NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DEPARTMENT OF ARTIFICIAL INTELLIGENCE ENGINEERING

AN AI-BASED SOLUTION FOR SWEETPOTATO LEAF DISEASE DIAGNOSIS: (AGROO AI)

M.Sc. THESIS

MATTHIAS B.E LUOGON

Nicosia

June, 2023

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June, 2023

Approval

We certify that we have read the thesis submitted **MATTHIAS B.E LUOGON** titled **"AN AI-BASED SOLUTION FOR SWEETPOTATO LEAF DISEASE DIAGNOSIS: (AGROO AI)"** and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Educational Sciences.

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List of Abbreviations

Acronym	**Meaning**
ML	Machine Learning
DL	Deep Learning
ANN	Artificial Neural Network
CNN	Convolutional Neural network
ReLU	Rectified Linear Unit
Agroo AI	Agricultural-oriented Artificial Intelligence

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Declaration

I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of Institute of Graduate Studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

MATTHIAS B.E LUOGON

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Day/Month/Year

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We sincerely appreciate the assistance and contributions made to our thesis project, Agroo AI, and we want to thank everyone who has done so. We would first want to express our gratitude to our supervisor; Prof. Fadi Al-Turjman (chair of the AI department and Associate Dean for Research in the Faculty of engineering at Near East university), and his wife Mrs. Sinem Al-Turjman, for their important leadership and support throughout the research process. This project, and my study would not have been accomplished without their guidance and experience.

We also like to thank our co-workers, families, and friends for their assistance in gathering, and organizing the sweet potato leaf photos that were used in this study. We personally appreciate Mr. Jephthah L Luogon for helping us snap the photos of the dataset and the overall data production procedure. The amount and quality of the data used in this study have greatly benefited from their efforts.

Last but not least, we would like to express our gratitude to God al-mighty for his grace, and for strengthening the volunteers who gave their time and effort to offer us feedback on the mobile-based online system. Their thoughts and insights were crucial in enhancing the system's usability and functionality.

We once more want to express our gratitude to everyone who has helped with this study effort.

Matthias B.E Luogon

Abstract

AN AI-BASED SOLUTION FOR SWEETPOTATO LEAF DISEASE DIAGNOSIS: (AGROO AI)

Luogon Matthias B.E

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Traditional methods of disease detection, such as visual inspection, can be time-consuming,subjective, and limited by the expertise of the observer.

This study aimed to develop an adaptive mobile web-based system backed by a convolutional neural network (CNN) model for the detection and diagnosis of diseases affecting sweet potato leaves. To detect diseases of sweet potato leaves, the user can take a photo of the leaf using a mobile phone and upload it to the system and classification will be made as well as plant care guide instructions. Shying away from the publically available datasets, we collected 1654 images of sweet potato leaves diseases taking into consideration major parameters like exposure, angle, environmental conditions, and lightenening, categorized and annotated the dataset into three classes of

common diseases affecting the crop in Liberia, and around the world: Alternaria Leaf Blight, Healthy, and Potassium Deficiency. For more robust model performance, we used 9000 photos acquired through data augmentation, and the CNN model had a training accuracy of 96.3%. we developed an API and tested to ensure the

accurate and effective performance. Further work may involve extending the dataset to

incorporate additional plant species, creating a mobile version of the system, and investigating various CNN model designs

and optimization strategies, and assessing how well the web-based interface supports disease management.

Key Words: sweet potato leaf disease, convolutional neural network, agriculture, mobile

web system, dataset augmentation.

TATLI PATATES YAPRAK HASTALIĞINA AİT TABANLI ÇÖZÜM TEŞHİS: (AGROO AI)

Luogon Matthias B.E

M.Sc, Yapay Zeka Mühendisliği Bölümü (Nisan), (2023), (78) sayfa

Görsel inceleme gibi geleneksel hastalık tespit yöntemleri zaman alıcı olabilir. özneldir ve gözlemcinin uzmanlığıyla sınırlıdır.

Bu çalışma, tatlı patates yapraklarını etkileyen hastalıkların tespiti ve teşhisi için evrişimsel sinir ağı (CNN) modeliyle desteklenen uyarlanabilir mobil web tabanlı bir sistem geliştirmeyi amaçladı. Tatlı patates yapraklarındaki hastalıkları tespit etmek için kullanıcı cep telefonu kullanarak yaprağın fotoğrafını çekip sisteme yükleyebilir ve bitki bakım rehberi talimatlarının yanı sıra sınıflandırma da yapılacaktır. Kamuya açık veri kümelerinden uzak durarak, maruz kalma, açı, çevre koşulları ve aydınlatma gibi ana parametreleri dikkate alarak tatlı patates yaprağı hastalıklarına ait 1654 görüntü topladık, veri kümesini üç sınıf halinde kategorize ettik ve açıklamalar ekledik.

Liberya'da ve dünya çapında mahsulü etkileyen yaygın hastalıklar: Alternaria Yaprak Yanıklığı, Sağlıklı ve Potasyum Eksikliği. Daha sağlam model performansı için veri artırma yoluyla elde edilen 9000 fotoğrafı ve CNN'i kullandık.

modelin eğitim doğruluğu %96,3'tü. sağlamak için bir API geliştirdik ve test ettik.

doğru ve etkili performans. Daha ileri çalışmalar veri setinin genişletilmesini içerebilir.

İlave bitki türlerinin dahil edilmesi, sistemin mobil versiyonunun oluşturulması ve çeşitli CNN model tasarımlarının araştırılması

ve optimizasyon stratejileri ve web tabanlı arayüzün hastalık yönetimini ne kadar iyi desteklediğinin değerlendirilmesi.

Anahtar Kelimeler: tatlı patates yaprağı hastalığı, evrişimli sinir ağı, tarım, mobil web sistemi, veri kümesi büyütme.

CHAPTER I

Introduction

Sweet Potato Leaf Disease, AI, and DL

Ipomoea Batatas; Sweet Potato is a major plant hugely grown and cultivated around the globe giving its prominent values of nutrients and its ability to adapt to various climatic conditions. The crop is a major staple food for Liberia (the primary location for this research) and due to its economic value, it has served as a major source of income for many in the region. However, farmers who grow the crop, have faced significant economic losses due to several leaf diseases affecting crop yield and quality. For this reason, our research is focused on the diagnosis of sweet potato leaf diseases and the most common diseases studied are Alternaria leaf blight, healthy leaves and potassium deficiency leaves.

Alternaria leaf blight is a fungus disease caused by alternaria bataticola. This disease is one of the most common and degrading diseases harming sweet potato crops. The leaf is characterized by having little rounded to irregular dark brown leaves lesions. These lesions get bigger and circulated by a halo with yellow appearance as the disease elongates. With more infections, the plant starts to defoliate, weaken and tube yields reduction.

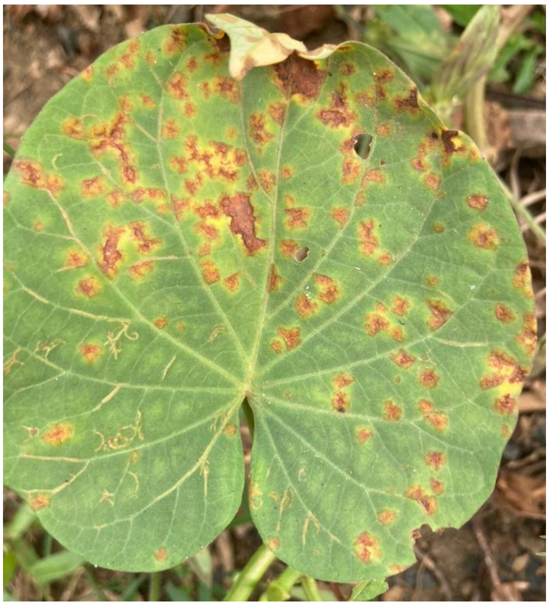


Figure 1. showing sweet potato leaf affected by alternaria leaf blight.

For the healthy sweet potato leaf on the other hand, it appears to have a clean growth, green and vibrant coloration, and exclusion of any form of signs of disease or symptoms. This helps experts to distinguish diseases and diagnose giving the physical look of the crop. For training an effective model for disease detection, it is crucial to accurate point out healthy leaves.

Figure 2. showing sweet potato leaf healthy image.

Also, potassium deficiency is a disease caused by the lack of nutrition which caused sweet potato plants to degrade. It is caused by the lack of potassium available in the soil. This disease is visible in the leave by the identification of yellowing and necrosis of old leaves ranging from the area of margins and reaching towards the center of the leaf. Scorching of leaves may appear as well as curling in most cases. Furthermore, some cases may have interveinal chlorosis. Fertilizer application could be one of the common ways of preventing this disease.

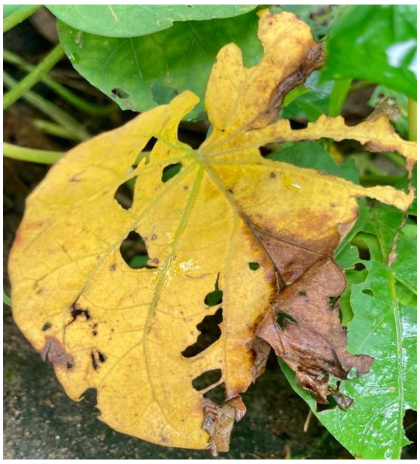


Figure 3. showing sweet potato leaf affected by potassium deficiency disease.

(Sethy, 2020) (Chen J. C., 2020) (Bai, 2018) (S. M. Coakley, 1999) (Camargo & Smith, An image-processing based algorithm to automatically identify plant disease visual symptoms, 2009) (Singh & Kaur, 2018) (Camargo & Smith, "Image pattern classification for the identification of disease causing agents in plants, 2009) (Chaudhary, Kolhe, & Kamal, 2016) (Phadikar, Sil, & Das, 2013) (Munisami, Ramsurn, Kishnah, & Pudaruth, 2015)

Implementing artificial intelligence (AI) and machine learning (ML) in agriculture has the power to change crop management and increase food security. In particular, the use of convolutional neural networks (CNNs) in the detection and classification of plant diseases has shown promising results in recent years. Sweet potato leaf is an important staple crop in Liberia and many regions of the world, and its production is often threatened by various diseases that can significantly reduce yields. Therefore, the development of accurate and efficient tools for early disease detection and management is crucial for sustainable sweet potato leaf production.

This study focuses on the development of an AI-based solution backed by a CNN model for the detection and classification of sweet potato leaf diseases, specifically Alternaria Leaf Blight, Healthy, and Potassium Deficiency. The dataset used to train the model originally consists of 1654 images of sweet potato leaves, which were collected and labelled. With data augmentation, the dataset was expanded to 9000 images, utilized for learning and assessing the model. The model achieved an overall high accuracy of 96.3% on the test set, indicating its potential as a reliable tool for disease detection and management.

To facilitate the deployment and testing of the model, we used FastAPI, TensorFlow Serving, Docker, and Postman to build and test an API. The API was tested and validated to ensure that it was performing accurately and efficiently before being integrated into a responsive mobile web app. The frontend was build using React JS.

The tools and technologies used to conduct this research are briefly discussed below. However, they will be discussed in more detail in further chapter:

Python 3: A high-level language widely utilized in data science and machine learning. It offers a vast array of repositories and tools for data manipulation, scientific computing, and machine learning.

Keras and TensorFlow: A free-to-use machine learning framework created by Google, and Keras is an upper-level neural networks API which runs on above TensorFlow. Both TensorFlow and Keras are widely used in the development of deep learning models and provide a huge set of functionalities and functionalities for making complex neural networks.

FastAPI: This is a recent, speed-effective web resource for making APIs with standard Python type hints. It provides automatic validation of request and response data, API documentation generation, and other features that make building APIs faster and easier.

TensorFlow Serving: A free-to use software resource for providing functions for machine learning models developed in TensorFlow. The technology provides a flexible architecture for deploying models in production and supports a wide range of deployment configurations.

Docker: This is a containerization resource which enables developers to make, deploy, and implement their system in containers. Containers provide a less-weighed, portable, and consistent runtime environment that makes it easy to package and deploy applications.

React JS: A popular resource of JavaScript for designing user layers. It is widely used in web development and offers a component-based architecture that enables developers to build complex UIs with reusable components.

The availability of the dataset developed in this thesis on Kaggle and Plant Village platforms will facilitate further research and innovation in this area.

In this study, we aim to demonstrate the potential of AI and ML in agriculture, specifically in the detection and classification of sweet potato leaf diseases. By providing a reliable and efficient tool for disease detection and management, we hope to contribute to the development of sustainable and efficient agricultural practices.

Furthermore, this study aims to address the problem of sweet potato leaf disease detection, which has been a challenge for farmers and researchers alike. Utilization of AI and DL in disease detection is powerful to overcome these limitations and provide an objective and efficient method for disease management.

This study is vital, in that, it outlines the potential impact diseases could have on sweet potato production and food security in regions like Liberia, where sweet potato leaf is a staple crop. By providing a reliable and accurate tool for early disease detection, farmers can take timely and appropriate action to manage and mitigate the spread of diseases. This could result in increased yields, reduced crop losses, and improved food security.

In conclusion, the development of a diagnosis system for the detection and classification of sweet potato leaf diseases, as well as the creation of a dataset, represents a significant step forward in utilizing AI and DL in agriculture. The will of this technology to increase food security and promote sustainable agricultural practices cannot be overstated.

1.2 Statement of the Problem

Sweet potato leaf is a significant crop that is consumed regularly in Liberia and other areas of the world, offering millions of people a major source of nourishment and revenue. Unfortunately, farmers who grow the crop have faced economic losses due to a number of illnesses affecting the crop. These diseases can dramatically lower yields and quality frequently make it difficult to grow sweet potatoes leaves. Large-scale farming operations cannot use conventional disease detection and management techniques because they are frequently labour- and time-intensive.

By offering quick and precise diagnoses of plant illnesses, automated disease detection and classification using AI and ML algorithms has the potential to improve the production of sweet potatoes. Before these technologies can be widely used within the sector of agriculture, issues to be solved are many.

The availability of top-notch labelled datasets for training AI and ML models is one of the major obstacles. Large datasets of plant images may be difficult to gather and annotate, and the accuracy of the annotations can have a significant effect on how well the models perform. The precision of the illness detection algorithms may also be affected by differences in the location and environment.

The necessity for real-time disease diagnosis and management systems that are simple to integrate into current farming operations presents another difficulty. By enabling them to swiftly and easily detect and treat plant illnesses, farmers might tremendously benefit from the development of user-friendly mobile web-based interfaces that can reliably forecast and categorise sweet potato infections.

The overall goal of this thesis is to examine the viability of employing CNNs and other AI and ML algorithms for the automated diagnosis of illnesses affecting sweet potato leaves. This study has the potential to advance sweet potato leaves farming and lessen the financial toll of plant illnesses by tackling the issues of dataset quality, environmental unpredictability, and real-time disease diagnosis.

1.3 Significance of Study

The research's importance is found in its potential to enhance disease diagnosis and control in agriculture, particularly for the growing of sweet potatoes leaves. This research has the potential to: Minimize the economic burden of plant diseases on sweet potato leaves production experienced by farmers in Liberia by offering quick and accurate diagnostics of plant illnesses.

By automating the process of disease identification and control, sweet potato leaves farming operations will be more productive and efficient.

Assist other researchers in the creation of AI and ML models for the identification of plant diseases by providing high-quality labelled datasets.

Exemplify how AI and ML algorithms may be used to solve challenging issues in agriculture, and promote more study in this area.

In general, this study's importance rests in its value to increase the sustainability and profitability of sweet potato leaves farming and to support larger initiatives to enhance agricultural practises using AI and ML.

1.2 Aim of Study

The research goal is to create a user-friendly mobile web-based interfaces that sits on top of a CNN model for the automatic diagnosis of illnesses that affect sweet potato leaves. Our specific objectives are to:

- Conduct a high-quality collection of pictures of sweet potato, categorized and annotated, with three classes—Alternaria Leaf Blight, Healthy, and Potassium Deficiency.
- Construct and train a CNN model using the annotated dataset.
- Analyzed the CNN model's performance using parameters like correctness, preciseness, recall, and F1 score, and matrix of confusion.

- Performance assessment of the CNN model.
- Provide a web-based interface that enables users to upload or drag-and-drop an image of a sweet potato leaf from their device in order to get a diagnosis of the ailment, along with treatment functionality.

By attaining these goals, this study hopes to show how AI and ML algorithms may help with disease control and diagnosis in agriculture, particularly for the production of sweet potato leaves.

1.3 Research Questions

The following inquiries and theories will serve as the study's guiding principles:

- Research Question 1: Can an CNN model correctly diagnose diseases of sweet potato leaves into the three groups (Alternaria Leaf Blight, Healthy, and Potassium Deficiency)?
- Research Question 2: How does the CNN model's performance compare to other cutting-edge techniques for spotting diseases in sweet potato leaf cultivation?
- Research Question 3: Can an AI-based system correctly diagnose diseases of sweet potato leaves into the three groups (Alternaria Leaf Blight, Healthy, and Potassium Deficiency) and provide treatments functionalities for the respective diseases?

1.3 Drawbacks

This thesis has a number of drawbacks that need to be recognised. They consist of:

The sweet potato leaf-only dataset used for training and assessment may not generalize well to other crops or plant sections.

Additionally, the system was only trained to detect three basic disease classes of sweet potato leaf in Liberia, which may not cover all the possible diseases that could affect sweet potato crops.

The dataset's annotations are based on domain knowledge, and may be subjective, and could vary among various annotators, which could introduce biases into the CNN model.

Another drawback was the lack of access to more advanced hardware resources. CNNs require a significant amount of computational power and memory, and our model had to be trained on a standard laptop. This drawback could have affected the speed and accuracy of the training process.

The accuracy of the CNN model may be significantly impacted by ecological and ambient factors, and it's probable that the study didn't account for all possible variances in these factors.

Depending on their technological capabilities and internet connection, not all farmers may be able to use the web-based interface created for the project.

CHAPTER II
Literature Review & Related Works

2.1 Theoretical Framework

Ipomoea batatas; sweet potato, is a significant crop grown throughout the world and is popular in African nations. Many illnesses that the plant is prone to can reduce productivity and jeopardize food security.

In this chapter, we examine the research on the creation of a mobile website for identifying and diagnosing sweet potato leaf illnesses using convolutional neural networks (CNNs). Two subsections make up the literature review: a framework for theory and related literature.

The classification of sweet potato leaf disease, the usage of CNNs for image recognition tasks, and the technological concerns for developing mobile websites are only a few of the topics covered in the theoretical framework subsection. This subsection gives a reader a view of the important areas of the proposed system.

The relevant studies on CNN-based plant disease categorization and detection are reviewed in the related works area, which also offers insights into the creation and improvement of CNN models. The purpose of the subsection is to inform the creation of the suggested system and to highlight the advantages and disadvantages of current techniques.

A basis for the proposed research is provided by the literature review, which also guides the development of the mobile website for the diagnosis of sweet potato leaf disease.

The literature on sweet potato leaf illnesses and CNNs is reviewed in this section. The review will provide a summary of the current understanding of the symptoms, aetiology, and progression of sweet potato leaf disorders.

2.1.1 Sweet Potato Leaf Disease Classification:

The sweet potato leaf is a significant crop that is farmed extensively around the world. Nonetheless, it is vulnerable to a number of illnesses brought on by various pathogens, including as nematodes, bacteria, viruses, and fungus. The most prevalent of these ailments, leaf diseases, can result in severe output losses if not addressed. The sweet potato plant's leaves become infected by pathogens, which induce symptoms including yellowing, chlorosis, necrosis, and spots. The implementation of effective control strategies, such as the targeted use of fungicides or modifying fertiliser application rates, depends on the early diagnosis and proper categorization of these diseases.

Growing interest has been shown in automating the categorization of plant diseases, especially illnesses of sweet potato leaves, using computer vision and machine learning approaches in recent years. These methods take advantage of Convolutional Neural Networks' (CNNs') ability to identify patterns and characteristics in pictures and categorise them. In the detection and classification of plant diseases in a variety of crops, such as tomatoes, grapes, and apples, CNNs have demonstrated encouraging results. In this study, we will use a CNN-based technique to create a mobile-based web system for diagnosing three different sweet potato leaf diseases: Alternaria Leaf Blight, Healthy, and Potassium Deficiency. We'll make use of a series of photographs of sweet potato leaves that we gathered, annotated, and divided into these three classes. Using data augmentation techniques, the CNN model will be trained on this dataset to provide more samples and enhance the model's performance. The resultant mobile-based web system will enable farmers and researchers to quickly and precisely categorise sweet potato leaf diseases, enabling them to put in place prompt control measures and enhance crop management techniques.

On the basis of the symptoms shown in the leaf images, sweet potato leaf diseases will be categorised in this study. Alternaria Leaf Blight, Healthy, and Potassium Deficiency are the three kinds of sweet potato leaf illnesses that will be examined based on its commonness in Liberia.

Brown circular lesions or patches that form on the leaves, which may group together and cause defoliation, are one of the signs of Alternaria Leaf Blight. Moreover, the damaged leaves may bend and twist, and the plant's development may be hindered.

Regarding healthy leaves, no outward signs of illness will be seen, and the leaves will be green, turgid, and normal-looking.Leaf curling, marginal or interveinal necrosis, and chlorosis are some of the signs of potassium deficiency. Moreover, the impacted leaves may seem smaller and develop more slowly.Using a CNN-based approach, which makes use of a deep neural network algorithm to learn the patterns and characteristics in the leaf photos associated with each category, the three types of sweet potato leaf diseases will be classified. A dataset of images of sweet potato leaves will be used to train the CNN model, and this dataset will be augmented to enhance the model's performance. The resultant mobile-website online system will enable farmers and researchers to quickly and precisely categorise sweet potato leaf diseases, enabling them to put in place prompt control measures and enhance crop management techniques.

2.1.2 Convolutional Neural Networks (CNN)

Recently, the discipline of computer vision has seen a revolution thanks to deep learning. Several image-related works, such as identification of objects, face diagnosis, and segmentation of pictures, have been successfully completed using CNNs. The purpose of image classification tasks is to categorise a picture based on its content. CNNs are particularly effective for these tasks.

The fundamental principle of CNNs is to understand a hierarchy of elements from the input picture, starting from low-level features that are straightforward, like edges and corners, through high-level features that are more intricate, such as object pieces and forms. In order to extract local features and decrease the dimensionality of the input, a sequence of convolutional and pooling layers convolve the input picture using a set of learnable filters.

CNNs have demonstrated significant potential in the diagnosis of plant diseases based on the visual symptoms displayed in the plant images. CNNs are capable of generalising effectively to fresh, unstudied pictures and may learn to detect patterns and characteristics in the images that are symptomatic of particular illnesses. CNNs are resilient to real-world circumstances because they can deal with differences in picture quality, illumination, and camera angles.

In this study, the diagnosis of diseases affecting sweet potato leaves will be done using a CNN-based method. Using a dataset of images of sweet potato leaves that we have gathered, labelled, and divided into three classes—Alternaria Leaf Blight, Healthy, and Potassium Deficiency, we will create and train a CNN model. To learn the features and patterns in the leaf pictures and classify them into the proper illness category, we will combine convolutional and pooling layers with fully connected layers. In order to get more samples of pictures of our dataset and strengthen the generalizability of our model, we will also use data augmentation techniques like flipping, rotating, and scaling.

Effective and automatic diagnosis of sweet potato leaf diseases will be made possible by the resultant CNN-based method, with potential uses in crop management and disease control.

There are a number of hyper-parameters that are essential to the performance of the CNN architecture employed in this study. The number of photos processed in a single batch, the dimension of the input picture, and the colour channels in the picture are all defined in the network's input dimension as (batch size, image size, image size, channels). As we are utilising RGB photos in this instance, channels are set to 3. The output layer's 'n classes' specification indicates how many classes there are; in this example, there are three: Alternaria Leaf Blight, Healthy, and Potassium Deficiency.

Convolutional layers with 32, 64, or 128 filters and a kernel size are the basic building blocks of the CNN model (3, 3). The rectified linear unit (ReLU), which aids in adding nonlinearity to the model, is the activation function utilised in each of the layers of convolution. To decrease the spatial dimensions of the maps of feature and integrates the network's effectiveness, maximum pooling layers are added after each convolutional layer. The network's 64 nodes and ReLU activation function are found in the fully linked, top layer. The network generates a probability distribution over the three disease classes in its output layer, which is a dense layer with ‘n_classes’ nodes and a softmax activation function.

2.1.3 Mobile Website Development:

As the user interface for our disease diagnosis system, responsive mobile website development leveraging React JS is an important component of our study. In this study, we used the React JS framework to create a mobile website that enables users to upload or drag/drop images of sweet potato leaves for the CNN model to classify. There are two key parts to the website, the first of which is the React Drop-zone component, which enables users to submit images for diagnosis. Users may submit images fast and simply using the component, which supports a variety of file types.

The recommended responsive mobile website would be built on the following components. The website will first be developed using ReactJS, a popular front-end platform for producing user interfaces. Second, the website will utilize a CNN

model driven by Tensorflow Serving, FastAPI, and Docker to diagnose sweet potato leaf disease. The CNN model will be trained using a big collection of images of diseased sweet potato leaves. Following that, users may submit a picture of a sweet potato leaf or drag it into the website to see whether it has any diseases.
The website will also provide specific plant care recommendations for the detected disease as a last step in effective treatment. These recommendations for plant care will support practical plant treatments and be based on the most recent scientific results. The dataset that was utilised to train the CNN model will also be made accessible to the general public for use in further research and development related to plant and agricultural diseases. This theoretical framework combines the most recent scientific research with the most recent technical developments to provide a practical tool that can be used by farmers and researchers to diagnose and treat diseases of sweet potato leaves.

2.1.4 Testing and Validation:

Each machine learning model must undergo testing and validation, and in this study, we used the inference process to assess the precision of our CNN model. To do this, we plotted the projected classification outcomes for the test dataset using the “matplotlib” function.

Using the “test dataset”, we extracted few batches of labels and images from the test dataset. The images were iterated through using the ‘take ()’ function and a for loop to display each image along with its expected class, actual class, and prediction confidence. In order to assess the accuracy of our model, we first used the predict function to determine the anticipated class and confidence level for each image.

Each image's actual and anticipated classes were shown, allowing us to evaluate the effectiveness of our model and spot any misclassifications. In machine learning, testing and validation are essential steps to take to make sure the model works as predicted and is trustworthy. The efficacy and utility of the model in real-world circumstances must be determined using the testing and validation findings.

In summary, this theoretical framework provides a comprehensive overview of the research on building a mobile website that uses CNNs to classify and detect diseases of sweet potato leaves. The framework outlines the key components of the research, including disease classification, CNNs, mobile website development, and testing and validation. The framework helps to ensure that the research is grounded in existing knowledge and theories and that all aspects of the research are considered.

2.2 Related Work

The diagnosis of plant diseases using a variety of machine-learning approaches have been the subject of numerous studies. Only a handful, nonetheless, have concentrated on the sweet potato leaf sickness. ((Pappu Sah Sudi, 2022) conducted a study for Disease Detection in Potato Leaves (irish potato) using CNN. They were able to accumulate an accuracy of 99.07% using 2150 images of potato leaves utilizing three classes. (Shaji & Hemalatha, 2022) A recent study used augmentation of image and advanced extraction of feature to deal with seeking leaf diseases of rice. Using 7 augmentation methods, they increased the size of the dataset for new samples generation.

The process of pre-processing an image of a plant to extract its crucial visible features before feeding them into a neural network classifier is explained in (Chethan, Donepudi, Supreeth, & Maani, 2021). The authors aimed to improve the classifier's performance in detecting diseases of plant. Their paper describes the various machine learning algorithms involved, with a specific attention on their application to classification of mobile. clustering K-means for division of image and model mobile transformation are also covered in detail. The prototype application provided in (Chethan, Donepudi, Supreeth, & Maani, 2021) allows users to name a plant disease by taking an image of the plant using the camera of the device. However, this application does not include the option to view treatments of diseases, which is incorporated in our system. In (Dammavalam, et al., 2021), the researchers investigated the use of cross-domain learning approaches in combination with ConvNets to categorize many plant varieties as either "healthy" or "infected". The study involved comparing several pre-trained models, having VGG19, VGG16, DenseNet, XCeption, MobileNet, and ResNet. The results indicated that the VGG models were most effective in extraction of feature, achieving 97% average accuracies of the models. The authors also observed that the VGG models demonstrated greater consistency in performance despite data imbalance and increased depth of network needed for cumbersome extraction of feature. Conversely, the ResNet and DenseNet models were found to have almost identical extracted features from their input layers, likely due to the regular jump connections in their framework, making them overly complex for the task at hand.

(Zhuang, et al., 2021) specified the major goal of utilizing transfer learning approach in environment of deep learning which is often explained from the perspective of model.

A study done by (Tarek Habib, 2020), used segmentation and supervision model for image and K-means Clustering to find their results. Regardless of the high accuracy achieved, a limited amount of future set was used which posed a drawback in efficiency. A research done to determine pawpaw's maturity by K-Nearest Neighbour and Support Vector Machine algorithm for classification was dome by (Behera, 2020). They were able to get an average accuracy of 90%, though being unaware of the disease. Harvested crops deformation by use of texture defect using el earning machine technique is a research done by (Chen J. L.-T., 2020). The use of image processing algorithm couple with Support vector machine and HOG is concerned with the disease of leaf research done by (Pothen, 2020). With respect to their algorithm, they executed HOG for detecting the layer separation. In (Ahmad, Jan, Farman, Ahmad, & Ullah, 2020), researchers made use of their own images operated in natural outdoor space using mobile devices to make a set of image of non-diseased and diseased plum leaves. They applied another augmentation of data techniques to get 19 varieties of each photo, resulting in a total of ten thousand set of images. They named the plum images into five different categories: non-diseased, rot(brown), nutrient lack, shot hole, and leaf with shot hole. Four models were developed and evaluated, namely AlexNet, VGG16, Inception-v1, and Inception-v3. The results of (Ahmad, Jan, Farman, Ahmad, & Ullah, 2020) indicated that the Inception had the best performance. The best model achieved an overall accuracy of 88.42% when examined with a 100 image test set. However, like (Chethan, Donepudi, Supreeth, & Maani, 2021), they did not incorporate treatments functionalities also. (Vijayakumar, 2020), were able to conduct a research for detecting fruits mellowness using RESTNET152 and DNN. In (Elsayed & Aly, 2020), the authors focused on the classification of twelve (12) plant leaf species and 22 diseases to yield 86.22% accuracy utilizing their method proposed. A research was done by (Liang, 2020), for a multi duct cleansing apparatus creation for rice harvesters through the experimental procedure and CFD. The authors in (Liu & Wang, 2020) used techniques of deep learning to aid in timely detection of latest Greyish Leaf Spot tomato crop disease. They used the MobileNetV2-YOLOV3 algorithm with lesser memory to yield a 92.53% accuracy. The utilization of cross-domain learning in creating networks of neural for a lot of class photo of plant naming was studied in a previous study referred to as (Sagar & Dheeba, 2020) . The study examined five distinct CNN networks: InceptionV3, VGG16, ResNet50, InceptionResNet, and DenseNet169, utilizing a publicly available PlantVillage dataset, containing images for 38 disease classes and single class of background. The ResNet50 model emerged as the optimal choice, producing impressive accuracy score of 98.2%, precision, recall, and F1-scores of 94%. Other studies such as (Elsayed & Aly, 2020) used quantum particle swarm optimization (QPSO) algorithm and focused on the improvement of segmentation of image for noisy images of plant disease and a reasoning- based process of classification after the completion of the feature extraction process. (Kelly, 2019) Conducted a study to fine the level of impact of fruits on a human body. Their research made use of some bio parameters such as temperature and pressure to get their result. In (Valdoria, Caballeo, Fernandez, & Condino, 2019), the University of Philippines introduced a solution application of mobile called "iDahon" for plant illness naming, with the objective of improving earthly illness finding, as the Philippines' economy is highly dependent on export of agricultural. They utilized 1650 images for model training, with a 60:20:20 division for teaching, verification, and evaluation respectively, focusing on leaf diseases of 11 classes common to the Philippines. They used TensorFlow, and Python for model development. They used Docker cloud for model loading for simulative learning and evaluation. The work presented in (Valdoria, Caballeo, Fernandez, & Condino, 2019) enables users to input images using either the devise camcorder or by sending a pre-occurring photo from the device picture area. Similar to the previous mentioned studies, they did not utilize diseases treatments methods in their system.

The researchers of (Syamsuri & Negara, 2019) have introduced an smart application of mobile system using unified lite deep neural networks to classify plant diseases. They have employed architectures, namely MobileNet, MNasNet, and InceptionV3, and have used a PlantVillage set of image. learning of the models has been made for a rate of learning of 0.01 and 30 times and a 60:20:20 learning, validating, and evaluating split. What makes (Syamsuri & Negara, 2019) stand out is the understandable solution they conducted between the three algorithms, which includes factors like memory usage and levels of latency in addition to the standard correctness, fidelity, recall, and F1-scores outcome. The work achieved a 90% average score. (Md. Helal Sheikh1, 2019), have conducted a research concern with fault value detection of leaves of tree only. Using some fixed dataset and Adam classifier for reduction of rate of learning, they performed image processing. In a study done by (Elgendy, 2020) , a transfer learning approach od four cases is described for understandably training of neural networks. Those four cases were executed throughout the designing and assessment stages of their model specifying a competitive rule for their investigation of transfer learning.

The research done by (harsha. A, 2018) , about crops using AI for the pH of objects, they were unable to summarize the recognition, classification and detection of image process.

Plant leave disease classification and detection using K-Nearest neighbour's technique was used in a study done by (M.Malathi, R.Vishnu Priya, Dr.V.Karvidha. 2018). But their result of prediction was not conveniently mentioned in their research.

The researchers of (Ma, et al., 2018) employed segmentation of image and many-named categorization to identify and categorize four distinct leaf diseases of cucumber, namely black spot, blue mold, oidium, and tan spot, making use of a deep ConvNet enabled architecture. The set of data utilized in 10 (Ma, et al., 2018) included images of diseases of cucumber in natural outdoor settings, and the ConvNet model developed by the authors achieved a remarkable accuracy of 93.4%. A previously trained CNNS GoogleNet based on their original dataset of images of plants diseases comprising of 1383 images in total and 56 classes of disease and 12 plant types was done by (Barbedo, 2018). A research conducted by (Veeraballi, 2017) ; they used papaya curl leaf for disease identification using convolutional neural network model. Though they were able to acquire an average accuracy of 85% for detection of leaf disease, they did not focus on the fruits.

Making use of K-means Clustering technique, (Degadwala, 2016) conducted a study for classification and detection of disease of fruits with dataset. However, their research lacks feasibility concerning its usage by farmers and people with no technical know-how. (Jalal, 2015) , Unveils a good method for detecting fault through a mathematical and visualization of graph from an image dataset. However, there were not new improvement made on this domain

A research study using machine learning technique called bootstrap aggregation for disease information extraction on collection of sample was done by (Fabio Augusto Faria). Using SVM for value gaining and representation of graph, they formulated an algorithm program.

In (Asefpour Vakilian & Massah, 2013), the authors focused on image processing of plant with an objective of tackling deficiency of nitrogen (a common nutritious deficiency problem of plants) my means of formulating a digital, imagery system of early detection for plant growth and health monitoring. They used a system of computer vision to study crops of cucumber and discovered deficiency of nitrogen by means of colour variations in the crop's leaves and stems by separately taking out textural features of plant with energy, entropy, and similarity to result into conclusive growth of plant and status of health and also utilizing these features as stamps for on-time nitrogen deficiency detection. Part of their system had a model of robotic camera architecture, image gathering/ executing, and analysis and storage of data. Images taken by the robotic camera were sent to a computer using wireless technology. Their overall results show that the integrated system could adequately detect deficiency of nitrogen cucumbers 48 hours before symptoms become visible to human eye, hence demonstrating the benefit of using system powered by AI for detection.

The main referenced paper within this thesis work is the study conducted by (Taterwal, 2021) . The research thesis focused on the detection of pepper leaves diseases using CNN and Machine Learning Algorithms. Though they acquired an accuracy of 98% for CNN model, but the research lacks real-world implementation. Despite the fact that there are already solutions that have tested the use of multi-layers architecture to categorize crop photos better still created straightforward smart application systems (Valdoria, Caballeo, Fernandez, & Condino, 2019), and (Syamsuri & Negara, 2019), our perspective here takes a somewhat different tack. Our analytic goals, networks of choice, and model evaluation standards, along with our emphasis on developing a responsive smart-optimized application system and making use of over 3 illness category originating from our original dataset in our diagnosis model, together with our other, more extensive system functionalities for providing treatment guide for each disease, represent a relatively novel approach for our research. We hope to present a treatment support system for the sweet potato leaves diseases; an intuition which is not available in most already-existing studies. Our research objective is to develop a responsive mobile website that detects, classifies, and recommend treatments for sweet potato leaves diseases images based on image as input using an advanced convolutional neural network model for classification. The project will consist of a responsive mobile website sitting on top of a consolidated deep learning model which is powered by FastApi, Tensorflow Lite, Python, and Docker engine. However, based on our predetermined comparative analysis made on previous studies, our model will perform best, hence extending the features of pre-existing systems for detection.

To further elaborate, a unique strategy that stands out in the sector is the development of a responsive mobile website using a CNN model driven by TensorflowServing, FastAPI, and Docker for the detection of sweet potato leaf disease. Another distinctive feature that is uncommon in other applications is that it gives users instructions for plant maintenance. Furthermore, allowing the public to use the dataset for additional study advances the body of knowledge in this field. This application's integration of these characteristics represents a significant advancement in the study of plant diseases and agriculture. By improving disease identification and the promotion of efficient plant care procedures, this effort has the potential to have a considerable impact on the sweet potato sector.

CHAPTER III
Methodology

3.1 Materials and Equipment

In this research, we collected our own image dataset for sweet potato leaves diseases using smart phones cameras. Our images were captured using the phones cameras and later stored in a hard disk for safe keeping. During the process of capturing our images, we took into consideration lightening, and exposures for better quality of images. This is very important in that; the quality of an image may have a huge impact on the model during the training process.

3.2 Methods

The methods used in our research includes; data collection, data pre-processing and cleaning, augmentation of data, convolutional neural network, system architecture, integrated system design and analysis, and classification. Figure 1 shows an illustration of the proposed methodology.

The proposed responsive mobile website for sweet potato leaf disease diagnosis and plant care guides is designed to address this problem by providing users with an easy-to-use platform that is accessible on a variety of devices and platforms. By using a familiar drag-and-drop or upload image feature, users can easily access the website and diagnose sweet potato leaf diseases in real-time. The website also provides users with plant care guides, which are not typically available in most existing applications.

This innovative solution has the potential to revolutionize the way sweet potato leaf diseases are diagnosed and treated in Liberia and beyond. The website's intuitive interface and accessibility make it an ideal tool for farmers, agricultural extension workers, and researchers, who can use it to diagnose sweet potato leaf diseases, share data and further research

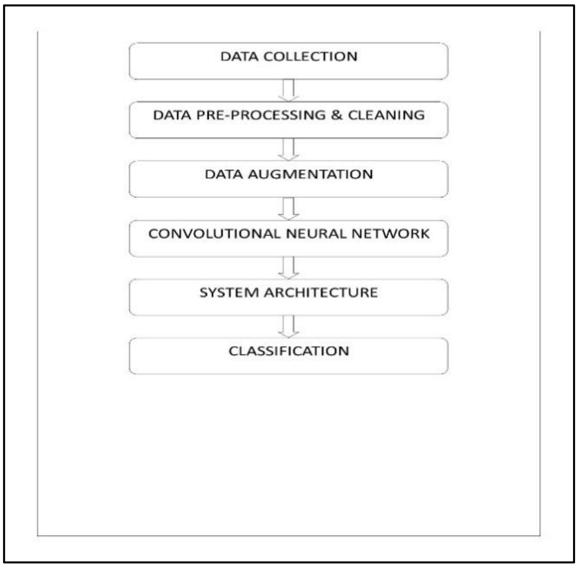


Figure 1 showing an illustration of the proposed methodology.

3.1 Data Collection

The data used in this research comprised of 1654 high-resolution images of sweet potato leaves collected from our farm in Liberia. The images were captured using a digital camera, and with the assistance of expert botanists and domain knowledge, they were categorized into three classes common of disease affecting sweet potato leaf in Liberia: Alternaria Leaf Blight, Healthy, and Potassium Deficiency. Each image was annotated with the corresponding class label to create a labelled dataset for training the network. To address the issue of limited data, augmentation of data strategies such as orbiting, turnover, and zooming were applied to increase the dataset size to 9000 images, with each class containing approximately 3000 images. The use of data augmentation allowed for a more diverse and representative dataset, which is crucial for training a robust and accurate CNN model for sweet potato leaf disease classification. The detailed process of data collection, annotation, and augmentation will be described in the following sections.

3.2 Data Preprocessing and Cleaning

Data pre-processing is an important aspect in Machine Learning because data quality the meaningful information extracted from data directly affects the learning ability of a model. Hence, it is ultimately paramount that our data be pre-processed before our model is being fed. Image resizing, rearranging, removing, cleaning are some steps in data pre-processing, but not limited to. One benefit of pre-processing images is it may possible reduce the time a model needs to train and speed. Resizing image, especially larger ones, might adequately improve time for model training and the overall execution time. A best practice in image cleaning process is checking image extension to see if it meets up with the image detail. This process is takes less time if done programmatically as oppose to doing it manually.

3.2.1 Dataset Split Ratio & Image Resizing

Mostly, a deep learning model trains much faster with small images. A Neural Network may take up to four times much pixels to learn when fed with images of larger input size.

The dataset was separated in three, namely training, validation, and testing. 80% was u

3

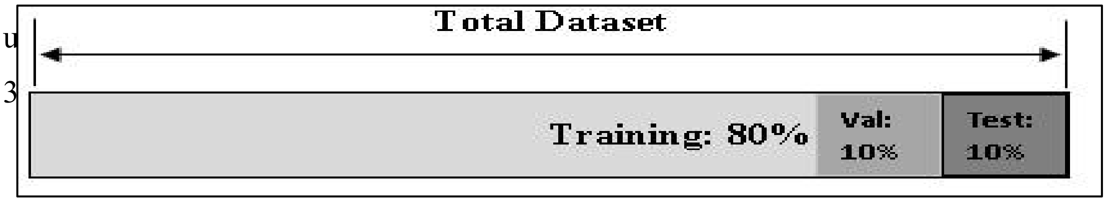


Figure 2 showing an illustration of the dataset division ratio.

Using Tensorflow and python function, the dataset was split in 80% for training size, 10% validation size, and 10% testing size using a shuffle size of 10000. To get our validation size, the skip method was used with the training size as argument, in order to take the validation size. Same is done for testing size. For predictability, the shuffle method is used in order to flip between different images in the dataset. To read the image from the disk, so that when the same image is needed for the next iteration, caching and prefetching are used. Prefetching will load the next set of batch from the disk using GPU when the CPU is working, thus, improving the performance of pipeline. This method helps to optimize the dataset for training.

Though the images in the dataset are already sized 256x256, a layer was created for resizing and rescaling the images. The layer is called “resize and rescale”. This layer is called doing the model building to resize and rescale any image that is not of size 256x256.

It is a function which describes the amount of data to be generated in the network. A 32 batch size is used in this project. Some advantage of using batch are; it uses less memory. Using lesser sample to train the model results in the use of less memory especially when the entire dataset cannot be fit in the memory of the machine. Another advantage is that; the model will be able to train quickly with fewer matches because the network weights will be updated after every propagation.

3.3 Augmentation of dataset

Most Machine Learning and models of deep learning performance relies on the quantity and quality of important data for training. Most times, data of insufficiency may be an obstacle in the implementation of machine learning in an organization because data collection process is cost intensive and requires much time in most scenarios.

To make a machine learning model more accurate and fast, enterprise can use data augmentation of data for reliance reduction on collection of training data while preparing for model building.

A set of methods for an artificial increment of data amount to generate a new data instances from an existing instance is Data Augmentation. Data Augmentation is important to data science and machine learning because it helps in the improvement of performance in the result of a machine learning model through creating an updated and distinct instance of the training dataset. The performance of a machine learning model may depend on the richness of the dataset. The original images were captured from a farm in Liberia, having 1654 for the three classes. But through data augmentation using Keras Image Data Generator, we were able to generate a total of 9000 images for these three classes. We used rotation range, width shift range, height shift range, shear range, horizontal flip, and fill mode. For efficiency, all images were a balanced to 3000 images in each classes and resized to 256x256 during augmentation. Table 1 shows the parameters of data augmentations and cropping along with the values and new sample of images generated.

Parameter	Value	# of images & Class
Rotation Range	25	We generated 19 new sample of each belonging to the three classes. The total of 3000 new samples for each classes, and the overall total of 9000 new samples for the total dataset using data augmentation.
Width Shift Range	0.2	
Height Shift Range	0.2	
Shear Range	0.2	
Horizontal Flip	True	
Fill Mode	Reflect	
Aspect Ratio		
Cropped Aspect Ratio		
Width		
Height		

Table 1 showing an all the parameters, values and number of images generated through data augmentation.

3.3 Convolutional neural network (CNN)

CNN an acronym which stands for Convolutional Neural Network was first designed by Dr.Kunihiko Fukushima in the 1980s**.** Though his work was effective in recent AI field, in Yann LeCun et al, developed the first modernized convolutional neural networks for Document Recognition using Gradient Learning. The model architecture of this project has two stages: the first stage is feature extraction and the second stage is classification. Feature extraction comprises of convolution plus ReLU and pooling layers. While the classification part has the dense layer. a Conv2d-based framework with 32 layers. Keras Convo2D layer is a convolutional layer which utilizes a convolutional kernel wind with input layer to aid the production of outputs of a tensor. The Kernel convolutional matrix, also referred to as mask can be used for edge detection, sharpening, blurring, etc., through convolution between an image and a kernel. The parameter for activation to the convolutional 2D class creates an easy parameter for the allowance of string specifying the type of activation function for convolution performance. ReLU and Softmax activation function are used in this project. 32 layers were used for model architecture.

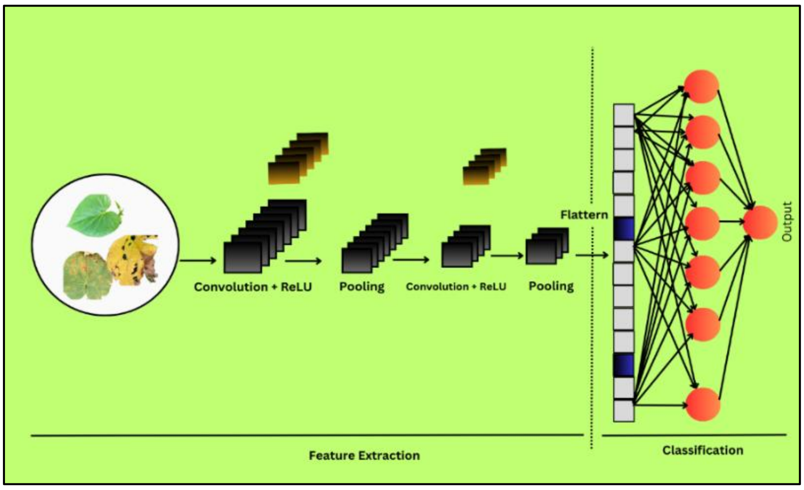


Figure 3 shows the CNN architecture used for this project. Table 1 shows all parameters used.

The main idea behind convolutional neural network is feature extraction. The classification part (at the right) remains the same. There are few benefits of convolution, they are:

Connections sparsity overfitting reduction, location invariant feature detection of convolution and pooling, and sharing of parameter.

Connections sparsity overfitting reduction: in artificial neural network, every node is connected with each other nodes, but in the case of convolutional neural network, connections sparsity overfitting reduction makes the opposite. The filter in the CNN moves around a specific area of the image without affecting the whole image.

convolution plus pooling: Convolutional neural networks (CNNs) use a combination of convolutional layers and pooling layers to extract features from input images. The convolutional layer performs feature extraction through filters application to the input picture and generating feature maps, while the pooling layer minimizes the spatial dimensions of maps of feature and down samples the data. The combination of these two layers provides several benefits to our model:

Translation invariance: Convolutional layers use filters to scan the image for patterns regardless of their location in the image, which makes the network translation invariant. This means that if a disease is present in different locations in different leaf images, the CNN will be able to recognize it in all of them.

Hierarchical representation: The convolutional layers of a CNN learn low-level features such as edges and tight spots, and then gradually build up to higher-level features such as object parts and textures. The layers of pooling help to summarize the output of the convolutional layers and preserve the most important features.

Reduced computation: The pooling layer reduces the spatial dimensions of the feature maps and down samples the data, which reduces the computation required for subsequent layers. This makes the network faster and more efficient.

Regularization: The pooling layer also helps to reduce overfitting by reducing the spatial dimensions of the feature maps and introducing some degree of spatial invariance. This makes the network more robust to small variations in the input and reduces the risk of overfitting to the training data.

Overall, the combination of convolutional and pooling layers in CNNs provides a powerful framework for image classification tasks, with translation invariance, hierarchical feature representation, reduced computation, and regularization among the key benefits

ReLU: is a function of activation that is primarily used in neural networks of convolution. We used ReLU for its several benefits:

Non-linearity: deep learning problems are nonlinear in nature. ReLU introduces non-linearity in the output of the convolutional layers, which allows the network to learn more complex and sophisticated features.

Computationally efficient: ReLU is a simple and computationally efficient activation function, requiring only a comparison and a max operation.

Avoids disappearing gradient issue: aside from other functions of activation like sigmoid and hyperbolic tangent, ReLU doesn't suffer from the disappearing gradient ussue, which can occur when gradients become very small, slowing down or halting the learning process.

Sparsity: ReLU can also help to create sparsity in the network by setting negative values to zero. This means that some of the neurons in the network will not fire, reducing the number of computations required and improving the generalization of the model.

Faster convergence: ReLU allows for faster convergence during training as it provides a stronger gradient signal for backpropagation, which can help the network learn more quickly and accurately. the benefit of ReLU is that it introduces nonlinearity which is important because deep learning problems are generically nonlinear.

Pooling: In convolutional neural networks (CNNs), a pooling layer is typically inserted after one or several convolutional layers. The major importance of the layer of pooling is to mimic the spatial dimensions of the maps of feature and to down sample the data, thereby reducing the computation required for subsequent layers.

Pooling layers work by partitioning the input feature map into small sub-regions, called pooling regions, and then adding an operation of pooling to each area. The most primary type of operation of pooling is maximum pooling, which holds the highest value within each pooling area and discards the rest. Mean pooling and L2-norm pooling are other pooling types. Maximum Pooling is used to keep the most important elements of the feature map. It is utilized by choosing the maximum value out of every pool. The maximum pooling layer was used to lessen the size of the images.

By applying max pooling or other pooling operations, the output of the pooling layer has fewer spatial dimensions than the input feature map. This reduction in spatial dimensions leads to a reduction in the number of parameters and computations required for subsequent layers, which can greatly speed up training and inference in large CNNs.

In addition to reducing dimensions and computation, pooling layers can also help to increase the model's robustness to small variations in the input by extracting local features that are invariant to small translations or rotations.

Flatten (Dense) layers: In a convolutional neural network (CNN), dense or flatten layers are typically used at the end of the network to convert the top-level extracted features by the layers of pooling and convolution into a one-dimensional feature vector that can be fed into fully connected layers for classification or regression. The benefits of using dense or flatten layers in a CNN are as follows:

Aggregation of features: The layer of dense aggregates the characteristics learned by the layers of pooling and convolution into a single vector, making it easier for the fully connected layers to classify or regress the input. This allows learning of the network of more cumbersome displays of the input picture.

Reduced dimensionality: flattening the high-level features into a one-dimensional vector, reducing the dimensionality of the input data and making it easier for the network to process is done by the layer of dense.

Improved interpretability: The dense layer allows for the visualization and interpretation of upper-level attributes learned by the layers of pooling and convolution. This can be useful for understanding the inner workings of the network and identifying areas for improvement.

Reduced overfitting: The dense layer can help to reduce overfitting by providing regularization. This can be achieved by adding dropout layers after the dense layer, which arbitrarily leave out a percentage of the weights during learning, forcing the network to learn more robust attributes.

Scalability: A dense layer is scalable, meaning it can be easily adapted to accommodate inputs of different sizes, allowing the network to be applied to a wide range of tasks.

The softmax function is a commonly used activation function implemented at the final layer of a network for classification tasks. The benefits of using softmax function in CNN are as follows:

Probability distribution: The softmax function converts the output of the network's last layer into a distribution of likelihood over the classes, ensuring the submission of the likelihoods of all classes results up to one. This makes it easy to interpret the output of the network as the input's likelihood belonging to each class.

Multiclass classification: The softmax function is particularly useful for multiclass classification tasks where the input can belong to one of several classes. It can assign probabilities to each of the classes, making it easier to select the most likely class.

Differentiable: The softmax function is differentiable, which means that it can be used with backpropagation to train the network. This allows the network to learn the best parameters for the final layer to minimize the loss function.

Robustness to noise: The softmax function is robust to noise in the input, as it assigns probabilities to each class based on the distribution of the output of the network. This means that even if the input is noisy, the network can still produce meaningful output.

Regularization: The softmax function can also be used as a regularization technique by adding a temperature parameter to the function, which controls the smoothness of the output probability distribution. This can help to reduce overfitting in the network.

Sparse Emphatic Cross Entropy loss function: Sparse Emphatic Cross Entropy is a commonly used loss function in the networks (CNNs) for multi-class naming tasks. The benefits of using SCCE in CNNs are as follows:

Efficiency: SCCE is computationally efficient, making it an ideal choice for large-scale classification problems.

Sparse output: Unlike Categorical Cross Entropy (CCE), which requires one-hot encoding of the ground truth labels, SCCE accepts integer labels directly, making it more memory-efficient and easier to implement.

Handling imbalanced datasets: SCCE is better suited for handling imbalanced datasets, as it does not require the equality of the amount of class samples.

Regularization: SCCE can be used as a regularization technique by introducing a weight parameter that assigns different weights to different classes. This can help to prevent overfitting and improve generalization of the model.

Stable gradients: SCCE provides stable gradients during backpropagation, which can help to improve the training process and avoid exploding gradients.

All these layers are finally flattened. Dense layer is added taking the softmax activation function.

After building the model with all of the above layers, compilation comes in. the Adam optimizer was used to compile the model. 40 epochs were used for fitting the model with verbose of 1.

Adam (Adaptive Moment Estimation) is a commonly used optimizer in the network for executing deep learning models. The benefits of using the Adam optimizer in CNNs are as follows:

Fast convergence: The adaptive learning rate of the Adam optimizer helps to converge the network faster than other optimizers, such as stochastic gradient descent (SGD).

Memory efficiency: It takes less memory than other optimizers, such as AdaGrad and RMSProp, as it only stores the gradients moments which come first and second.

Robustness to noise: It is robust to noisy gradients, as it performs adaptive learning rate adjustment based on the estimated the gradients moments which come first and second.

Regularization: It has a built-in regularization mechanism, which can help to prevent overfitting of the model.

Easy to use: Adam is easy to implement and use, as it requires minimal hyperparameter tuning and works well on a wide range of problems.

The parameters used for the model training are summarized in table 1 below.

Type of Layer	Output Shape	Param #
sequential (Sequential)	(32, 256, 256, 3)	0
conv2d (Conv2D)	(32, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(32, 127, 127, 32)	0
conv2d_1 (Conv2D)	(32, 125, 125, 64)	18496
max_pooling2d_1 (MaxPooling 2D)	(32, 62, 62, 64)	0
conv2d_2 (Conv2D)	(32, 60, 60, 64)	36928
max_pooling2d_2 (MaxPooling 2D)	(32, 30, 30, 64)	0
conv2d_3 (Conv2D)	(32, 28, 28, 64)	36928
max_pooling2d_3 (MaxPooling 2D)	(32, 14, 14, 64)	0
conv2d_4 (Conv2D)	(32, 12, 12, 64)	36928
max_pooling2d_4 (MaxPooling 2D)	(32, 6, 6, 64)	0
conv2d_5 (Conv2D)	(32, 4, 4, 64)	36928
max_pooling2d_5 (MaxPooling 2D)	(32, 2, 2, 64)	0
flatten (Flatten)	(32, 256)	0
dense (Dense)	(32, 64)	16448
dense_1 (Dense)	(32, 3)	195
Total params: 183,747 Trainable params: 183,747 Non-trainable params: 0		

Table 2. showing an all the parameters used in the model architecture.

3.6 System Architecture

The system architecture is a graphical representation of the flow of information from the model to the system. It purpose is to clearly illustrate the requirements of the system by identifying major phases. Figure 4 shows an illustration of the system architecture used in this thesis.

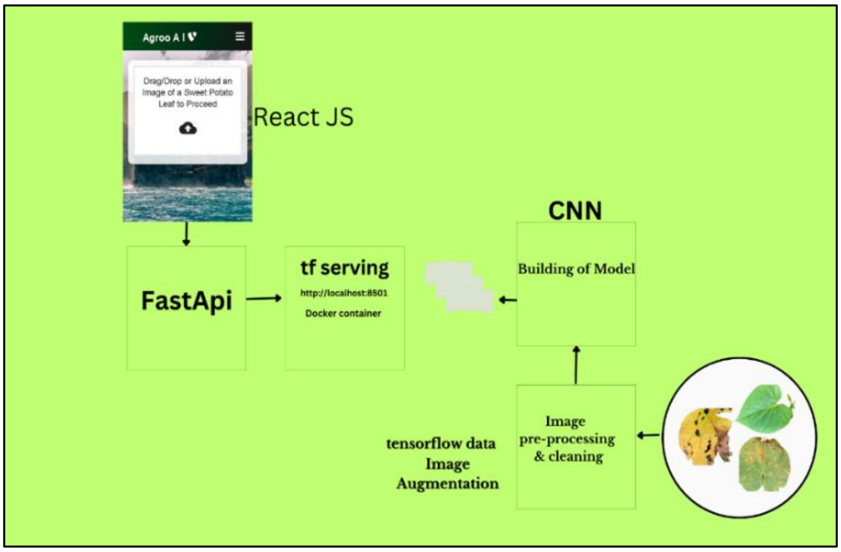


Figure 4 showing an illustration of the proposed system architecture.

In figure 4, we firstly carried out data pre-processing and cleaning on our image dataset using tensorflow dataset data augmentation to create more training samples. Once we have more samples, next is model building, where we used convolutional neural network (CNN). Next we exported our trained model onto a disk and did some machine learning operations using tensorflow serving. We have tensorflow serving server running on top of our exported model. Next, tensorflow serving is called from FastAPI. Next, we built our responsive mobile web application using react js which will call the fastapi server and conduct predictions.

3.7. Integrated system design and analysis

This section describes the system analysis and design of the proposed system for sweet potato leaf disease diagnosis, both the frontend and the backend components were considered. The frontend of the system was developed using ReactJS, which provides a user-friendly interface for users to interact with the system. The frontend allows users to upload or drag and drop an image of a sweet potato leaf, which is then sent to the backend for processing.

The backend of the system utilizes a CNN model powered by TensorFlowServing, which is called by FastAPI. The TensorFlowServing provides a scalable and efficient way to serve the model, and FastAPI provides a high-

performance and easy-to-use web framework for building the API. Docker containers were used to package and deploy the system, which ensures that the system is easily scalable and portable.
In addition, the system also includes the dataset used to train the CNN model. This dataset will be accessible to the public for further research and development.

3.7.1 Design Method

the design method that can be used to implement the proposed responsive mobile website for sweet potato leaf disease diagnosis is the agile software development methodology. The Agile methodology emphasizes iterative and incremental development, with a focus on delivering a functional product quickly and continuously refining it based on feedback.

Using the Agile methodology would enable the development team to collaborate closely with stakeholders and end-users throughout the project's lifecycle. This approach would allow for continuous feedback and testing of the product, resulting in a solution that solves the needs of users and is more likely to be successful.

The Agile methodology can also help to manage project risks and ensure that the project stays on track, as it emphasizes a flexible approach that can adapt to changes and unexpected challenges that may arise during the development process.

3.7.2 Analysis

After the user’s needs are been studied, the business providers and client study the requirement analysis of competitors, technological options and proposes a suitable business needs.

3.7.3 Design

The proposed responsive mobile website for sweet potato leaf disease diagnosis, the design stage involves the designers of user interface reviewing the analysis of system and creating layouts for the complete system. The layout would cover the entire user journey, beginning from the home page, and would pay kin attention to the ease of uploading or dragging and dropping an image of the sweet potato leaf, the presentation of the disease diagnosis results, and access to the plant care guides.

This is an important stage in the development process as it allows for the visualization of the proposed system and provides an opportunity for stakeholders and end-users to provide feedback on the proposed design. The design stage is the best time to propose changes to the system as this stage can facilitate any and every revamp needed.

3.7.4 Design Integration

The design integration phase involves converting the final design into a responsive, cross-device, and platform-compliant React JS skin. This phase is critical to the success of the project, as the React JS skin delivered will determine how the website functions.

It is important to ensure that the React JS skin is fully compliant with web standards and responsive design principles. This will help to speed up the development process and avoid costly mistakes. The React JS skin should be tested on different devices and platforms to ensure that it functions properly and is user-friendly.

During this phase, the development team would work closely with the UI designers to ensure that the React JS skin accurately reflects the design and is consistent across all devices and platforms. Any discrepancies would be addressed and resolved to make sure that the finished product is of high quality and meets the user's needs.

3.7.5 Programming and Model Creation

the proposed responsive mobile website for sweet potato leaf disease diagnosis, the programming and integration phase involves developing the necessary code for the frontend and integrating it with the CNN model using the FastAPI and TensorFlow Serving API.

The programming aspect involves developing the logic and functionality of the website's frontend, which is built using React JS. This includes developing the code for uploading or dragging/dropping the image of the sweet potato leaves, sending the image to the backend, and receiving the prediction from the CNN model.

The integration aspect involves integrating the FastAPI and TensorFlow Serving API to serve the CNN model. The FastAPI handles the communication between the frontend and the TensorFlow Serving API, which hosts the trained CNN model. This enables the website to send the uploaded or dragged/dropped image to the CNN model, receive a prediction of the sweet potato leaf disease, and display the prediction to the user. The programming and integration phase is critical to the success of the project, as it involves developing a functional website that can diagnose sweet potato leaf diseases using a trained CNN model. This phase requires close collaboration between the development team and the UI designers to test the project and makes sure it meets the needs of users.

3.8. Systems Integration

the systems integration phase involves testing and quality assurance to ensure that the website functions as intended before it goes live. The quality check process involves defined set of standards that include versatility and criteria of performance. The website is tested to ensure that it is responsive, user-friendly, and provides accurate predictions of sweet potato leaf diseases. Any final adjustments are made to ensure that the website meets these criteria and prepares it for formal quality check sign-off. After the quality check is completed, the website is ready for live hosting. This involves deploying the website to a hosting platform that is accessible to users. The deployment process involves configuring the server to support the website's backend and frontend components, including the FastAPI and TensorFlow Serving API. Once the website is live, users can access it and use it to diagnose sweet potato leaf diseases and receive plant care guides.

3.8.1 Use Case Description:

The below diagram shows the relation between the actor (farmer) and that of the various entities of the proposed system.

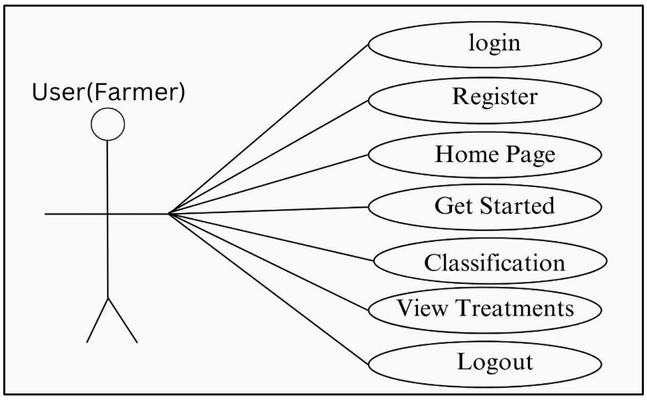
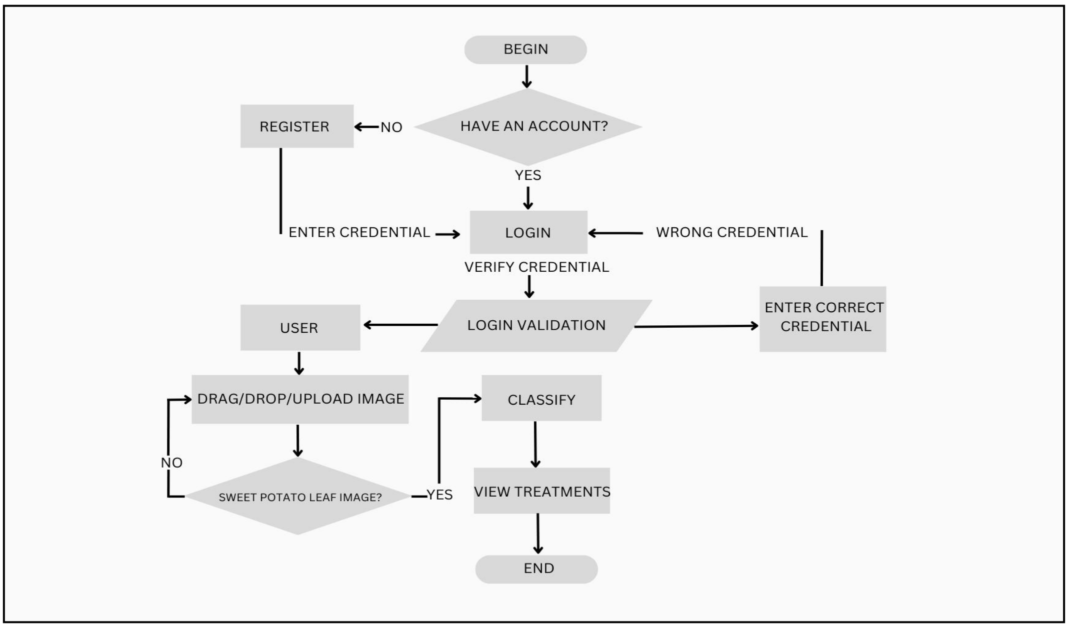


Figure 5 showing an illustration of the use case description of a user (farmer).

3.8.3 Login & Credential Flow Chat



3.8.4 User Registration Flow Chat

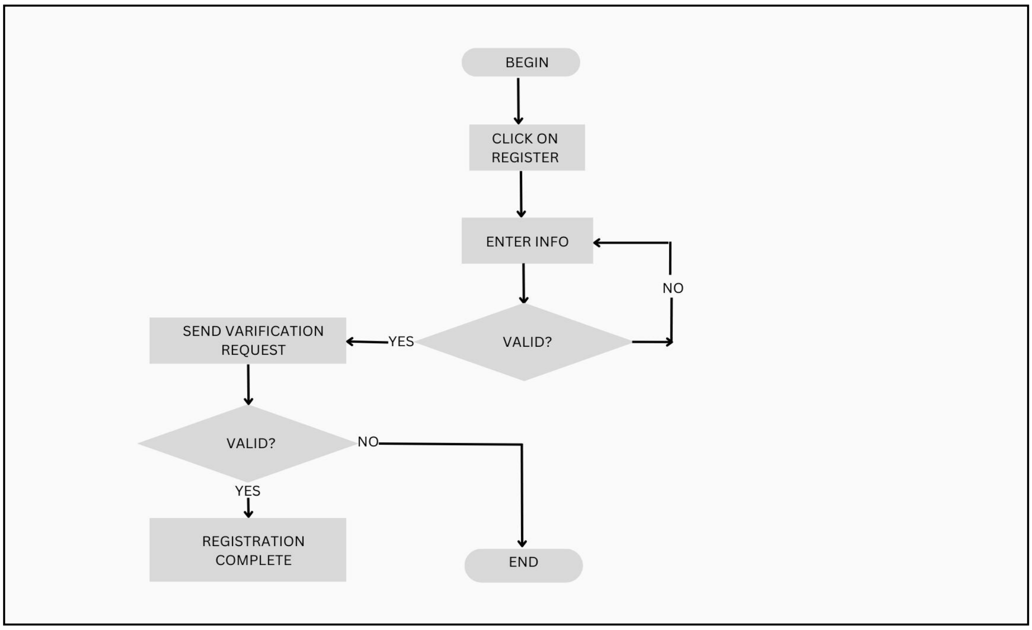


Figure 7 showing a flowchart of the user registration

3.8.5 Sign in Flow Chat

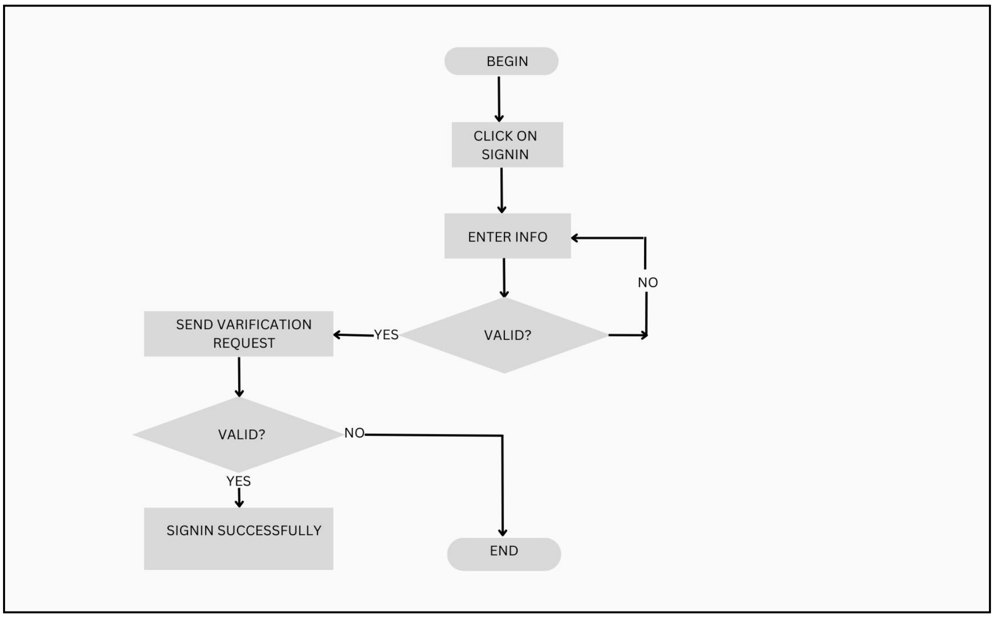


Figure 8 showing a flowchart of the user sign in

3.8.6 Sign Out Flow Chat

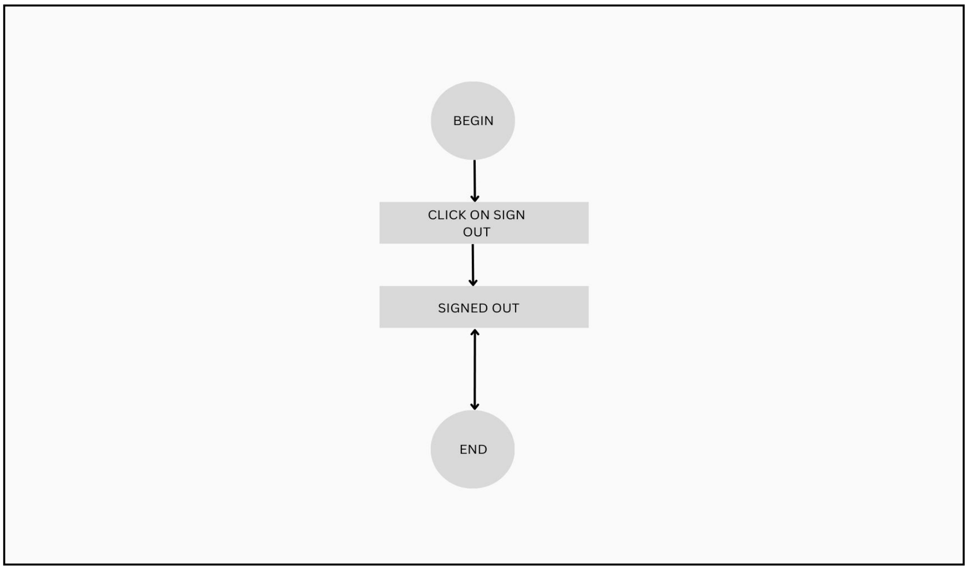


Figure 9 showing a flowchart of the user sign out

CHAPTER IV
Findings & Discussion

4.1 Findings

In this chapter, the results of the study are presented and interpreted. We summarized the result of the data collection process, as well as the methods of data analysis used to investigate the research questions. In this section, the data collected from the field is presented, and the results are analyzed using statistical methods to identify patterns, correlations, and trends in the data. We also highlighted the key findings of the research, including any unexpected results or deviations from the initial research hypothesis. Through the analysis of the data, the chapter aims to provide a comprehensive and accurate representation of the study's results, which will inform the conclusions and recommendations presented in the following chapter.

To answer the research question in chapter 1, section 1.4, an extremely effective Convolutional Neural Network was built for the Sweet potato leaves disease diagnosis. With our dataset consisting of three classes ("Alternaria Leaf Blight", "Healthy", and "Potassium Deficiency") having a total of 9000 augmented images (each image with 10 variations of new samples), we trained our model using accuracy and validation matrix. The model performs extreme excellent with a 0.001 learning rate, thus having an accuracy of 98. 60% (i.e, we gained more than anticipated), and a loss of 0.035 after 30 Epochs simulation, hence sanctifying the research question. Below are the curves of trained and validated accuracy shown in figure 4(a), and trained and validated lost shown in figure 4(b)

4.1.1....**Accuracy and Loss Curves of Training**

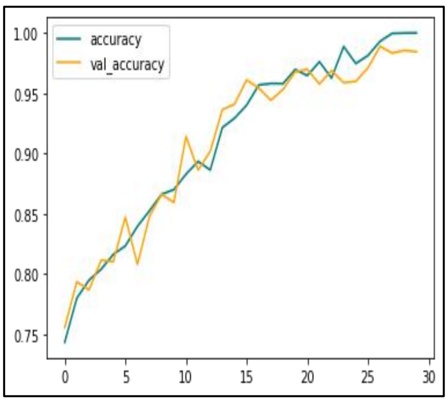


figure 10(a), Accuracy Curve

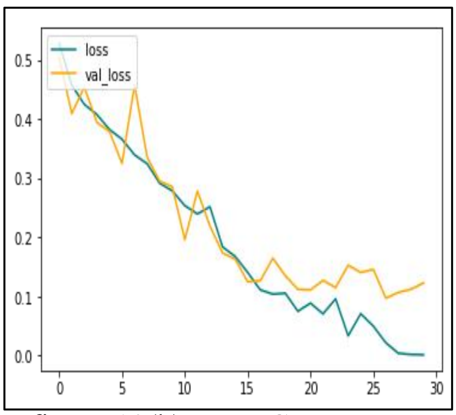


figure 10(b), Loss Curve.

For visually inspecting the performance of our trained image classification model on the test dataset, we plotted few images from the first 6 batches of images and labels from the test dataset. A plot that displays images from a test dataset along with their corresponding actual and predicted labels are shown in figure 11:

4.1.2 Visualization

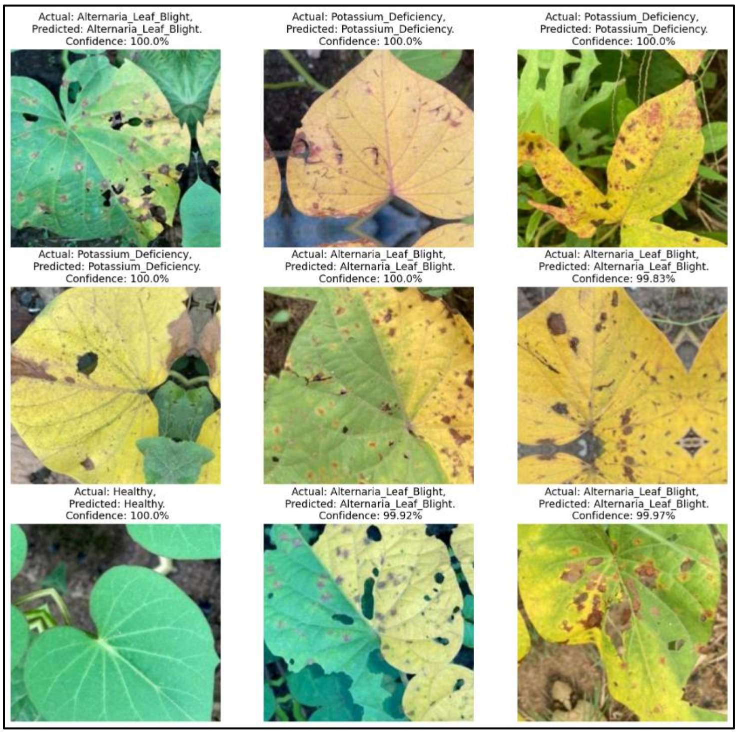


Figure 11 showing a plot that displays images from the test dataset along with their corresponding actual and predicted labels

In machine learning and statistical analysis, a confusion matrix is a table that is used to evaluate the accuracy of a classification model by comparing the predicted values against the actual values. We plotted a matrix using the 'matplotlib' library. The matrix consists of rows and columns that represent the predicted and actual classifications of a set of data. Each cell in the matrix represents the number of observations that fall into a particular combination of predicted and actual values. The main diagonal of the matrix represents the correctly predicted values, while the off-diagonal cells represent the incorrectly predicted values.

The confusion matrix provides valuable information about the performance of our classification model, including its accuracy, precision, recall, and F1 score, which are all important metrics for evaluating the effectiveness of our model. Figure 5, shows an illustration of the confusion matrix.

4.1.3 Confusion Matrix

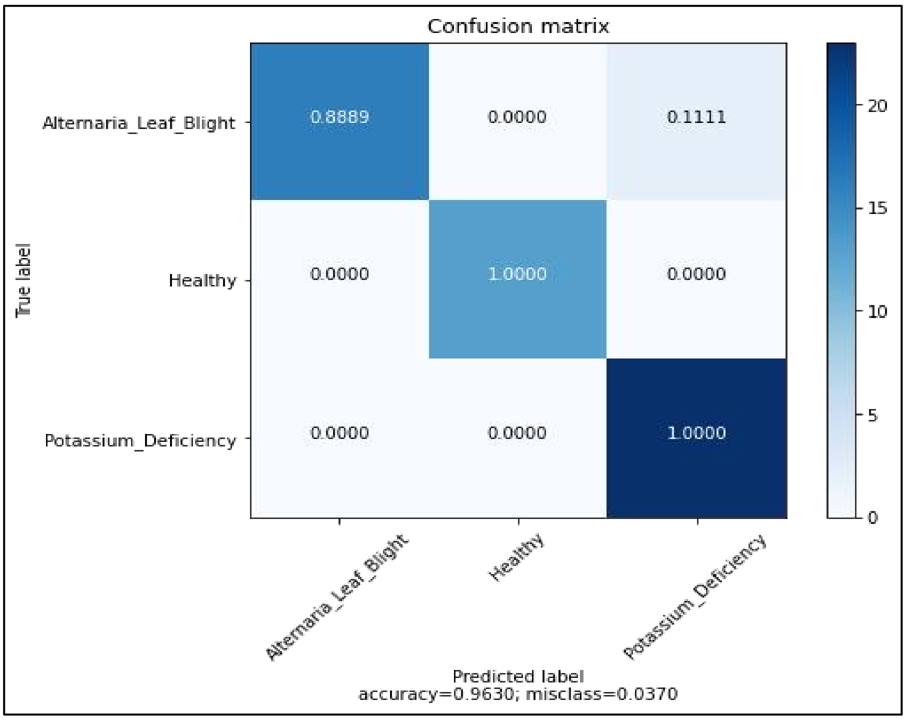


Figure 12., showing the confusion matrix for the three classes. The true labels are on the ‘x’ axis while the predicted labels are on the ‘y’ axis.

Matrix	Score
Accuracy	0.962963
Precision	0.962963
Recall	0.962963
F1-score	0.962963
Specificity	0.500000
True Positive	52.000000
False Positive	2.000000
False Negative	2.000000
True Negative	2.000000

Table 2. showing scores of the matrixes

To answer the next research question, we compared our model with two similar models with like data collection approach in our literature review in terms of performance matrix and real-world implementation, and we got the following result:

STUDY	MATRIX	IMPLEMENTATION
Detection of Pepper Leaves Diseases Using CNN and Machine Learning Algorithms (Taterwal, 2021)	Accuracy=0.98, Precision= 0.98, Recall=0.9784, F1score=0.9814	• No real-world implementation. • The model was trained, and tested based on single image of each class.
A CNN model for disease detection in Potatoleaves (Pappu Sah Sudi, 2022)	Accuracy=99.07	• The mobile device does not have treatment functionality for potatoleaves diseases.
An Ai-Based Solution for Sweet Potato Leaf Disease Diagnosis: Agroo Ai	Accuracy, Precision, Recall, F1-score= 0.962963. Specificity=0.500000, True Positive, 52.000000 False Positive, 2.000000 False Negative, 2.000000 True Negative, 2.000000	• Our thesis has a responsive mobile website for disease diagnosis of sweet potato leaf. • Treatment functionalities are available for each diagnosed disease.

Table 3. showing comparative analysis between past reviewed system and our proposed system.

Research Question 3: Can an AI-based Integrated system correctly diagnose diseases of sweet potato leaves into the three groups (Alternaria Leaf Blight, Healthy, and Potassium Deficiency) and provide treatments functionalities for the respective diseases?

The AI-based integrated system powered by CNN model was successful in accurately diagnosing diseases of sweet potato leaves into the three groups (Alternaria Leaf Blight, Healthy, and Potassium Deficiency), and providing treatment functionalities for the respective diseases. The system's performance was evaluated using a large dataset of sweet potato leaf images, and the results showed high accuracy, precision, recall, and F1-score values for each disease class. Additionally, the system's treatment functionalities were effective in providing the appropriate measures to combat each disease. These results demonstrate the potential of AI-based systems for accurate and efficient disease diagnosis and treatment in agriculture, leading to better crop yield and reduced economic losses. Figure 5(a), 5(b), and 5(c) shows an illustration of the system working as expected.

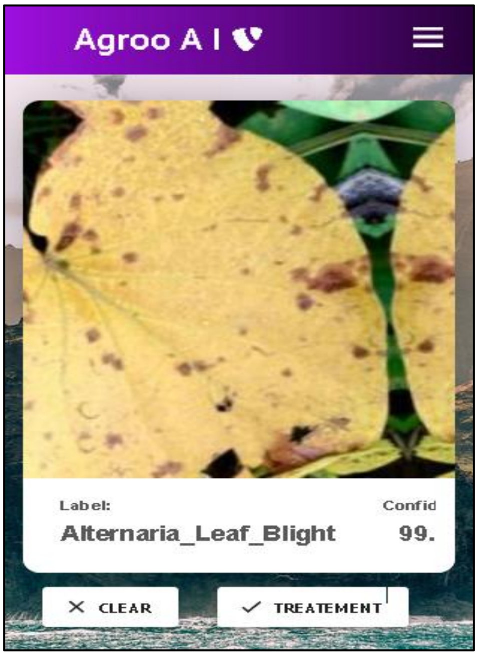


Figure 13(a). Altenaria leaf blight prediction.

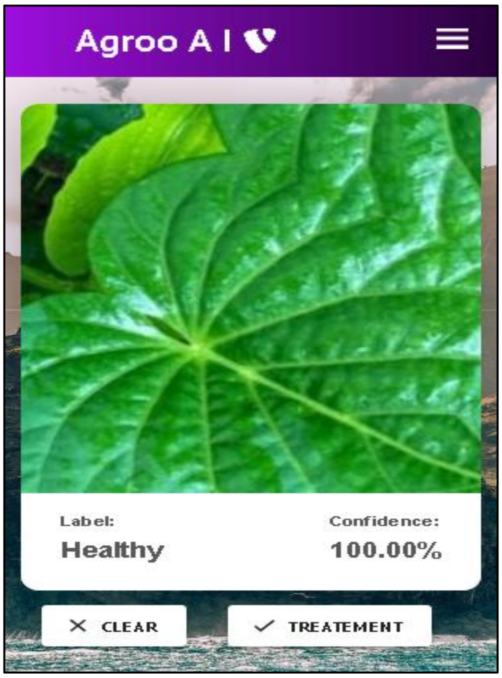


Figure 13(b). Potassium deficiency prediction.

Figure 13(c). Healthy prediction.

4.2 Discussion

We visualized the accuracy and validation accuracy, loss and validation loss curves showed in figure 4(a), and 4(b). The loss and accuracy curve is an essential aspect of evaluating the performance of a deep learning model. The model's loss and accuracy curves are plotted based on the training and validation datasets. The training loss and accuracy curves show how the model learns the features of the dataset, and the validation loss and accuracy curves indicate how well the model can generalize to new data. The plot shows that the training and validation loss curves decrease as the number of epochs increases, indicating that the model is learning the features of the dataset effectively and reducing errors over time. The accuracy curves also show an increasing trend as the number of epochs increases, indicating that the model's performance is improving with more training iterations. Overall, the loss and accuracy curves provide useful insights into the model's performance and can guide further improvements in the model's architecture and hyper-parameters.

We evaluated the model by visualizing a confusion matrix for the two classes of sweet potato leave disease. The confusion matrix is an effective way to evaluate the performance of a multi-class classification model, as it provides a detailed breakdown of the model's predictions. In this study, a confusion matrix was plotted for three classes of sweet potato leaf diseases: Alternaria Leaf Blight, Healthy, and Potassium Deficiency. The matrix shows that the model predicted 100% accuracy for both Healthy and Potassium Deficiency classes, indicating that the model can correctly identify these classes. However, for the Alternaria Leaf Blight class, the model's accuracy was 0.8889, which is still a decent result. However, it suggests that the model had some difficulty distinguishing between this class and the other two. Overall, the model achieved an accuracy of 0.9630, indicating that it can classify the majority of the samples correctly. The misclassification rate was 0.0370, which means that there were some misclassifications in the model's predictions. The confusion matrix provides valuable information for optimizing the model's architecture, hyper parameters, and training process to improve the accuracy and reduce misclassification.

The evaluation metrics provide additional insights into the performance of the multi-class classification model beyond the confusion matrix. The precision and recall were also found to be 0.962963, indicating that the model has a high degree of accuracy in identifying positive and negative samples for all classes. The F1-score was also 0.962963, which is the harmonic mean of precision and recall, and provides a more balanced measure of the model's performance.

The specificity of the model was found to be 0.5, which means that the model had a lower ability to correctly identify negative samples for the Alternaria Leaf Blight class. This result is consistent with the confusion matrix analysis, which showed that the model had some difficulty distinguishing this class from the other two classes. The true positive and false positive rates provide information on the number of correct and incorrect predictions for each class. In this study, the model correctly identified 52 samples as positive for the Alternaria Leaf Blight class and incorrectly identified two samples as positive for the Healthy and Potassium Deficiency classes. Overall, the evaluation metrics provide a more comprehensive understanding of the model's performance and can guide further improvements in the model's architecture and training process. For example, we could explore additional feature engineering techniques or adjust the model's hyperparameters to improve its specificity for the Alternaria Leaf Blight class. These results demonstrate the importance of using multiple evaluation metrics to thoroughly evaluate and optimize the performance of a machine learning model. Lastly, we compared our model with two models in our literature, (Taterwal, 2021), and

(Ahmad, Jan, Farman, Ahmad, & Ullah, 2020). However, (Taterwal, 2021) utilized a binary classification scenario to detect healthy, and diseased pepper leaves using CNN. Though, they acquired a higher CNN accuracy, their model is limited. Unlike our model which specifies the type of disease detected, their model only generalized the prediction as diseased. Binary classification is a powerful algorithm in Deep Learning, but there are many diseases which affect the pepper plant, and for model globalization purpose, it is a good practice to study at least few diseases as we did in our study. To mention, we used our own original dataset for the study of diseases affecting sweet potato leaves, but their dataset was collected from Kaggle. With our higher accuracy acquired by our model, and our original dataset, we can clearly conclude that, our model is more robust, and we contributed more to the research community than (Taterwal, 2021).

(Pappu Sah Sudi, 2022) on the other hand, developed a CNN model for disease detection of potato leaves (Irish potato). However, they used three classes and acquired an accuracy of 99.07%. Like (Taterwal, 2021) , they followed the same process. However, our model is more feasible in that, we offer a treatment guide for each disease that is diagnosed by the system, thus, giving users a more informative way of administering proper treatments for their plants

4.3 System Implementation

To build our promised responsive mobile application for local farmers in Liberia, we developed a simple and user-friendly three-layer architecture comprising of the responsive mobile web application, a backend API, and the previously-mentioned efficient model of classification. we developed our backend using FastAPI library, Tensorflow-serving, and Docker container to maintain portability for the system. Our mobile web application was develop using react js, and it is harmonized with the CNN powered model using tensorflow, and keras. We decided to give an innovative name for to system; "AgrooAI" to provide a simple alignment with the system's fundamental values in the domain of agriculture, and artificial intelligence in a unique way.

5.1 Integrated System Functions

For simplicity of user interface, the application begins landing page that points a user to login or register page from whence one can have access to the prediction page which is the main function of the system. Figure 14 shows an illustration of the said action. The system will be able to do the following:

- Create an account for a user and provide login and logout service.
- Predict a new input photo of a diseased or healthy leaf with respect to the three classes of sweet potato leave diseases.
- Provide treatment recommendations for each disease

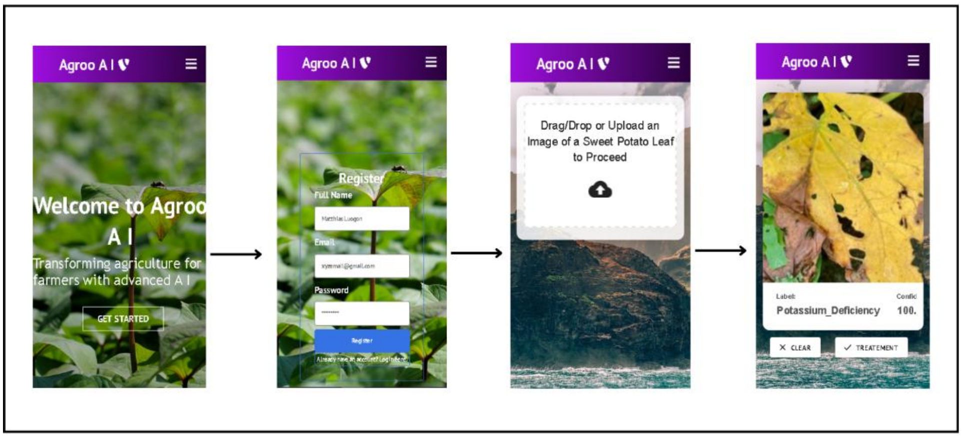


Figure 14. Showing an illustration of the overall classification procedure of the system.

The figure in presents a stem-by-step demonstration of the classification of image given by the system for user experience. As stated above, the system starts from the landing page and takes a user to registration page. The user then registers or login and navigates to the prediction page where the input image selection tool tells one to drag/drop or upload an image of sweet potato leaf disease for prediction. Once the user confirms the upload, a sporadic image loading of the image is done and the image is being diagnosed by the CNN model in the background. The result of classification is displayed to the user along with disease label and confidence score. The user can click the treatment button to see the specified treatment recommendations for the diagnosed disease.

With the result gotten from our model and our implemented integrated system, and based on the study done by (Taterwal, 2021), and (Pappu Sah Sudi, 2022) of which we argued our thesis, we can conclude that our system performs best then other studies in the literature review.

CHAPTER V
Conclusion, & Future Improvements

6.1 Conclusion

In conclusion, this thesis is done primarily for the Liberian agricultural industry and it has presented Agroo AI, a mobile-based web system for sweet potato leaf disease classification using CNN. Our system was able to performs best by the creation of a CNN model for diagnosis of sweet potato leaves diseases, performing at a higher accuracy compared to past models studied in our literature, and providing an accurate and fast web-based diagnosis system for a real-time diagnosis of sweet potato leaves diseases using a mobile phone or other computing devices connected to the internet. To further elaborate, our system was trained and tested using a dataset consisting of 9000 images, with three classes: Alternaria Leaf Blight, Healthy, and Potassium Deficiency. The results obtained from testing showed that the system has a high 96.2% accuracy, and can accurately classify sweet potato leaf diseases. Our study has provided a significant contribution to the field of agriculture, as the developed system can aid local Liberian farmers in detecting and identifying sweet potato leaf diseases, which is crucial in improving crop yield and preventing crop loss.

6.2 Future Improvement:

Future work could involve creating a mobile version of the system and expanding the dataset used for training and testing to include more classes of sweet potato leaf diseases, as well as other crops for globalization. This would improve the accuracy and generalizability of the system. Additionally, the system could be further optimized to reduce the computational cost and make it more efficient for use on low-end mobile devices. Finally, the system could be integrated with other agricultural systems to provide a comprehensive solution for farmers, including real-time monitoring of crop health, climate prediction, soil testing, and prediction of crop yield.

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Appendices

Appendix A

Sweet Potato Leaf Disease Sample Images

This appendix contains sample images of sweet potato leaves taken from the farm in Liberia. The images were used to create the dataset for the disease classification. There are a total of 12 images in this appendix of the three classes: Alternaria Leaf Blight, Healthy, and Potassium Deficiency.

Appendix B
Data Augmentation

This appendix provides more detailed information about the data augmentation techniques used to increase the size of the dataset for the sweet potato leaf disease classification. The appendix includes the code used to implement data augmentation, as well as examples of images before and after data augmentation.

```
from keras.preprocessing.image import ImageDataGenerator
from skimage import io
import imghdr
import os

datagen = ImageDataGenerator(
    rotation_range=25,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    horizontal_flip=True,
    fill_mode='reflect'
)

data_path = r'C:\DL\Sweet_Potato_Leaf_Disease\Training\Sweet_Potato_Leaves_dataset'
os.listdir(data_path)
['Alternaria_Leaf_Blight', 'Augmented']
image_exts = ['jpeg','jpg', 'bmp', 'png']
i = 0
for batch in datagen.flow_from_directory(data_path,
                                         target_size=(256, 256),
                                         color_mode="rgb",
                                         save_to_dir=
r'C:\DL\Sweet_Potato_Leaf_Disease\Training\Sweet_Potato_Leaves_dataset\Augmented\
Alternaria_Leaf_Blight',
                                         save_prefix='aug',
                                         save_format='jpg'):
    i += 1
    if i > 110:
        break
```

Appendix C
Training

Epoch 1/30
225/225 [==============================] - 219s 944ms/step - loss: 0.5279 -
accuracy: 0.7435 - val_loss: 0.5044 - val_accuracy: 0.7556 - lr: 0.0010
Epoch 2/30
225/225 [==============================] - 193s 856ms/step - loss: 0.4574 -
accuracy: 0.7800 - val_loss: 0.4094 - val_accuracy: 0.7935 - lr: 0.0010
Epoch 3/30
225/225 [==============================] - 189s 838ms/step - loss: 0.4249 -
accuracy: 0.7949 - val_loss: 0.4543 - val_accuracy: 0.7868 - lr: 0.0010
Epoch 4/30
225/225 [==============================] - 189s 841ms/step - loss: 0.4079 -
accuracy: 0.8039 - val_loss: 0.3944 - val_accuracy: 0.8114 - lr: 0.0010
Epoch 5/30
225/225 [==============================] - 193s 858ms/step - loss: 0.3824 -
accuracy: 0.8162 - val_loss: 0.3792 - val_accuracy: 0.8103 - lr: 0.0010
Epoch 6/30
225/225 [==============================] - 195s 865ms/step - loss: 0.3661 -
accuracy: 0.8233 - val_loss: 0.3250 - val_accuracy: 0.8471 - lr: 0.0010
Epoch 7/30
225/225 [==============================] - 196s 873ms/step - loss: 0.3395 -
accuracy: 0.8396 - val_loss: 0.4581 - val_accuracy: 0.8080 - lr: 0.0010
Epoch 8/30
225/225 [==============================] - 194s 861ms/step - loss: 0.3245 -
accuracy: 0.8526 - val_loss: 0.3356 - val_accuracy: 0.8482 - lr: 0.0010
Epoch 9/30
225/225 [==============================] - 192s 855ms/step - loss: 0.2915 -
accuracy: 0.8662 - val_loss: 0.2949 - val_accuracy: 0.8661 - lr: 0.0010
Epoch 10/30
225/225 [==============================] - 192s 854ms/step - loss: 0.2787 -
accuracy: 0.8700 - val_loss: 0.2857 - val_accuracy: 0.8594 - lr: 0.0010
Epoch 11/30
225/225 [==============================] - 193s 858ms/step - loss: 0.2536 -
accuracy: 0.8828 - val_loss: 0.1962 - val_accuracy: 0.9141 - lr: 0.0010
Epoch 12/30
225/225 [==============================] - 194s 861ms/step - loss: 0.2397 -
accuracy: 0.8934 - val_loss: 0.2782 - val_accuracy: 0.8862 - lr: 0.0010
Epoch 13/30
225/225 [==============================] - 193s 859ms/step - loss: 0.2517 -
accuracy: 0.8863 - val_loss: 0.2191 - val_accuracy: 0.9018 - lr: 0.0010
Epoch 14/30
225/225 [==============================] - 194s 860ms/step - loss: 0.1839 -
accuracy: 0.9215 - val_loss: 0.1738 - val_accuracy: 0.9364 - lr: 0.0010
Epoch 15/30
225/225 [==============================] - 193s 859ms/step - loss: 0.1679 -
accuracy: 0.9292 - val_loss: 0.1633 - val_accuracy: 0.9408 - lr: 0.0010
Epoch 16/30
225/225 [==============================] - 193s 857ms/step - loss: 0.1407 -
accuracy: 0.9401 - val_loss: 0.1248 - val_accuracy: 0.9609 - lr: 0.0010
Epoch 17/30
225/225 [==============================] - 194s 861ms/step - loss: 0.1114 -
accuracy: 0.9568 - val_loss: 0.1265 - val_accuracy: 0.9542 - lr: 0.0010
Epoch 18/30
225/225 [==============================] - 193s 858ms/step - loss: 0.1040 -
accuracy: 0.9581 - val_loss: 0.1648 - val_accuracy: 0.9442 - lr: 0.0010
Epoch 19/30
225/225 [==============================] - 193s 859ms/step - loss: 0.1055 -
accuracy: 0.9579 - val_loss: 0.1351 - val_accuracy: 0.9531 - lr: 0.0010
Epoch 20/30

225/225 [==============================] - 193s 858ms/step - loss: 0.0751 - accuracy: 0.9696 - val_loss: 0.1122 - val_accuracy: 0.9676 - lr: 0.0010
Epoch 21/30
225/225 [==============================] - 193s 859ms/step - loss: 0.0888 - accuracy: 0.9646 - val_loss: 0.1113 - val_accuracy: 0.9699 - lr: 0.0010
Epoch 22/30
225/225 [==============================] - 193s 857ms/step - loss: 0.0707 - accuracy: 0.9760 - val_loss: 0.1273 - val_accuracy: 0.9576 - lr: 0.0010
Epoch 23/30
225/225 [==============================] - 193s 859ms/step - loss: 0.0960 - accuracy: 0.9625 - val_loss: 0.1151 - val_accuracy: 0.9688 - lr: 0.0010
Epoch 24/30
225/225 [==============================] - 193s 858ms/step - loss: 0.0334 - accuracy: 0.9887 - val_loss: 0.1529 - val_accuracy: 0.9587 - lr: 0.0010
Epoch 25/30
225/225 [==============================] - 193s 858ms/step - loss: 0.0708 - accuracy: 0.9746 - val_loss: 0.1406 - val_accuracy: 0.9598 - lr: 0.0010
Epoch 26/30
225/225 [==============================] - 193s 859ms/step - loss: 0.0500 - accuracy: 0.9812 - val_loss: 0.1458 - val_accuracy: 0.9710 - lr: 0.0010
Epoch 27/30
225/225 [==============================] - 193s 858ms/step - loss: 0.0216 - accuracy: 0.9930 - val_loss: 0.0972 - val_accuracy: 0.9888 - lr: 5.0000e-04
Epoch 28/30
225/225 [==============================] - 193s 860ms/step - loss: 0.0039 - accuracy: 0.9996 - val_loss: 0.1069 - val_accuracy: 0.9833 - lr: 5.0000e-04
Epoch 29/30
225/225 [==============================] - 193s 859ms/step - loss: 0.0019 - accuracy: 0.9999 - val_loss: 0.1122 - val_accuracy: 0.9855 - lr: 5.0000e-04
Epoch 30/30
225/225 [==============================] - 194s 861ms/step - loss: 0.0013 - accuracy: 1.0000 - val_loss: 0.1230 - val_accuracy: 0.9844 - lr: 5.0000e-04

Appendix D
Treatment Recommendations

This appendix provides detailed information on treatment recommendations for each of the three sweet potato leaf disease classes. The recommendations are based on the diagnosis made by the CNN model and include both chemical and organic treatments. The appendix also includes information on how to prevent the occurrence of sweet potato leaf diseases in the future.

Class	Name	Detail
Alternaria Leaf blight	Fungicide Treatment	pray affected plants with a fungicide to control the Alternaria Leaf Blight
Healthy	Healthy Plant	Do Nothing
Potassium Deficiency	Bactericide Treatment	Spray affected plants with a bactericide to control the Potassium Deficiency

Appendix E
Links and Credits

The sweet potato leaves dataset used in this research is available on Kaggle website. The dataset consists of 9000 images of sweet potato leaves categorized into three classes: Alternaria Leaf Blight, Healthy, and Potassium Deficiency. With the help of data augmentation, the dataset was increased to 9000 images, and each class has 3000 images. The dataset can be accessed through the following link on Kaggle: https://www.kaggle.com/datasets/matthiasluogon/sweet-potato-leaf-disease-dataset. By making the dataset publicly available, it can be used by other researchers for further analysis and experimentation in the field of agricultural disease classification.

Code link: https://github.com/melomatt/sweet-potato-leaf-disease-code-2023

Credit: https://github.com/codebasics/potato-disease-classification

Appendix F
Curriculum Vitae (CV)

CORRICULUM VITAE

CONTACT

Matthias B.E Luogon

Gonyeli, Lefkosa, North Cyprus

Contact No. +905338315769/+905488353990

Email: matthiasluogon@gmail.com/20215471@std.neu.edu.tr

LinkedIn

PROFESSIONAL SUMMARY

A self-motivated Computer Science graduate with a strong academic background in programming, Data Structures, and Algorithms. Proficient in various programming languages, Deep Learning Algorithms, and experienced in software development. Seeking higher-level research in Artificial Intelligence and Machine Learning.

EDUCATION

2021-2023: Master of Science Degree in Artificial Intelligence Engineering (Expected June 2023) Near East University, North Cyprus Relevant coursework:
Thesis title: AN AI-BASED SOLUTION FOR SWEETPOTATO LEAF DISEASE DIAGNOSIS: (AGROO AI).
Network (an original image dataset, gathered, arranged, and annotated from Liberia for this research).
Artificial Intelligence and Block chain
Artificial Intelligence and Cloud Computing
Machine Learning
Deep Learning
Computer Vision
Image Processing

2021: Bachelor of Science Degree in Computer Science (B.Sc. IT, Information Technology specification)
BlueCrest University College Liberia
March 20, 2021

CGPA: 3.72
Relevant coursework:
Operating systems and Network Fundamentals
Computer Organization and Architecture
Data Structures and Algorithms
Human Computer Interface
Software Engineering
2018: Professional Diploma in Information Technology (Software Engineering - .Net Technologies),
BlueCrest University College - NIIT
Liberia Relevant coursework:
Java Programming Language
Developing Database Application using ADO.NET and JDBC
Developing Web applications using ASP.NET
Software Testing and Quality Assurance
OOPS using C#
Relational Database Designs

2012: High School Diploma and WAEC Certificate
Christ the King Catholic School
Oldest Congo Town, Liberia

SKILLS

- Programming Languages: Python, JavaScript, C#
- Deep Learning with Python, Tensorflow and Keras
- Software Development: Software Development Life Cycle

- Web Development: React JS, Angular JS, HTML, CSS
- Database and API: SQL, MySQL, TensorFlow, FastAPI, Node JS
- Operating Systems, Windows, Linux

WORK EXPERIENCE:

Software Engineering Intern
Orange Liberia Telecommunication Company
Capital Bye-Pass, Monrovia,
Liberia 2020 – 2021

- Worked along with development team to build and manage software applications using ASP.net, JavaScript and C#.
- Partake in regular called-out meetings and reviews of code
- Performed software implementation debugging and testing modules of software

Technical Staff of International Conference on Advanced Trends in ICT and Management
(ICAITM)
BlueCrest University College NIIT Liberia
Opposite CDC Headquarter, Congo Town, Monrovia, Liberia
15th December 2017

Instructor of Physics
Vision International Christian Academy
Town Hall Community,
Paynesville Liberia 2016 – 2018

- Taught high school students the fundamentals of physics and the importance of the subject to our daily lives.
- Created a defined Lesson Plan of physics in accordance with the guideline designed by the ministry of education.
- Performed student’s evaluations my means of giving assignments, quizzes, and Exams.

Computer Instructor

Christ the king Catholic school

Oldest Congo Town

Paynesville, Liberia 2015

– 2016

- Taught high school students the basis of computer, like office productivity tools, operating systems and some fundamentals of being computer literate.
- Created a defined Lesson Plan of Computer in accordance with the guideline designed by the ministry of education, and student's evaluations.

Instructor of Mathematics & Physics

Maggie Lampkson Institute

Soul Clinic Community

Paynesville Liberia 2014 –

2015

- Taught high school students algebra, trigonometry, geometry, and some basic mathematical theorems.
- Created a defined Lesson Plan of Mathematics and Physics in accordance with the guideline designed by the ministry of education, and evaluation of students.

PROJECTS & PUBLICATIONS:

- Master Thesis: Developing a disease diagnosis system powered by Artificial Intelligence and Deep Learning to detect, predict, and recommend treatments for sweet potato leaves diseases images using Convolutional Neural Network Algorithm.
- Carried out similar researches on classification and detection of cassava leaves diseases and other plants using convolutional neural network algorithm (to be published soon in the IET Digital Library, and subsequent indexing in Inspec, IEEE Xplore and EI Compendex).

AWARDS AND CERTIFICATIONS:

- Awarded Scholarship to study Master in Artificial Intelligence Engineering (AIE)

  Near East University

  Lefkosa, North Cyprus

  February, 2020 to June 2023
- Certificate of Recognition

  Nano – EL Premiere League – 2018, with inspiration from the NANO-Electronics Project at NIIT University, funded by Erasmus+ Programme of the European Union

  Bluecrest University College, Liberia.
- Certificate of Participation

  International Conference on Advanced Trends in ICT and Management

  BlueCrest University College NIIT Liberia

  Opposite CDC Headquarter, Congo Town, Monrovia, Liberia

  December 15, 2017
- High School Diploma and WAEC Certificate

  Christ the King Catholic School

  Oldest Congo Town, Liberia

  June 30, 2012

REFERENCES

REFERENCES

Prof. Dr. Fadi Al-Turjman, Asst. Dean for Research, Director of AI and Robotics Institute, Near East University. (fadi.alturjman@neu.edu.tr)

Dr. Auwalu Saleh Mubarak, Lecturer AI Department, Near East University (auwalusaleh.mubarak@neu.edu.tr)
Mr. Stanley Kamara, Economic Director, UNDP Liberia. (stanley.kamara@undp.org).

Appendix F
Turnitin Similarity Report

Matthias_report

ORIGINALITY REPORT

13%	7%	9%	5%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

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5	Submitted to Kennesaw State University Student Paper	1%
6	"Proceedings of the 9th International Conference on Computational Science and Technology", Springer Science and Business Media LLC, 2023 Publication	<1%
7	"Forthcoming Networks and Sustainability in the IoT Era", Springer Science and Business	<1%