for the Digital Imaging Model for Plant Stress

The scalar summary graph as seen in the figure 5.9, visualizes scalar values that represent classification accuracy. The x-axis represents 100 steps for our model used for training, the y-axis represents the corresponding random loss values with a smoothing value set at 0.6 during the training from a normal distribution of the variables.

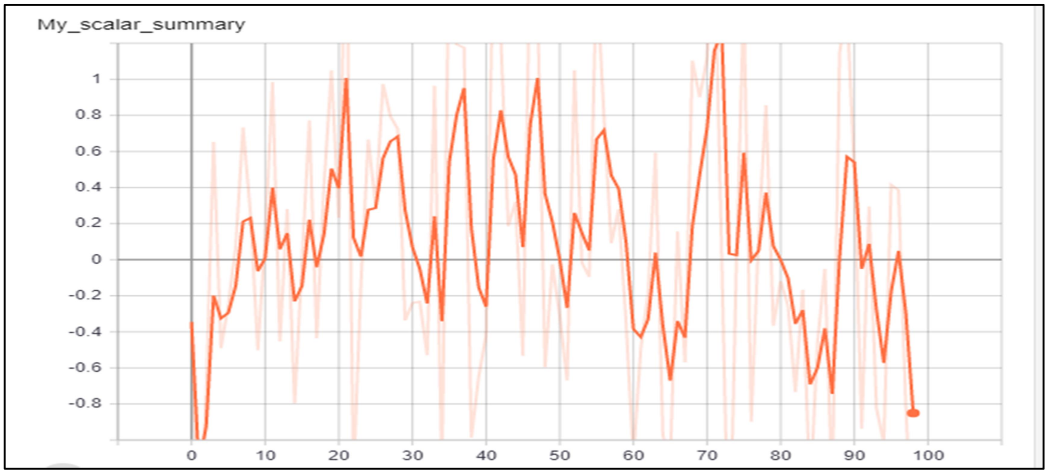


Figure 5. 9: Scalar Summary Line graph for the TensorBoard Digital Imaging Model

The distribution histogram view of the TensorBoard visualizes how the data for the digital imaging model changes over time through adjustments of the weights of the Neural Network Model.

Figure 5.10 illustrates the distribution view. The distribution view is a top view of the histogram summary. The tensor values are as shown in the y-axis whereas the steps are as illustrated in the x-axis. The different light and dark colors represents the percentile in the distribution. The very light color in the bottom section illustrates the change in the minimum value over time. The middle section illustrates the change of the median as shown from bottom to top the lines mean [minimum, 8%, 18%, 34%, 50%, 72%, 86%, 96%, maximum]. The interpretation from top to bottom shows that the lines which shows the maximum and minimum values and percentile values based on standard deviations boundaries with a [maximum normal distribution of μ+1.5σ, followed by μ+σ, μ+0.5σ, μ, μ-0.5σ, μ-σ, and minimum of μ-1.5σ], whereas the colored regions, as read from the inside going to outside have a width of [σ, 2σ, and 3σ] respectively.

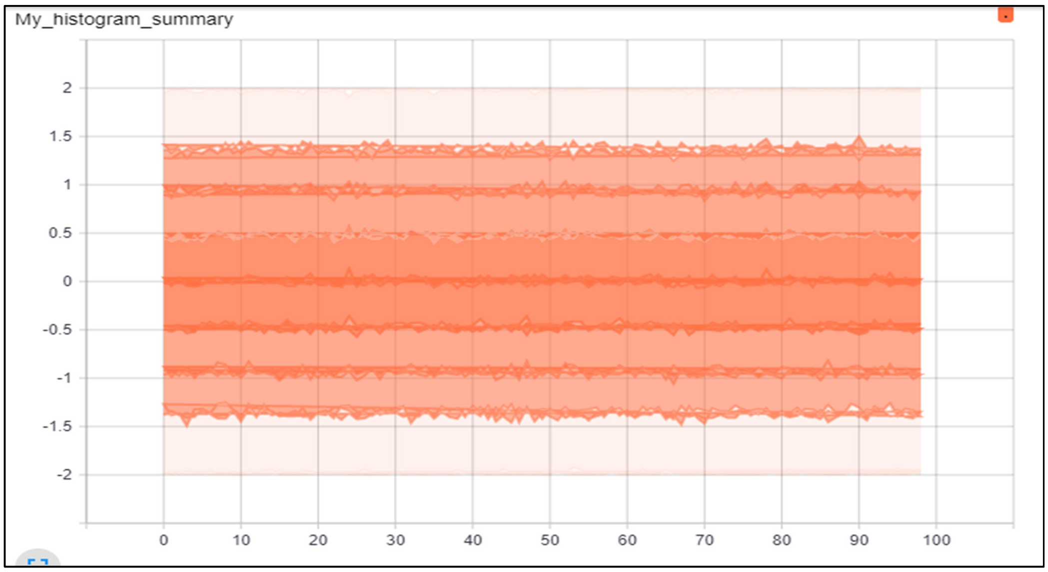


Figure 5. 10: Distribution View of the Histogram Summary for the TensorBoard Digital Imaging Model

The histogram panel illustrates sections of data, whereby each of the sections on the histogram shows a tensor per given section organized to show the newest timestamp in the front while the older timestamp on the background. This makes it possible to monitor values of the histogram at any step through hovering the mouse pointer over the histogram plot along the x-axis as seen in Figures 5.11 showing the offset histogram summary and the Figure 5.12 showing the overlay histogram of the digital imaging model with the x-y values.

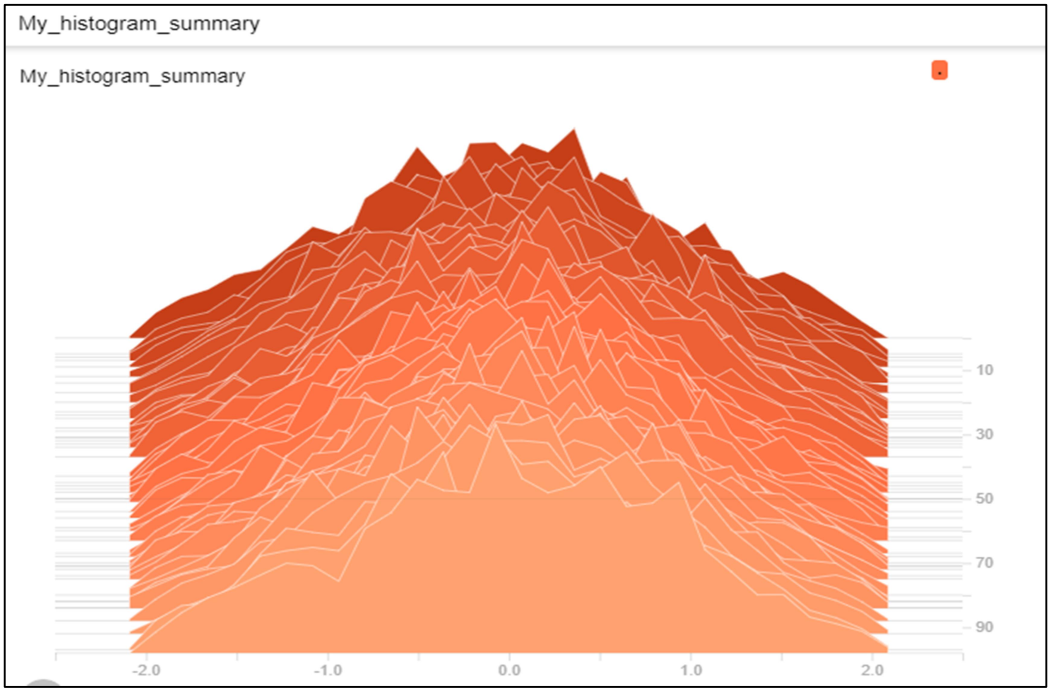


Figure 5. 11: Offset Histogram Summary for the 2-d tensor values of the TensorBorad Digital Imaging Model

The x-y values on the histogram in every step can be viewed by moving the mouse pointer on the plot as seen in Figure 5.12.

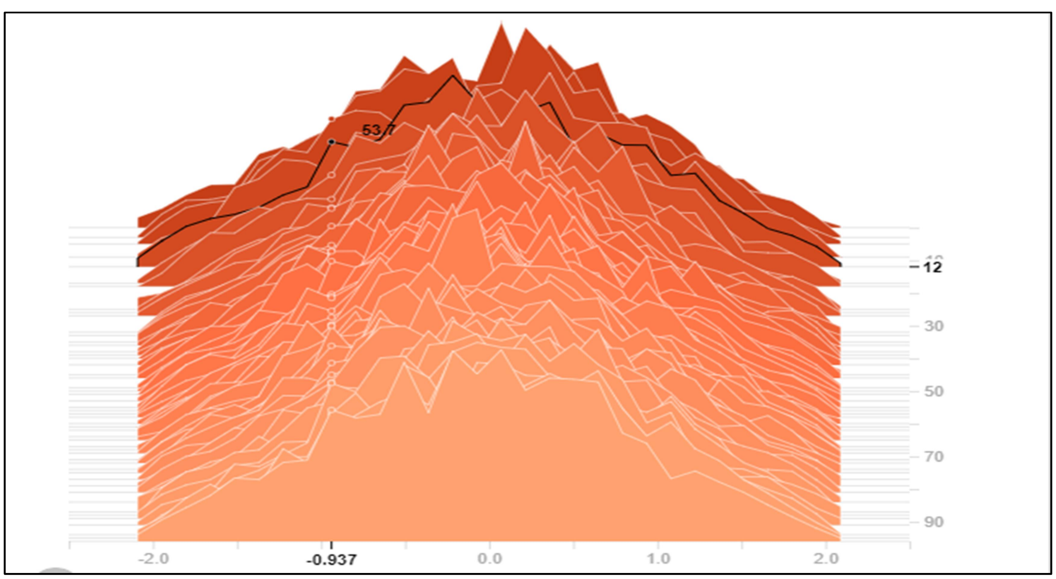


Figure 5. 12: Overlay Histogram for the TensorBoard Digital Imaging Model

The histogram above is a grouping of values by frequency that the value has in the collection. The histogram shows the weights varying with time.it is comprised of three axes which are X axis representing time, Y axis representing value and Z axis represents frequency. The dark parts of the histogram represent old data while the lighter parts represent new data. The mode of the histogram in figure 5.11can be changed from offset to overlay as seen in the TensorBoard Histogram when offset time is relative for the Digital Imaging Model as shown in figure 5.13 so as to be able to interpret the histogram while overlaid over each other.

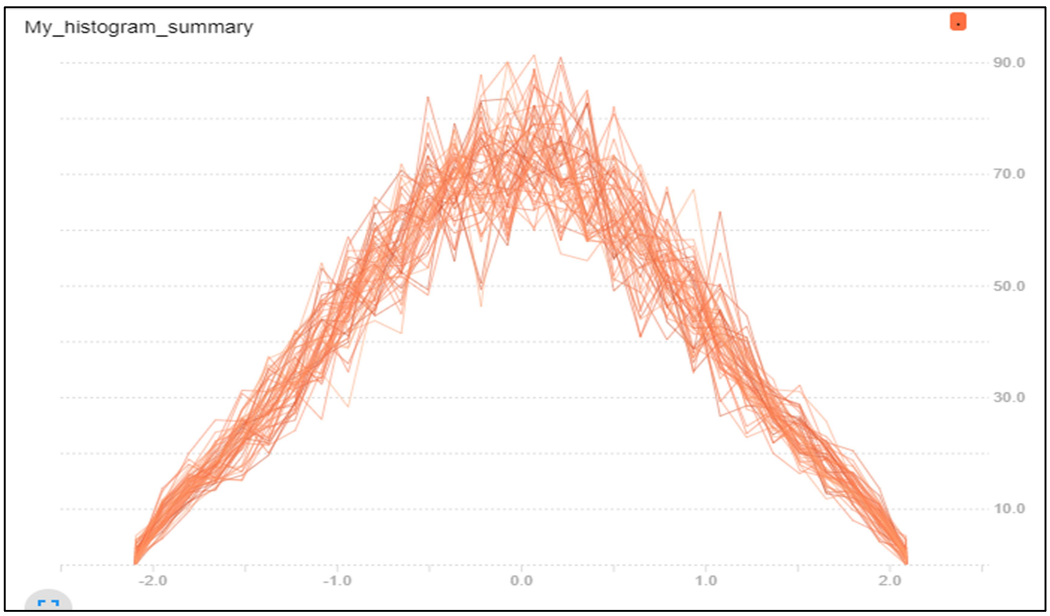


Figure 5. 13: Overlay Histogram for the TensorBoard Digital Imaging Model

5.5 Description of the Digital Imaging Model

The model architecture adopted is MobileNetV2, a light weight model. There are two types of blocks in MobileNetv2, a residual block with stride of 1 and one is a block with stride of 2 used for downsizing. There are 3 layers for both types of convolution layer blocks. The first layer is 1×1 convolution with ReLU 6, The second layer is the depth wise, the third layer is another 1×1 convolution but without any non-linearity. An expansion factor t is present, where t=6 for all main experiments. For example, if the input got 32 channels, the internal output would get 32 $\times$t = 32 $\times$6=192 channels.

Table 5. 1: Bottleneck of MobileNetV2

Input	Operator	Output
$h \times w \times k$	1×1 conv2d, ReLU6	$h \times w \times (tk)$
$h \times w \times tk$	3×3 dwise s=s, ReLU6	$\frac{h}{s} \times \frac{w}{s} \times (tk)$
$\frac{h}{s} \times \frac{w}{s} \times tk$	Linear 1×1 conv2d	$\frac{h}{s} \times \frac{w}{s} \times k'$

Table 5.1 illustrates the bottleneck residual Block transforming from k to k 0 channels, with strides, and expansion factor t. Kernel size 3 ×3 is always used as it is standard for modern networks, and utilize dropout and batch normalization during training. Except the first layer constant expansion is used throughout the network.

5.6 Overall Architecture

MobileNetV2 architecture is based on the VGC architecture. Each of the lines in the table describes a sequence of one or more identical (modulo stride) layers, repeated n times where t: expansion factor, c: number of output channels, n: repeating number, s: stride 3 × 3 kernels are used for spatial convolution. Table 5.2 illustrates the overall network structure of MobileNetV2.

Table 5. 2: The Overall Network Structure of MobileNetV2

Input Shape	Operator	*t*	*c*	*n*	*s*
224 × 224 × 3	conv2d	-	32	1	2
122 × 122 × 32	bottleneck	1	16	1	1
122 × 122 × 16	bottleneck	6	24	2	2
56 × 56 × 24	bottleneck	6	32	3	2
28 × 28 × 32	bottleneck	6	64	4	2
14 × 14 × 64	bottleneck	6	96	3	1
14 × 14 × 96	bottleneck	6	160	3	2
7 × 7 × 160	bottleneck	6	320	1	1
7 × 7 × 320	conv2d 1×1	-	1280	1	1
7 × 7 × 1280	Avgpool 7 × 7	-	-	1	-
1 × 1 × 1280	conv2d 1×1	-	k	-	

In typical, the primary network (width multiplier 1, 224 × 224), has a computational cost of 300 million multiply-adds and uses 3.4 million parameters. The performance tradeoffs are further explored, for input resolutions from 96 to 224, and width multipliers of 0.35 to 1.4. The network computational cost up to 585 multiply-adds, while the model size varies between 1.7M and 6.9M parameters.

5.6.1 Feature extraction for tomato diseases

Features for the tomato diseases were automatically extracted as discussed in Section 4.3 through deep learning. The architecture discussed in section 5.6 is used for feature extraction is a Convolutional Neural Network (CNN). Convolutional Neural Networks was used as it performs well in image classification tasks.

5.7 Discussion

This study analysed existing image based plant stress detection approaches to establish the physical features of stress in plants. The researcher went ahead to map the physical features into digital imaging signatures characterising stress in plants. A digital imaging model for timely detection and accurate diagnosis of plant pest and disease stress was developed and validated for enhancement of food security.

5.7.1 Existing Image based plant stress detection Approaches

Results of this study showed that the developed model performed optimally as compared to the existing models. This was later analysing the existing visible light imaging model that was used to classify healthy and stressed plants which was done as seen in Chapter Two section 2.2, 2.3, 2. 6. It was found to perform poorly at 89.93% as opposed to the proposed imaging model that performed at 95% accuracy. When compared with Chlorpophyll flouresncence and thermal imaging models used for detection of pre-symptomatic indicators of plant diseases and pest, flourecsence parameter measures were found to change in photosynthetic systems due to pest and diseases resulting to 75% accuracy against 96% accuracy levels of the proposed imaging model when compared with hyperspectral imaging that employed reflectance measures it performed at 87% accuracy level as opposed to the proposed model that performed at 96% model accuracy.

5.7.2 Established Physical Features of Stress in Plants

Results from the experimental groups of this study indicated 89% response rate as opposed to the controlled group that had 86% resulting to an average response rate of 87.5% showing findings from this study can be applicable in other plants as seen in Chapter Two section 2.1, 2.4, Chapter Three Section 3.8.1 and Chapter Four section 4.2. Tomato plants in this study indicated susceptibility to pest and disease stresses. These stresses were physically visible on the leaves and fruits and could be easily calibrated in the developed model. The patterns of the leaves were considered to locate the actual pest or disease affecting the crop. Images features detected were extracted digitally from images acquired using the smartphone cameras. This study was able to calibrate the physical features as a result of pest and disease infestation for timely detection and accurate diagnosis of plant stress as a result of pest and disease for enhanced food security. These features informed the calibration of the physical features to digital imaging signatures characterising stress in plants.

5.7.3 Physical Features Mapped to Digital Plant Stress Signatures

The results from this study showed the possibility of applying digital imaging techniques in detection of physical features in plants using digital camera in a smartphone running the developed mobile application as done and achieved in Chapter Two sections 2.1, 2.7 and Chapter Four Section 4.3. The process involved color transformations and segmentation of hue saturation and intensity, where the green color pixel was used to show healthy regions of a leaf. The web interface was used to validate the feedback received by the farmers on their devices. The developed model as seen in Chapter four section 4.4, and Chapter Five sections 5.0 to 5.2.8, was calibrated on the mobile application after application of image enhancement and transformation techniques and adjustment of weights on the neural network, it was possible to timely detect and accurately diagnose pest and disease stress in plants.

5.7.4 Validity of the Digital Imaging Model for Plant stress detection

Training a deep convolution neural network from scratch takes a surmountable amount of time, and requires large dataset to reach an acceptable level of accuracy as achieved in Chapter Three Section 3.7, 3.7.1, 3.7.2, 3.8.4 and 3.8.5, and Chapter Five, sections 5.2.8, 5.3 to 5.6.2. Results of this study showed high levels of accuracy compared to existing models. This was as a result of comparing the model with other pre-trained networks, contrasting with experiments extending the steps of MobileNetV2. In order to test the method applied on the developed model, the Model was deployed on an Oppo F9 Android smart phone CPH1823 Android Version 9, running on an Octa Core processor, with 6 GB RAM, and replicated on farmers'

Android Smart Phones of diverse specifications. The algorithmic digital imaging model was deployed on a web interface and validated running on an Alienware GPU, with 32 GB Ram, 6 Core CPU and 2 TB Hard Disc Capacity. The deployment of the developed model on Android smartphone devices enables the model to be broadly used and applied on broad areas. The dataset resulting from this model can be applied for training data and applied on other plant categories apart from tomato. Model validation was done by applying the Confusion matrix displaying the accuracy levels and tested against training steps, sets and epochs.

5.8 Summary

This section proposed the new digital imaging model for timely detection and accurate diagnosis of plant stress. The Model was visualized using the TensorBoard for optimization. The model outlines the image acquisition approach, training, testing and validation. The SoftMax activation function optimized with the Adam Optimizer algorithm is also discussed. Feature extraction through transfer learning and classification is also discussed. The proposed model was trained with transfer learning hence resulted to speeding up the training process. The digital imaging model overall architecture is finally discussed and represented graphically. Finally, a detailed section is dedicated to objectively discussing the model developed in the study.

CHAPTER SIX

CONCLUSION, RECOMMENDATION AND FUTURE WORK

6.0 Overview

Chapter Six comprises of three sub sections that discuss the details related to the conclusion, recommendation and future work proposed for the study. These are outlined in line with the study objectives. This chapter presents a summary of the study conclusion, recommendation, and future work to be explored. Section 6.1 Concludes the research work by highlighting the achievements of each objective. Section 6.2 contains Recommendation, which recommends the developed solution for use and Section 6.3 gives the limelight for future work that can be conducted to extend the findings of this study to benefit the other areas highlighted. These are presented under the themes derived from the objectives of the study which are; to analyze the existing image-based plant stress detection approaches; to establish the physical features of stress in plants; to map the physical features into digital imaging signatures characterizing stress in plants; to develop a digital imaging analysis model for plant stress detection and to validate the digital imaging model for detection of plant stress.

6.1 Conclusion

This study sought to develop a model for timely detection accurate diagnosis of plant stress through digital imaging for enhanced productivity of crops and food security. To achieve this, the study identified four specific objectives. The first specific objective was to analyze the existing image-based plant stress detection approaches which has been tackled in Chapter Two section 2.2, 2.3, 2.6. This was tackled through the carrying out of a literature review and as a result of the gap identified which was lack of a digital imaging model that would be able to execute timely detection and accurate diagnosis of plant pest and disease stress, a digital imaging model for detection of plant stress was developed. The proposed model identified physical features characterizing stress in plants, which include pest and disease affecting leaves and fruits on tomato plants. The second Objective was to establish the physical features of stress in plants, which has been tackled in Chapter Two section 2.1, 2.4, Chapter Three Section 3.8.1 and Chapter Four section 4.2. The study found out that the existing approaches for detection of physical features characterizing stress in plants contained low levels of accuracy. Image transformation techniques were employed on the acquired images. A feature extraction algorithm was developed and by employing transfer learning it was possible to classify different categories of stresses in the plants. The stresses ranged from pest and disease stresses.

The third specific objective was to map the physical features into digital imaging signatures characterizing stress in plants, this was achieved in Chapter Two sections 2.1, 2.7 and Chapter Four Section 4.3. Color transformations of hue, saturation and intensity, segmentation and mean shifts were applied on the acquired images for preprocessing. Green color pixels were used to represent health plant sections. Image classifiers were built using Keras to enable estimation of target location of the stress detected. A number of twenty-seven different pest and disease stresses were classified. The model also extended the MobileNetV2 architecture and visualized it through the TensorBoard, and Validation done on the Confusion Matrix and Web Interface. The fourth objective was to develop a digital imaging model for plant stress detection, which were achieved in Chapter four section 4.4, and Chapter Five sections 5.0 to 5.2.8. The Convolution Neural Network was used to Develop the model. The model is made up of three broad areas which include data processing module, CNN training module and CNN prediction Module. In the data processing module, a total of 8745 images were captured 80% of which were used for training and validation whereas 20% was used for testing. Images were acquired using digital smartphone cameras. The CNN formation involved the calibration of the model on a Web Interface and a Mobile phone application referred to as Tunza Leaf. The SoftMax model activation function was selected and weights modified for accuracy. The fifth objective was to validate the digital imaging model for detection of plant stress, which were achieved in Chapter Three Section 3.7, 3.7.1, 3.7.2, 3.8.4 and 3.8.5, and Chapter Five, sections 5.2.8, 5.3 to 5.6.2. The CNN prediction module was employed to ensure accuracy improves during the transfer learning process as the model continues to improve. Validation was conducted using the output functions in the Web Interface and Confusion Matrix as per the transfer learning architecture extended on the MobileNetV2. The TensorBoard Graph was used for visualization of the Digital Imaging model for plant stress detection. Line graphs, Scalar graphs, histograms and distribution graphs were used to demonstrate the levels of accuracy of the developed model to prove its validity.

This study informs policy in the Ministry of Agriculture and Ministry of Education, in the area of embracing deep learning in smart farming for food security. This study also informs knowledge in the area of smart farming through embracing smartphone technology, imaging and computer vision in curbing plant stress at an early stage for food security and enhanced productivity of food crops.

6.2 Recommendation

The developed model, the Tunza Leaf mobile application and web interface is recommended for adoption as a solution to detection of the impending danger posed by pests and disease stresses, over traditional approaches. The developed model is recommended for enhanced food security to aid farmers in rural and urban areas to enable farmers to access the relevant certified seedlings, herbicides, pesticides and fungicides from certified chemical distributors. The developed solution will also enable them to precisely detect and predict presence of plant stress and receive diagnosis messages on the impending stresses on their crops. There may be other optimal image-based approaches for detection of pests and diseases in plants which could be identified through research without being entirely limited to the approach used in this research. Any future search for optimal approaches for detection and prediction of plant stresses both disease and pests are recommended.

6.3 Future Work

Future work related to digital imaging model for plant stress can focus on configuration of the model on drones. The model can further be extended to cover tomato fruits and a variety of plants as opposed to the current that only focuses on tomatoes. The model can further be extended to address other stresses in plants including weeds, climate change, water deficiency, human settlement effect on farms, as opposed to only pests and diseases. The mobile phone application can also be configured to cover also prediction of ripening periods, and detection weeds, water floods, drought, and detection of multiple stress on a single leaf, plant fruit or stem.

The web interface can be also upgraded to be receiving images in real time and give feedback to the farmers in real-time through deployment of satellite cameras in the stratosphere that monitors land cover over large regions of land cover by identification of plots numbers and geographical positioning and location (GPS) so as to give accurate locality of farms, through studying historical data to predict future status of landmass, Landover, waterbodies, human settlements and stress effects on crops. This solution can be extended further to enable crowdsourcing of land ownership through calibration of plot numbers with owner details and activities carried out on specific localities.

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APPENDICES

APPENDIX I: INTERVIEW TO FARMERS

Evaluation and validation of the Tunza Leaf web and mobile application in the course of the research study titled “A digital imaging model for detection of plant stress”

<u>Interview on the use of the Tunza Leaf Web and Mobile Application Interfaces</u>

1. Please describe briefly how you installed and used the Tunza Leaf Mobile Application. (Input process: starting the app, registration, capturing images; and the output process: reading and interpreting the recommendations)

Input Process

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Output Process

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2. Have you had any physical challenge while using the Tunza Leaf Mobile Application?

No

Yes, the following

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3. Did you experience any technical problem while using the Tunza Leaf Mobile Application (e.g. Program not responding, no recommendation? no feedback)

No

Yes, the following

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4. Do you have any concerns or doubts using the Tunza Leaf Mobile Application?

No

Yes, the following

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5. What was the most positive experience while using the Tunza Leaf Mobile Application?

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6. What was the most negative experience while using the Tunza Leaf Mobile Application?

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7. How often did you use the Tunza Leaf Mobile Application in detection of plant pests and diseases stresses? (daily, twice a week, only for evaluation session)

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8. What was the duration of time of use on each session (eg 30 minutes, 1 hour)

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9. How long was the overall period of use for the evaluation and validation of the Tunza Leaf mobile application?

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10. What do you think should be improved on the Tunza Leaf Mobile Application?

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11. Do you think the Tunza Leaf Mobile Application is useful for the farmer?

No

Yes, Why

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12. Would you like to use the Tunza Leaf Mobile Application More Often for detection of Plant pests and diseases stress on your tomato?

No

Yes, Why

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Tunza Leaf Mobile Application System Usability Scale

Please score the following ten items with one of the five responses that range from strongly agree (1) to strongly disagree (5)

	SCORE	Strongly Agree	2	3	4	Strongly Disagree
	ITEM	1	2	3	4	5
1.	I enjoyed using the system and can use it more frequently					
2.	I found the application unnecessarily complex					
3.	I thought the application was easy to use					
4.	I think that I would need the support of a technical person to be able to use the mobile application					
5.	I found the various functions in this application were well integrated					
6.	The system looked inconsistent in applicability					
7.	The system looks so easy to learn					
8.	My experience with the application was cumbersome					
9.	I felt very confident using the application					
10.	I needed to learn a lot of things before I could get going with this system					

APPENDIX II: INTERVIEW TO AGRONOMIST

The agronomists were administered with two interviews. The first one was focused on the experience of the farmers before use of the Tunza Leaf App and the second one was after the used were able to use the Tunza Leaf app in prediction, detection of plant stresses. The fists interview was made up of four questions while the second one also had four questions.

Interview Question to Agronomist at the Start of the study

To measure content validity of the mobile phone application, examine carefully the items included in the research instruments so as check the instruments validity in feedback related to the average rating ranging from a score of 1 (extremely invalid), 2 (fairly valid), 3 (valid), 4 (highly valid) and 5 (Extremely Valid).

	SCORE	Extremely Invalid	2	3	4	Highly Valid
	ITEM	1	2	3	4	5
1.	The system gave consistent feedback					
2.	The system was not complex to use					
3.	The application was easy to use					
4.	I received support of a technical person to be able to use the mobile application					
5.	The various functions in this application were well integrated					
6.	The system was inconsistent in applicability					
7.	I took long to learn the system					
8.	The application was very cumbersome to use					
9.	The application was not able to give me confidence while using					
10.	I required too much learning sessions					

	to be able to use the system					

Question One

Which methods do farmers use in prediction and detection of pests and diseases on their crops?

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Question Two

How do they access the remedies to their crops from the agrovet stors and what challenges do you notice in their response to the stresses detected?

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Question Three

Which Challenges do you face as agronomists in recommending the right remedies to the farmers?

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Question Four

Do you have any proposed ways of assisting framers on detection of the stresses and remedies using ICT technologies?

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Interview to the Agronomist after Design and Testing of the Tunza Leaf App

After interviewing the farmers, the agronomists were also interviewed. The questions are shown in this Section. The first question sought to collect the satisfaction of the agronomist with regards to the collection method, the second third and fourth questions sought to collect and evaluate comments on the agronomist review of the applications.

Question One

Which plant stress prediction detection method will you prefer to use in future? Why?

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Question Two

Which type of plant pests and disease detection approach do you think can best be supported by the Tunza Leaf App? and Why?

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Question Three

Which design of the Tunza Leaf App do you think is the Best?

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Question Four

Dou you have any suggestions to the “Tunza Leaf App?

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APPENDIX III: TUNZA LEAF WEB AND MOBILE APP INTERFACE USER MANUAL

This section comprises of two sections. The Web interface called Tunza Leaf Web User Manual, and The Mobile Interface for the Mobile Application Interface herein called the Mobile Interface User Manual. This section presents a summary of the graphical user interface developed for the user side and the server side that consists of the Tunza Leaf Mobile Application and the Web interface for the Tunza Leaf. These are presented under the themes derived from the objectives of the study that aims at calibration of stress.

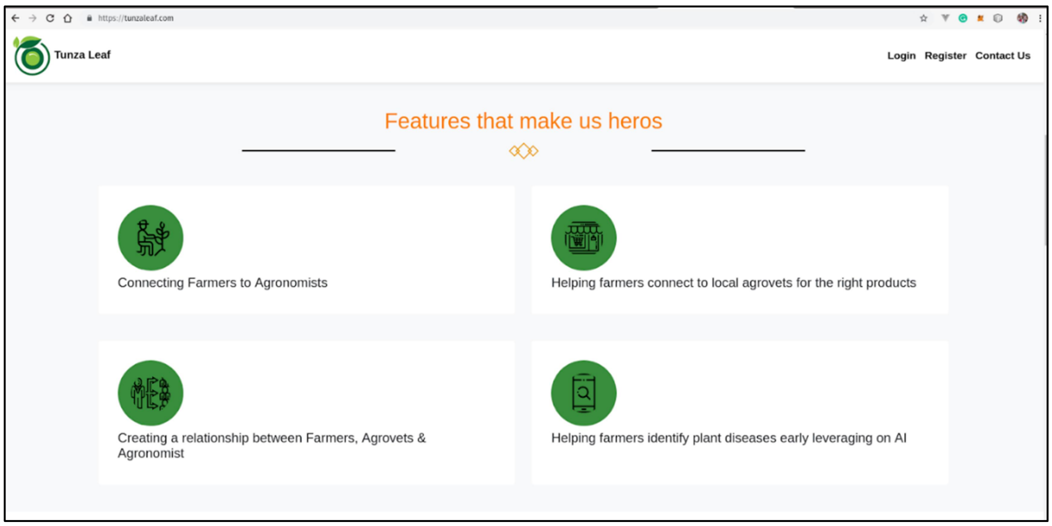
TUNZA LEAF WEB USER MANUAL

The term "Tunza", Swahili for preserve which derives the motivation behind this study of preserving the leaves of Tomato plants through early diagnosis of an impending stress that is likely to affect a plant. This section covers the landing page, login, registration and administration portal, and the administration modules. The administrator modules are made up of the dashboard, the products that can be acquired from agrovets for remedying the crop stresses, the list pf agronomists and agrovets, a list of detected plant stresses, a history of crop scans, a list of farmers that used the solution during the validation process, system logs of the scans, and access management interface for the administrator to interact with the user permission in utilization of the system.

1. **Landing page**

The Tunza Leaf mobile app can be downloaded from google play while the web interface can be accessed through the landing page is accessible through http://www.tunzaleaf.com/. It aims at enticing potential users of our technology with the core benefits that we are focusing on. It contains details of interesting interfaces that a user can benefit from by interacting with the system which includes the ability of connecting farmers with agronomists and helping farmers connect with local agronomist that stock the right products. It also connects the farmers with information on the stresses that affect their crops and leveraging Artificial Intelligence solution that they may utilize in the interface.

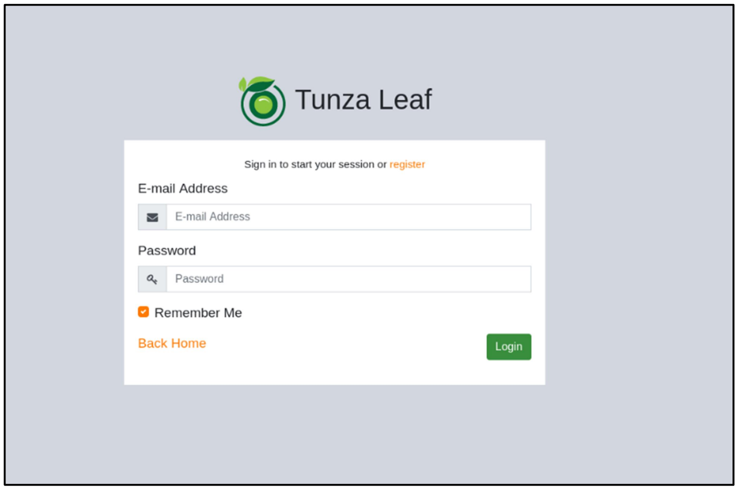
It lists modules and other interesting sub features as shown:-



The Module Web feature interface

2. Login

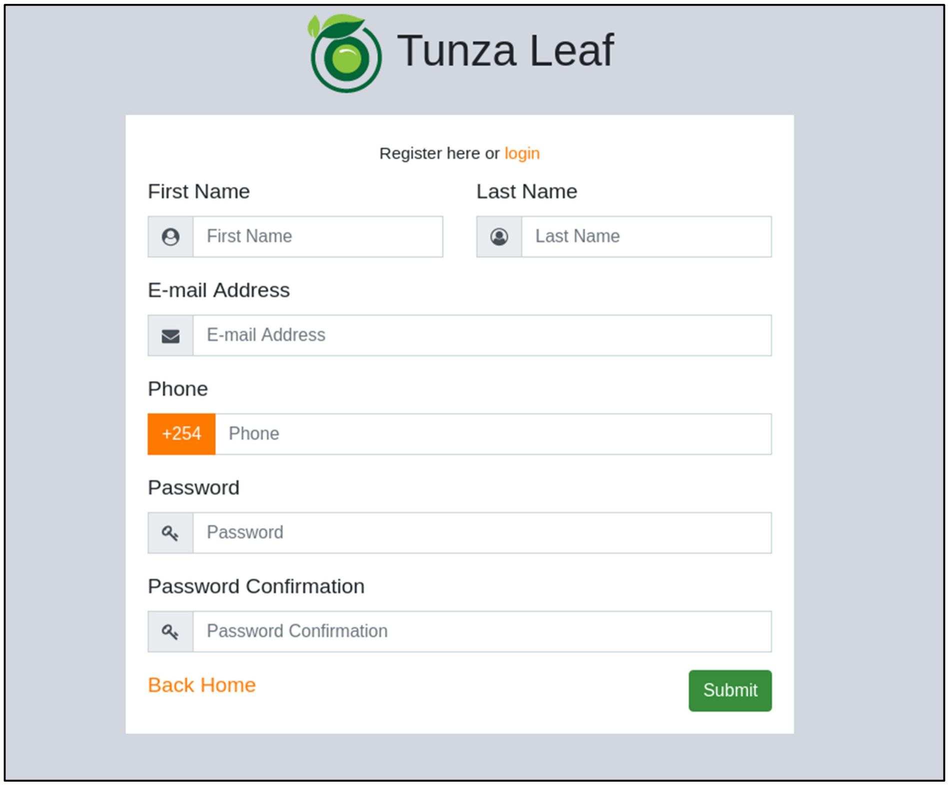
The Web login is dedicated for Administrators, at the moment, but in future, it will be used by key data providers such as Agrovets, Chemical manufacturers and other agencies on a limited/guided access basis using our roles system. It is an interface that currently is accessible with the capability of enabling the user to interact with the web interface. It enables users to register new accounts or login with a new user account.



Tunza Leaf Web Interface Login Page

3. Register

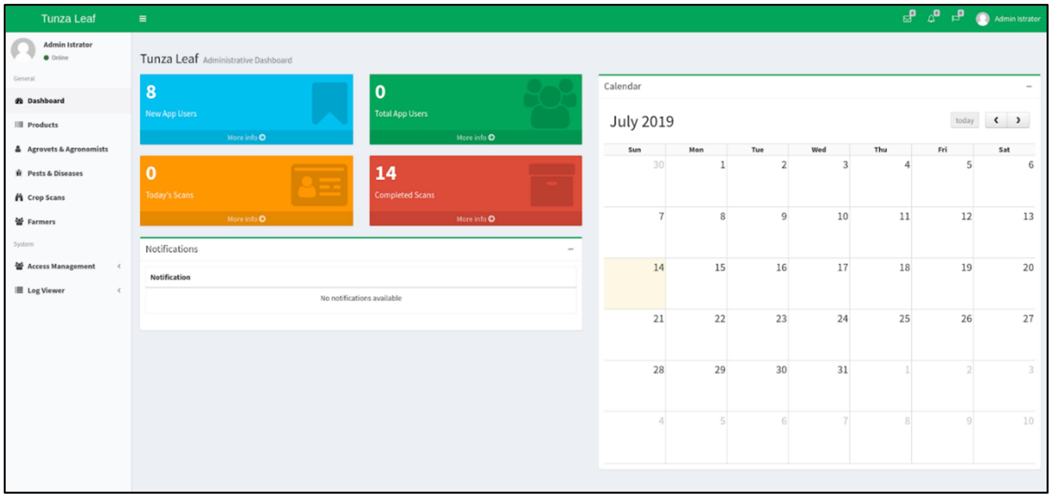
The register for Web portal is currently in demo mode as only admins use this feature. The users registering via the web register must be approved and given privileges by the admin through the user management system. The user is required to enter their first and last name, email address and mobile phone number. The user is also required to create a password for use in the web interface. The mobile phone number is very crucial in this stage bearing in mind the proliferation of mobile technology ("Kenya's mobile penetration hits 88 per cent," n.d.; Kimutai et al., 2010; Maina, Njoroge, Waiganjo, & Gitonga, 2015) and the statistical level of ownership of Smartphone among Kenyans (Smartphone & Industry, 2018).



Registration web interface

4. Administrator Portal

The administrator portal contains the core features for coordination and operation of the mobile application. The web interface for the administrator portal include the interface with links to the different menu options that relate to the administrator modules. It also contains an interface that contains statistical information in summary form of the number of new scans, total number of application users, todays scans, complete scans and notifications that can be distributed to the users in cases where there exists information that needs to be sent to the users.



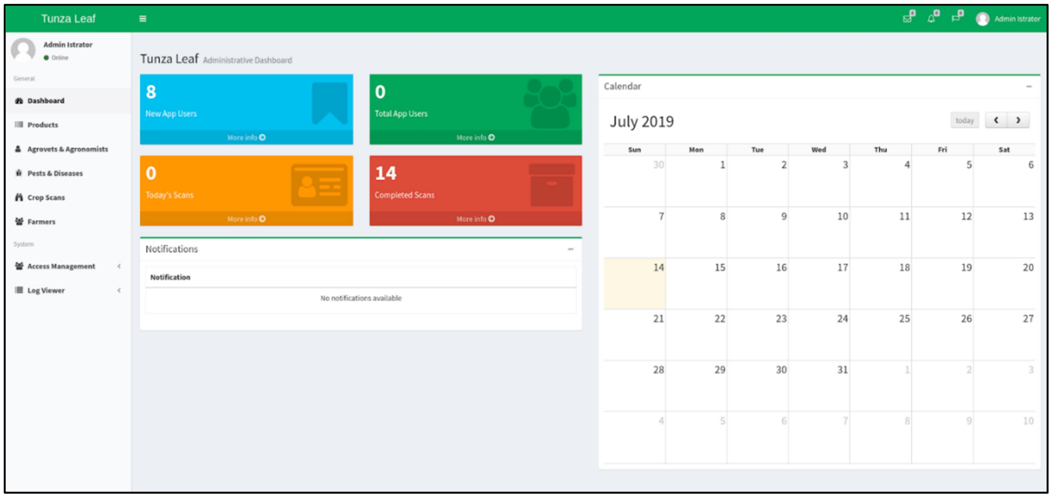
Administrator Portal Interface

5. Admin Modules

The administrator module contains the administrator dashboard, the list of products stocked by different agrovets and agronomists, the list of detected plant stresses as per the model developed, the total number of crop scans done by users. The crop scans capture the GPS location of the region a stress has been detected so as to aid the agronomists in mapping out regions of crop stress detection for demarcation of stress regions and for future diagnosis to the farmers of impending danger. This aids in quarantine and monitoring and prediction of the spread of a pest or disease. Notification of the same are sent to the farmers through messaging or emails as per captured emails provided by the users.

a. Dashboard

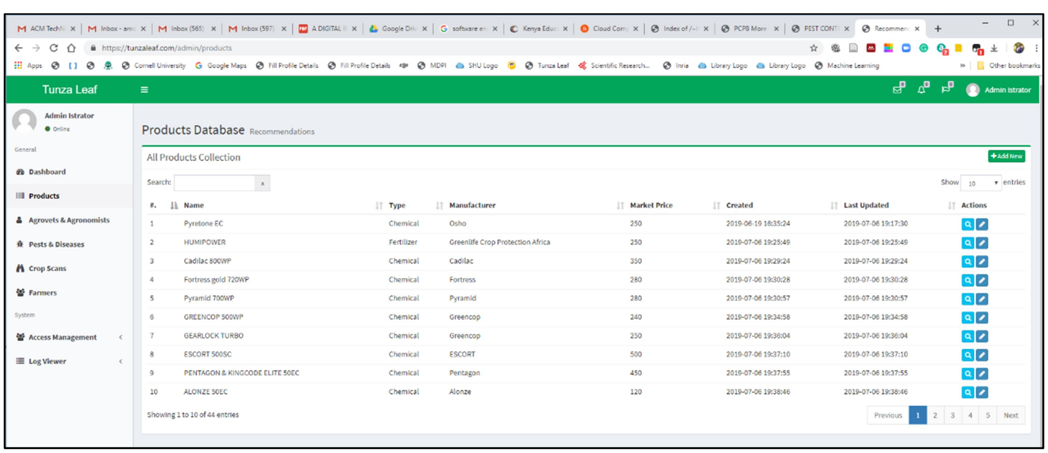
The dashboard provides the user with metric of the system and notifications. It highlights daily usage and overall usages, which includes the Total number of users and totals of Crop Scans activity.



The Web Interface Dashboard

b. Products

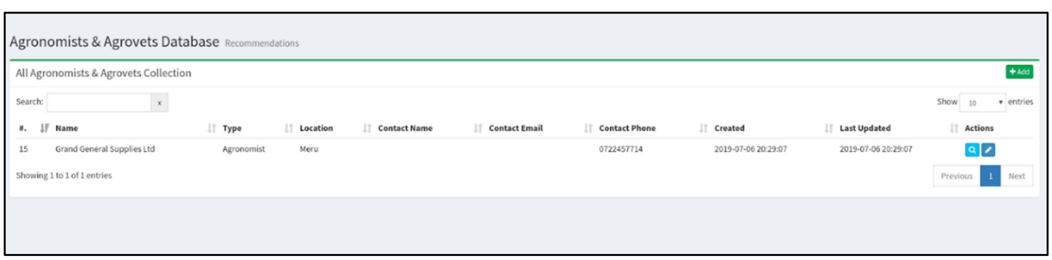
This feature provides access to registered products from manufacturers. It has an easier to use recording plugin that allows the admin to add a product. Any new products that is certified by the Pest Control Product Board (PCPB) (Board, 2019). The certified products are providing the farmer with information about the chemical products to be used on the plants as per the accredited institutions that are allowed to supply the chemical products and the post-harvest index (PHI) of each chemical product. The list of accredited products is updated for the framers by the administrator and a list of added products as necessary are shown.



List of Accredited Products for use by Farmers

c. Agrovets & Agronomists

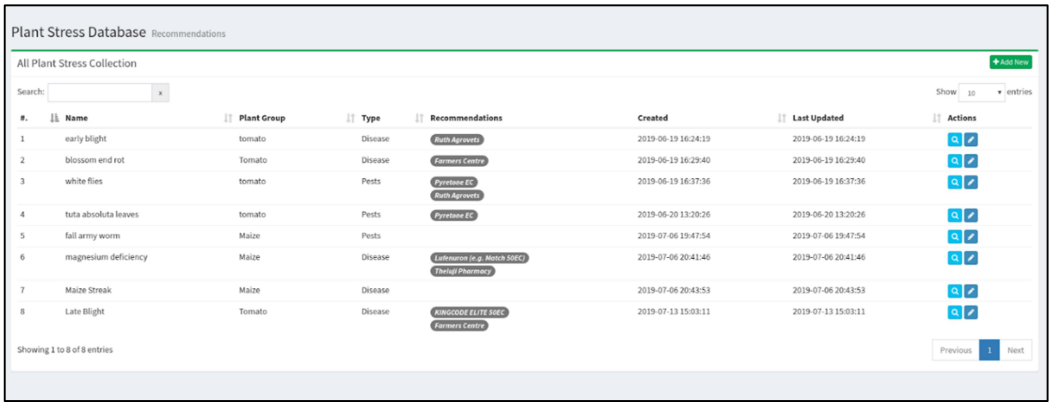
This module is for managing collaborators who provide help to farmers on selected issues. The agronomists and agrovet stores are referred as collaborators for this study. They are the stores who stock products for the farmers t the identified regions of study. They include stores in Maili Saba, Tutwa, Rwarera, Nchiru and Meru Town. These stores stock products that are applicable for the tomato plant in this study among other products. This bring a solution to the challenge that farmers at the moment face in identification of the correct stockiest with the recommended product. Farmers have been facing the challenge of utilization of the wrong chemicals for the products as the existing agronomists just stock products that are either outlawed or affordable to the whereas they are not recommended by the PCPB. With this interface the collaborators will be required to stock products that farmers are aware as per expert knowledge gathered from the agronomists. The system here acts as a recommender system that allows the users to be able to know the exact product needed to remedy the impending stress in their crops, early before the effect is caused on the crops.



List of Agrovet stores and Agrovets involved in sales

d. Plant Stress

Plant Stress is complex mapping engine for the recommender and links to the AI panel. It allows the administrator to create links between crop stress and products and collaborators to help improve a stress help recommender. Once a user detects a stress on the plants in the field, the mobile phone application communicates with the web interface showing the name of the stress detected, the plant affected, the type of stress detected, the recommended agrovet store or agrovet that stocks the recommended chemical product to be applied on the crop, then the date and time the stress was detected.


Plant Stress Database Recommendations

All Plant Stress Collection

Search: x

Show 10 entries

+ Add New

#.	Name	Plant Group	Type	Recommendations	Created	Last Updated	Actions
1	early blight	tomato	Disease	Ruth Agrovets	2019-06-19 16:24:19	2019-06-19 16:24:19	
2	blossom end rot	Tomato	Disease	Farmers Centre	2019-06-19 16:29:40	2019-06-19 16:29:40	
3	white flies	tomato	Pests	Pyretone EC Ruth Agrovets	2019-06-19 16:37:36	2019-06-19 16:37:36	
4	tuta absoluta leaves	tomato	Pests	Pyretone EC	2019-06-20 13:20:26	2019-06-20 13:20:26	
5	fall army worm	Maize	Pests		2019-07-06 19:47:54	2019-07-06 19:47:54	
6	magnesium deficiency	Maize	Disease	Lufenuron (e.g. Match 50EC) Theluji Pharmacy	2019-07-06 20:41:46	2019-07-06 20:41:46	
7	Maize Streak	Maize	Disease		2019-07-06 20:43:53	2019-07-06 20:43:53	
8	Late Blight	Tomato	Disease	KINGCODE ELITE 50EC Farmers Centre	2019-07-13 15:03:11	2019-07-13 15:03:11	

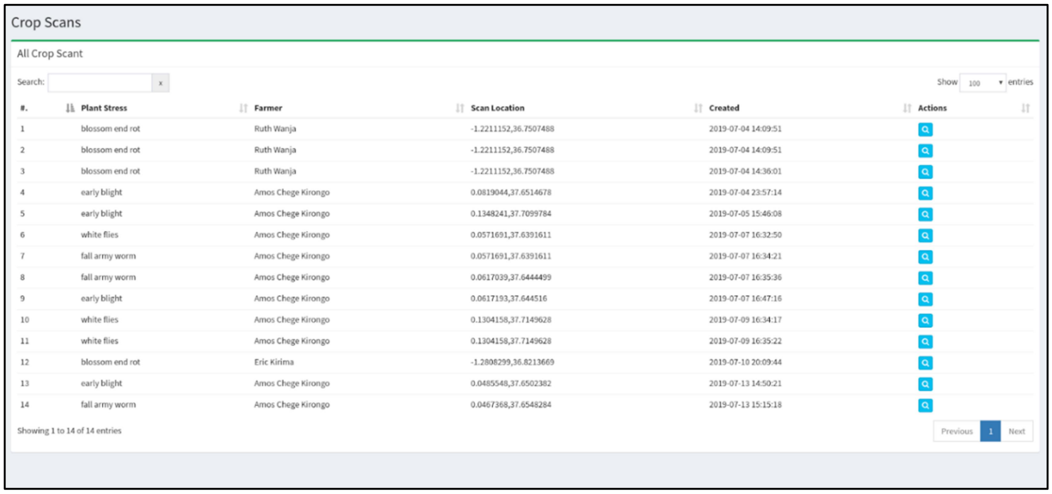
Showing 1 to 8 of 8 entries

Previous 1 Next

Plant Stress Database

e. Crop Scans

The crop scans are records of identified plant stress detected by the mobile phone application installed on the mobile phone owned by individual farmers. It includes the type of plant stress detected, the farmer who detected the stress, the location of the crop that was scanned and found to e stressed through indication by the geographical positioning GPS location log for easier mapping of where the scan was done at and for improving recommendation engine, and the date and time of the detection. This is enabled by the proliferation of internet as per the ("CA report: Kenya's internet penetration up by 12.5% | CIO East Africa," n.d.; Dominic Omondi, 2018; Internet World Statistics, 2019) statistics of number of internet users and Smartphone users among the Kenyan population.



Crop Scans

All Crop Scant

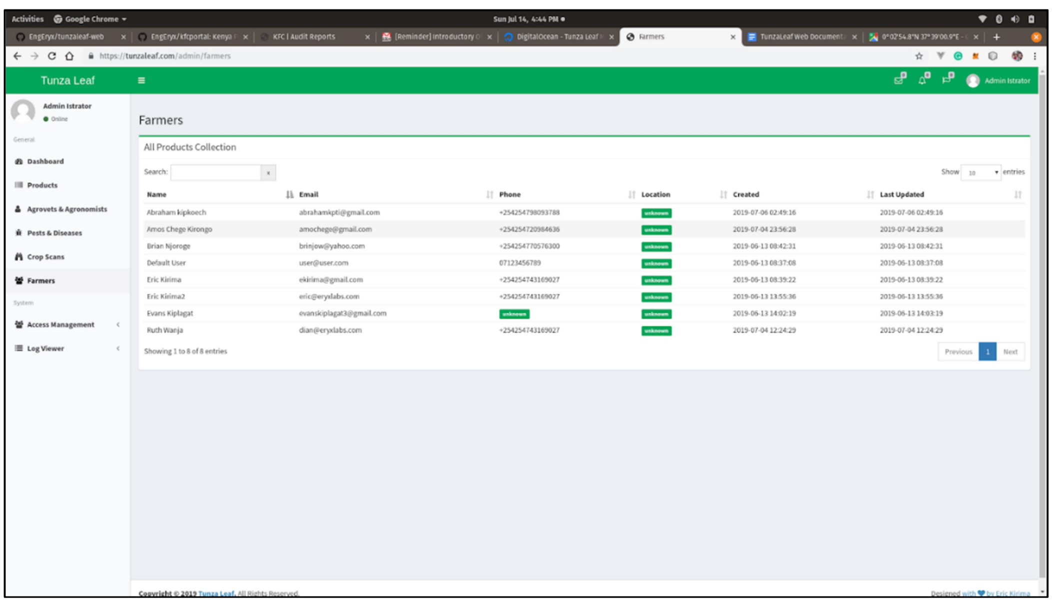
#.	Plant Stress	Farmer	Scan Location	Created	Actions
1	blossom end rot	Ruth Wanja	-1.2211152,36.7507488	2019-07-04 14:09:51	
2	blossom end rot	Ruth Wanja	-1.2211152,36.7507488	2019-07-04 14:09:51	
3	blossom end rot	Ruth Wanja	-1.2211152,36.7507488	2019-07-04 14:36:01	
4	early blight	Amos Chege Kirongo	0.0819044,37.6514678	2019-07-04 23:57:14	
5	early blight	Amos Chege Kirongo	0.1348241,37.7099784	2019-07-05 15:46:08	
6	white flies	Amos Chege Kirongo	0.0571691,37.6391611	2019-07-07 16:32:50	
7	fall army worm	Amos Chege Kirongo	0.0571691,37.6391611	2019-07-07 16:34:21	
8	fall army worm	Amos Chege Kirongo	0.0617039,37.6444499	2019-07-07 16:35:36	
9	early blight	Amos Chege Kirongo	0.0617193,37.644516	2019-07-07 16:47:16	
10	white flies	Amos Chege Kirongo	0.1304158,37.7149628	2019-07-09 16:34:17	
11	white flies	Amos Chege Kirongo	0.1304158,37.7149628	2019-07-09 16:35:22	
12	blossom end rot	Eric Kirima	-1.2808299,36.8213669	2019-07-10 20:09:44	
13	early blight	Amos Chege Kirongo	0.0485548,37.6502382	2019-07-13 14:50:21	
14	fall army worm	Amos Chege Kirongo	0.0467368,37.6548284	2019-07-13 15:15:18	

Showing 1 to 14 of 14 entries

Crop Scans Showing the Plant Stress detected, Farmer crop GPS Location date and time

f. Farmers

The farmers interface entails the details of all farmers using the system. The farmers are required to register their details in the system. The farmer details include the name, email, phone number, location and date and time each farmer registered.



Farmers

All Products Collection

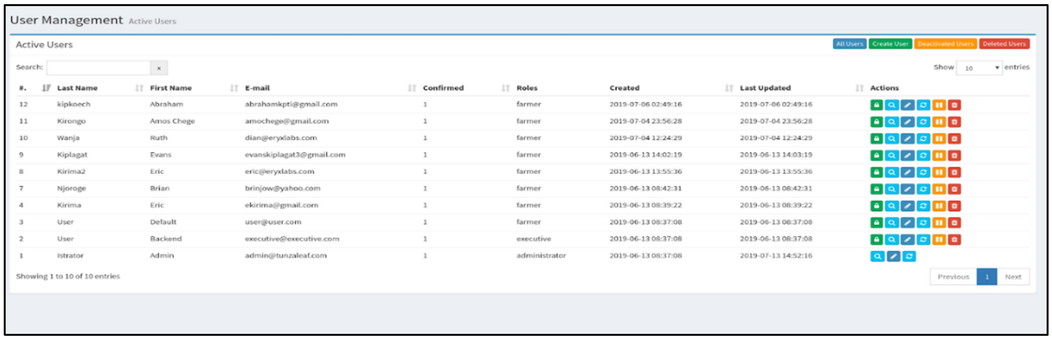
Name	Email	Phone	Location	Created	Last Updated
Abraham kipkoech	abrahamkpti@gmail.com	+254254798093788	unknown	2019-07-06 02:49:16	2019-07-06 02:49:16
Amos Chege Kirongo	amochege@gmail.com	+254254720984636	unknown	2019-07-04 23:56:28	2019-07-04 23:56:28
Brian Njoroge	brinjow@yahoo.com	+254254770576300	unknown	2019-06-13 08:42:31	2019-06-13 08:42:31
Default User	user@user.com	07123456789	unknown	2019-06-13 08:37:08	2019-06-13 08:37:08
Eric Kirima	ekirima@gmail.com	+254254743169027	unknown	2019-06-13 08:39:22	2019-06-13 08:39:22
Eric Kirima2	eric@eryxlabs.com	+254254743169027	unknown	2019-06-13 13:55:36	2019-06-13 13:55:36
Evans Kiplagat	evanskiplagat3@gmail.com	unknown	unknown	2019-06-13 14:02:19	2019-06-13 14:03:19
Ruth Wanja	dian@eryxlabs.com	+254254743169027	unknown	2019-07-04 12:24:29	2019-07-04 12:24:29

Showing 1 to 8 of 8 entries

List of Farmers registered in the web interface

g. Access Management

Access management entails role setting and permission fine-tuning by the administrator. The administrator of the web interface can assign specific roles to specific people or administrators. The roles can either be an administrator, farmer, or executive. It contains the first name and last name, the email addresses roles and date each user was registered.



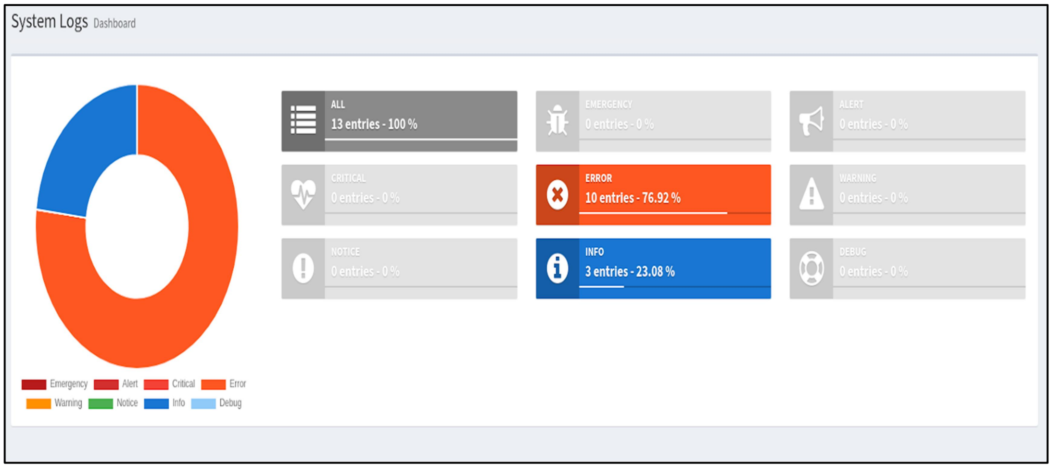
Access Management Interface

Role management as per figure below entails the user roles allocated as permissions based on their role categories. An administrator is allocated all the permissions whereas the test of the users' permissions differs based on the preferred roles. The role manager interface indicates the different number of uses and actions that each user is allowed to do in the interface.

Role management as per user roles in the web interface

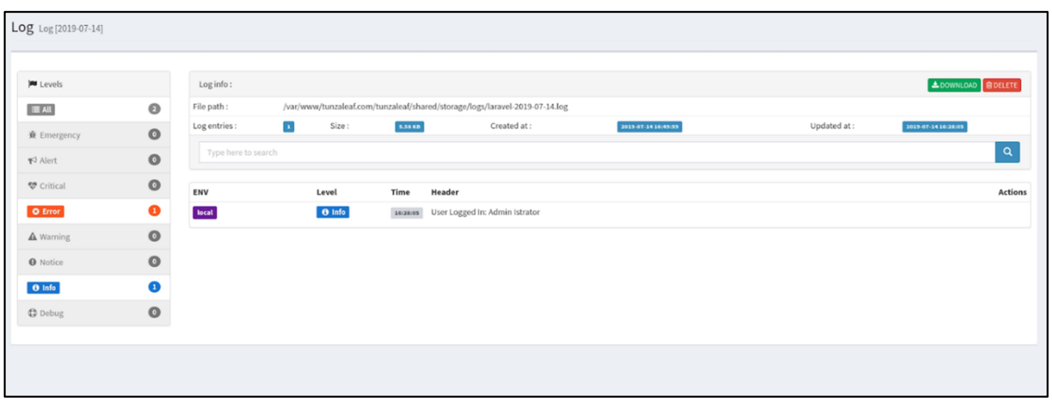
h. System Logs

System logs dashboard as per figure below indicates the system monitoring interface with the purposes of debugging or troubleshooting. It contains information related to alerts that are generated as per the errors, information and any other vital information that can be consumed by the administrator in moments where errors occur on the course of the web interface running. This relates to information which indicates the severity of the error as to whether it is an alert, debugging, warning or error.



System Logs Dashboard

Figure above indicates the interface that illustrates the log file information with log entries and the file path to the log file, time and date created, the size, the environment in which the error occurs, and the level of the error information and the user who was logged in at the time the error occurred.

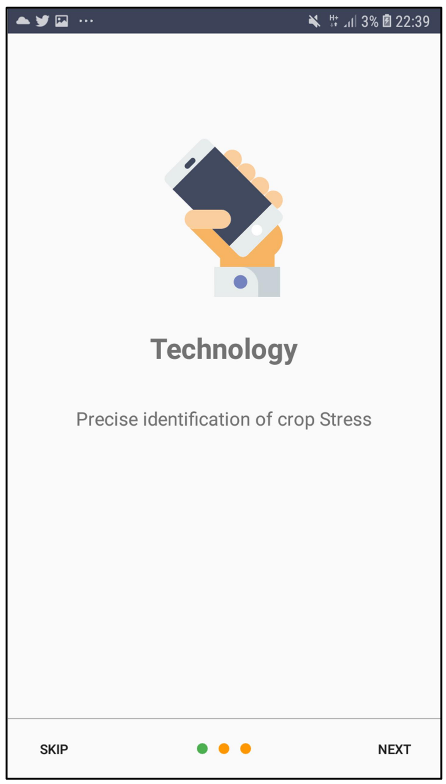


Log file information

TUNZA LEAF ANDROID MOBILE APP USER MANUAL

1. Onboarding process

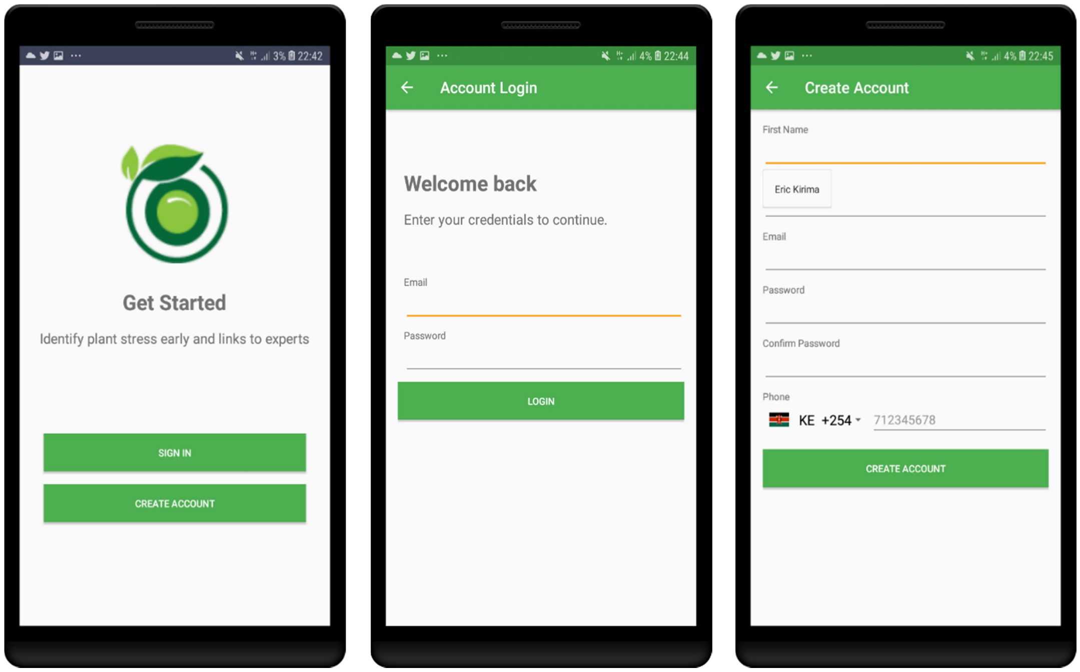
The onboarding process aims at explaining to the end user what the mobile application is about, it should be loaded with appropriate graphics that communicate purpose of the app and Tunza brand as shown in the figure below.



Mobile Application Onboarding Interface

2. User Identification

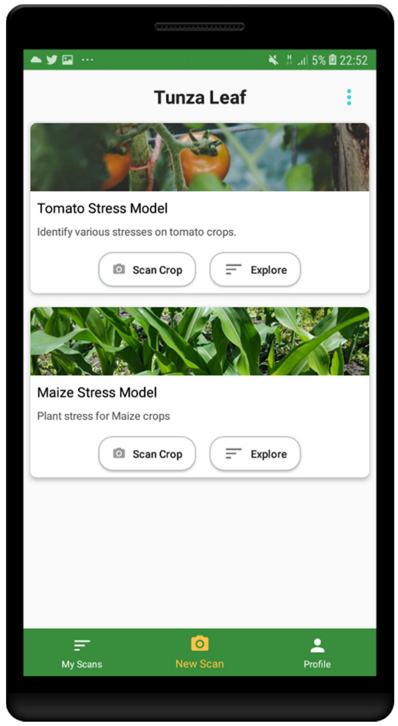
This module involves Registration/Login where we can be able to collect details about the end user. Only few details are collected to make the process as smooth as possible. The information gathered from the users is captured in the create account tab. The information includes the first name last name, email address password and phone number of the user as seen in the figure below.



User Registration interface

3. Models View

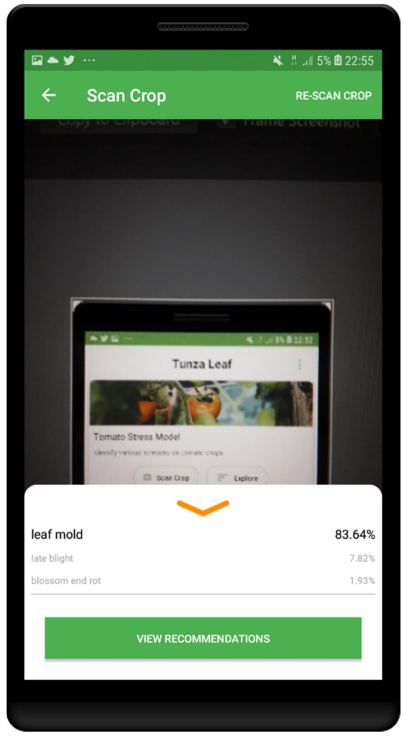
This aims at listing the various plant stress models that are available and the disease set. For this study, tomato stress model has been calibrated on the mobile phone application. Once a user taps on the tomato stress model, and taps on the scan crop option, the user is taken to the interface that enables the user to capture images of the stressed plant. The mobile phone application is based on the model discussed in Chapter Five. The explore function lets the user see a list of possible stress the model has been trained on. Scan Crop, allows the user to access the camera and be able to automatically identify the crop stress using the model.



Tunza Leaf Tomato Stress Model
Mobile App Interface

4. Scanning View

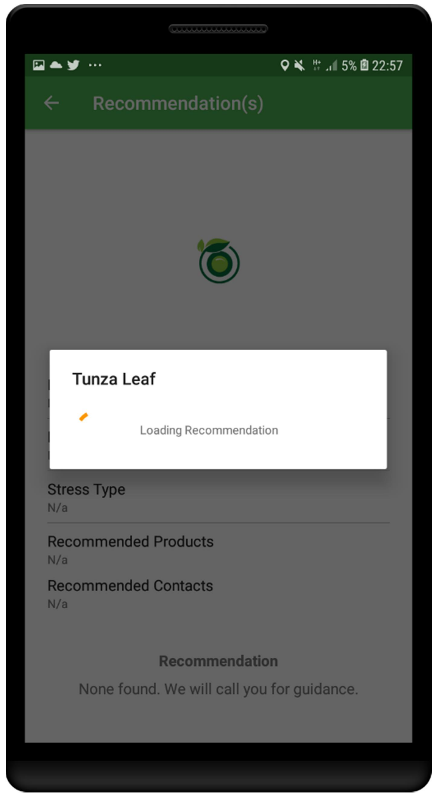
Plant stress identification is done in real time from the phone camera video input which is broken down as series of images, as the user scans the crop, the app will look for patterns of a particular illness and vibrate if it finds any stress on the crop. It vibrates immediately and shows some recommendations, on top of the detected illness for the user to follow so that they can be able to treat the crop. The percentages shown at the bottom of the interface shows the level at which the application is able to detect the stress by showing the accuracy level at which the phone is able to detect the stress. The higher the percentage the higher are the chances of accurately detecting the stress. These details are shown in the figure below.



Scanning Views for plant Stresses

5. **Recommendation Engine**

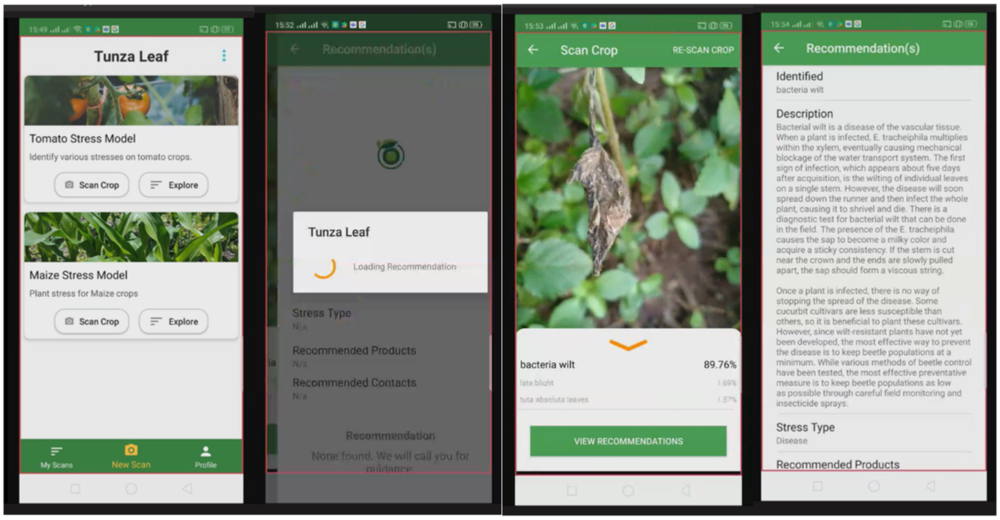
The step shown in the figure below has a menu option for viewing recommendations. Once a stress has been categorized and detected at a high accuracy level of above 80%, the user can tap on the view recommendations tab to view the recommendations as per the recommendation engine. The recommendation engine helps the end user get helpful information on how to combat the crop stress. The recommendation engine contains the information related to the type of stress detected, the recommended chemical product to remedy the stress detected, the recommended contact of the agrovet or the agronomist in the region where the stress has been detected. The recommendation engine is basically a structure that recommends the best agricultural products in the market the user can buy to be able to treat the various plant stresses. The recommendation goes further to connect the user to shops (agrovets around them) as well as provide details of agronomist experts within their geolocation.



Recommendation Engine showing recommended product and contact person for the detected stress

6. User History

Entails a list of scans by the user over time. For record keeping purposes. This is replicated in the web interface where previous scans are archived in the mobile interface for future reference. This is found in the figure below showing the scan history.



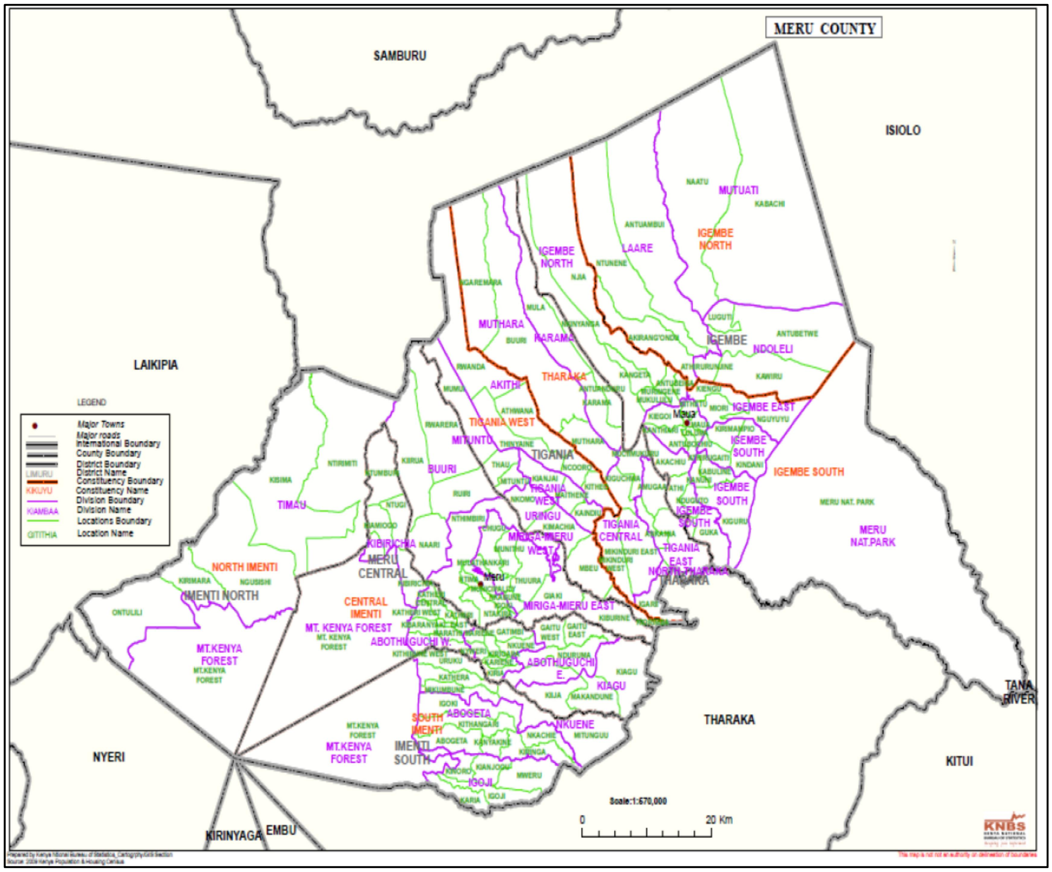
Scan History

The scan history contains images captured having been categorized based on the stress detected, the confidence level and the plant group. It also contains recommendation information that relates to the agrovet store recommended for the farmers, the contact of the agrovet store and the contact of the agronomist residents in the region that can be contacted for further advice. The scan history adds up to the database which can be utilized in future studies for research and mapping of the areas affected by specific stresses.

This section covered the Web interface called Tunza Leaf Web Interface User Manual, and the Mobile Interface for the Mobile Application Interface User Manual with details of the graphical user interface developed for the user side and the server side that consists of the Tunza Leaf Mobile Application and the Web interface for the Tunza Leaf as derived from the objectives of the study that aims at calibration of stress signatures to mobile interfaces that resemble the digital imaging model developed.

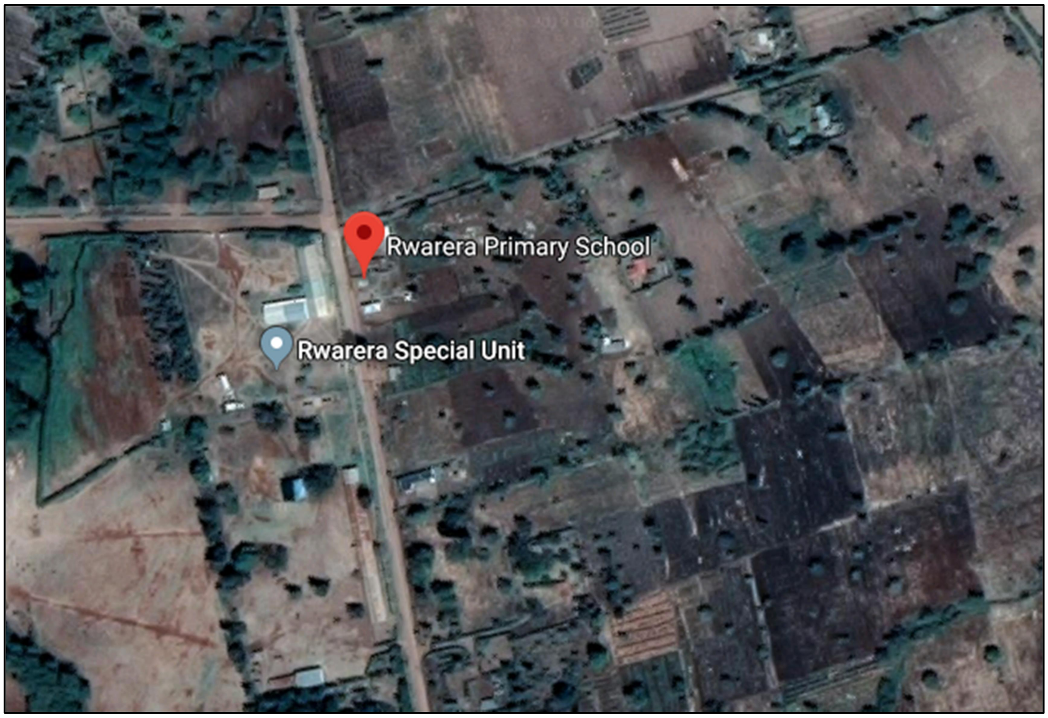
APPENDIX IV: POSITION OF MERU COUNTY

Location of Meru County on the Kenyan Map

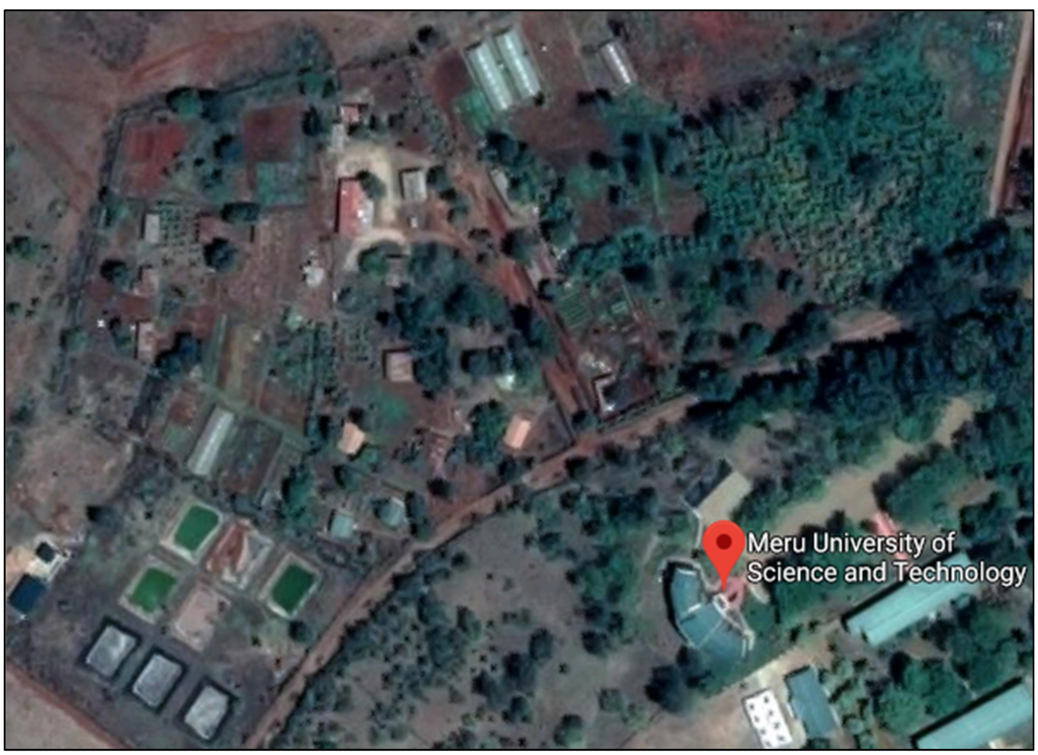


The Map of Meru County Government Showing Boundaries of the Sub Counties

APPENDIX V: GOOGLE MAP LOCATIONS OF THE RESEARCH FIELDS



Map of Rwarera farms where farmers set up experimental farms and images were captured



Map Showing the Location of the Meru University of Science and Technology farm in Nchiru Market where the Experiments were done

Map Showing the Location of the Farms in Maili Saba Market where the Experiments were done

Map of Tutua Market where the farmers were engaged in Setting up experimental farms for capturing images

APPENDIX VI: BUDGET

S/NO	Item	Specifications	Quantity	Unit Price (KShs)
1	GPU Computer	2018 Alienware Area 51 R2 Gaming Desktop, Intel Core i7-6800K 6-Core up to 3.6GHz, 32GB DDR4, 2TB 7200RPM + 512GB SSD, Nvidia GeForce GTX 1080 8GB GDDR5X, Bluetooth 4.0, WIFI 802.11ac, Windows 10	1	425,000
2	2 Mega Pixel Smart Phone	Itel Itel A11D - 8GB - 512MB RAM - 2MP Camera - Dual Sim - Grey	2	17,000
3	8 Mega Pixel Smart Phone	Infinix Smart (X5010)-[16GB+1GB RAM]-Dual SIM-Sandstone Black	2	28,000
5	Researcher overheads	12 Months, field visits and motorcycles hiring costs	48 days	120,000
6	Cost for Field visits by Researcher and Four research assistants	Quarterly Visits to Tutua, Rwarera, Maili Saba, Motony and Meru University Nchiru Farms	16	400,000
7	Internet bundles for farmers	50 Farmers	1000	50,000
8	Training of Research Assistants, Agronomist and Farmers	Training Workshops	14 days	250,000
9	Dissemination in Conference and Workshops	PAIRC 2018, Meru University and KeMU Conferences	3	60,000
10	Webhosting and Mobile Application Development	Annual fee	1	6,000
11	Publishing	Two publications	4	10,000
			TOTAL	**1,366,000**

APPENDIX VII: WORKPLAN

Plan of Activities: Work Plan	2018					2019							
Months in the Year 2018-2019	8	9	10	11	12	1	2	3	4	5	6	7	8
	Year 1												
Project Month	1	2	3	4	5	6		7	8	9	10	11	12
Milestones	**1**		**2**			**3**			**4**		**5**		
WP1: Thesis Proposal Approval and Project Kick-Off													
WP1.1 Procurement of 1 GPU Computers, 4 Smart Phones, 2 Nvidias for the project, Power Bank, Office application and Antivirus acquisition.													
WP1.2 Procurement of Lab media, Plate, Seeds, Fertilizers and Chemicals, stationery													
WP1.3 Installation and Configuration of GPU and Nvidia with TensorFlow, Python, and Visual Studio. Presentation to at the Seminar in MMUST													
WP2: Field work Preparations													
WP2.1 Recruitment and Training of Research Assistants													
WP2.2 Reconnaissance visits to Farmers													
WP2.3 Identification and training of farmers													
WP3: Image acquisition and labelling													
WP 3.1 Image verification and validation in the LAB													
WP4: Training of Machine Learning Models to perform Tomato pest and disease Identification													
WP4.1 Image preprocessing: resizing & rescaling													
WP4.2 Training of the CNN disease and pests Classifiers													
WP4.3 Testing of the trained CNN Classifiers													
WP4.4 Deployment of the trained model to the smart phone as a mobile application													
WP4.5 Development of the web server to support the app													
WP4.6 Deployment of the mobile app to farmers smart phones													
WP4.7 Evaluation of the performance of the app													
WP5: Thesis Report Preparation and Dissemination													
WP5.1 Presentation in Workshops and Seminars													
WP5.2 Two Publications done													

Milestones:

M1: Proposal presentation and Approval. Project Kick-Off, Procurement of GPU Computers, mobile devices, seeds, chemicals and stationery, TensorFlow, Python and Visual Studio installed

M2: Research Assistants and Farmers recruited and trained and reconnaissance visits done

M3: Images Acquired, labelled, verified and validated in the LAB

M4: ML Models trained, web server and mobile app developed and deployed to farmers, performance of the app tested

M5: Report writing, presentation, publications, information dissemination carried out, and document preparation and submission

APPENDIX VIII: APPROVAL OF PROPOSAL

MASINDE MULIRO UNIVERSITY OF SCIENCE AND TECHNOLOGY (MMUST)

Tel: 056-30870
Fax: 056-30153
E-mail: directordps@mmust.ac.ke
Website: www.mmust.ac.ke

P.O Box 190
Kakamega – 50100
Kenya

Directorate of Postgraduate Studies

Ref: MMU/COR: 509099

Date: 7th September 2018

Amos Chege Kirongo,
SIT/H/14-57870/2016
P.O. Box 190-50100,
KAKAMEGA.

Dear Mr. Kirongo,

RE: APPROVAL OF PROPOSAL

I am pleased to inform you that the Directorate of Postgraduate Studies has considered and approved your Ph.D proposal entitled: ***'A Digital Imaging Model for Early Detection and Warning of Plant Drought Stress"*** and appointed the following as supervisors:

1. Dr. Kelvin Omieno - School of Computing and Informatics, MMUST
2. Dr. Stephen Mutua Makau - School of Computing and Informatics, MMUST
3. Dr. Vitalis Ogemah - SAVET, MMUST

You are required to submit through your supervisor(s) progress reports every three months to the Director Postgraduate Studies. Such reports should be copied to the following: Chairman, School of Computing and Informatics Graduate Studies Committee and Chairman, Computer Science Department. Kindly adhere to research ethics consideration in conducting research.

It is the policy and regulations of the University that you observe a deadline of three years from the date of registration to complete your Ph.D thesis. Do not hesitate to consult this office in case of any problem encountered in the course of your work.

We wish you the best in your research and hope the study will make original contribution to knowledge.

Yours Sincerely,

Prof. John Obiri
DIRECTOR, DIRECTORATE OF POSTGRADUATE STUDIES

APPENDIX IX: RESEARCH AUTHORIZATION FROM NACOSTI

NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY AND INNOVATION

Telephone:+254-20-2213471,
2241349,3310571,2219420
Fax:+254-20-318245,318249
Email: dg@nacosti.go.ke
Website : www.nacosti.go.ke
When replying please quote

NACOSTI, Upper Kabete
Off Waiyaki Way
P.O. Box 30623-00100
NAIROBI-KENYA

Ref. No. **NACOSTI/P/18/58635/25690**

Date: **18th October, 2018**

Amos Chege Kirongo
Masinde Muliro University of Science and Technology
P. O Box 190-50100
KAKAMEGA

RE: RESEARCH AUTHORIZATION

Following your application for authority to carry out research on ***"A digital imaging model for early detection and warning of plant drought stress"*** I am pleased to inform you that you have been authorized to undertake research in **Meru County** for the period ending **12th October, 2019.**

You are advised to report to **the County Commissioner and the County Director of Education, Meru County** before embarking on the research project.

Kindly note that, as an applicant who has been licensed under the Science, Technology and Innovation Act, 2013 to conduct research in Kenya, you shall deposit **a copy** of the final research report to the Commission within **one year** of completion. The soft copy of the same should be submitted through the Online Research Information System.

BONIFACE WANYAMA
FOR: DIRECTOR-GENERAL/CEO

Copy to:

The County Commissioner
Meru County.

The County Director of Education
Meru County.

APPENDIX X: RESEARCH PERMIT FROM NACOSTI

THE SCIENCE, TECHNOLOGY AND INNOVATION ACT, 2013

The Grant of Research Licenses is guided by the Science, Technology and Innovation (Research Licensing) Regulations, 2014.

CONDITIONS

1. **The License is valid for the proposed research, location and specified period.**
2. **The License and any rights thereunder are non-transferable.**
3. **The Licensee shall inform the County Governor before commencement of the research.**
4. **Excavation, filming and collection of specimens are subject to further necessary clearance from relevant Government Agencies.**
5. **The License does not give authority to transfer research materials.**
6. **NACOSTI may monitor and evaluate the licensed research project.**
7. **The Licensee shall submit one hard copy and upload a soft copy of their final report within one year of completion of the research.**
8. **NACOSTI reserves the right to modify the conditions of the License including cancellation without prior notice.**

National Commission for Science, Technology and innovation
P.O. Box 30623 - 00100, Nairobi, Kenya
TEL: 020 400 7000, 0713 788787, 0735 404245
Email: dg@nacosti.go.ke, registry@nacosti.go.ke
Website: www.nacosti.go.ke

REPUBLIC OF KENYA

NACOSTI

National Commission for Science, Technology and Innovation

RESEARCH LICENSE

Serial No.A 21366

CONDITIONS: see back page

THIS IS TO CERTIFY THAT:
MR. AMOS CHEGE KIRONGO
of MASINDE MULIRO UNIVERSITY OF SCIENCE AND TECHNOLOGY, 972-60200 MERU,has been permitted to conduct research in *Meru County*

on the topic: *A DIGITAL IMAGING MODEL FOR EARLY DETECTION AND WARNING OF PLANT DROUGHT STRESS*

for the period ending:
12th October,2019

Permit No : NACOSTI/P/18/58635/25690
Date Of Issue : 18th October,2018
Fee Recieved :Ksh 2000

Applicant's Signature

Director General
National Commission for Science, Technology & Innovation

APPENDIX XI: AUTHORIZATION FROM COUNTY COMMISSIONER

THE PRESIDENCY
MINISTRY OF INTERIOR AND COORDINATION OF NATIONAL GOVERNMENT

Telegrams:
Telephone:
Email: ccmeru@yahoo.com
Fax:

COUNTY COMMISSIONER
MERU COUNTY
P.O. BOX 703-60200
MERU.

When replying please quote
Ref: **ED.12/VOL.III/62**
And Date

22nd October 2018

TO WHOM IT MAY CONCERN

RE: RESEARCH AUTHORIZATION – AMOS CHEGE KIRONGO

This is to inform you that **Amos Chege Kirongo** of Masinde Muliro University of Science and Technology – Kakamega, has reported to this office as directed by the Commission for Science, Technology and Innovation and will be carrying out Research on "**A digital imaging model for early detection and warning of plant drought stress in Meru County, Kenya.**"

Since authority has been granted by the said Commission, and the above named student has reported to this office, he can embark on his research project for a period ending **12th October, 2019**.

Kindly accord him any necessary assistance he may require.

COUNTY COMMISSIONER
MERU COUNTY
P. O. Box 70_-60200, MERU

W K KATONON
FOR: COUNTY COMMISSIONER
MERU

APPENDIX XII: AUTHORIZATION FROM COUNTY DIRECTOR OF EDUCATION

REPUBLIC OF KENYA
MINISTRY OF EDUCATION
State Department of Early Learning and Basic Education

Telegrams: " ELIMU " Meru
EMAIL: cdemerucounty@gmail.com
When Replying please quote

County Director Of Education
Meru County
P.O. Box 61
MERU

Ref: MRU/C/EDU/11/1/215

22nd October, 2018

TO WHOM IT MAY CONCERN

<u>RE: RESEARCH AUTHORIZATON – AMOS CHEGE KIRONGO</u>

Reference is made to letter Ref: NACOSTI/P/18/58635/25690 dated 18th October, 2018,

Authority is hereby granted to **Amos Chege Kirongo** to carry out research on "***A digital imaging model for early detection and warning of plant drought stress***" in ***Meru County, Kenya,*** for the period ending **12th October, 2019.**

Kindly accord him the necessary assistance.

COUNTY DIRECTOR OF EDUCATION
MERU COUNTY
P. O. Box 61-60200
TEL: 064-32372 MERU

Nkonge J. E.
For: County Director of Education
MERU