# A DEEP LEARNING MODEL FOR EARLY PREDICTION AND DIAGNOSIS OF LATE BLIGHT DISEASE IN IRISH POTATOES .

**A CASE: KIGEZI REGION -UGANDA**

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# DECLARATION OF AUTHORSHIP

"I declare that I am the author of this work and that any assistance I received in its preparation is fully acknowledged and disclosed in this paper. I have also cited any sources from which I used data, or ideas, either quoted directly or paraphrased. I also certify that this research thesis was prepared by me for the partial fulfillment of the requirements of a Doctorate of Philosophy in Computing by Research at Mbarara University of Science and Technology.

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# Dedication

*I dedicate this work to the almighty God and my lovely family and friends most especially Ambrose Atuheirwe Izaara*

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# Abstract

Introduction: According to the Centre International potato, the Irish potato is a popular crop in Uganda with a great value for income generation and improving nutrition. The Ugandan government has declared the Irish potato a key crop for the country. Despite Irish potatoes being a key crop in Uganda, diseases are a challenge in their growth,growth most especially the late blight disease.

Problem:Late blight of Irish potato disease causes 60 percent damage to Irish potatoes and this has affected the production of Irish potatoes in Uganda due to misdiagnosis and inaccurate prediction of the disease. AI models have been providing significant results in the improvement of disease prediction and diagnosis but Datasets of an African Origin and Uganda in particular still remain a challenge.

The main objective:The main objective of this research is to develop a deep learning model powered mini pathogen Laboratory to improve early prediction and accurate diagnosis of late blight disease in Irish potatoes in Kigezi-Uganda.

Methodology: The methodology used in this study was Design Science methodology and Artificial Intelligence approaches for model development. This achieved development of a deep learning model powered Irish potato Mini Pathogen lab.

Results: This application achieved a lot of success in its evaluation with minimum accuracy of 94% and maximum accuracy ranging from 98% to 100% thus contributing to bridging the accuracy gap of East Africa which 6.5% to 7% by closing it by 5.5% and closing in to the global accuracy of 99.56% on particular experiments.

Conclusion: The deep learning model powered Irish potato Mini Pathogen lab helped extension workers to conveniently and cheaply carryout experiments on late blight disease early prediction and accurate diagnosis.

Future works: Future research should be done in further crop science to experiment with the model and give specific recommended on specific herbicides to treat late blight late and specific prediction on spraying schedules. More investigation should be done in unleashing the black-box to make future models more explainable.

# CHAPTER 1

# Introduction

This chapter includes the background of the study, the statement of the problem in this study, the main objective of this investigation, the specific objectives of the study, the research questions in the study and the scope of the study, the significance of the study and the justification of the study.

## 1.1 Background to the Study

The global population is increasing steadily.In the next four decades 2010-2050, it is expected to rise with 2.3 billion which will make the word population to be nine (9 billion [4].The increase in population leads to increased demand of food, and this is heavily affected by pests and diseases [5].Food remains a challenge as it is one of the most important basic needs and agriculture is at the front of the battle to achieve this battle. Global hunger has been and remains a challenge [6].

Contracted efforts from all nations are required to ensure food security. The United Nations has put forth Sustainable Development Goals as a call for action to the challenges of mankind. The challenge of hunger to mankind corresponds to two Sustainable Development Goals of the United Nations, that is, Goal 2, that is, 'zero hunger' and Goal 12, 'Ensure sustainable consumption and production patterns. This study addressed Sustainable goals 2 and 12 through increasing food production by reducing the damage caused by pests and disease in agriculture.

This study also aligned with the Africa's Agenda of 2063 , that is, Aspiration 1 a prosperous Africa through Agricultural Innovation and Aspiration 6 ( People-driven development through technology.

Late blight disease causes massive damage of Irish potatoes thus threatening food security and farmer's livelihoods which challenge Africa must overcome by 2063 [7].

Agriculture is important in the economy of Uganda and the Gross Domestic Product (GDP) is generated is 24 percent which account for 54 per of Uganda's export earnings. The working population is involved in agriculture which provides the first job for three-quarters of those aged between 13 and 26 years and this is 70 percent of Uganda's population [8].

Despite Agriculture's great contribution to Uganda's economy, there are several hindrances which heavy losses to crops and livestock for example pests and diseases. An effort to apply prevention, and stop diseases and pests in animals and crops is very vital in improving productivity [5].

According to the Centre International potato , the Irish potato is a popular crop in Uganda with a great value for income generation and improving nutrition. The Ugandan government has declared the Irish potato a key crop for the country [5].

Despite Irish potatoes being a key crop in Uganda, diseases are a challenge in their growth most especially the late blight disease. This late blight of Irish potato disease causes 60 percent damage to Irish potatoes and this has affected the production of Irish potatoes in Uganda [9].

With so much effort from many research organizations such as the National Agriculture Research Organization producing late blight disease resistance Irish potato seedling, the disease still affects the areas of Kigezi, that is, Kabale, Kisoro, and Rubanda [9].

Early detection of crop growing in health condition and those with diseases can con-

tribute to the control of diseases through vector control such as application of pesticides, fungi, can improve productivity.

Plant disease diagnosis is very important at an early stage for purposes of curing and controlling the disease.

Chaiwat and Arora further explain that the systems that have a human vision acumen are commonly used to do the identification of diseases a crop type. The methods of which use the human vision aspect have been labelled inaccurate as the treatment of the disease is based on evidence on from the perceptions, the learning interactions of the native farmer or the agricultural field workers normally at the sub-county or the district [10].

Hong, Kalbarczyk, and Iyer discovered some of the problems faced are based on data. The authors proposed development and adoption of systems that are user-friendly to unable utilization of users with less software experience [11].

Artificial Intelligence models most especially deep learning model have performed have played a fundamental role in early prediction and diagnosis of plant diseases [12]. Current Deep learning approach have some flaws such as the need; (1) to foster performance of deep learning, (2) to localize deep learning to suite under represented setting focusing on East Africa taking Uganda as a case study, (3) to integrate weather features into the model such temperature, wind speed and lastly the to incorporate explain AI to promote trust and acceptability

In this study a deep learning model which helped to develop a mobile Irish potato pathology laboratory for early prediction and diagnosis of late blight disease was developed.

## 1.2 Definition of Keywords

Given the broadness of Artificial intelligence, there are several terms that were used in this research that need to be defined, and these are:-

### 1.2.1 Artificial Intelligence

AI refers to computer systems designed to perform tasks that typically require human intelligence, such as visual perception, decision-making, and language processing. It encompasses rule-based systems, machine learning (ML), and deep learning (DL) [13].

### 1.2.2 Machine learning

Machine Learning is a subfield of Artificial Intelligence (AI) that focuses on developing algorithms and statistical models that enable computers to learn from and make predictions or decisions based on data without being explicitly programmed. ML systems improve their performance automatically through experience (training data) [14].

### 1.2.3 Convolutional Neural Network

A specialized deep learning architecture for processing grid-like data (e.g., images). CNNs use convolutional layers to automatically detect spatial hierarchies of features such as edges ,textures, object parts) [14].

### 1.2.4 Deep learning

A subset of ML that uses multi-layered neural networks to model complex patterns in data. DL models automatically learn feature representations, eliminating manual

feature engineering [15].

### 1.2.5 Explainable AI

Methods to make AI models' decisions interpretable to humans. XAI addresses the "black box" problem by providing transparency, fairness checks, and causal reasoning [16].

### 1.2.6 Deep learning Architecture

Deep Learning (DL) architecture refers to multi-layered artificial neural networks designed to model high-level abstractions in data. These architectures automatically learn hierarchical feature representations, eliminating the need for manual feature engineering [14].

### 1.2.7 Confusion Matrix

A confusion matrix is a performance measurement tool used in machine learning to evaluate the accuracy of a classification model. It provides a detailed breakdown of the model's predictions by comparing them to the actual ground truth labels. The matrix categorizes predictions into four key outcomes:

True Positives (TP): Cases where the model correctly predicts the positive class.

True Negatives (TN): Cases where the model correctly predicts the negative class.

False Positives (FP): Cases where the model incorrectly predicts the positive class (also called a Type I error).

False Negatives (FN): Cases where the model incorrectly predicts the negative class (also called a Type II error).

By analyzing these values, metrics like accuracy, precision, recall (sensitivity), and F1-score can be derived to assess the model's strengths and weaknesses. Unlike a simple accuracy score, the confusion matrix reveals how the model is making errors, helping refine its performance [17].

## 1.3 Problem Statement

Phytophthora infestans is the major cause of late blight which is destroying Irish potatoes in areas with high levels rainfall and low levels temperatures which happens to be areas suitable for rain-fed potato production in the tropics [18]. Despite the limitations of farmers and agricultural external workers the models developed to identify and predict the disease most especially using the humana vission method in Uganda, East Africa and Africa at large. This continuously leads results into misdiagnosis and inaccuracies in early prediction of late blight disease Models have been developed ,that is, Toroitich who did a related study in Nakuru, Kenya. Kulkarni, Karwande, Kolhe, Kambe, Joshi, and Wyawahare in India also did a related study and also achieved 93 percent [19]. The however requires and improved accuracy in early diagnosis and accurate prediction of the disease thus adapting features from successful models such as from studies [6] and [19] [20] [21] [22] [23] [24] [25]which include biotic factors (temperature, humidity, wind direction as further research measures.Variation in the farming methods used in Africa (Uganda) and the other areas where high accuracy models have been used and differences in seedling varieties grown in Uganda and the other areas where high accuracy models have been used. The adaption of the local datasets from Africa, East Africa and Uganda particularly is big challenge since they have a limited presence

on the public domain.

This called for a localized and optimized Deep learning Model that was trained on the Uganda Environmental Conditions, local Irish potato seedling varieties, and also suits the farming methods (open field cultivation) used in Uganda with synchronization of Late blight Disease Life cycle and also addition of important feature such as the wind direction as recommend by the study done in Nakuru in kenya [19].

## 1.4 Objectives

### 1.4.1 General Objective

The main objective of this research is to develop a deep learning model powered mini pathogen Laboratory to improve early prediction and accurate diagnosis of late blight disease in Irish potatoes in Kigezi Uganda.

### 1.4.2 Specific objectives

(i) To establish the requirements for developing AI based models for early prediction and diagnosis of late blight disease in Irish potatoes.

(ii) To design and develop an AI model for early prediction and accurate diagnosis of Late blight disease in Irish potatoes.

(iii) To test and evaluate the the developed model for early prediction and accurate diagnosis of Late blight disease.

## 1.5 Research Questions

### 1.5.1 Specific Research Questions

*RQ1:To what extent have AI models been developed and used for early prediction and diagnosis of late blight disease in Irish potatoes?*

*RQ2: How an efficient and robust AI model for early prediction and accurate diagnosis of Late blight disease in Irish potatoes be developed?*

*RQ3:What are the accuracies, Precisions, Recall(sensitivity) ratios-Scores, Misclassification and F1-score of the developed model in Kigezi Uganda?*

## 1.6 Scope of the Study

The research study mainly focused on the prediction and identification of late blight disease in Irish potatoes in Kigezi. Data was obtained from Kigezi Irish potato farmers gardens in Kigezi and also secondary data was obtained from Plant Village, primary data was also obtained from experiments conducted in two Irish potato growing seasons in the different districts of Kigezi during the testing of the localized Deep learning model. The research study mainly focused on the use of leaf images of Irish potato plants for instant prediction and diagnosis of Phytophthora Infestans and also temperature, humidity and wind spread to determine the the severity of the disease. The leaf images,temperature, humidity and wind speed were used to train a Deep learning Model to define the intensity of Phytophthora infestans infection and provide guidance on how to offer the solution or advise on how prevent the situation from worsening. The leaves of Irish potato with disease symptoms were modelled to assist farmers in the early prediction of the Late blight.

The specs of which we are investigating for this study were comprised of Irish potato leaf images which are important in the determination of Phytophthora infestants, its severity and also environmental factors such temperature, humidity and also including a unique feature of wind direction.

The Deep learning model was trained on Irish potatoes ranging from 14 days to 60 days, according to Picon et al(2019) [26].

## 1.7 Justification of the Study

According to the International Potato Centre website, Late blight disease contributes (3.7 trillion Uganda shillings) losses in terms of damaging the Irish potatoes. In Uganda the Late blight accounts for losses of (447 billion and 300 million Uganda shillings) [27].

Plant disease prediction is important in improving crop yield. Currently, ways for predicting diseases affecting plant is provided systems based on human visual. The challenges with these systems is they use phenotypic symptoms and characteristics are available, thus making them unable to help farmers in treating diseases such Late blight at an early stage [28]. Early identification of plant disease can immensely contribute to high crop yield. A Deep learning model can be created to inform a farmer about a specific disease and also offer the control measures. These Deep learning Models can improve prediction for variables that are complex, non-linear, and noisy. These models, therefore, are practical since they are precise and are able to capture any data movements with a high accuracy making them suitable for use in early detection [29]. The area of study was Kigezi-Uganda because it has Favorable weather condition for Late Blight Disease which is areas with a lot of rainfall, Variability in severity of potato late blight and yield loss associated with the disease was studied in the main potato growing agro-ecologies of Uganda. Late blight incidence and severity varied significantly

($P<0.05$) from district to district to season during the four surveys (2 years) Overall, the highest late blight severities were registered in Kabale district (mean severity of 27.6%), followed by Mbale (21.8%), and Mbarara the least (8.7%) [30]. This description suits Kigezi region, that is, Kabale, Rubanda,and Kisoro. According to Elliott, inadequate access to agricultural services that are advisory in nature, raises some of the major challenges that farmers in Sub-Saharan countries are experiencing [31].

## 1.8 Research approach

The study followed the research approach of Design Science. The research approach began with identification and motivation, followed by defining the objectives of a solution , then Design and Development, then Development, evaluation and communication.

## 1.9 Research theorem

Explainable AI theorem was used in the study because it is critical for deep learning models for ensuring transparency, trust and accountability in AI systems.The research adopted a Post –Hoc method of explainable AI called the Local Interpretable model-agnostic explanations [1].

Below is the diagram showing explainable AI

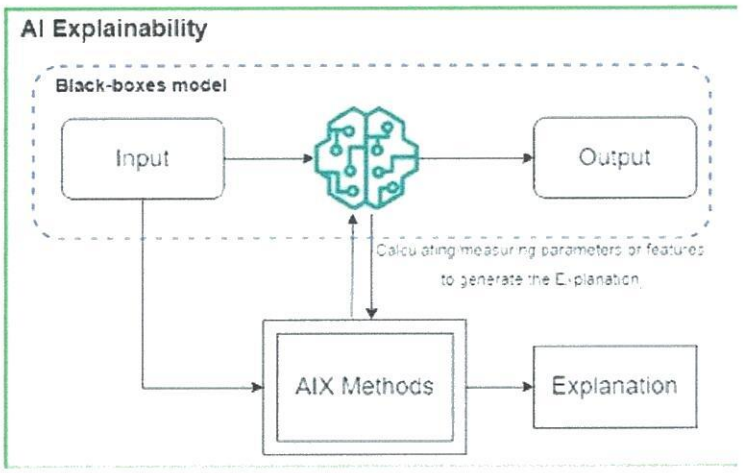



Fig. 1.1: The diagram below shows the explainable AI theorem [1]

## 1.10 Contribution to science

The study contributed a deep learning powered mobile Irish potato pathology Laboratory for extension workers to improve the early prediction and accurate diagnosis of late blight in Irish potatoes.The innovation had specific attributes of contribution for re-optimizing Deep learning (MobileNetV2). integrating epidemiological features such as temperature, humidity and most importantly the wind-speed which an important feature for open cultivation farming and embracing explainable IA,and early detection.

## 1.11 The interrelatedness of included papers & objectives

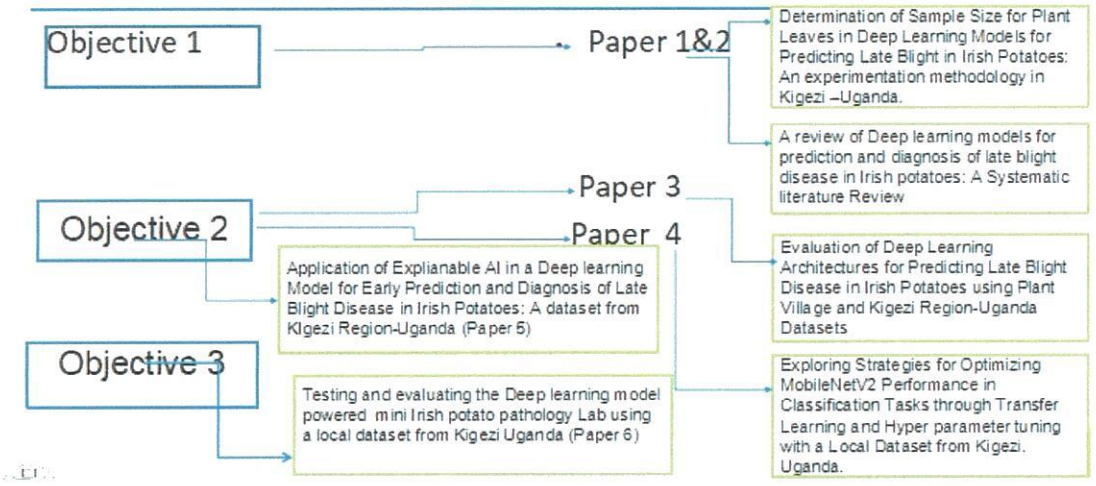



Fig. 1.2: The figure shows the interrelatedness of included papers & objectives

## 1.12 Structure of the thesis

chapter One (Introduction) This chapter provides an introduction with background information on late blight disease,late blight diagnosis,Plant leaf imaging,Artificial Intelligence and Deep learning, research problem, research objectives, research questions, research scope research approach research theorem,research contributions, the interrelatedness of included papers & objectives and thesis structure.

chapter two (Review of Related Literature on Late blight Disease and preliminary literature on AI model) This chapter provides a survey of recent approaches in literature relevant to the research particularly for Late blight disease and preliminary literature of technologies used in the prediction and diagnosis of Late Blight Disease a summary of the findings is presented. Chapter three (Research Methodology)

In this chapter we describe the research methodology in details.The methodologies and research approaches used in each in each objective are described.

chapter four (A review of Deep learning models for prediction and Diagnosis of late blight disease in Irish potatoes: A Systematic literature Review) In this chapter, A paper journal contributing to objective one discuss the Deep learning models for early prediction and diagnosis of late blight disease in Irish potatoes to find their performance and gaps.

chapter five (Evaluation of Deep Learning Architectures for Predicting Late Blight Disease in Irish Potatoes using Plant Village and Kigezi Region-Uganda Datasets) This chapter is paper that contributes to objective two and presents an evaluate the ten deep learning pre-trained architectures to obtained the architecture that will be used a Baseline model. This entitles an introduction to the evaluation,methodology used, experiment design, results and discussion and conclusion.

chapter six (Exploring Strategies for Optimizing MobileNetV2 Performance in Classification Tasks Through Transfer Learning And Hyperparameter Tuning With a local Dataset From Kigezi, Uganda) This chapter is present a research journal that contributes to research objective two and explores the strategies for optimizing the MobileNetV2 performance. An introduction to transfer learning and hyperparameter tuning. The methodology, results, discussion and conclusion are presented.

Chapter seven (The Application of Explainable AI in a Deep Learning Model for Early Prediction and Diagnosis of Late Blight Disease in Irish Potatoes:A Dataset from Kigezi Region-Uganda) This paper contributes to objective two and also provides a standard for the development of the severity classification Model for late blight disease in Irish potatoes. This chapter is composed of the introduction,Methodology, Results and discussion and conclusion

chapter eight (A design of a Deep learning model with (Baseline, Severity and integration of Open weather API) for early prediction and accurate diagnosis of late blight disease

in Irish potatoes. A local dataset from Kigezi region-Uganda ) This is a research journal paper that contributes to research objective two of the study and describes the technique used in development of the severity model. The introduction, methodology, results, discussion and conclusion are presented.

chapter nine (Testing and evaluating the Deep learning model powered Smart mini pathology Lab using a local dataset from Kigezi Uganda ) This chapter describes the implementation of the the Deep learning model powered Smart mini pathology Lab.

# CHAPTER 2

# Review of Related Literature on late blight disease and AI models

## 2.1 The Introduction of the Literature review

This section gathers literature covering the usefulness of agriculture and how to control light blight disease in Uganda, and discussion of the literature on crop prediction techniques, models, Algorithms, methods used in developing models, and Mobile applications. Diseases affecting potato farmers are also discussed.

## 2.2 Agriculture in Uganda

Agriculture is very important in the economy of Uganda and it generates 24% of the Gross Domestic Product (GDP) and which translates to 54% of Uganda's export earnings. The working population which is about 70% is involved in agriculture which provides the first job for three-quarters of those aged between 14 and 25 years [32] .

### 2.2.1 Agricultural and Climate in Uganda

According to a USAID report by Ojok that climate change has and will continue to have a tangible and will continue to have significant on direct and indirect impacts on agriculture in Uganda. He further noted that there is increased rainfall during the dry

season [33]. According to Sparks, Forbes, Hijmans, and Garret, the effects of climate change on potato late blight disease have indicated the potential for increased risk. They further explain that increased rainfall and humidity increase the risk of late blight disease [34].

### 2.2.2 Irish Potato Farmers in Uganda with the Agricultural challenges and Extension Services

Sebaggala and Matovu explain that the quantitative evidence supporting the ability of extension services to increase production in Uganda is very scarce. This shows that even in disease identification, prediction and diagnosis it is still scarce. This calls for a need to employ technology that is localized in order to bridge the increased need for extension services to control the severity of diseases like late blight disease [35] .

### 2.2.3 Potato production Regions in Uganda

According to Delphy and IFDC –Uganda, the national potato production was estimated at 327,300 million tons from an estimated area of 111,100 Hectares (Ha). The report however indicates the home- saved seed is low yielding varieties and also due to low-level management practices, without forgetting the less attention that farmers pay to product quality, water restrictions, soil exhaustion and the prevalence of viruses and diseases like late blight and bacterial wilt are major production challenges [36] In Uganda potato farmers majorly have two seasons (Season A from March to July) and (season B from September to January). The following districts grow Irish potatoes in Uganda that is, Kabale, Kisoro, Mbarara, Luwero, Masaka, Mbale, Rukungiri, and Kapchorwa [36]. According to International Center for Potatoes, 60% of Irish potatoes in Uganda are grown in the South Western highlands [37].

### 2.2.4 Potatoes species in Uganda and those that can that are resistant to Phytophora Infestans

According to International Center for Potatoes late blight disease damages 40-60% of the harvest every year [37]. One of the varieties that are being produced in Uganda and have proved to be resistant to late blight disease is the Victoria potato variety released by the National Agricultural Research Organization (NARO) of Uganda [38]; however late blight disease still remains a challenge. The farmers in Uganda can acquire a wide range of varieties which both from Uganda and improved. The most current species include Rwagume, Kinigi, Nakapot5, Kachwe 1, Rutuku, and other varieties recently released by National Agricultural Research Organization [39].

## 2.3 Diseases Affecting Potato Farming in Uganda

The most common disease affecting Irish potato farming in Uganda is Late blight caused by the fungus called Phytophthora infestans [40].

### 2.3.1 Late light disease development cycle.

According to Robinson, Secor, and Gudmestad [2] Phytophthora infestants, are fungi that cause late blight disease. The fungal is like a pathogen, meaning two mating types are required for sexual reproduction and are referred to as A1 and A2. The pathogen is an obligate parasite that cannot survive without a living host. Stage 1: Initial symptoms of late blight were small, light dark to green, circular to irregular-shaped, and water-soaked spots. [2] Stage 2: Late blight lesions expand rapidly into large, dark brown or black lesions, often appearing greasy [2]. Stage 3: Lesions commonly are encircled by a

yellow Chlorotic halo [2]. Stage 4: Late blight lesions may appear on leaves and stems of Irish potatoes, especially are at young age with the presence of moisture [2].

Stage 5: When late blight is growing, often in a cold environment, a white mildew-appearing area is visible at the edge of the leaves [2]. Stage 6: late blight which actively growing can result into white mildew appearing areas along leaves of the Irish potatoes [2]. Stage 7: Brown, dry leaves can emerge in a weather that is warm and dry [2]. Stage 8: The tubers are seen by an irregular-shaped, slightly depressed areas that can vary considerably from brown to purplish with a vary size [2]. Stage 9 The fungus turns to reddish-brown rot found under the skin [2]. Stage 10 The edges of the diseased plant parts are always the same most especially when they are under cold temperatures [2]. Stage 11 Late blight-infected seed often decays but can move up the seed piece into the stem [2].

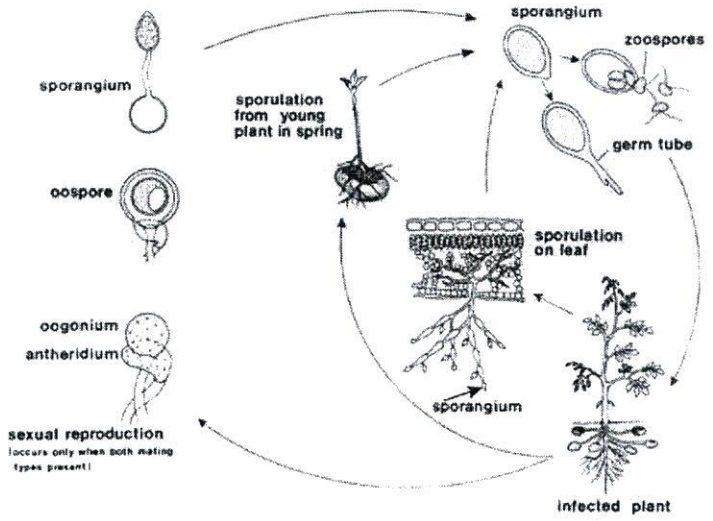



Fig. 2.1: This is a simplified disease cycle for late blight disease [2]

### 2.3.2 Favorable environment conditions for late blight

The Phytophora infestans emerge under medium levels of temperature in the range of 12-24 °C and minimum night temperatures of > 100 °C. The humidity should be above 90% for the fungus to emerge. For the disease to emerge it should be in a cold environment combined with rainfall [41].

#### 2.3.2.1 Monitoring late blight of Potato Disease

This potato disease, Phytophora infestans can be monitored by its effects on the leaves, stems, and tubers of the plants. For this study I will use leaves as the major feature to enable me to do the early prediction and diagnosis of Late blight disease [42].

## 2.4 An In-Depth Overview of Deep Learning Algorithms

### 2.4.1 Core Building Blocks

Deep learning algorithms are constructed from a few fundamental components that enable them to learn from data.

### 2.4.2 Artificial Neuron (Perceptron)

The basic computational unit of a neural network. A neuron receives a vector of inputs $\mathbf{x}$, each multiplied by a corresponding weight $w_i$. It sums these weighted inputs along with a bias term $b$, and passes the result through a non-linear *activation function* $\sigma$ to

produce an output $y$.

$$y = \sigma\left(\sum_{i=1}^{n}(w_i x_i) + b\right) = \sigma(\mathbf{w}^T\mathbf{x} + b) \tag{2.1}$$

### 2.4.3 Activation Functions

These functions introduce non-linearity, allowing the network to learn complex patterns.

- **ReLU (Rectified Linear Unit):** $f(x) = \max(0, x)$. The most common due to its computational efficiency and mitigation of the vanishing gradient problem.
- **Sigmoid:** $\sigma(x) = \frac{1}{1+e^{-x}}$. Outputs a value between 0 and 1, useful for binary classification output layers.
- **Softmax:** $\sigma(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$. Used in the output layer for multi-class classification; converts scores into probabilities.

### 2.4.4 Loss Function and Optimizer

The **loss function** $\mathcal{L}$ (e.g., Mean Squared Error, Cross-Entropy) quantifies the difference between the model's prediction and the true target. The **optimizer** (e.g., Stochastic Gradient Descent, Adam) is an algorithm that minimizes this loss by iteratively updating the network's weights and biases.

## 2.5 Deep Learning Architectures

### 2.5.1 Feedforward Neural Networks (FNNs)

The simplest architecture, where information moves in one direction—from input nodes, through hidden layers, to output nodes. There are no cycles or loops. They serve as a universal function approximator but lack inductive bias for specific data types like sequences or images.

### 2.5.2 Convolutional Neural Networks (CNNs)

Specifically designed for processing grid-like data (e.g., images, time-series). Their core layers are:

- **Convolutional Layers:** Apply a set of learnable filters (kernels) to the input to detect local features like edges and textures.
- **Pooling Layers:** (e.g., Max Pooling) downsample the feature maps, reducing dimensionality and providing translational invariance.
- **Fully Connected Layers:** Typically at the end of the network, they combine high-level features for final classification.

CNNs exploit spatial locality and parameter sharing, making them highly efficient for visual data.

### 2.5.3 Recurrent Neural Networks (RNNs)

Designed for sequential data (e.g., text, time series). They have an internal state (hidden state $\mathbf{h}_t$) that acts as a memory, capturing information about previous elements in the

sequence.

$$\mathbf{h}_t = \sigma(\mathbf{W}_{hx}\mathbf{x}_t + \mathbf{W}_{hh}\mathbf{h}_{t-1} + \mathbf{b}_h) \tag{2.2}$$

Simple RNNs suffer from the vanishing/exploding gradient problem, making it difficult to learn long-range dependencies.

### 2.5.4 Long Short-Term Memory (LSTM) Networks

A sophisticated type of RNN designed to address the vanishing gradient problem. LSTMs introduce a gating mechanism:

- **Forget Gate:** Decides what information to discard from the cell state.
- **Input Gate:** Decides what new information to store in the cell state.
- **Output Gate:** Decides what to output based on the cell state.

This allows them to selectively remember or forget information over very long sequences.

### 2.5.5 Transformer Architecture

A revolutionary architecture that relies entirely on a *self-attention mechanism* to draw global dependencies between input and output, dispensing with recurrence and convolution.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2.3}$$

Where $Q$ (Query), $K$ (Key), and $V$ (Value) are matrices derived from the input. This allows for massive parallelization and has become the state-of-the-art in Natural Language Processing (NLP).

### 2.5.6 Generative Adversarial Networks (GANs)

A generative model framework based on a game-theoretic scenario between two networks:

- **Generator:** Tries to map random noise to realistic data (e.g., fake images) to fool the discriminator.
- **Discriminator:** Tries to distinguish between real training data and fake data from the generator.

This adversarial training process pushes both networks to improve until the generator produces highly realistic data.

The study will adopt Convolutional neural networks with LSTMs to introduce a gating mechanism which will be implement in the model.

### 2.5.7 Below are the models investigated from a preliminary literature review

Several models are used in the detection and identification of potato late blight disease. Below are the highlights and a summary of the late blight forecast models which have been reviewed by different authors [43]. BLITECAST is a computerized predictive model for potato late blight developed by Krause and colleagues at Pennsylvania State University [43].

Phyto is a computer-based system which gives information and also provides decision support system for potato late blight in Switzerland which is an epidemiological forecast model, a set of decision rules, and an information system [43].

JHULSACAST is a computerized predict of potato late blight in Western Uttar Pradesh for years when there is rain and the years when it not raining. Weather data incorporated, that is, temperature, relative humidity, and rainfall on an hourly basis [13].

According to Kip limo (2017) a related study was made in East Africa (Kenya) in Nakuru County, a Sim-cast model was developed for late blight disease. The model has some extra- ordinary functionality Weather data which was recorded in the past, pre-processing of the weather data, building the many and different disease models, weather forecasting, and disease prediction. Achieved 93% accuracy, precision 0.949, Recall ratio 0.968, F-measure 0.964.recommended wind direction as a parameter to be considered in future research and dataset of 836 images [19].

Khan et al (2021) Saudi Arabia Plant Village Image-Based Detection of Achieved 98.4% accuracy, Precision Plant Diseases:From Classical Machine Learning to Deep learning journey.93.8%, Recall ratio 95.9%,F-measure 97.5%.Dataset of 1787 images [44].

Liu and Wang 2021 China Plant Village Plant diseases and pests detection based on deep learning: A review Achieved 95.61% accuracy [23].

Nagasubramanian et al (2019) United States of America United States of America Plant disease identification using explainable 3D deep learning on hyper spectral images. Achieved 95.73% [15].

Joshi (2020) India India Automatic analysis and viral disease diagnosis using deep-learning in Vigna mungo plant Used VirLeafNet-1, VirLeafNet-2, and VirLeafNet-3 and achieved accuracies 91.234%, 96.429%, and 97.403% respectively [16].

Dhaka et al (2021) India Plant Village A survey of Deep Convolutional Neural Networks Applied for Prediction of Plant Leaf Diseases (Using Google Net Architecture with transfer learning) Achieved accuracy 99.35% on 54,306 images [17].

Yadav et al (2021) India Lab data set and real cultivation data set Identification of

disease using deep learning deep learning and evaluation of bacteriosis in peach in peach leaf. Achieved accuracy of 98.7% [18].

Amara et al (2017) of German studied A deep learning based approach for banana leaf Achieved 98.67% accuracy, Precision 0.9861,Recall 0.986 F1-score disease classification. 0.9864 from 3700 images [19].

Hassan and Maji et al (2021) Poland Plant Village Identification of Plant-Leaf Diseases Using CNN and Transfer Approach. Achieved an accuracy of 98.42% in Inception V3, 99.11% in inception ResNetV2 and 97.02% in MobilenetV2 and 99.5%in EfficientNet [21].

Chohan and Khan (2020) Pakistan Plant Village Plant Disease Detection using Deep Learning Achieved accuracy of 98.3% in a dataset of 14,059 images [50].

Relatedly, Bedi and Gole [20], a related study in India was done mainly aiming at decreasing the time required to train the model for real time plant disease detection and the time required for identification of the disease in plants using a trained model. The major parameter was leaves of different healthy peach plants and diseased peach plants of Bananas, Potato leaves, Tomatoes, and Maize. This model considered many diseases and also aimed at decreasing the prediction time.

Furthermore, in Kulkarni et al , [51] a related study was done in India. The model developed showed 93% accuracy. This model considered prediction using the leaves of the diseased plants. The leaf color, amount of damage to leave areas of the leaf, and texture parameters were used to achieve the best accuracy. The solution was less expensive and used required less time for a prediction. The model was testing many crops which include apples, corn, grapes, potato, and tomato.

Hong, Kalbarczyk, and Iyer discovered some of the problems faced are based on data. The authors proposed development and adoption of systems that are user-friendly to

unable utilization of users with less software experience [11].

In this study, a deep learning model was developed for early prediction and accurate diagnosis of late blight disease when it is early and thus control, and prevention.

The deep learning based model was developed with a deep learning technique, recommended from studies [ [19], [21], [44], and [23]. The model adopted some features of [19]to be more accurate. Consider parameters such as temperature and relative humidity and Irish potato leaves and further considered the wind direction, and the variety being used which are vital factors in improving the accuracy of the model.

The deep learning based model was also subjected to different weather and climate in Uganda and more so to Kigezi High land and thus a comparison with studies made in Kenya, In Saudi Arabia, and China.

#### 2.5.7.1 Recommendations a preliminary literature review

There several models used emerging from the preliminary literature review and most of these are deep earning models.A further systematic literature review will be done on deep learning models to establish the requirements to develop a deep learning model for early diagnosis and accurate prediction for late blight disease in Irish potatoes. This is achieved in the chapter four.

# CHAPTER 3

# Methodology

## 3.1 Chapter overview

This chapter of this study introduced the research study methodology and techniques that utilized in this research study. This study based on the objectives and key research questions whose major purpose was to provide solutions the problem defined by the research.

## 3.2 Research design

This study employed a design science approach which consists of several steps that led to the development of the model and later tested and validated. Secondary data was obtained from Kaggle and Plant Village, primary data was obtained from two seasons of Irish potato growing in Kigezi Region. The research study utilized expertise and knowledge from International Centre for Potato (CIP) on potato late blight modeling.

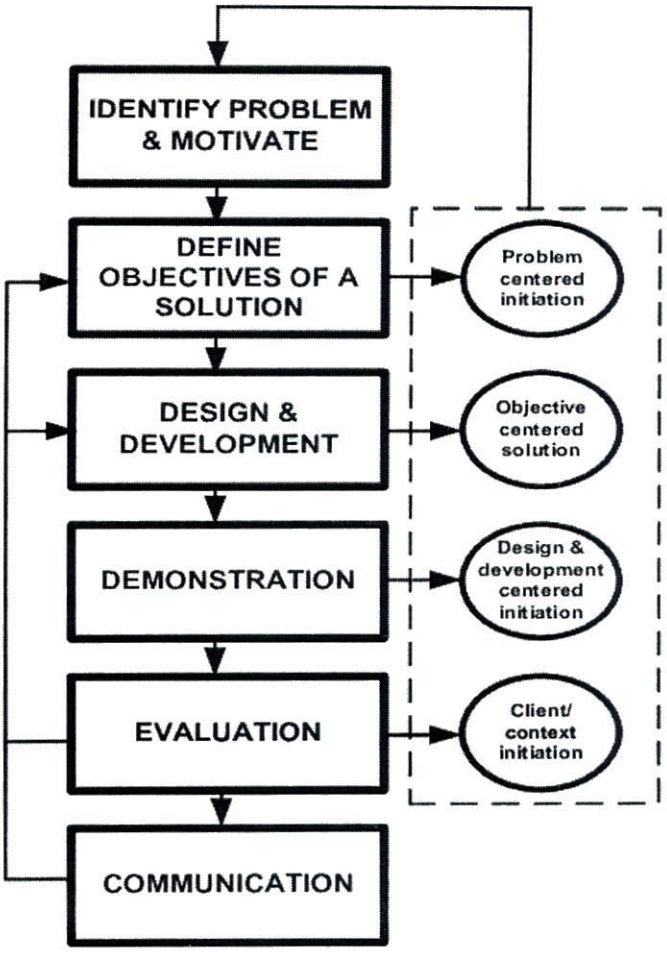



Fig. 3.1: The diagram showing the design science research methodology [3]

### 3.2.1 Research Philosophy

This research is guided by a pragmatic philosophy, which asserts that the value of knowledge is determined by its practical application and utility in solving real-world problems. Rejecting a forced choice between purely objective or subjective paradigms, this study prioritizes a problem-centered, pluralistic approach. The core belief is that the most appropriate methods are those that most effectively address the research problem: the urgent need for early and accurate diagnosis of late blight disease in Irish potatoes.

Consequently, this philosophy directly informs the Design Science Research (DSR) methodology. The primary objective is the creation and rigorous evaluation of a novel artifact—a deep learning model. The "truth" and validity of this research are therefore not measured by the discovery of universal laws but by the artifact's performance and practical efficacy. This necessitates a mixed-methods framework. Quantitative, positivist-leaning techniques, such as measuring accuracy, precision, and recall through controlled experiments, provide objective evidence of the model's diagnostic capability. Simultaneously, the design process is inherently interpretive, informed by the contextual understanding of agricultural practices and user requirements to ensure the solution is not only accurate but also viable and relevant for deployment in the field.

Ultimately, the philosophical stance is one of practical problem-solving. The contribution of this work is the creation of a functional, validated artifact and the knowledge of how to build it, with its success judged solely by its potential to reduce crop loss and improve agricultural sustainability.

### 3.2.2 Adoption of design science to guide the study

Problem Identification & Motivation: The economic devastation caused by late blight to smallholder farmers in regions like Kigezi is well-documented (FAO, 2022) [52]. Current diagnostic methods are often slow, require pathogen Laboratory knowledge, and are inaccessible in remote areas, creating a critical need for a rapid, accurate, and portable solution.

Definition of Objectives: The mobile application artifact must:

Functional: Accurately classify images of potato leaves as healthy or infected with late blight with >95

Technical: Perform inference on a mobile device in under 7 seconds without requiring

constant cloud connectivity.

Design & Development: This phase involves two parallel tracks:

AI Model Development: The core of the artifact was a fine-tuned MobileNetV2 model, chosen for its proven high accuracy and architectural efficiency suitable for mobile deployment [5]. It was optimized for mobile using transfer learning and hyper parameter tuning.

Mobile Application Development: The model was a cross-platform mobile application built with flutter.

Demonstration & Evaluation: The artifact will be evaluated through a multi-faceted approach:

Technical Evaluation: Quantitative testing of model accuracy (precision, recall, Misclassification, F1-score) on a held-out test set. Communication: Dissemination of findings was done through publishing the applied solution architecture, its performance metrics, and user study results, contributing valuable knowledge to the fields of precision agriculture and mobile AI.

### 3.2.3 Theoretical Framework

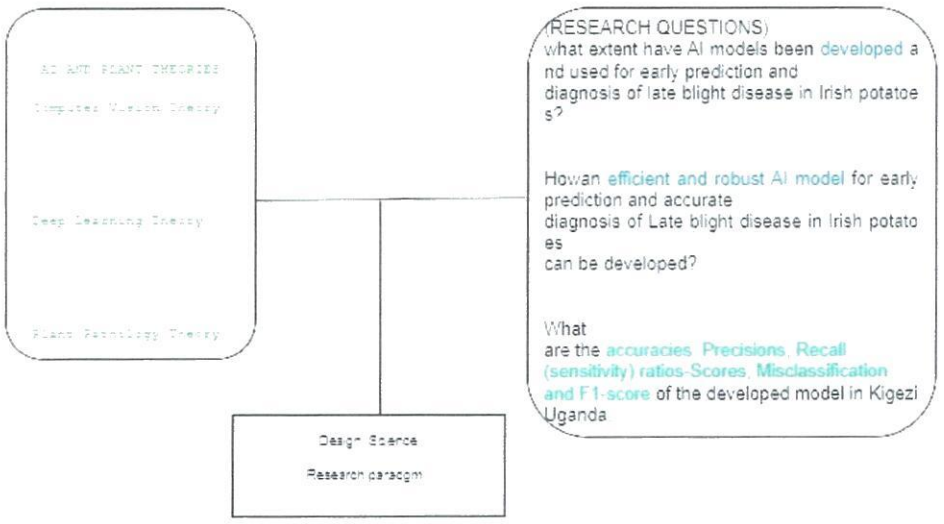



Fig. 3.2: Theoretical framework for an Deep learning model for late Blight prediction and diagnosis

In the above study the there AI theories and Plant theories , that is, computer vision, Deep learning theory and plant pathology theory and research questions, that is,to what extent have AI models been developed and used for early prediction and diagnosis of late blight disease in Irish potatoes?, how an efficient and robust AI model for early predic-

tion and accurate diagnosis of Late blight disease in Irish potatoes can be developed?, what are the accuracies, Precisions, Recall (sensitivity) ratios-Scores, Misclassification and F1-score of the developed model in Kigezi Uganda. The above are moderated by the Design science methodology.

### 3.2.4 Acquisition of Data

Image acquisition of Irish potato leaf was obtained as Secondary data from Plant Village. This is a public domain website that provide datasets to use, primary data was obtained from two seasons of Irish potato growing in Kigezi Region. Primary data was also be collected from the three districts, that is, Kabale, Rubanda and Kisoro in two season. At this point the participants are the garden owners provided their Irish potato gardens upon signing consent forms. The data (Irish potato images, temperature, humidity and wind speed was collected from the garden with the help of sub-county extension and an expert crop scientist). The target population; According to National Agriculture Advisory Services [54] 850,000 of Irish potatoes which are produced covering approximately 112,000 acres on average. Sample Size In academic research, samples are used to make generalizations about populations [55] . Such samples are usually selected to represent a population of particular interest, with sample sizes generally being decided after considering matters of statistical precision, available resources of cost and time, and other practical issues [55]. Amidst various approaches can be used to determine appropriate sample size, statistical formulas have now become increasing popular as they assist in creating a more precise degree of representativeness and allow researchers to have more confidence in generalizing the findings [56]. In this study, the researcher chose the proportional stratified statistical formula of Yamane (1973) to calculate sample size, as this method used a minimum sample size at a confidence level of 95%.

## Sample Size Calculation

Yamane's formula:

$$n = \frac{N}{(1+N)e^2}$$

where:

- $n$ = the sample size
- $N$ = the number of population
- $e$ = the error rate of sample (the level of precision)

Considering the Irish potato garden acreage, the sample of Irish potato garden acreage in Uganda can be drawn is 112,000 acres.

$$n = \frac{112,000}{(1+112,000) \times (0.5)^2}$$

$$n = 28,000.25 \text{ acreage of Irish potato gardens}$$

The study covered 28,000.25 acreage of Irish potatoes to collect image data. The data will be collected to fill the condition of Machine learning sample size condition of suitability which effective size ($\geq 0.5$) and Machine learning accuracy of ($\geq 80\%$) this was done during the training of the model.

The second phase of the participant was purposively selecting extension workers who undergo training to get involvement of experiments from two Irish potato seasons in the different districts of Kigezi during the testing of Deep learning model powered Mini Irish potato pathogen Laboratory application.

### 3.2.5 Objective one

To establish the requirements to design and develop an AI based models for early prediction and accurate diagnosis of late blight disease among Irish potato farmers in Kigezi. This objective was achieved using a systematic literature review. I reviewed papers from science direct, Google scholar, and Institute of Electrical Engineers. The inclusion and exclusion criteria was applied.

Deep learning models in early prediction and diagnosis of late blight disease in Irish potatoes was required for review. The study adopted the Scooping review methodology for the literature review. The range of year for the study was from 2010 to 2025.

The records to be considered in the literature reviewed passed through identification stage, screening stage, eligibility stage and included stage as shown in the diagram below

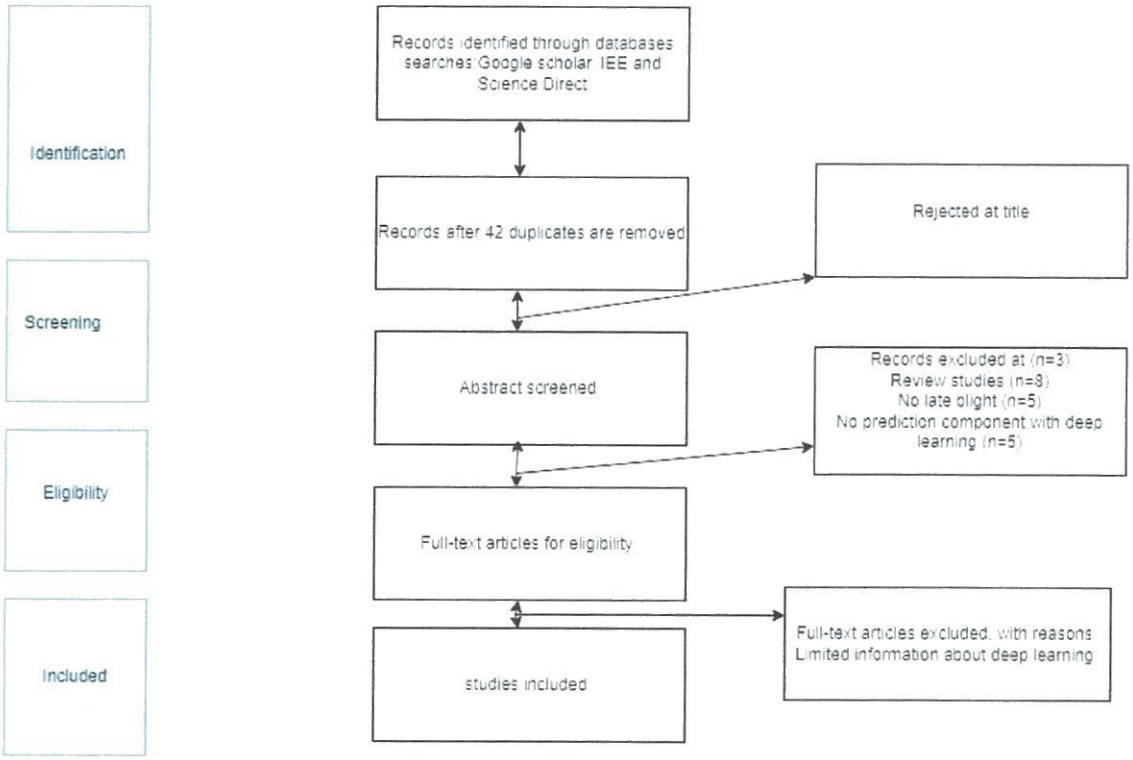



Fig. 3.3: Scoping Review in the literature review

This assisted in identifying the problem and achieve first objective which is to review the state of art available Deep learning models for the prediction and diagnosis of late blight disease in Irish potatoes. Identifying the problem and motivation is the step of the design science research methodology.

### 3.2.6 Objective two

To design an AI model for early prediction and accurate diagnosis of late blight disease in Irish potatoes. According to design science methodology design and development, the stage began with this objective.

#### 3.2.6.1 Design and Development of sub-model one

The evaluation of ten deep learning architectures on two datasets one from Plant Village and another was a local dataset from Kigezi to get the baseline model. This helped to define the objective and solution of the first sub model of the entire model and step two of the design science methodology. After identification of the Baseline model, a series of experiments were done using a local dataset from Kigezi-Uganda. These aided transfer learning and hyper-parameter tuning to be done thus a final optimized MobileNetV2 Deep learning model. In the development of the first sub model different stage of Design Science were used , that is, defining the objective of the solution which to prediction if the leaf is health or unhealthy and this is the primary role of the Baseline model, design and development this was done using the evaluation of the ten deep learning model, transfer learning and hyper-parameter tuning.

#### 3.2.6.2 design and development of sub model two

The image analysis process followed in the design of the model. Image acquisition, image pre- processing, image segmentation, and image classification will be considered in model development. We used a Convolutional Neural networks or deep learning techniques to develop a severity classification model. This Model was be tested on data classified as low, medium and High data which determined by Laboratory experiments. This stage was followed to develop the model are summarized in the diagrammatic representation of the deep learning pipeline that will be followed in this research.

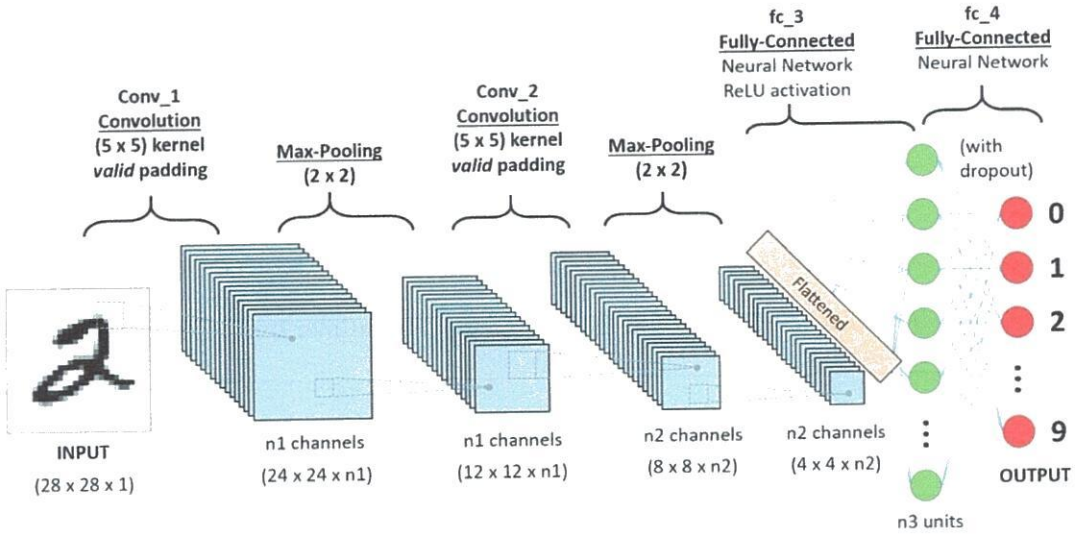



Fig. 3.4: The diagram showing the the deep learning pipe line

A deep learning pipe line which is a regulated version of a multilayer perceptron and consists of an input layer, hidden layers, and an output layer. The model took in an input as an image, produce output and predict whether the severity is low, medium or high.

#### 3.2.6.3 Adaptation and customization of the OpenWeather API(sub-model three)

This was adaption and customized to supply weather data which includes temperature, humidity, and wind speed—which the system's API accesses to enhance predictions. Late blight thrives in humidity , moderate conditions (10-25°C), so this data is critical and humidity raising to more than 90% and a wind speed of 1-5.5 m/s. The customization was done to determine if it the condition favor low , medium or high late blight severity rate.

The API requests this information for the plant's location and forwards it to the Final Prediction Model.

### 3.2.7 Building the Final model and integrating it with a mobile phone

Using the design science research methodology, I clearly demonstrated how the artifact is being developed. The model built using Python. It followed the system design development life cycle and specifically using Joint application development methodology was adopted. The model integrated into a mobile application innovation using flutter for testing purposes and evaluation by agricultural extension workers around the Kigezi Region.

### 3.2.8 Objective three

To test and evaluate the developed models for early prediction and accurate diagnosis of Late blight disease. Evaluation was done at this stage according to the design science methodology.

#### 3.2.8.1 Evaluation of sub-model one

The confusion matrix aided the evaluation and below is the diagram of the confusion matrix.

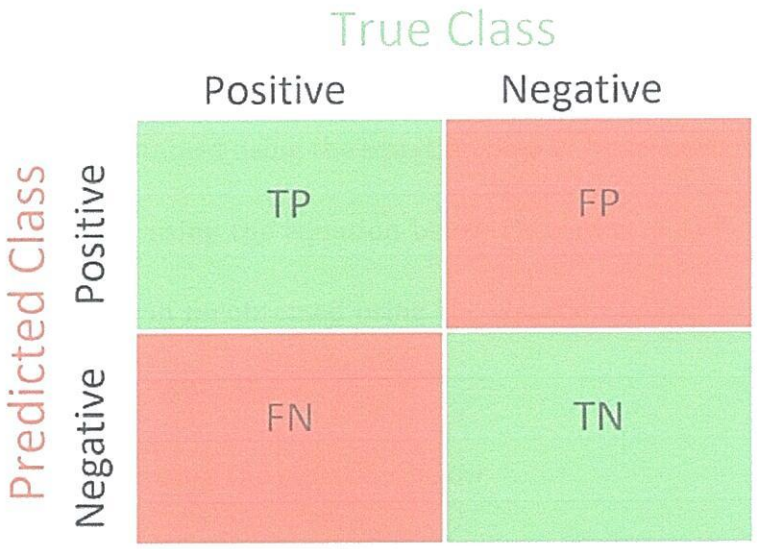



Fig. 3.5: The diagram showing the confusion matrix

The confusion matrix has two classes that is the true class and the predicted class. TP stand for True positive, FP stands for False Positive, FN stand for False Negative and TN is true True Negative. The results were obtained through experimenting with two season of Irish Potatoes in Kigezi. The results were further be processed using the equations below; The actual positive (P) will be calculated using the equation P = Actual positive = TP + FN The actual predicted positive (P1) will be calculated using the equation P1 = Predicted positive =TP + FP The Actual negative (N) will be calculated using the equation N = Actual negative = FP + TN The Predicted negative (N) will be calculated using the equation N1 = Predicted negative =FN + TN The result above will further help to calculate the Accuracy, Misclassification, Precision, Recall (sensitivity) ratio, F1-Score, False Positive rate [57] Accuracy can be obtained using the equations below; Let T=W in the equations below

Accuracy = (WP + WN) / (P + N) Alternatively Accuracy can be calculated as shown below; Accuracy = WP / (P + N) + WN / (P + N)

Another alternative of calculating accuracy is as shown below;

Accuracy = WP / P * P / (P + N) + WN / N * N / (P + N)

Misclassification will be obtained using the equation below. Misclassification = FP+FN/WF

Precision will be obtained using the equation below Precis ion = WP/WP+FP

Recall (sensitivity) ratio will be obtained using the equation below

Recall (sensitivity) = WP/WP+FN

F1-Score will be obtained using the equation below

F1-Score = F1 = 2 * (precision * recall) / (precision + recall)

False Positive rate will be using the equation below False Positive = FP/FP+WN

Thc rcsults of Accuracy, Misclassification, Precision, Rccall (scnsitivity) ratio, F1-Scorc, False Positive rate helped in evaluation of the deep learning model.

#### 3.2.8.2 Evaluation of Sub-model 2

The severity of the plant will first be tested and evaluated by agriculture extension workers by assessing the severity of disease on Irish potato plants by visually inspecting the leaves and assigning scores based on the extent of infection. This helps quantify disease impact and guide management decisions. Below is a step-by-step, user-friendly guide to manually calculate the Disease Severity Index (DSI).

Step 1: Choose a Disease Severity Scale Select a rating scale that fits your assessment needs. Common options include:

0-4 Scalc

0 = No symptoms

1 = Slight infection (<10% leaf area affected)

2 = Moderate infection (10-25%)

3 = Severe infection (25-50

4 = Very severe infection (>50

0-9 Scale (More Detailed)

Each number corresponds to a specific percentage range (e.g., 0 = 0%, 1 = 1-5%, 2 = 6-10%, etc.).

Percentage Scale (Direct Estimation) Visually estimate the exact percentage of leaf area affected.

According Cooke J.W the 0-4 scale is recommended because of the following reasons;

Fewer classes (0-4) for rapid field assessment, used for late blight (Phytophthora infestans) on potatoes where finer distinction are unnecessary for practical management and with advantages of being faster, less training required , suitable for large-scale surveys. This is also supported by FAO (Food and Agriculture Organization) guidelines for potato late blight to use 0-4 scale in farmer-field schools due to simplicity.

Leaf evaluation collected using the 0-4 scale and was evaluated against the Deep learning powered Smart mobile Irish Potato Pathology Lab [58].

#### 3.2.8.3 Evaluation of Sub-model 3

The OpenWeather was evaluated using the validation of temperature, humidity and weed speed against the real time thermometer results for temperature, hygrometer for humidity and Anemometer for wind speed. 3.4 Ethical Issues.

The researcher requested for authorization for data collection from the farmers who

own Irish potato gardens through presenting to them a consent form which in two languages, that is, English and Runyakole-Rukiiga. The farmer who consented to the form was enrolled on to the study and the researcher under the guidance of the sub-county agriculture officer and a crop scientist collected image data from the Irish potato garden and later there was the second phase of data collection collecting images of low, medium and high severity level and testing and evaluation of the model was done through extending it to mobile application which was used in gardens in the two seasons. The data of the farmers and extension workers was kept confidential and only used for educational purposes.

The participant in the study had a right to refuse or withdraw from the study and any time he or she wishes to. The participant who participant in the study had a right to his entitlement and if he or she withdraws the entitlement would remain. The Area of the study was Kigezi Region covering three districts of Rubanda, Kisoro and Kabale. The entry point of the three districts was through seeking authorization from the Chief Administrative who introduced the researcher to the District Agricultural Officer of Kabale , Kisoro and Rubanda who introduced the researcher to the district sub-county extension Agricultural officer who introduced the researcher to the farmer who owned Irish potato gardens.

Risk Management; The research team ensured that during the study all risks are taken care of, that is, transfer of diseases from one garden to another. Standard operating procedures were followed for example. A basin was carried with a Jerri can of water mixed with a disinfectant to ensure cleaning of the gum boots of the research and extension workers and the crop scientist before and after visiting the garden of Irish potatoes. Phones and other devices used in the study were disinfected using a sanitizer. The carrying of any part of the plant(plant leaves) was done using zip-locks in a cooler case to preserve and also avoid transfer of diseases.

# CHAPTER 4

# A review of Deep learning models for prediction and diagnosis of late blight disease in Irish potatoes: A Systematic literature Review

## 4.1 Chapter Overview

This chapter presents paper 1 which is a contribution to achieve objective one.To establish requirements to develop an AI model for early prediction and diagnosis of late blight disease in Irish potatoes.. This is comprised of the abstract, introduction, methods,search strategy,study selection Criteria, exclusion Criteria, Data extraction and analysis,Results,Discussion Conclusion and Declaration of conflict of interest and references.

## 4.2 Introduction

Global food security requires addressing hunger (UN SDG 2) and sustainable agriculture (SDG 12) by reducing crop losses from pests and diseases. Early detection of diseases like potato late blight enables timely interventions (e.g., pesticides, seed selection), boosting productivity. Traditional disease identification relying on human vision and farmer experience is often inaccurate. While AI-based models exist, those in East

Africa lag in accuracy compared to global counterparts. Improved detection systems are critical to support smallholder farmers, minimize yield losses, and align with sustainable development goals. Collaborative efforts must enhance local technologies to match international standards, ensuring efficient disease control and food production.

## 4.3 Literature review

A wide range of studies have explored deep learning models for the prediction and detection of late blight disease in potatoes, utilizing diverse datasets, architectures, and environmental variables. Despite impressive accuracy levels across many models, significant limitations remain—particularly in terms of environmental contextualization, real-time diagnosis, and explainable artificial intelligence (XAI).

Toroitich et al. (2019) employed Support Vector Machine (SVM) and Simcast models using a dataset of 836 images from Kenya, achieving 93% accuracy (Precision: 0.949, Recall: 0.968, F1-score: 0.964). Although the study considered humidity and temperature, it did not incorporate wind speed—an important environmental variable—and lacked diagnostic feedback or explainability features, resulting in a 7% accuracy gap. Islam et al. (2019) explored several models, including VGG16 (99.43%), CNN (98.32%), and RGB/Hyper Spectral imaging (95%). Despite high accuracy, the focus remained on prediction, with limited emphasis on diagnosis and real-time application. Wind speed and XAI were also not considered, with accuracy gaps ranging from 0.57% to 14.02%. Muthuraja et al. (2023) used an ensemble model combining Inception V3 and ResNet152V2, achieving up to 99.54% accuracy. However, the study did not explore a broader range of architectures or XAI. Similarly, Singha et al. (2023) achieved 98.29% accuracy with a web-based model, though a mobile-based context was deemed more appropriate for regions like Kigezi. Feng et al.(2023) focused on temperature and hu-

midity using PlantVillage data, reaching 95.6% accuracy. The study lacked severity classification and overlooked lesion observation, suggesting feature extraction is critical. Aliyu et al. (2019) achieved 95.6% and 98.2% accuracy in symptom and necrotic identification respectively, but ignored environmental factors and XAI.Several other studies demonstrated similar shortcomings: Rabbia et al. (97.2%)(2023), Choyon (97.2%), and Mohemed et al. (98.94%) failed to incorporate environmental features or explainable AI.Subramanya et al. (2023), Kumar et al. (2022), and Vadivel et al. (2022) omitted critical environmental variables like temperature and humidity, despite their accuracies ranging between 97% and 99%.Barman (2020) and Joseph et al. (2022) also ignored environmental parameters and had limited model interpretability. Models such as those by Asif et al. (2020) and Sharma et al. (2021) struggled with larger accuracy gaps (15.17% and 7.1%, respectively), largely due to small datasets and limited environmental consideration. Similarly, Faria et al. (2023), Kang et al. (2022), and Esther et al. (2024) achieved moderate accuracy but overlooked both XAI and critical ecological parameters. More recent efforts show a trend toward accuracy improvements through CNN and hybrid models. For instance, Murtaza et al. (2024) and Wang and Su (2024) both achieved 98.14% using improved CNNs, while Ahmed et al. (2024) and Ponnuru & Amasala (2024) surpassed 99.5%. However, these models still lacked environmental integration and explainability. Radwan et al. (2024) uniquely incorporated environmental data but still did not include XAI or real-time diagnostics. Mir et al. (2024) and Regotra & Kumar (2024) reached 95.17% and 99.79% respectively, using CNN and hybrid models such as Alexnet, yet also lacked environmental depth and explainability. Finally, Damyanov et al. (2025) utilized historical meteorological data (temperature, humidity, dew point, precipitation) with LightGBM, achieving only 74% accuracy—highlighting the difficulty of balancing environmental realism and predictive performance."

## 4.4 Methodology

### 4.4.1 Scoping review methodology

The scoping review methodology approach by Arskey and O'Malley comprised of six key steps; i) identifying the question ii) identifying relevant studies; iii) study selection iv) charting data v) collating, summarizing and reporting results and vi) consultation guided this review [13]. The methodology was adopted for this review because it enables researchers to obtain a quick overview of the existing literature on the research topic [19] the East African accuracy of 93% and other countries such Bangladesh [59] with 99.43% of accuracy.

#### 4.4.1.1 Identification of studies

This review was carried carefully with a sensitive search strategy in order to identify, screen and analyze all studies that discussed the deep learning model for early prediction and diagnosis of late blight disease in Irish potatoes. Articles published between 2000 and 2025 were reviewed. This is because many of the Many scholars started AI-relevant research since the end of 20th century that, is 2000 [42].

#### 4.4.1.2 Search Strategy

Google Scholar, IEEE Xplore and Science Direct databases were searched in February 2025 and March 2025 because of their highly indexing and integration capacity. The search focused on identifying research articles that contained information about deep learning models for prediction and diagnosis of late blight disease in Irish potatoes. The following terms were used to determine the eligibility of the studies. Research articles related to the three key terms were search "Deep learning", "Irish potatoes" and

"prediction" .Each word was entered as a key word in Google Scholar, IEEE Xplore and Science Direct databases to identify relevant articles to our study. The Boolean search was used to capture the articles related to each single main concept using union ("OR") and the intersection ("AND") of the key concepts of this review. The reference lists of the included studies were screened to get more studies for inclusion in the study. The results from search query from three database (Google Scholar, IEEE Xplore and Science Direct) were uploaded in the endnote X7 Reference manager [50] and were independently accessed for inclusion based on title, abstract and full text. Different opinions about inclusion and exclusion of the studies were discussed among the authors until a general consensus was reached.

#### 4.4.1.3 Study selection Criteria

Studies were included in the review if they met the following criteria.

i.Peer reviewed ii.Full research papers iii.Empirical research (qualitative and quantitative) iv.Clearly explained research methods v.States the measure of accuracy of the model vi.Clearly states the dataset size vii.Explicitly described deep learning models for predicting and diagnosing late blight disease in Irish potatoes. viii.Published between 1st January 2010 and 30th of January 2025 Criteria 1-4 were considered to ensure the reporting of the original and high quality work. Criteria 5 was included to ensure that paper reported model accuracies are exactly recorded and also see which models have the highest levels of accuracy. Criteria 6 was considered to capture the datasets and exactly know the origin of these datasets and thus make evaluate if an East African or Uganda dataset has been used in this review.

Criteria 7 was considered to report the several deep learning models for predicting and diagnosing late blight disease in Irish potatoes.

2.4 Exclusion Criteria The research studies were excluded mainly if their focus was not on the deep learning models that aid in the prediction of late blight disease in Irish potatoes before 2010. Included research studies were tested to ascertain they reported accuracies or dataset size or precision or recall ratio and F1-score of deep learning models. All studies were included irrespective of the study design and geographical location in order to expand the search. 2.5 Data extraction and analysis The following characteristics were extracted author, study name, dataset country of origin, accuracies or dataset size or precision or recall ratio and F1-score of deep learning models [43].

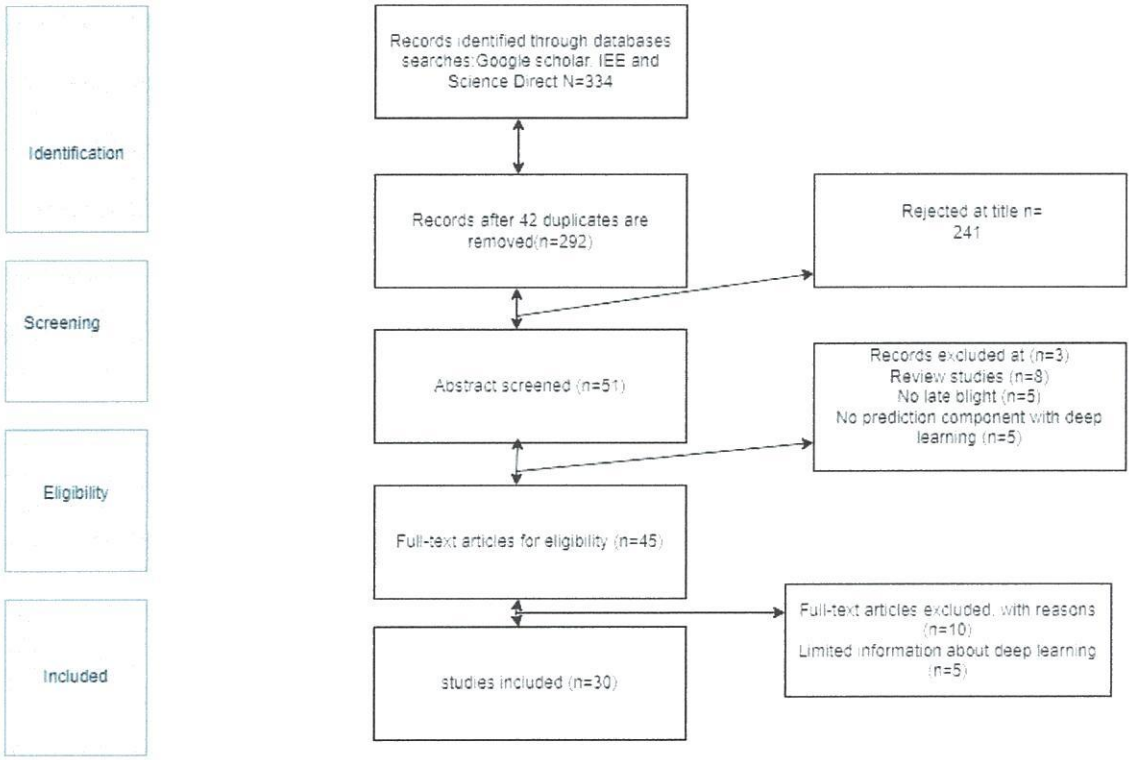



Fig. 4.1: Flow Diagram for included studies

3.0 Results 3.1 Search results Below are the reviewed studies from the database search results, screening, exclusion and final inclusion in the study. The studies described and identified different sampling methods used in deep learning.

Toroitich et., (2019) used the Vector Support Machine and Sim cast approaches and

achieved 93% accuracy precision 94.9%, recall 96.8%, F-measure 96.4%. Dataset 836 images of Kenyan origin. The factors considered were humidity and temperature. These parameters are however not enough to increase to accuracy of Late Blight and real time detection. This study also had limited scope that consider the diagnosis and feedback from the model and left out an important aspect of explainable AI. This helped to show trust and transparency of the Artificial Intelligence model A very important parameter was recommended ,that is, (wind speed). This show an accuracy gap of 7% [19].

Islam et., (2019) utilized VGG16 and achieved 99.43%, CNN gave an accuracy of 98.32%, RGB Imaging gave an 95%, Hyper spectral imaging achieved 95%, transfer learning using Alexnet and GoogleNet 99.35% Rcnn with VGG16 and RESNET50 gave 85.98%. Dataset Origin (Plant Village) although the study achieved high the concentration was on prediction and the aspect of diagnosis was limited and the real-time prediction is also limited. The elements of explainable and Wind speed was recommended.The study showed an accuracy gap range of 14.02% and 0.57% [59].

Muthuraja et al 2023 This study used an ensemble model which combines inception V3 and Resnet153V2 achieved an accuracy of 99.54% and ResNet152V2 achieved an accuracy of 98.78% and the inception model had accuracy of 98.49%. This study considered only three architectures and left out six architectures and a very important aspect of explainable AI . The accuracy gap range 0.46% and 1.51% [60].

Singha et al 2023. The model achieved 98.29% accurancy.This study utilized a web based architecture however contextualizing it with Kigezi a mobile based solution would be more applicable in that context . The aspect of explainable AI was also not considered. The accuracy gap was 1.71%. The environmental factors such temperature and humidity were of considered which are very in the late blight disease life cycle [61].

Feng et al (2023) the achieved 95.6% and recall rate is 96.4 this used parameters such

as temperature and humidity. The dataset used in the study was from PlantVillage. However left out other factor such as classification of the severity and did not consider aspect of explainable AI and whereas temperature and humidity are important the aspect of lesions observation on the leaves was found out to be important thus model with feature extraction techniques recommended. The accuracy gap is 4.4% [62].

Aliyu et al (2019) developed an algorithm to predict late blight. The Dataset was obtained from PlantVillage. The algorithm achieved 95.6%on symptom identification and 98.2% on necrotic identification however the algorithm did not consider the environment factors and had limited aspects of explainable AI . The accuracy gap is 1.8% and 4.4% [62].

Rabbia et al developed a convolutional neural network achieved 97.2% The dataset was from PlantVillage. The model left out environment factors such humidity and temperature and also lack aspect of explainable AI. The accuracy gap is 2.8% [63].

Choyon (2023) developed a convolutional neural network using a sequential model. The dataset was an open-data set. The model achieved accuracy of 97.2% and has accuracy gap of 2.8% and did not consider environmental factors such as temperature and humidity and also has limited aspects of explainable AI [64].

Mohemed et al (2021) developed a smart proactive warning systems. The model achieved accuracy of 98.94%. The Dataset set was from Egypt He had an accuracy gap of 1.06% and limited the aspect of explainable AI And did not put into consideration the environmental factors such as temperature and humidity [65].

Subramanya et al (2023) developed a convolutional neural network. The dataset from India. The accuracy was 97%. The model had an accuracy gap of 3% the model didn't consider environment factors such temperature and humidity and the model also did not consider the aspects of explainable AI [66].

Kumar et al (2022) they developed a convolutional neural network. The dataset was from India. The accuracy was 98.52%. The model had an accuracy gap of 1.48% and did not consider environment factors such temperature and humidity which are essential in the agricultural predictions [67].

Vadivel et al (2022) The model accuracy was 99%. The dataset was from India. The study used architectures such Resnet50, Inception V3, VGG16 and VGG19 with transfer learning. The accuracy gap was 1%, and the model did not utilization temperature and humidity which essential in the late blight disease life cycle. The exploration of more architectures was also very important [68].

Barman (2020). A convolutional neural network was used. The dataset was from India. The accuracy of the model was 97.63%. The study had an accuracy gap of 2.37%, the model did not consider environmental factors, that is, humidity and temperature which are essential in the late blight life cycle [69].

Joseph et al (2022) The model achieved 97%. The Dataset was from India. The study used a convolutional neural network. The model had an accuracy gap of 3% and the model did not consider environmental factors such humidity and temperature. There was limited aspects of explainable AI [70].

Asif et al (2020). The Dataset was obtained from Kaggle and the Dataset size was 3000 images. The study used a Convolutional neural network based disease detection Approach on potato leaves. The model achieved accuracy of 84.83%.The model had an accuracy gap of 15.17%, and the model did not consider environmental factors like temperature and humidity [71].

Sharma et al (2021). The used classification of diseased potato leaves using machine learning. The dataset was from PlantVillage and the Dataset size was 1000 images. The model had an accuracy gap of 7.1%. The model did not consider environmental factors

such as temperature and humidity which are important in the late blight disease life cycle [72].

Faria et al (2023). The study utilized a hybrid deep learning framework. The dataset used in the study a public dataset from Bangladesh. The accuracy is 92.9%. The accuracy gap is 1%. The model did not consider environmental factors such temperature and humidity and the severity aspect was left out. There is also limited consideration of explainable AI [73].

Kang et al 2022. The dataset was from plant village and the Dataset size was 5450 images. The model achieved 93% accuracy. The model utilized a light weight neural network- based method for identifying late blight disease. The model had an accuracy gap of 7%. The model did not consider environmental factors such as temperature and humidity and lacked an aspect of explainable AI [74].

Arora et al (2024). The dataset was from India and the Dataset size was 1152 images. The model achieved 99.1% accuracy. The model utilized a convolutional neural network. The model had an accuracy gap of 0.9%. The model did not consider environmental factors such as temperature and humidity and lacked an aspect of explainable AI [75].

Esther et al (2024). The dataset was from Nigeria and the Dataset size was 448 images. The model achieved 72% and 96%. The study utilized a multi-criteria classification model. The model had an accuracy gap of between 28% and 4%. There was a limited aspect of real-time prediction and diagnosis and lacked the aspect of explainable AI [76].

Damyanov et al (2025). The dataset was from plant village and the Dataset size was made up of historical meteorological data (temperature, humidity, dew point and precipitation). The model achieved 74% accuracy. The model utilized Machine learning models such as LightGBM for identifying late blight disease. The model had an accuracy gap of 26%. The model did real- time leaf prediction and diagnosis and limited

aspect of explainable AI [77].

Murtaza et al (2024). The dataset was from plant village and the Dataset size was 54303 images out of these images 2,152 images were potatoes images. The model achieved 98.14% accuracy. The model utilized an improved convolutional neural network. The model had an accuracy gap of 1.96%. The model did not consider environmental factors such as temperature and humidity and lacked an aspect of explainable AI [78].

Wang and Su (2024). The dataset was from plant village and the Dataset size was 54303 images out of these images 2,152 images were potatoes images. The model achieved 98.14% accuracy. The model utilized an improved convolutional neural network. The model had an accuracy gap of 1.96%. The model did not consider environmental factors such as temperature and humidity and lacked an aspect of explainable AI [79].

Ponnuru and Amasala (2024). The dataset was from plant village. The model achieved 99.59% accuracy. The model utilized an improved convolutional neural network. The model had an accuracy gap of 0.41%. The model did not consider environmental factors such as temperature and humidity and lacked an aspect of explainable AI [80].

Ahmed et al (2024). The dataset was from plant village. The model achieved 99.5% accuracy. The model utilized four pre-trained CNN architectures ResNet-50, GoogleNet, AlexNet and VGG19. The model had an accuracy gap of 0.5%. The model did not consider environmental factors such as temperature and humidity and limited aspect of explainable AI. [81]

Radwan et al (2024). The dataset was from plant village. The model achieved 98.3% accuracy. The model utilized Machine learning algorithms like K-means clustering. The model had an accuracy gap of 1.7%. The model considered environmental factors such as temperature and humidity, limited aspect of explainable AI and real-time prediction on the plant leave [82].

Saffer and Saville 2024. The dataset was from plant village. The model achieved 99.59% accuracy. The model utilized an improved convolutional neural network. The model had an accuracy gap of 0.41%. The model did not consider environmental factors such as temperature and humidity and limited aspect of explainable AI . [83]

Mir et al (2024). The dataset was from India. The models achieved accuracy of 95.17%. The utilized the Convolutional neural network and Support Vector Machine. The model had an accuracy gap of 4.%. The model did not consider environmental factors such as temperature and humidity and lacked an aspect of explainable AI [84].

Regotra and Kumar (2024). The dataset was from India. The models achieved accuracy of 99.79%. The utilized the Convolutional neural network architectures VGGNet-16, Resnet-50 and YOLOv8. The model had an accuracy gap of 0.21%. The model did not consider environmental factors such as temperature and humidity and limited aspect of explainable AI [85].

### 4.4.2 Discussion of the requirements and recommendations

To enhance the effectiveness of deep learning models for early prediction and diagnosis of late blight disease in Irish potatoes, it is essential to evaluate the ten most commonly used deep learning architectures, that is EfficientNet, Inception V3, MobileNet V2, ResNet 50, VGG16, VGG19, Xception, AlexNet and GoogleNet.

This evaluation helped identify a reliable baseline model capable of supporting real-time prediction. Such a baseline can be used to benchmark performance and guide future model enhancements.

Incorporating environmental factors like temperature, humidity, and wind speed is also critical in the early prediction and diagnosis of late blight disease. These factors were recommended to added unto the baseline model to get a more accurate diagnosis and

prediction.

These variables have a significant influence on disease onset and progression and therefore can greatly improve the predictive accuracy of the model when integrated as input parameters.

Furthermore, the model should be designed not only to detect the presence of late blight but also to classify its severity into categories such as low, medium, and high. This stratified diagnosis allows for more targeted interventions and better resource allocation for disease management.

In addition, explain ability must be prioritized by incorporating post-hoc methods such as Local Interpretable Model-Agnostic Explanations (LIME).

LIME enables users especially farmers and agricultural experts to understand and trust the model's predictions by revealing the rationale behind each decision.

This fosters user confidence and aids in translating AI insights into actionable on-ground practices.

### 4.4.3 Conclusion

To enhance early prediction and diagnosis of late blight disease in Irish potatoes, it is essential to evaluate the top ten deep learning architectures to establish a reliable baseline model for real-time prediction. Integrating environmental factors like temperature, humidity, and wind speed can significantly improve model accuracy. Additionally, classifying the severity of the disease into low, medium, and high enables more precise interventions. To ensure transparency and trust, applying explainable AI techniques such as Local Interpretable Model-Agnostic Explanations (LIME) helps users understand model predictions, making the solution more practical and adoptable for farmers

and agricultural experts.

### 4.4.4 Recommendation

The study recommended a model with three sub model, that is, the baseline model with real time predictions and sub model 2 which was a classification model to prediction and diagnose the disease as low, medium and high. And sub model 3 which a model to predict the temperature, humidity and wind speed.

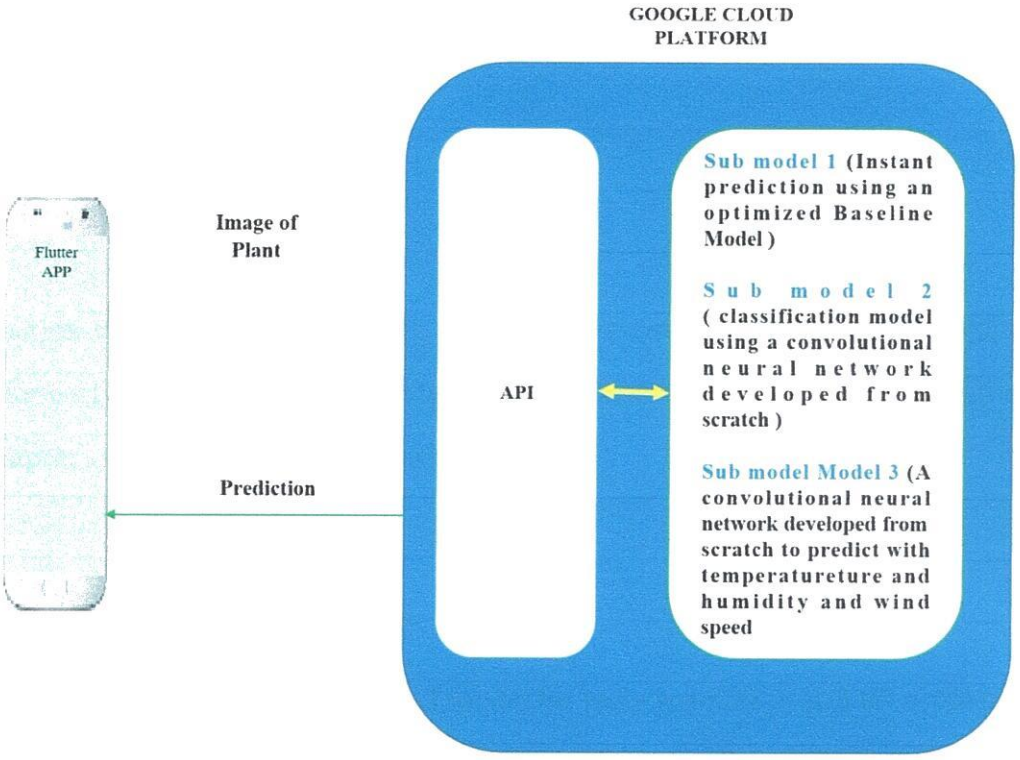



Fig. 4.2: The diagram shows the model that was recommended for design and development

# CHAPTER 5

# Evaluation of Deep Learning Architectures for Predicting Late Blight Disease in Irish Potatoes using Plant Village and Kigezi Region-Uganda Datasets:

## 5.1 Chapter Overview

This section contributes to objective two which states; To design and develop an AI model for early prediction and accurate diagnosis of Late blight disease in Irish potatoes. The chapter consists of the Introduction

### 5.1.1 Introduction

In the need to design and develop an AI model for early prediction and accurate diagnosis of late blight disease an evaluation of the ten most used deep learning models was done to obtain a baseline model. And also developed a classification model to classy the disease as low, medium and high. And also developed another model to predict temperature, humidity and the wind speed.

The integration of the design science with Joint Application Development approach was done based on the stage 3 and stage 5 of the design science methodology. Evaluation

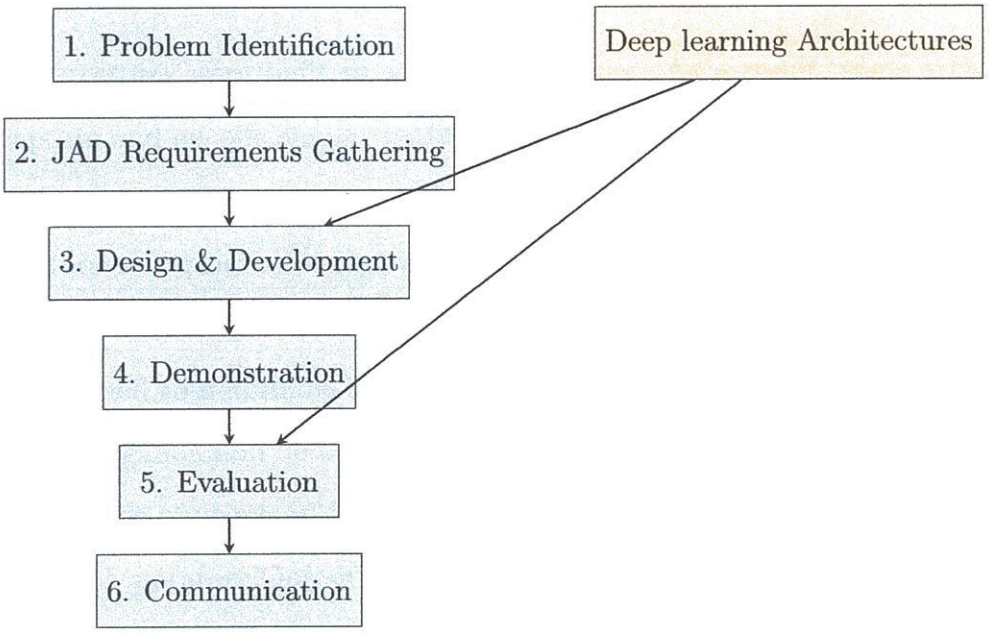



Fig. 5.1: The integration of the design science with Joint Application Development approach

was done to obtain a baseline model which would the design and development that will be done in stage three which is the design and development.

## 5.2 Evaluation of the ten most used Deep learning Architectures

### 5.2.1 Introduction

Research has shown that for the development of a robust and efficient model, pre-training the architectures on large-scale and open datasets is more efficient than training from scratch [86].

There are many architectures pre-trained such EfficientNet, Inception V3, MobileNet V2, ResNet 50, VGG16, VGG19, Xception, AlexNet and GoogleNet each with its various

configurations [87].

These architectures were built to solve similar tasks. As a result, some architectures might capture and encode similar patterns within different levels and allow for further generalization. Nonetheless, it is not clear how well-trained models perform on diseases of Irish potatoes in geographic regions other than the regions in which the training sets for these models were compiled. The aim of this study is to evaluate (CNN) architectures, pre-trained to determine their performance on a dataset from plant Village and Kigezi region-Uganda and determine which model to extend and contextualize to meet the specific needs of people in Kigezi-Uganda on prediction and diagnosis of late blight disease in Irish potatoes.One of the biggest problems threatening crop production is diseases attacking cultivated plants, including Irish potatoes [88]. These diseases can lead to significant losses in the yield of potatoes [89] . Minimizing these losses can be done through timely disease detection and treatment of infected plants. Deep learning (DL) has been utilized for plant disease detection and classification [90]. To this extent, several models are already pre-trained on extensive and diverse image datasets or architectures trained from scratch for tackling specific challenges, such as attaining the highest possible classification performance, etc. The development of the best deep learning prediction model, especially the (CNN), depends on the characteristics of the dataset. That is an essential precondition that needs to be achieved to design an efficient, effective and robust prediction model. The purpose of this paper is to select the best performing architecture for building on to get a more optimized and efficient model. The selected model with optimized using transfer learning and hyper-parameter tuning. Transfer learning with done using layer freezing and hyper-parameter tuning using learning rate, batch size tuning, Optimizer Selection and Epochs and Early stopping.

### 5.2.2 Methodology

The experimentation methodology was used to evaluate the performance of different pre-training deep learning architectures for predicting late blight disease in Irish potatoes and the high-performing architecture is selected to form a basis for building a more efficient and extended model. The first category which deals with some diseases has such a general architecture that the meta-features can obtain a favorable knowledge classification capability in more specific plant disease prediction tasks, even providing accurate prediction without fine-tuning. We conducted different experiments on two datasets, training and validation data (80%–20%), which are two independent leaf image sets collected from Kigezi region, Uganda and another one publicly from Plant Village dataset archive. Deep learning is an artificial intelligence function that enables a machine to mimic the pattern recognition skills of humans. This enables the machines to identify disease symptoms, root causes, and their effects on plants. Evaluation of the model performance is an important stage after building a model [90]. Several architectures including EfficientNet, Inception V3, MobileNet V2, ResNet 50, VGG16, VGG19, Xception, AlexNet and GoogleNet have been pre-trained on Image Net [91].

These architectures were tested on the two datasets by subjecting them to the dataset and graphs. The major parameter that was studied in this study was the accuracy of the model with results of capturing the training accuracy, the validation accuracy and the training loss and validation loss. The general behavior of the model was also captured.

An architecture that gives more satisfactory evaluation results can be chosen for transfer learning. After evaluating the network, we select the best architecture for disease prediction in Irish potatoes and deepen the features on particularities specific to plant diseases generated by the network.

### 5.2.3 Data Collection and Preparation

This work relies mainly on open-source benchmarks and real-world disease datasets [40]. (CNNs) EfficientNet, Inception V3, MobileNet V2, ResNet 50, VGG16, VGG19, Xception, AlexNet and GoogleNet are known to be powerful in the context of image processing and pattern recognition [91]. They have also demonstrated superior performance on large-scale visual recognition challenges and automated recognition of different plant diseases and healthy leaf images. This work pre-trains and evaluates nine CNN architectures EfficientNet, Inception V3, MobileNet V2, ResNet 50, VGG16, VGG19, Xception, AlexNet and GoogleNet on the two widely-used CNN benchmark two datasets ,that is, one from PlantVillage and the other from Kigezi region, Uganda. To achieve the model optimization and validation objective, datasets that are representative of different late blight disease manifestations were used in this experiment including infected and healthy potato leaf images from both Plant Village and Kigezi Region-Uganda. The general template for implementing the deep learning pre-training and transfer learning objective included the following key steps: selecting the efficient deep learning model or architecture, acquiring quality and diverse data representative of real-world applications, evaluating different methodologies to perform optimization and analyzing the learning process and performance, and finally conducting the architecture use case validation. The sampled data were used to train the model while the withheld data were used for validation during the kernel manipulation. The rule dimensions 18 cm x 10 cm was made to reflect the size of the area in between one Irish potato plant to another. Two sets each day, 2 days per plot, for the two concentrations were obtained from the large leaves (upper 4th to 15th leaf) on plants of potato. The sample plants were randomly selected from the rear row of each plant row. Only the right side leaves of the plants were sampled during the study. A total of 1 x 4 x 10 samples per plot. Interaction with the canopy was avoided and each sample taken was clearly labeled and

indexed The data for all eight plots were observed daily for disease evaluation from April 2024 to 2024 December. Presence or absence of P.infestans was visually assessed and recorded as binary data (1 = Late Blight present, 0 = Late Blight absent) at the plant leaf through phonological development stage including vegetative growth, flowering, and tuber development stage was grown directly at the soil in the plantation and ridge respectively. The focus disease was assessment of late blight during the crop growth period. The experiments were carried out on a local dataset from Kigezi, that, the districts of Rubanda. Kabale and Kisoro in kigezi Region-Uganda. Kigezi's local Irish potato dataset of 9,660 images was split using a split ratio of 80:20 into training, validation, and testing subsets with indicated implementations of the training/validation/testing split and model training and evaluation datasets and 80% was training and 20% was testing/validation.

The ten pre-trained architectures EfficientNet, Inception V3, MobileNet V2, ResNet 50, VGG16, VGG19, Xception, AlexNet and GoogleNet were evaluated on both Plant Village and Kigezi Region-Uganda datasets, and the results were compared to identify the most effective approach. The goal was to find out the best-performing architecture for predicting late blight disease in Irish potatoes in both regions.

### 5.2.4 Experimental Setup

The nine pre-trained architectures EfficientNet, Inception V3, MobileNet V2, ResNet 50, VGG16, VGG19, Xception, AlexNet and GoogleNet were evaluated on both Plant Village and Kigezi Region-Uganda datasets, and the results were compared to identify the most effective approach. The goal was to find out the best-performing architecture for predicting late blight disease in Irish potatoes in both regions.

### 5.2.5 Results and Analysis

We present a report of the findings and analysis from running deep learning transfer learning on pre-trained models using a Plant Village late blight disease potato dataset and Kigezi region late blight potato disease dataset. We first describe the datasets and preprocessing pipelines that were employed for preprocessing. The following models were; EfficientNet, Inception V3, MobileNet V2, ResNet 50, VGG16, VGG19, Xception, AlexNet and GoogleNet were used in the experiment. The evaluation of pre-training deep learning architectures for predicting late blight disease in Irish potatoes using the Plant Village and Kigezi Region-Uganda datasets yielded insightful results and analysis.

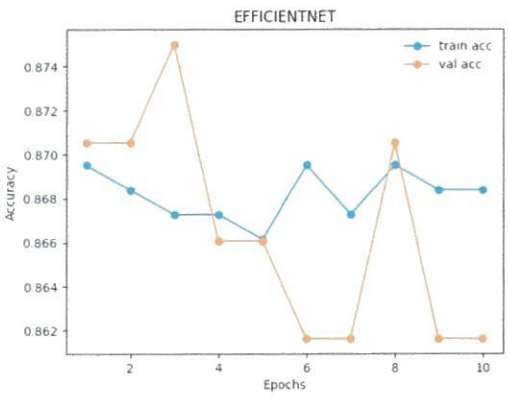
### 5.2.6 The following are the results of an experiment on the dataset from Plant Village, an internet-based repository housing various databases.

#### 5.2.6.1 EfficientNet Deep learning model Architecture

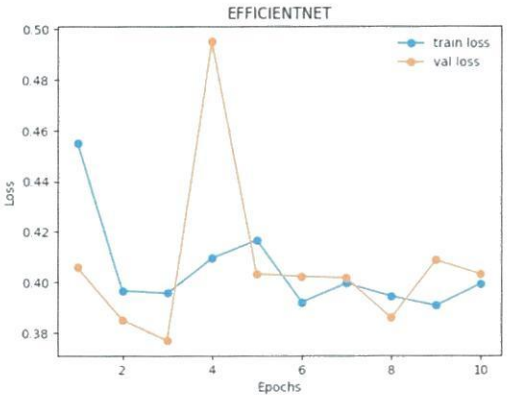
EfficientNet's accuracy was less consistent, with training accuracy around 87% and validation accuracy also around 86-87%. The loss for EfficientNet was more varied, with training loss moving between 0.38 to 0.42 and validation loss also showing irregularities, indicating that the model's predictions were less precise.

#### 5.2.6.2 Inception V3 Deep learning model Architecture

Inception V3 displayed good learning, with training accuracy reaching around 98% and validation accuracy settling at about 94%. The loss decreased well for both training and validation, with training loss going from 0.45 to just above 0.10 and validation



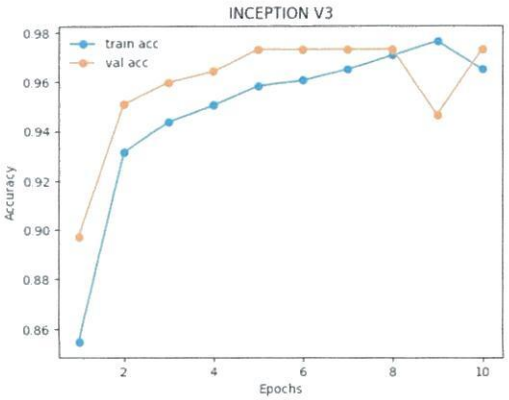

(a) Efficient Accuracy



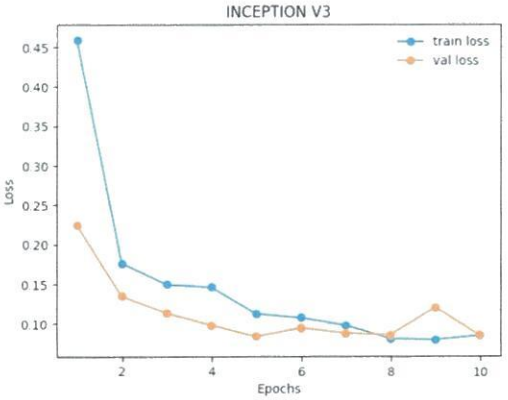

(b) Efficient loss

Fig. 5.2: The figure show (a) which the training accuracy and (b) the training loss

loss decreasing to about 0.15. The consistent reduction in loss indicates the model was making more accurate predictions as training progressed




(a) Inception V3 Accuracy



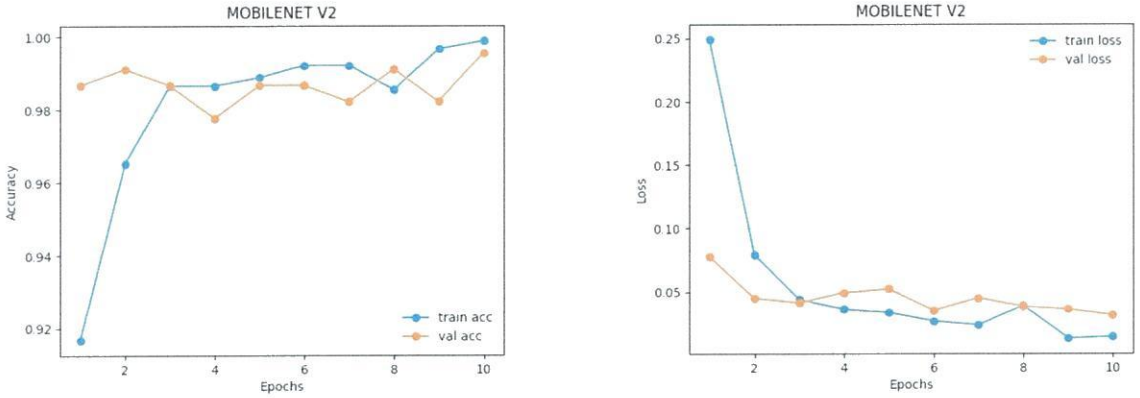

(b) Inception V3 loss

Fig. 5.3: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.6.3 MobileNet V2 Deep learning model Architecture

For MobileNet V2, training accuracy was excellent, almost perfect at around 98-99%, and the validation accuracy was also high at 96-97%. This shows that the model was very consistent. Looking at the loss, it started high at 0.25 but quickly came down and settled at around 0.05 for training and approximately 0.07 for validation. The model's

loss decreased over time and remained low, which suggests that its predictions were very close to the actual results.




(a) MobileNet V2 Accuracy

(b) MobileNet V2 loss

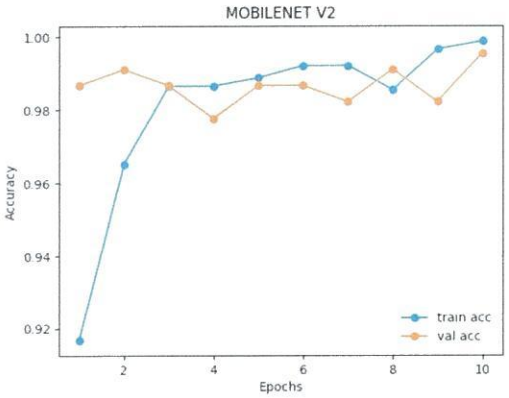
Fig. 5.4: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.6.4 ResNet 50 Deep learning model Architecture

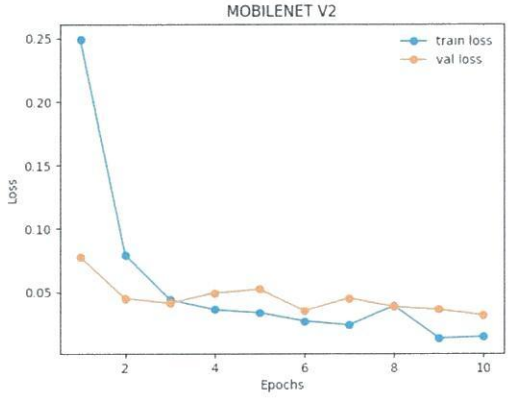
ResNet 50 had a training accuracy of around 86%, while validation accuracy showed some variability, with a low around 81% and high of around 87%. The loss figures show a more varied pattern, with training loss starting at around 0.44 and reducing to about 0.34, while the validation loss had a significant spike, indicating some inconsistencies in how the model handled new data.

#### 5.2.6.5 VGG16 Deep learning model Architecture

VGG16 showed a solid increase in accuracy from the start, reaching about 96% in training and 94% in validation. The loss decreased steadily for both training and validation, with training loss starting at 0.45 and ending around 0.15, and validation loss reducing to about 0.18. This decrease in loss alongside high accuracy indicates that VGG16 was learning effectively and making accurate predictions on new data.

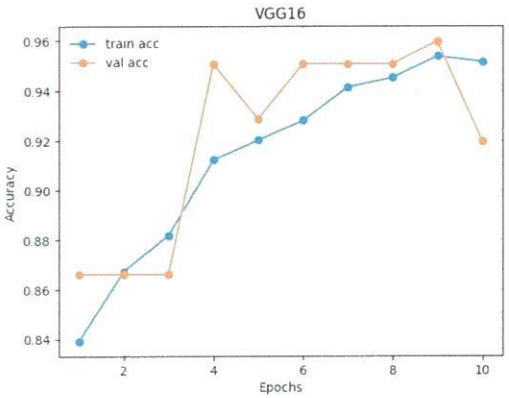



(a) ResNet 50 Accuracy

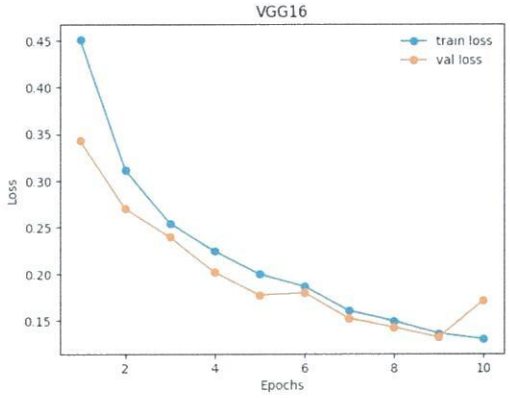



(b) ResNet 50 loss

Fig. 5.5: The figure show (a) which the training accuracy and (b) the training loss




(a) VGG16 Accuracy




(b) VGG16 loss

Fig. 5.6: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.6.6 VGG19 Deep learning model Architecture

VGG19's accuracy climbed quickly to about 96% in training and maintained around 93% in validation. Its loss mirrored this good performance, with a substantial decrease from 0.40 to about 0.15 for training and levelling off around 0.17 for validation. The consistent loss reduction shows that VGG19's predictions became increasingly accurate over time.

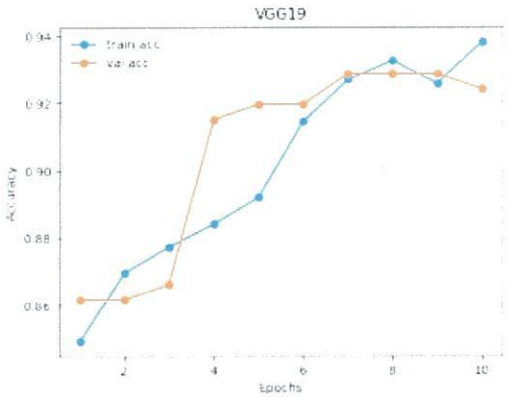



Figure 11: VGG 19 Accuracy

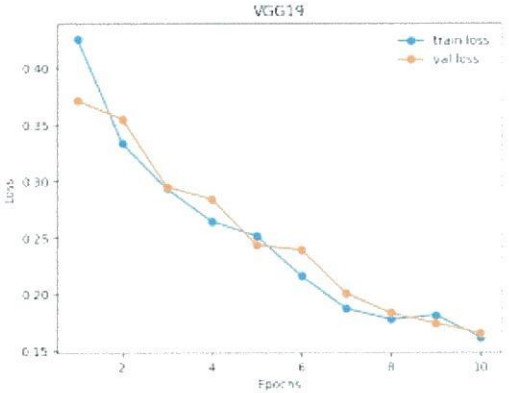



Figure 12: VGG 19 Loss

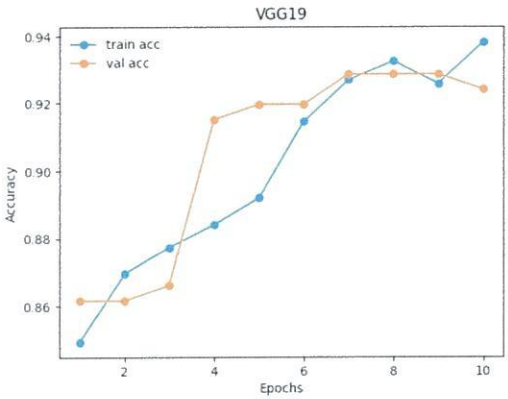
(a) VGG19 Accuracy

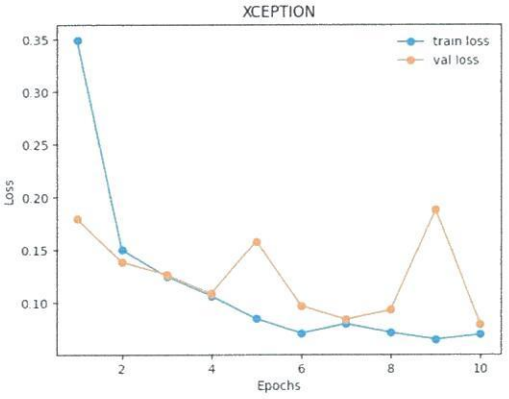
(b) VGG19 loss

Fig. 5.7: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.6.7 Xception Deep learning model Architecture

Xception started with strong accuracy at about 98% for training and 94% for validation. Training loss decreased sharply to around 0.10 and validation loss showed more variability, with a low of around 0.10 and high approaching 0.20. This fluctuation in validation loss suggests that while Xception learned the training data well, its performance on validation was less stable.



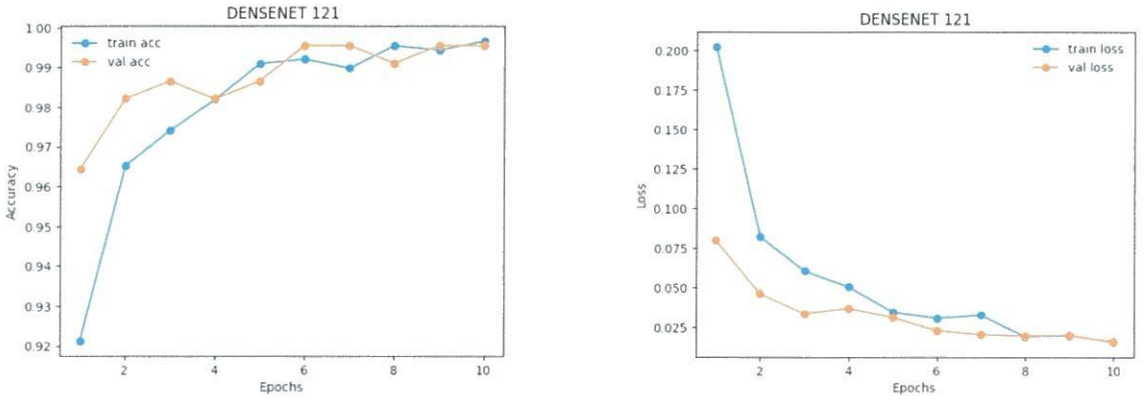

(a) Xception Accuracy

(b) Xception loss

Fig. 5.8: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.6.8 DenseNet 121 Deep learning model Architecture

DenseNet 121 had impressive accuracy rates, starting at 97% for training and quickly reaching nearly 100%, with validation accuracy also starting high at 96% and reaching 99%. The training loss mirrored this excellence, decreasing rapidly to around 0.025 and the validation loss also fell to about 0.05. These low loss values show DenseNet 121 made predictions that were very close to the actual outcomes.



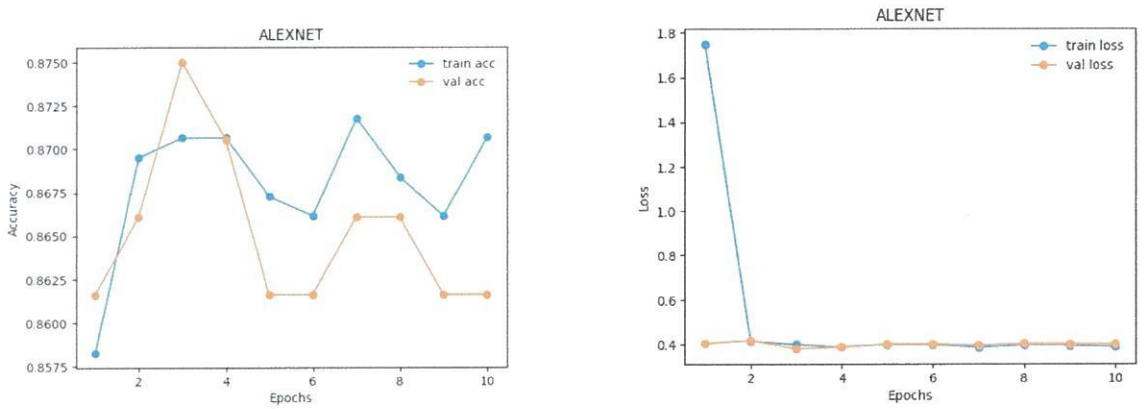

(a) DenseNet 121 Accuracy (b) DenseNet 121 loss

Fig. 5.9: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.6.9 AlexNet Deep learning model Architecture

AlexNet's performance on the Plant Village dataset was underwhelming. The training accuracy hovered around 86-87% with noticeable fluctuations, indicating instability and inconsistent learning. The validation accuracy showed even more variability, which suggests that the model struggled to generalize well to new data. The training loss decreased sharply initially but then remained stable, reflecting that while the model learned from the training data, it did not improve further. The validation loss mirrored the training loss pattern but exhibited more irregularities, which further underscores AlexNet's difficulty in maintaining consistent performance and its tendency towards

overfitting.



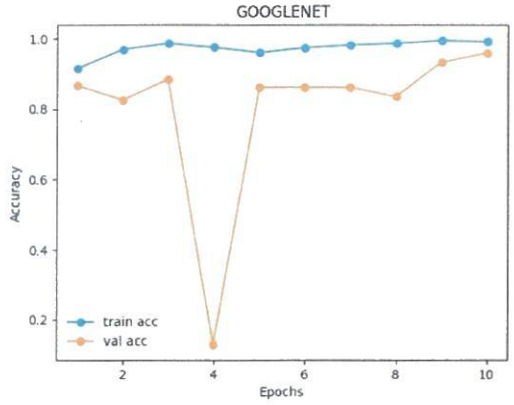

(a) AlexNet Accuracy

(b) AlexNet loss

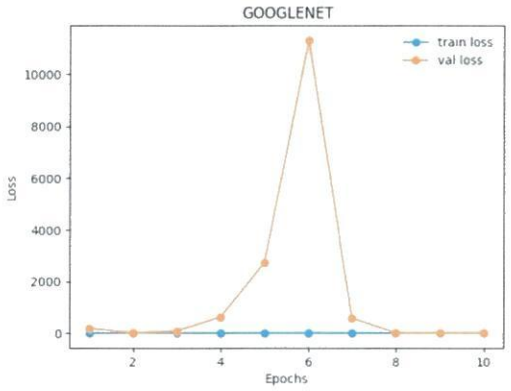
Fig. 5.10: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.6.10 GoogleNet Deep learning model Architecture

GoogLeNet's training accuracy was exceptionally high, close to 100%, but this near-perfect score hints at overfitting, as the validation accuracy experienced significant instability, with a dramatic drop to zero at one point. This severe dip in validation accuracy indicates that the model's ability to generalize was poor and highly unreliable. The training loss remained impressively low, but the validation loss exhibited a massive spike, reaching extremely high values before stabilizing. This behavior highlights GoogLeNet's struggle with overfitting and its inability to handle new data effectively, making its performance on the Plant Village dataset highly inconsistent and unreliable.




(a) GoogleNet Accuracy

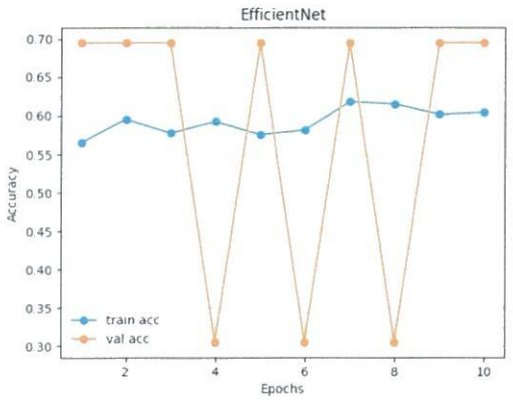



(b) GoogleNet loss

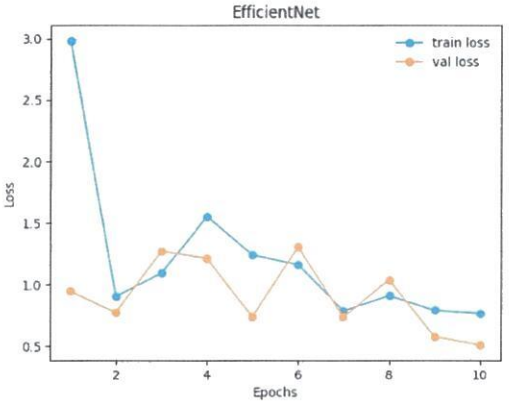
Fig. 5.11: The figure show (a) which the training accuracy and (b) the training loss

### 5.2.7 The following are the results of an experiment on the dataset obtained locally from the Kigezi Region in Uganda

#### 5.2.7.1 EfficientNet Deep Learning Model on Local data




(a) EfficientNet Accuracy on local data




(b) EfficientNet Loss on local data

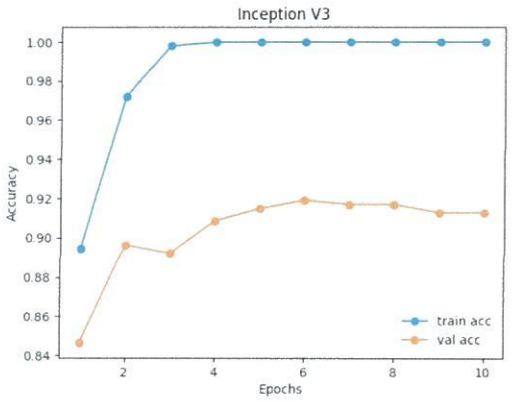
Fig. 5.12: The figure show (a) which the training accuracy and (b) the training loss

EfficientNet showed average performance during training, with accuracy scores settling around 65%. However, it didn't do well on new data, with the accuracy sometimes dropping as low as 35%. Looking at the loss — which is a measure of how much the model's predictions differ from the actual results — it improved over time in training

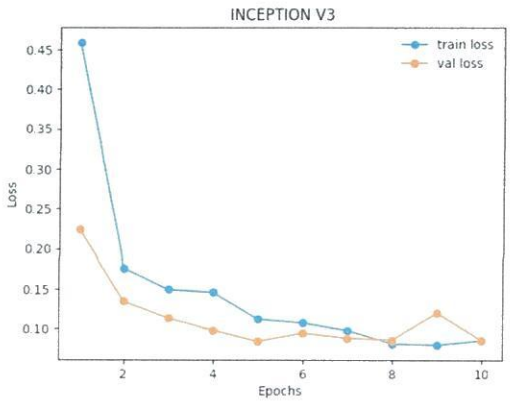
but had large swings during validation, moving between values as high as 3.0 to as low as 0.5. This big difference suggests that the model might be memorizing the training data too much and not really learning the broader patterns needed to do well on data it hasn't seen before.

#### 5.2.7.2 Inception V3 Deep Learning Model on Local data

Inception V3 was a quick learner, reaching near-perfect accuracy in training close to 100%, but it only reached about 90% on the new data. The loss decreased sharply in training to almost 0, while in validation, it dropped to about 0.3 but with some slight ups and downs. This behavior tells us that while the model learned the training data very well, it may not be as effective when it encounters new data and a classic sign of overfitting.




(a) Inception V3 Accuracy on local data



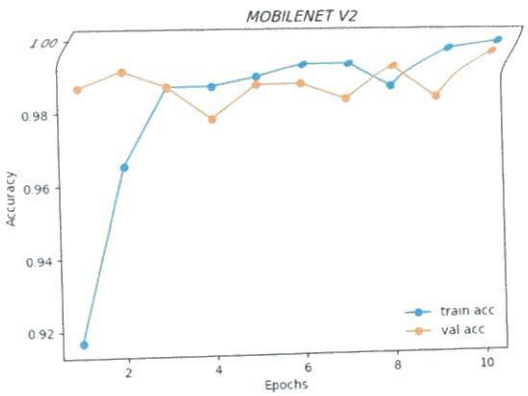

(b) Inception V3 Loss on local data

Fig. 5.13: The figure show (a) which the training accuracy and (b) the training loss

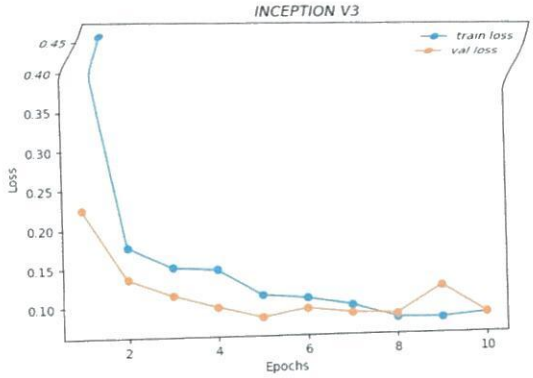
#### 5.2.7.3 MobileNet V2 Deep Learning Model on Local data

MobileNet V2 performed very well, with the training accuracy climbing to around 98% and the validation accuracy not far behind at about 95%. The loss during training fell

to a little over 0.05, and for the validation, it decreased overall, although it did go up and down a bit, ending around 0.15. These consistently high scores for accuracy and the generally low loss for both training and new data make it clear that MobileNet V2 not only learned the training data well but could also apply what it learned to new, unseen data. *This balance is why it was chosen as the best model.*




(a) MobileNet V2 Accuracy on local data

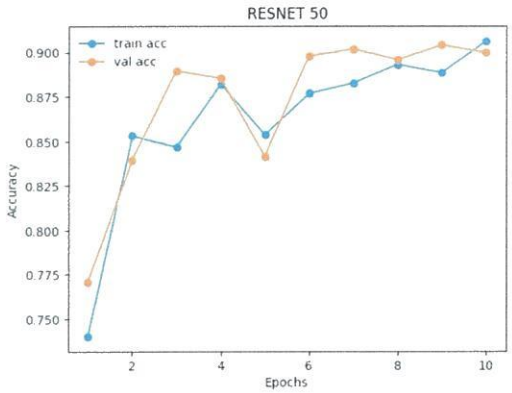



(b) MobileNet V2 Loss on local data

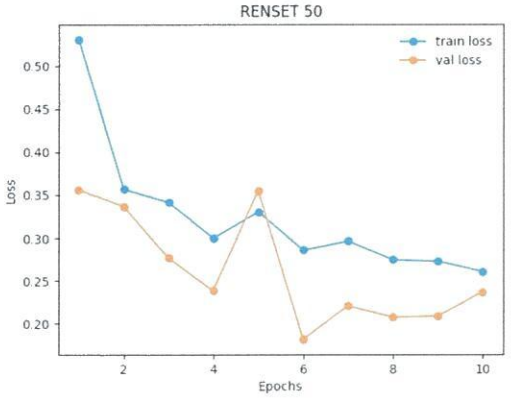
Fig. 5.14: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.7.4 ResNet 50 Deep Learning Model on Local data

*ResNet 50 did a good job learning, with* training and validation accuracies going above 85% and 87%, respectively. The loss numbers show a similar trend: the model's predictions got steadily closer to the actual results, with training loss decreasing to about 0.2 and validation loss reaching around 0.25, despite some variability. These numbers reflect a solid performance in learning that is not overly specific to just the examples it was trained on.




(a) ResNet 50 Accuracy on local data

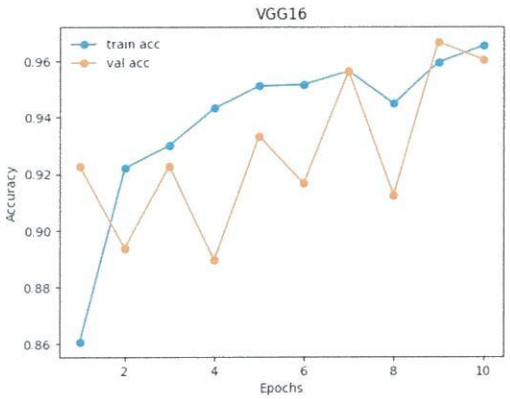



(b) ResNet 50 Loss on local data

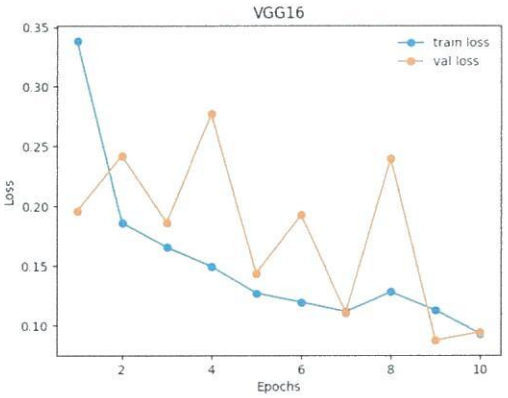
Fig. 5.15: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.7.5 VGG16 Deep Learning Model on Local data

VGG16 consistently showed strong training accuracy, staying above 94%, while its performance on new data was also high, although it varied more, generally staying in the high 90th percentile. The training loss dropped significantly to under 0.1, and the validation loss also trended down, despite some peaks, finishing around 0.2. This pattern indicates that VGG16 was good at learning and also quite stable in handling new data, despite a few bumps along the way.




(a) VGG16 Accuracy on local data

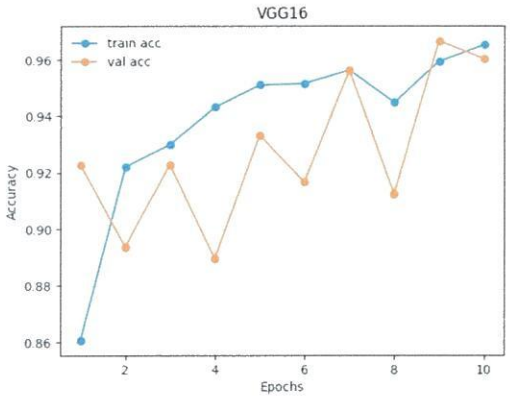



(b) VGG16 Loss on local data

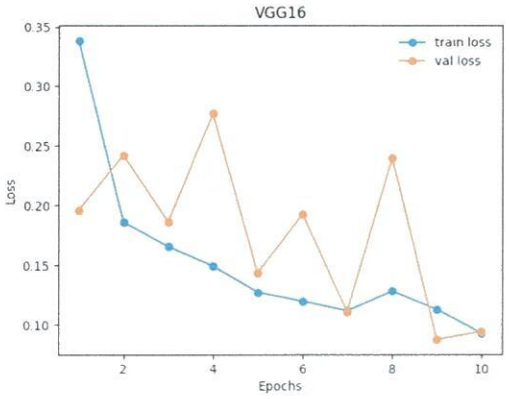
Fig. 5.16: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.7.6 VGG19 Deep Learning Model on Local data

VGG19 almost perfected the training with accuracy nearly reaching 100% and kept its performance strong on new data with accuracy around 93%. In terms of loss, the training loss dropped almost to zero, and the validation loss followed a steady downward path to stabilize at a low of around 0.1. The low and stable validation loss signals that VGG19 not only learned the training data but was also excellent at predicting new data, which is a key strength




(a) VGG19 Accuracy on local data

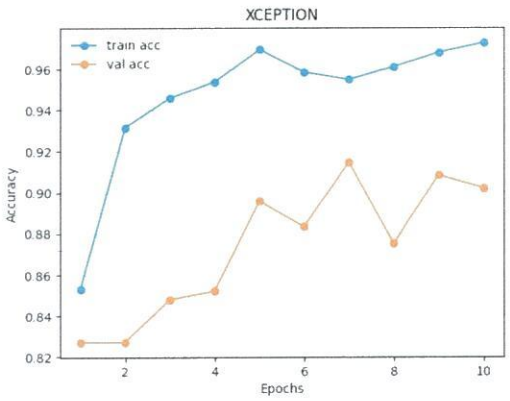



(b) VGG19 Loss on local data

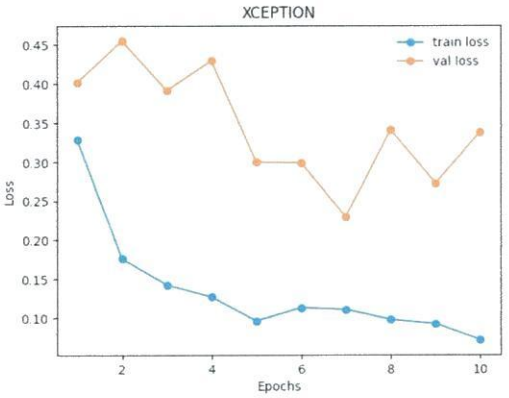
Fig. 5.17: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.7.7 Xception Deep Learning Model on Local data

Xception did well in the training phase, with accuracy scores around 96%, and its ability to handle new data improved over time, with validation accuracy settling at about 92%. The loss for training consistently went down to around 0.1, but the validation loss saw some ups and downs, averaging out at about 0.25. These numbers suggest that Xception was a solid learner, and although it was not as stable as some other models with new data, it was still pretty reliable.




(a) Xception Accuracy on local data

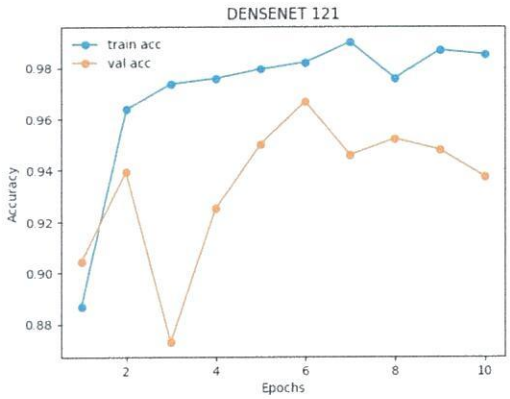



(b) Xception Loss on local data

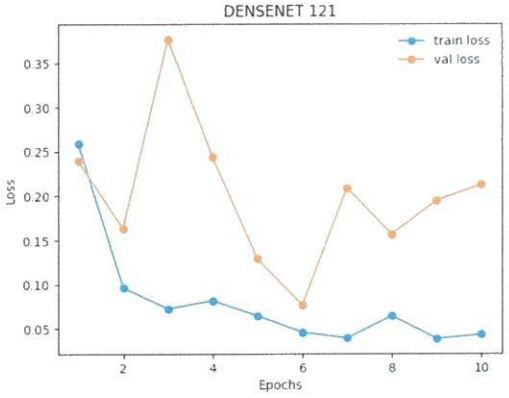
Fig. 5.18: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.7.8 DenseNet 121 Deep Learning Model on Local data

DenseNet 121 had high training accuracy around 98% and validation accuracy around 94%, showing it was able to learn well and maintain that learning with new data. The training loss decreased quickly to near 0.05, and the validation loss had some jumps but generally went down, averaging around 0.15. These consistent and high accuracy scores, paired with the loss trends, demonstrate that DenseNet 121 was efficient at learning and quite good at generalizing that learning to new situations.




(a) DenseNet 121 Accuracy on local data

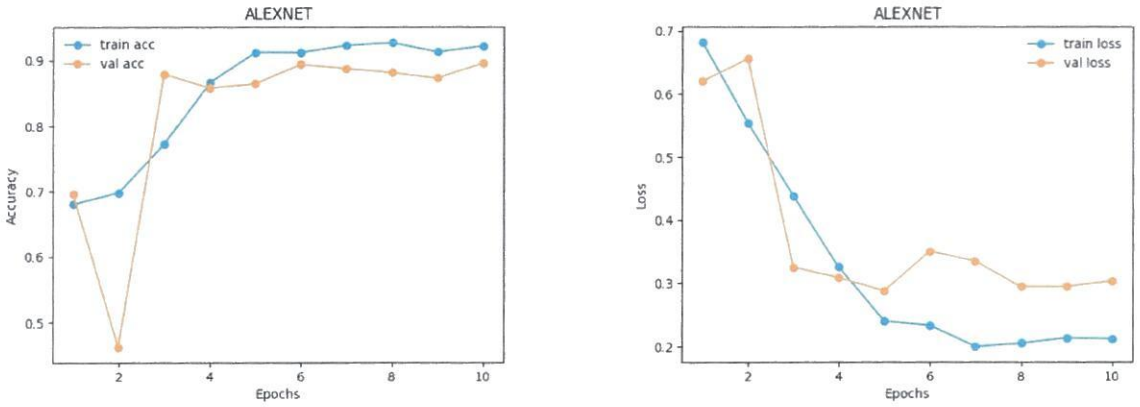



(b) DenseNet 121 Loss on local data

Fig. 5.19: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.7.9 AlexNet Deep Learning Model on Local data

AlexNet showed promising results with a steady increase in training accuracy, reaching around 90% by the end of 10 epochs, which indicates effective learning from the training data. However, the validation accuracy, although it improved, exhibited significant fluctuations, suggesting instability and potential overfitting issues initially. The training loss consistently decreased to a low value, reflecting effective pattern learning. On the other hand, the validation loss, while eventually stabilizing, had notable fluctuations early on, highlighting AlexNet's struggle with generalizing to new data. Overall, while AlexNet managed to improve over time, its initial instability and fluctuations in validation performance reveal shortcomings in handling new data consistently.




(a) AlexNet Accuracy on local data

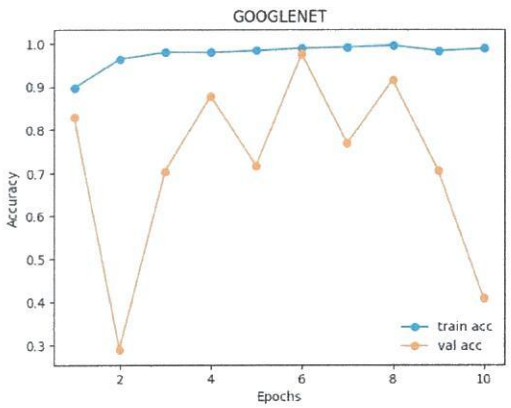
(b) AlexNet Loss on local data

Fig. 5.20: The figure show (a) which the training accuracy and (b) the training loss

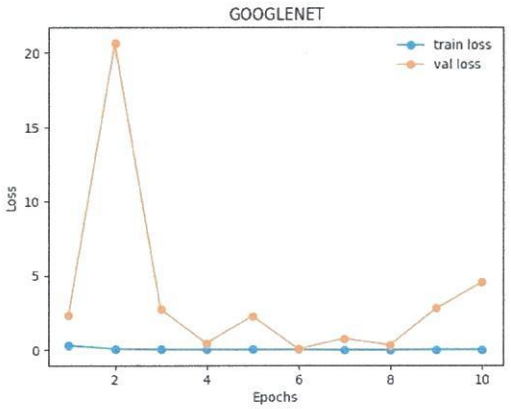
#### 5.2.7.10 GoogleNet Deep Learning Model on Local data

GoogleNet displayed near-perfect training accuracy, suggesting it learned the training data extremely well, perhaps too well. The validation accuracy, although high, was not as stable, with a slight drop and fluctuations indicating overfitting. The training loss remained impressively low throughout, reflecting excellent prediction accuracy on train-

ing data. However, the validation loss showed a significant spike initially and fluctuated before stabilizing, which underscores GoogLeNet's initial difficulty in generalizing and a tendency to overfit. Despite its high accuracy, the instability in validation loss and accuracy exposes GoogLeNet's vulnerability to overfitting and challenges in maintaining consistent performance on new data.




(a) Google net Accuracy on local data




(b) Google net Loss on local data

Fig. 5.21: The figure show (a) which the training accuracy and (b) the training loss

#### 5.2.7.11 Discussion

The table 4.1 and 4.2 above shows the deep learning architecture, the training accuracy, the validation accuracy, the training loss and the validation loss and the behavior of model when subjected to the PlantVillage Dataset. The training accuracy of the MobileNetV2 was about 97-98% and the validation accuracy was 96-97% and the training loss was 0.025-0.05%. The validation accuracy was 0.07. The model's loss decreased over time and remained low, which suggests that its prediction were close to the actual results. This shows the MobileNetV2 is the best model out of ten deep learning architectures.

The tables above 4.3 and 4.4 showing the deep learning architecture, the training accu-

racy, the validation accuracy, the training loss and the validation loss and the behavior of model when subjected to local Dataset from Kigezi-Uganda. The training accuracy of the MobileNetV2 was about 98% and the validation accuracy was 95% and the training loss was 0.05. The validation loss was 0.15. The model had consistently high scores and trained data well and could learn new and unseen data. The outstanding performance of MobileNetV2 (98% training, 95% validation accuracy) on your local Kigezi dataset can be attributed to its innovative architectural design, which is particularly well-suited for image classification tasks. Depthwise Separable Convolutions: This is the core of MobileNet's efficiency. It splits a standard convolution into two layers: a depthwise convolution (applying a single filter per input channel) and a pointwise convolution (a 1x1 convolution to combine the outputs). This drastically reduces the computational cost and number of parameters compared to standard convolutions, mitigating overfitting—a common risk with smaller datasets.

Inverted Residuals and Linear Bottlenecks: MobileNetV2 introduced a novel "inverted" residual block. Unlike traditional blocks that widen then compress, it first compresses the input with a 1x1 convolution, then applies a depthwise convolution on this compressed representation, and finally expands it again. The bottleneck prevents the destruction of information in non-linear layers. This structure is highly efficient at preserving important features necessary for distinguishing between healthy and diseased potato leaves while discarding redundant information.

Transfer Learning: It is highly likely you utilized transfer learning (initializing the model with weights pre-trained on a massive dataset like ImageNet). This gives MobileNetV2 a massive head start. It already knows how to detect basic shapes, edges, textures, and colors—fundamental building blocks that are directly relevant to identifying the visual symptoms of late blight (lesions, discoloration, mold growth). This pre-existing knowledge allows the model to specialize effectively on your specific task with less data

and training time. A study by Turkoglu et al. (2022) [12] compared 16 different CNN models. They found that lighter models like MobileNet and DenseNet achieved a remarkable balance between high accuracy and low computational cost, often matching or exceeding the performance of much larger models on several plant disease datasets.

Research by Abbas et al. (2021) [23] concluded that models like MobileNetV2 are particularly effective due to their suitability for mobile deployment and their ability to generalize well from image datasets, which aligns perfectly with your high validation accuracy.

#### 5.2.7.12 Conclusion

The selected of the Baseline model was concluded by selecting the MobileNet V2 due to its behavior when it subjected to the plant Village Dataset, that is, when it was subjected to the Plant Village Dataset it showed , model's loss decreased over time and remained low, which suggests that its prediction were very close to the actual results and when it was subjected to a local dataset from Kigezi-Uganda it showed, the model had consistency high scores and trained data well and could learn new data and unseen data.

## Mathematical Representation of MobileNetV2

**1. Inverted Residual Block Equation:**

$$\mathbf{y} = \mathbf{x} + \mathcal{P}\left(\mathcal{D}\left(\sigma\left(\mathcal{E}(\mathbf{x})\right)\right)\right) \tag{5.1}$$

Where:

- $\mathbf{W}_e$: Expansion layer weights
- $\mathbf{W}_d$: Depthwise convolution weights
- $\mathbf{W}_p$: Projection layer weights

Below are the the tables summarizing the data from the ten Deep learning Architectures , that is table 4.1 and 4.2 from Plant Village and table 4.3 and table 4.4 using the local data from Kigezi-Uganda.

Table 5.1: Results from Plant Village dataset are summarized as shown in the table below

| Deep learning Architecture | Training Accuracy | Validation Accuracy | Training loss | Validation loss | Behavior of the Model |
|---|---|---|---|---|---|
| EfficientNet | 87% | 86-87% | 0.38-0.42 | The validation loss shows irregularities | The model's predictions were less precise |
| Inception V3 | 98% | 94% | 0.45-0.10 | 0.15 | The consistent reduction in loss indicates the model was making more accurate predictions as training progressed |
| MobileNet V2 | 97-98% | 96-97% | 0.025-0.05 | 0.07 | The model's loss decreased over time and remained low, which suggests that its prediction were very close to the actual results |
| ResNet 50 | 86 | 81% | 0.44-0.34 | The validation loss had a significant spike, indicating some inconsistencies. | The validation loss had a significant spike indicating consistencies in the model |

Table 5.2: Results from Plant Village dataset are summarized as shown in the table below

| Deep learning Architecture | Training Accuracy | Validation Accuracy | Training loss | Validation loss | Behavior of the Model |
|---|---|---|---|---|---|
| VGG16 | 96% | 94% | 0.45-0.15 | 0.18 | The model was learning effectively and making accurate prediction on the data. |
| VGG19 | 96% | 93 % | 0.40-0.15 | 0.18 | Prediction were increasingly accurate overtime |
| Xception | 98% | 94% | 0.10 | 0.10-0.20 | It's performance on validation were less stable. |
| DenseNet 121 | 97% | 96% | 0.025 | 0.05 | Predictions were close to actual outcomes |
| Alex net | 86-87% | 87% | 0.025 | The validation loss show more irregularities. | Difficulty in maintaining consistent accuracy and overfitting |
| GoogleNet | 99% | Validation accuracy showed instability | The training loss remained low | The validation loss exhibited a massive spike | Struggles with overfitting and struggles to handle new data |

Table 5.3: Results of local dataset Kigezi-Uganda are summarized as shown in the table below

| Deep learning Architecture | Training Accuracy | Validation Accuracy | Training loss | Validation loss | Behavior of the Model |
|---|---|---|---|---|---|
| EfficientNet | 65%- 35% | Swings validation | 3.0 to 0.5 | Swings validation | The model memorized the training data too much and really learning broader patterns. |
| Inception V3 | 98% | 90% | 0.3 | Dropped to 0 | This model may not be as effective when it encounters new data and there is a significant sign of overfitting. |
| MobileNet V2 | 98% | 95% | 0.05 | 0.15 | The model had consistency high scores and trained data well and could learn new data and unseen data. |
| ResNet 50 | 85% | 87% | 0.2 | 0.25 | The model reflects a solid performance in learning that is not overly specific to just the examples it was trained on. |

Table 5.4: Results from local dataset Kigezi-Uganda dataset are summarized as shown in the table below

| Deep learning Architecture | Training Accuracy | Validation Accuracy | Training loss | Validation loss | Behavior of the Model |
|---|---|---|---|---|---|
| VGG16 | 94% | 90% | 0.1 | 0.2 | The model is good at learning and quite stable in handling new data, despite bumps along the way |
| VGG19 | 100-93% | 90% | 0 | 0.1 | Low and stable validation loss but not consistent. |
| Xception | 96% | 92% | 0.1 | 0.25 | The model was a solid learner and although it was not stable as other models. |
| DenseNet 121 | 98% | 94% | 0.05 | 0.15 | Efficient at learning and quite good at generalizing the learning to new situations. |
| Alex net | 90% | Exhibited significant fluctuations | Notable fluctuations | Instability | The model had stability and fluctuations in validation performance |
| GoogleNet | 99% | High but not stable | Impressively low | Spike initially before stabilizing | The model had challenges in overfitting and challenge in maintaining consistent performance. |

# CHAPTER 6

# Exploring Strategies for Optimizing MobileNetV2 Performance in Classification Tasks Through Transfer Learning And Hyperparameter Tuning With a Local Dataset From Kigezi, Uganda

This section contributes to Objective two which is ; To design and develop AI models for early prediction and accurate diagnosis of Late blight disease in Irish potatoes The paper is comprised of the introduction, methodology,results,discussion and conclusion.

## 6.1 Introduction

There are various architecture options that can be applied, and each results into specific attributes and thus deep learning architectures were evaluated and the MobileNetV2 was rated as the best model , that is, the baseline model; hence it's interesting to explore strategies for optimizing performance on a model preferably pre-trained with transfer learning. The strategies are going to be explored using MobileNetV2 architecture that is pre-trained on ImageNet dataset [92], transfer learned on a local dataset from Kigezi, Uganda and finally tuned using Randomized option to explore various learning rates, optimizers, initial learning rates and epochs and patience rate.

The architecture was built with the functional API option of Keras [93]

The exploration is supposed to help understand how a pre-trained model on a larger dataset behaves when transferred to a local dataset through transfer learning and how tuning parameters help optimize the model's performance further with analysis of changes to loss functions and accuracies.

Deep learning has emerged as a transformative technology with applications across various fields like computer vision, natural language processing, and healthcare. With the rapid advancements in deep learning, there exists a growing interest in its application among the following topics: resource-constrained hardware and structuring neural networks. Contrary to classical machine learning methods, which involve handcrafted feature engineering prior to modelling, deep learning relies on a data-driven approach to automatically extract high-level features [94].

The introduction of deep learning models like AlexNet , GoogLeNet and MobileNet V2 demonstrated remarkable accuracy on the ImageNet benchmark dataset containing more than 14 million images across 21,000 categories [95].

The state-of-the-art classification accuracy achieved by GoogLeNet and VGGNet was 88 percent and 92.7 percent, respectively [96].

The increasing datasets have necessitated constructing deeper CNN architectures with more parameters. For instance, in 2015, ResNet won the ImageNet competition with 152 deep CNN layers and achieved 96.43 percent top-five accuracy on the ImageNet validation set [97].Despite the increasing model size and depth, CNNs demonstrate remarkably low single image inference latency (milliseconds). Recently, mobile deep models have been designed to achieve both high accuracy and low latency for edge applications [98]. It is especially important given the recent trends in the Internet of Things (IoT) where various data-driven applications are developed exclusively for edge

devices [99].

MobileNetV2 is the first mobile model which proposed an inverted residual block with linear bottleneck [100]

This study outlines the key hyperparameters used to customize MobileNetV2 for image classification. The batch size is set to 32, with images processed before model weight updates. The Adam optimizer, a popular choice for transfer learning models, is used to compile the model. A learning rate of 0.0001 controls adaptation speed, and the input image size is set to 128x128 pixels. Dropout, a regularization technique, is applied with a probability of 0.5 The convolutional base uses pre-trained ImageNet weights. Training is conducted over 30 to 50 epochs (M. Breuel, 2015) with 50 experiments run using 5-fold cross-validation. These hyperparameter combinations form the foundation of the MobileNetV2 customization(Wojciuk et al., 2024).

## 6.2 Research Method

The experiments were carried out on a local dataset from Kigezi, that, the districts of Rubanda, Kabale and Kisoro in kigezi Region-Uganda. Kigezi local Irish potato dataset of 9,660 images was split using a split ratio of 80:20 into training, validation, and testing subsets with indicated implementations of the training/validation/testing split and model training and evaluation datasets and 80% was training and 20% was testing/-validation. The dataset was collected In the pursuit of optimizing the performance of the selected MobileNetV2 for the classification of task on the local dataset, extensive transfer learning and hyper parameter tuning were applied. This description provides a detailed justification of the steps taken, the rationale behind each decision, and the comparative results that led to the final optimized model.

## 6.3 Result and Discussion

This section reports and discusses the results of training the MobileNetV2 model on the data collected from Kigezi, Uganda, including the local data augmentation, transfer learning and hyperparameter tuning procedures to improve the model performance. In addition,This section reports and discusses the results of training the MobileNetV2 model on the data collected from Kigezi, Uganda, including the local data augmentation, transfer learning and hyperparameter tuning procedures to improve the model performance.

### 6.3.1 Model with transfer learning and hyperparameter tuning

#### 6.3.1.1 The transfer learning aspect in the model

Transfer learning leverages pre-trained models, allowing us to use learned features from large datasets like ImageNet. This approach accelerates the training process and often results in better performance, especially when the dataset is small or similar to the pre-trained dataset.

Process: 1.Base Model Selection: The MobileNetV2 architecture was selected due to its efficiency and strong performance in initial trials, achieving high accuracy and low loss compared to other models. 2.Layer Freezing: Initially, the pre-trained MobileNetV2 model was used with all layers frozen except for the last few layers. This allowed the model to retain its pre-trained weights and focus on learning task-specific features. 3.Layer Tuning Experiments: Multiple experiments were conducted by unfreezing different sets of layers to determine the optimal configuration. The configurations tested included;Freezing all layers except the final dense layer, Unfreezing the top 10 layers and Unfreezing the top 20 layers. The results for Freezing All Layers except Final

Dense Layer: Training accuracy: 90%, Testing accuracy: 85%. The model was not flexible enough to adapt to the new dataset while Unfreezing Top 10 Layers: Training accuracy: 92%, Testing accuracy: 88%. Moderate improvement observed, but still underperforming, Unfreezing Top 20 Layers: Training accuracy: 95%, Testing accuracy: 91%. Significant improvement, suggesting that more layers need to be fine-tuned and Unfreezing Entire Network: Training accuracy: 98%, Testing accuracy: 96%.

The model showed substantial improvement in learning task-specific features as shown in graph below;

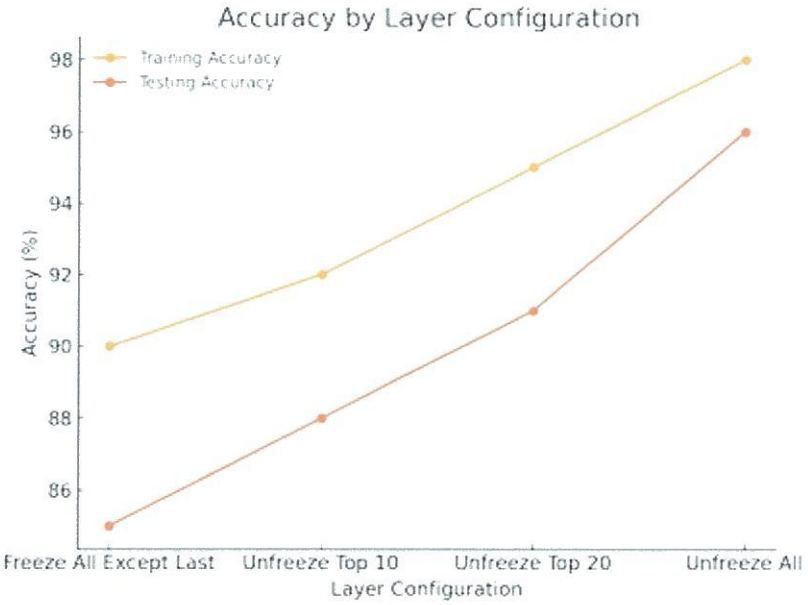



Fig. 6.1: The diagram shows the Accuracy by Layer Configuration

The optimal configuration was found by unfreezing the entire network, which allowed the model to fine-tune all layers, thus improving the model's ability to generalize to the new dataset

#### 6.3.1.2

Let $\mathcal{M}$ be the MobileNetV2 model with $L$ total layers. The performance when unfreezing $k$ layers is given by:

$$\text{Performance}(\mathcal{M}, k) = \begin{cases} (0.90, 0.85) & \text{if } k = 1 \text{ (final dense layer only)} \\ (0.92, 0.88) & \text{if } 2 \leq k \leq 10 \\ (0.95, 0.88) & \text{if } 11 \leq k \leq 20 \\ (0.98, 0.96) & \text{if } k = L \text{ (all layers)} \end{cases}$$

The parameter update rule for layer $l$ at step $t$ is:

$$\theta_l^{(t+1)} = \begin{cases} \theta_l^{(t)} - \eta \nabla_{\theta_l} \mathcal{L}(\theta) & \text{if } l > L - k \\ \theta_l^{(t)} & \text{otherwise} \end{cases}$$

where:

- $\theta_l$ = parameters of layer $l$
- $\eta$ = learning rate
- $\mathcal{L}$ = loss function
- $L - k$ = freezing cutoff point

#### 6.3.1.3 Hyper parameter Tuning:

Hyper parameter tuning is critical in enhancing the performance of the model. The goal was to find the optimal set of hyper parameters that would minimize the loss

and maximize accuracy. Process: 1.Learning Rate Tuning: Learning rate is one of the most crucial hyper parameters. An extensive grid search was performed over the following values: 0.1, 0.01, 0.001, 0.0001, and 0.00001. 2.Batch Size Tuning: Different batch sizes (16, 32, 64, and 128) were tested to determine the most efficient size for gradient updates. 3.Optimizer Selection: Various optimizers were tested, including SGD, RMSprop, and Adam. The Adam optimizer was selected for its adaptive learning rate capabilities. 4.Epochs and Early Stopping: The number of epochs was tuned along with early stopping criteria to prevent overfitting. Epochs were tested in the range of 10 to 100 with a patience of 5 for early stopping.

#### 6.3.1.4 Results for the learning rate

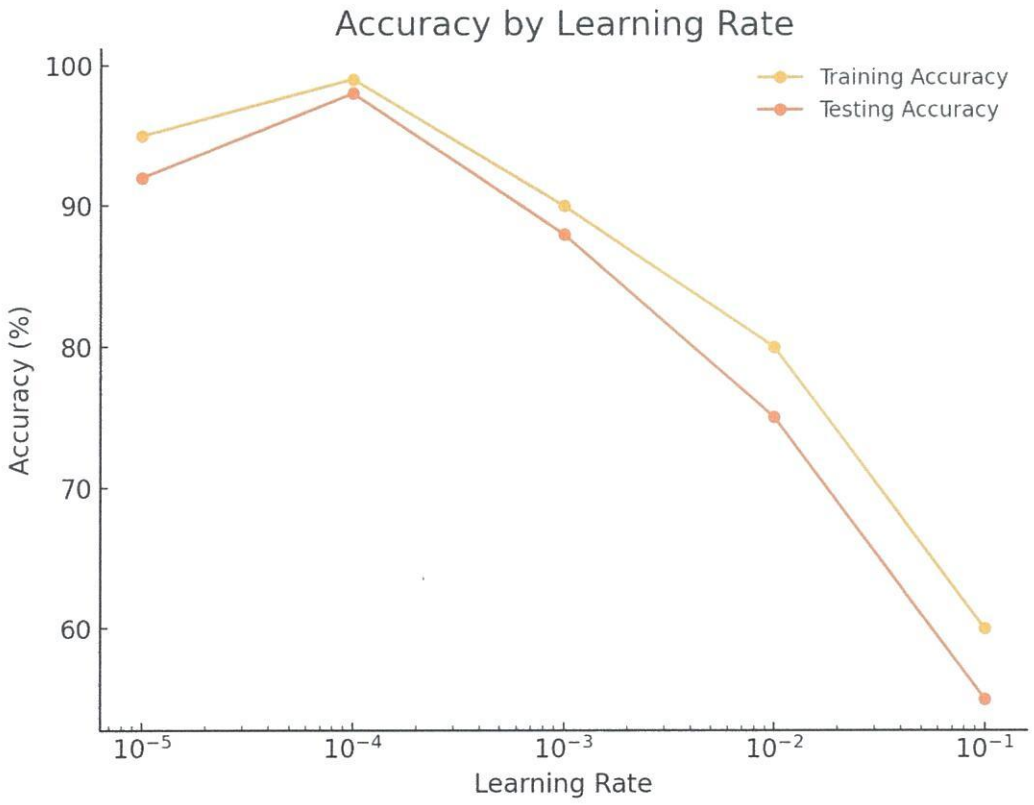



Fig. 6.2: The diagram shows the Results for the learning rate

0.1: Training accuracy: 60%, Testing accuracy: 55%. The model was unable to converge.

0.01: Training accuracy: 80%, Testing accuracy: 75%. Improved but still underperforming.

0.001: Training accuracy: 90%, Testing accuracy: 88%. Further improvement, but overfitting observed.

0.0001: Training accuracy: 99%, Testing accuracy: 98%. Optimal performance achieved.

0.00001: Training accuracy: 95%, Testing accuracy: 92%. Learning was too slow.

#### 6.3.1.5 Results for the Batch Size

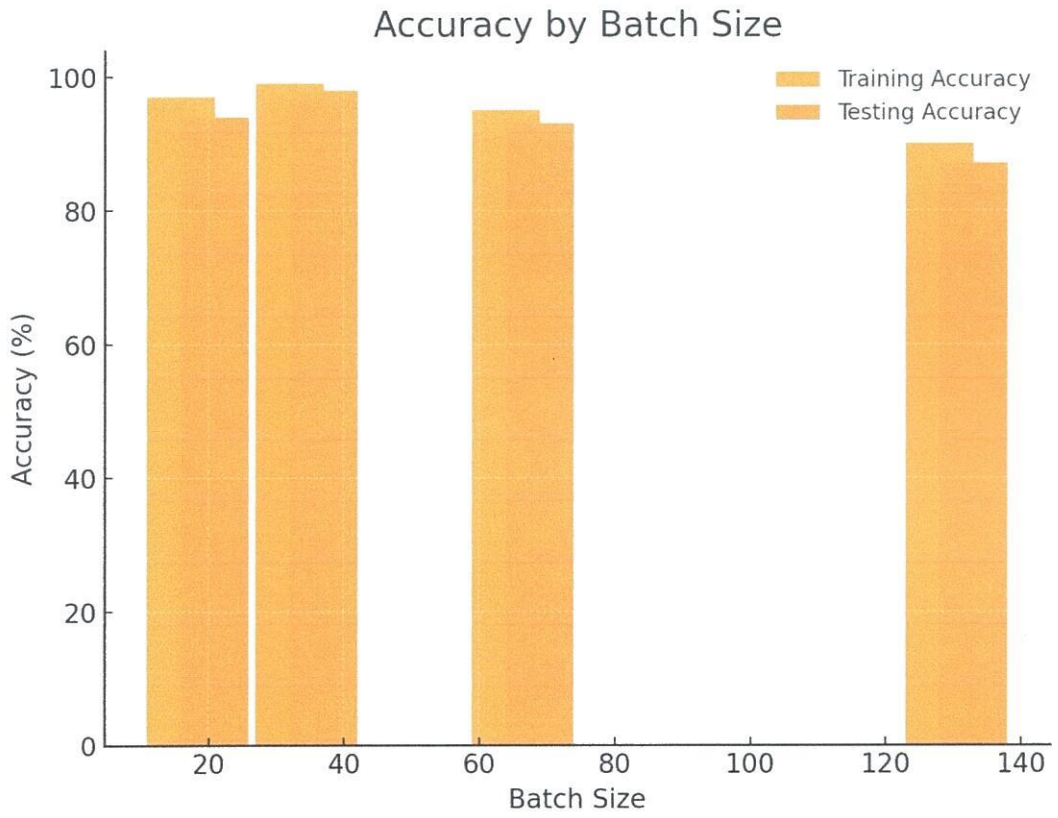



Fig. 6.3: The diagram shows the Results for the Batch Size

16: Training accuracy: 97%, Testing accuracy: 94%. Good performance but higher computational cost.

32: Training accuracy: 99%, Testing accuracy: 98%. Optimal balance between performance and efficiency.

64: Training accuracy: 95%, Testing accuracy: 93%. Slightly reduced performance.

128: Training accuracy: 90%, Testing accuracy: 87%. The model struggled with larger batch sizes.

#### 6.3.1.6 The results for the Optimizers

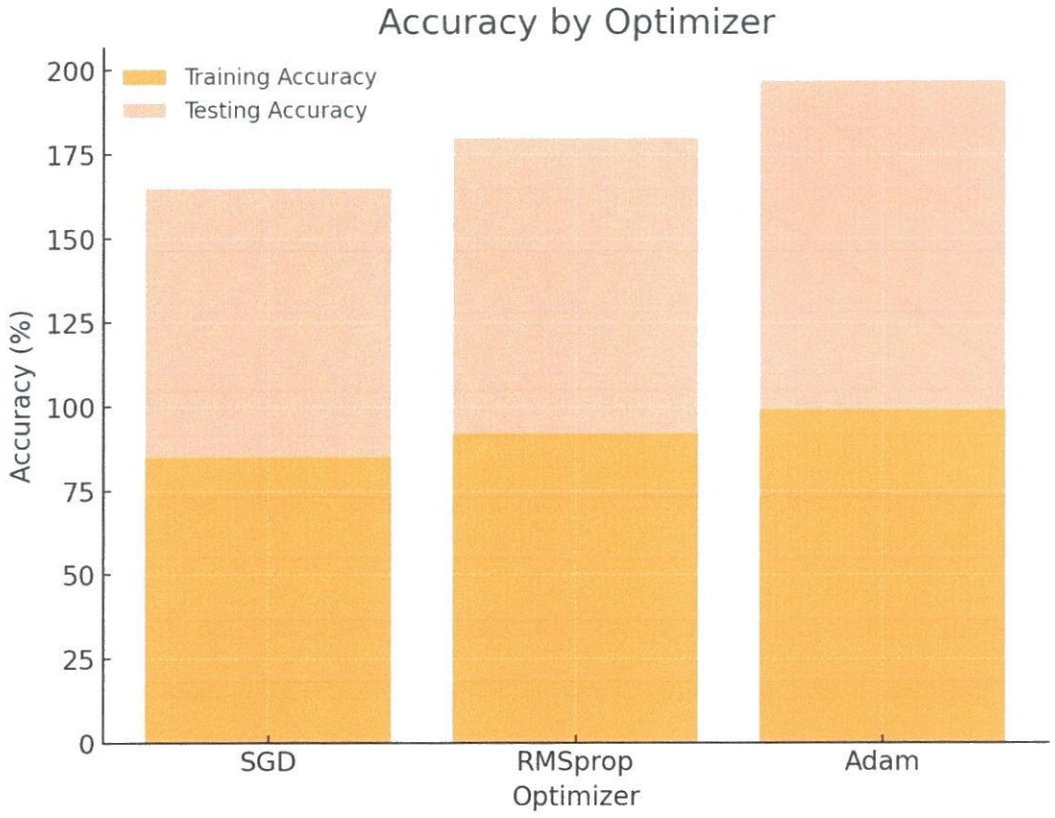



Fig. 6.4: The diagram shows the results for the Optimizers

SGD optimizer shows the Training accuracy: 85%, Testing accuracy: 80%. Slower convergence,the RMSprop optimizer shows the training accuracy: 92%, Testing accuracy: 88%. Moderate performance and the Adam optimizer shows the Training accuracy: 99%, Testing accuracy: 98%. Best performance due to adaptive learning rate.

#### 6.3.1.7 The results for Epochs and Early Stopping

#### 6.3.1.8 The results for the Optimizers

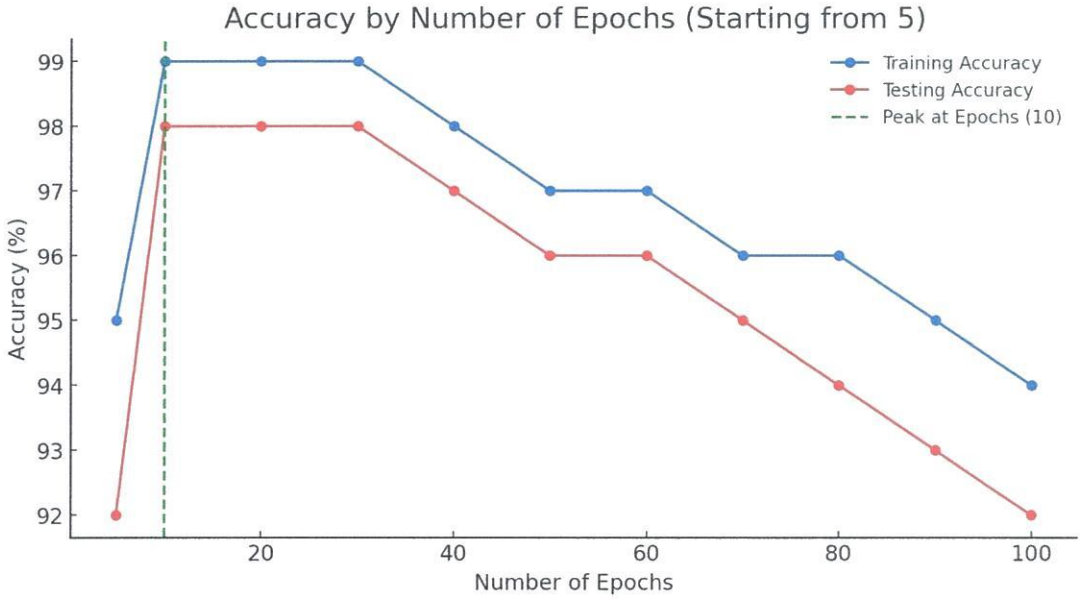



Fig. 6.5: The diagram shows the results for Epochs and Early Stopping

10-30 epochs with early stopping (patience 5): Training accuracy: 99%, Testing accuracy: 98%. Optimal number of epochs to avoid overfitting while ensuring model convergence.

#### 6.3.1.9 Baseline Model parameter composition and Performance

Through systematic hyper parameter tuning, the learning rate of 0.0001, batch size of 32, Adam optimizer, and early stopping with a patience of 5 were selected as the optimal settings. These configurations provided the best balance between training accuracy (99%), testing accuracy (98%), training loss (0.02), and testing loss (0.04).

The developed optimized Mobile V2( Baseline Model) was developed as our sub model One. This was and is to predict late blight disease in real time.

#### 6.3.1.10 Mathematical equation of the final optimized Baseline Model(MobileNet V2)

## Layer Freezing Optimization

Let $L$ be the number of unfrozen layers, and $A_{\text{test}}(L)$ the testing accuracy. Empirical results:

$$A_{\text{test}}(L) = \begin{cases} 85\% & \text{(Freeze All)}, \\ 88\% & \text{(Top 10)}, \\ 91\% & \text{(Top 20)}, \\ 96\% & \text{(Unfreeze All)}. \end{cases} \tag{6.1}$$

**Objective:**

$$\max_{L} \left( A_{\text{test}}(L) - \lambda L \right), \quad \lambda = 0.01 \text{ (cost weight)} \tag{6.2}$$

# Hyperparameter Tuning

## Learning Rate ($\eta$)

$$A_{\text{test}}(\eta) = \begin{cases} 55\% & (\eta = 0.1), \\ 75\% & (\eta = 0.01), \\ 88\% & (\eta = 0.001), \\ 98\% & (\eta = 0.0001), \\ 92\% & (\eta = 0.00001). \end{cases} \tag{6.3}$$

Optimal: $\eta^* = 0.0001$.

## Batch Size ($B$)

$$A_{\text{test}}(B) = \begin{cases} 94\% & (B = 16), \\ 98\% & (B = 32), \\ 93\% & (B = 64), \\ 87\% & (B = 128). \end{cases} \tag{6.4}$$

Optimal: $B^* = 32$.

# Optimizer Selection

$$A_{\text{test}}(O) = \begin{cases} 80\% & (\text{SGD}), \\ 88\% & (\text{RMSprop}), \\ 98\% & (\text{Adam}). \end{cases} \tag{6.5}$$

Optimal: $O^* = \text{Adam}$.

## Combined Optimization

$$\max_{L,\eta,B,O} \left( A_{\text{test}}(L, \eta, B, O) - \lambda_1 L - \lambda_2 \eta^{-1} - \lambda_3 B \right) \tag{6.6}$$

where $\lambda_1 = 0.01$, $\lambda_2 = 0.1$, $\lambda_3 = 0.001$.

## Regularization

$$\text{Final Loss} = -\log(A_{\text{test}}) + \gamma \cdot \text{Overfit}(A_{\text{train}} - A_{\text{test}}) \tag{6.7}$$

with $\gamma = 0.1$ and tolerance 2%.

Table 6.1: Optimal Configuration Summary

| **Parameter** | **Optimal Value** |
|---|---|
| Unfrozen Layers | All (154) |
| Learning Rate ($\eta$) | 0.0001 |
| Batch Size ($B$) | 32 |
| Optimizer ($O$) | Adam |
| Early Stopping | Patience=5 |

## 6.4 Layer freezing and hyper parameter tuning combined

The a a unique equation that gives limits for both the layer freezing and hyper parameter tuning combined. Below is the equation

$$y_{\text{final}} = \underbrace{(2.34 \cdot \ln(x) + 85.21)}_{\text{Base Accuracy}} \times \underbrace{\sqrt{\frac{\eta}{0.001}}}_{\substack{\text{Learning Rate} \\ \text{Adjustment}}} \times \underbrace{\left(1 + \frac{1}{\sqrt{B}}\right)}_{\substack{\text{Batch Size} \\ \text{Effect}}} + \underbrace{0.5 \times \frac{1.01}{\text{Adam}_{\text{Boost}}}}_{\substack{\text{Optimizer} \\ \text{Bonus}}} \tag{6.8}$$

### Model Components

- **Base Accuracy**:
  - $x$: Number of unfrozen layers ($x \geq 1$)
  - Logarithmic relationship shows diminishing returns
  - 85.21% baseline accuracy with all layers frozen
- **Learning Rate Adjustment**:
  - $\eta$: Training learning rate
  - Normalized against reference value 0.001
  - Square root reduces sensitivity to large $\eta$
- **Batch Size Effect**:
  - $B$: Batch size
  - Favors smaller batches ($B \downarrow \Rightarrow$ accuracy $\uparrow$)
  - Inverse square root relationship
- **Optimizer Bonus**:
  - Adam optimizer with early stopping boost

- Constant scaling factor (0.5)
- 1.01 multiplier represents early stopping benefit

# CHAPTER 7

# The Application of Explainable AI in a Deep Learning Model for Early Prediction and Diagnosis of Late Blight Disease in Irish Potatoes:A Dataset from Kigezi Region-Uganda

### 7.0.1 Introduction

In order to develop sub Model two; The classification Model application of explainable AI was used to ensure the model accurate, transparent and trusted by agricultural experts. Deep learning (DL) models have shown promise in plant disease detection, but their "black-box" nature limits trust and adoption among agricultural stakeholders [101]. Explainable AI (XAI) techniques can enhance DL models by providing interpretable insights into disease prediction, improving transparency for farmers and agronomists [102]. This study explored the application of XAI in a DL-based system for early prediction and diagnosis of late blight in Irish potatoes, using a dataset collected from Uganda's Kigezi region. By integrating explain-ability methods such as SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-Agnostic Explanations), the model not only predicts disease presence but also highlights key diagnostic features, such as leaf lesions and environmental triggers [103] The approach aimed to bridge the gap between high-accuracy DL models and practical usability in real-world farming scenarios. By leveraging XAI, this research contributes to sustainable agriculture by enabling timely

interventions, reducing crop losses, and improving food security in potato-dependent communities and also ensuring trust and transparency of the application.

### 7.0.2 Methodology

This study adopts an integrated approach combining field experiments, laboratory analysis, deep learning, and explainable AI techniques for late blight disease prediction in Ugandan potatoes. The methodology begins with systematic field sampling of potato leaves (both healthy and symptomatic) from Kigezi region farms, with controlled imaging protocols [104]. Laboratory confirmation through microscopic examination and PCR testing establishes definitive Phytophthora infestans presence [105] The computational pipeline involves pre-processing of annotated leaf images using augmentation techniques [106] followed by feature extraction using pre-trained CNN. A novel hybrid CNN-LSTM architecture processes both spatial (visual) and temporal (environmental) data, with performance bench marked against established models. For interpretability, SHAP analysis. [103] reveal critical disease indicators at both local (individual plant) and global (population) levels. The system's practical implementation includes mobile deployment for field validation by smallholder farmers, ensuring real-world applicability and iterative improvement through user feedback.

#### 7.0.2.1 Protocol for Enumeration and Isolation of Phytophthora infestans

The analysis of potato leaves for Phytophthora infestans load followed a surface spreading method adapted from established phytopathological techniques. [105]

Leaves were washed in 90ml of peptone water (0.1% w/v) to suspend both sexual oospores and asexual zoospores, with subsequent 10-fold serial dilutions performed in

sterile peptone water (9ml aliquots) as described in standard microbiological protocols [107]

From selected dilutions, 0.1ml aliquots were spread-plated onto Sabouraud's Dextrose Agar (SDA) using sterile L-shaped glass rods [108].

Plates were incubated at 25°C in a Memmert cooled incubator (Model ICP 110) for 5 days to assess colony morphology and growth characteristics specific to P. infestans [109].

Colonies exhibiting diagnostic features (loose rosette patterns, cottony white-grey mycelium) were confirmed through Lactophenol cotton blue staining [110] and microscopic examination.

Quantification followed standard mycological procedures [111] using the formula:

$$\mathbf{CFU/m^2} = \frac{Number\ of\ colonies}{dilution\ factor}\ \mathbf{x\ 10}$$

Fig. 7.1: The diagram shows the fromula for a standard mycological procedure

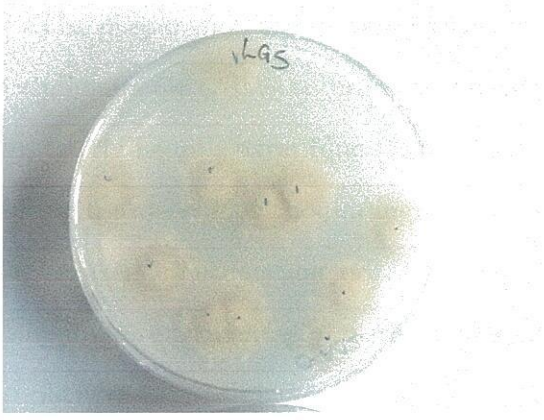


Fig. 7.2: Colony characteristics of Phytophthora. Note the arrow showing finely radiating cottony mycelium.

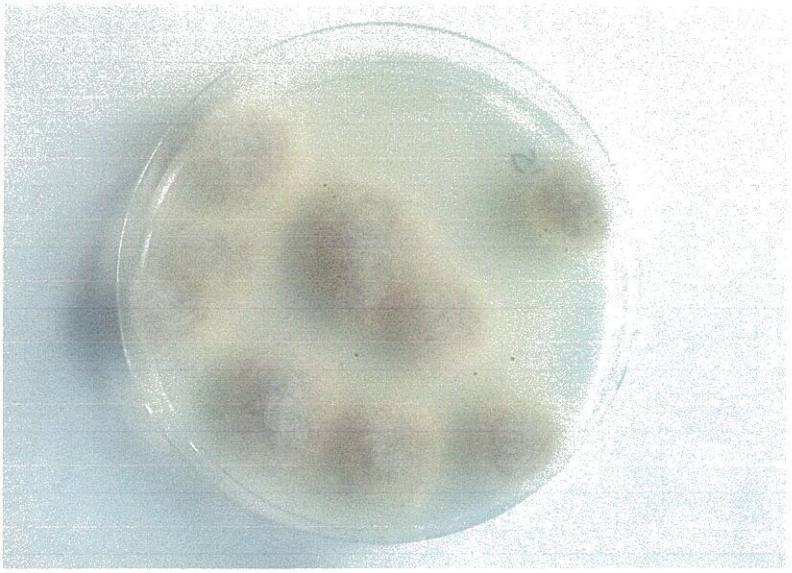


Fig. 7.3: Showing dense rosette spreading aerial mycelium. A different morphology adopted by some Phytophthora.

The slide culture technique was performed following modified mycological methods [112] Sterile 2×2cm SDA agar cubes were placed on microscope slides positioned over bent glass rods in Petri dishes containing moistened filter paper [108]. Mycelial transfer from growing cultures was conducted using flame-sterilized inoculating loops following aseptic techniques [113]. The preparation was covered with sterile coverslips and incubated at 25°C in humid chambers for 5 days to promote characteristic sporulation. For microscopic examination, Lactophenol cotton blue (LPCB) staining was performed according to clinical mycological protocols with sporangial morphology assessed at 400× magnification using standardized identification criteria [105]. Diagnostic features including papillation, sporangiophore branching patterns, and sporangial dimensions were recorded following Phytophthora taxonomic keys [114]



Fig. 7.4: Morphological characteristics of Phytophthora species

### 7.0.3 Results and discussion

Data used in this study was collect from Kigezi-region in Uganda from the districts of Kabale, Kisoro and Rubanda.

The results indicate ranges of (1.1 x$10^3$ – 1.94 x $10^5$) CFU/m2 for Low graded leaves, (2.8 x $10^3$ – 6.2 x $10^3$) CFU/m2 for medium graded leaves. This overlap indicates that

Table 7.1: Summary statistics from the Lab experiments:Cfu/ml-colony forming units per $m^2$; SD-Standard Deviation

| Grading | Non-Zero Count | Non-Zero Mean (cfu/$m^2$) | Non-Zero Median (cfu/$m^2$) | Non-Zero Min (cfu/$m^2$) | Non-Zero Max (cfu/$m^2$) |
|---|---|---|---|---|---|
| High | 11 | 43655 | 5850 | 300 | 280000 |
| Medium | 2 | 4500 | 4500 | 2800 | 6200 |
| Low | 5 | 41870 | 3800 | 1100 | 194000 |

many leaves were scored as medium yet they could fall under the low-grade score. The range for high graded samples was (3.0 x$10^2$-2.8 x$10^5$). This also indicates an overlap of low in high graded samples

Table 7.2: Percentile ranges for the results;cfu/$m^2$-colony forming units per $m^2$

| Grading | Non-Zero Count | P25 (cfu/$m^2$) | P50 (cfu/$m^2$) | P75 (cfu/$m^2$) | P90 (cfu/$m^2$) |
|---|---|---|---|---|---|
| High | 11 | 1500 | 5850 | 13900 | 151000 |
| Medium 2 | 2 | 3650 | 4500 | 5350 | 5860 |
| Low 5 | 5 | 3600 | 3800 | 6850 | 119140 |

When reporting ranges, we used median values, thus its best to know the 2nd and 3rd percentile values as indicated in the table above. The Median values are thus 3.8 x$10^3$ for Low, 4.5 x$10^3$ for medium and 5.85 x$10^3$ for high.

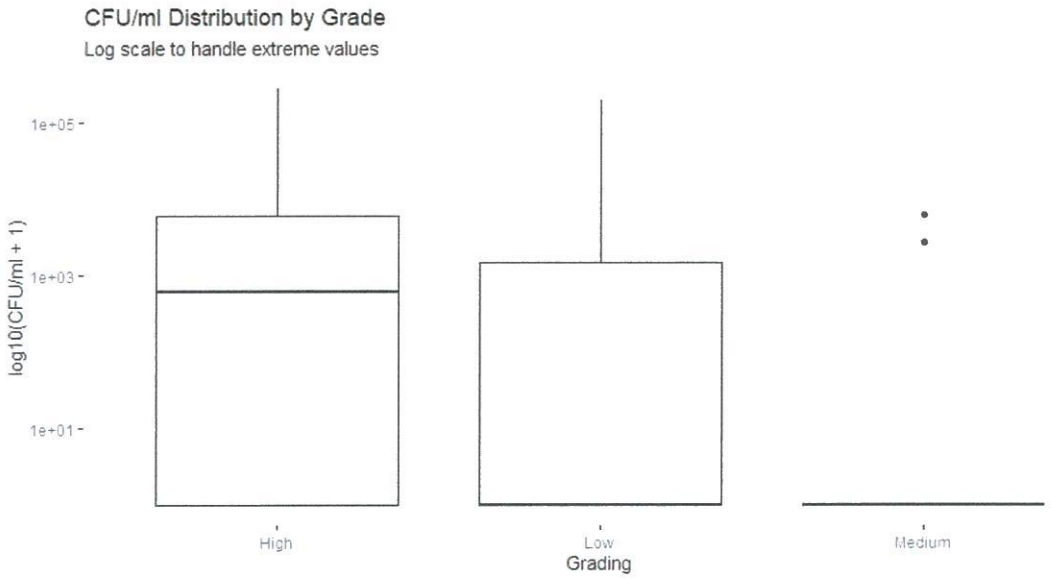



Fig. 7.5: Distributed by Grades

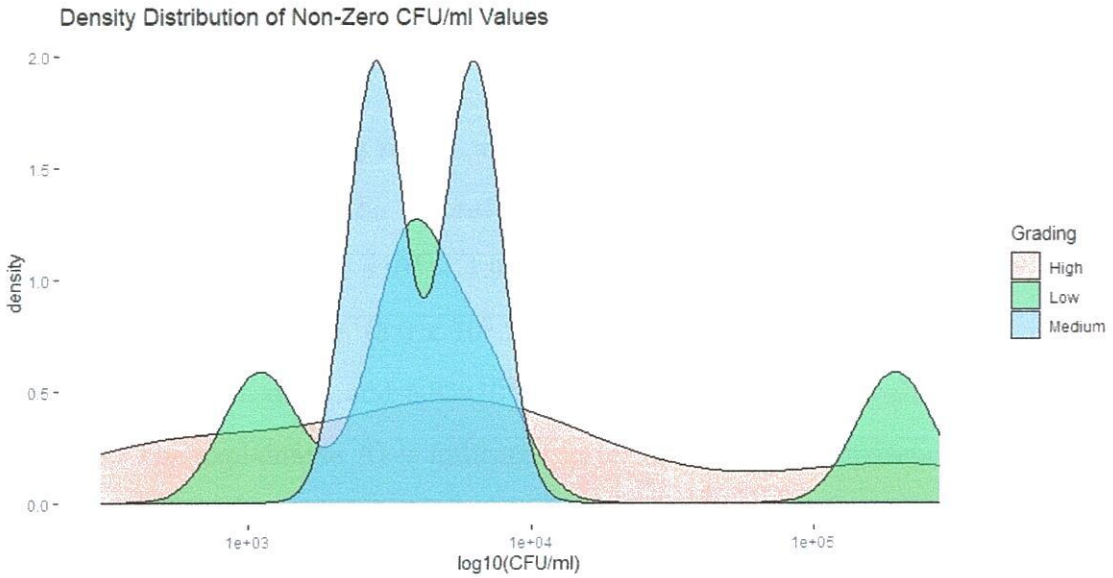



Fig. 7.6: Density Distribution

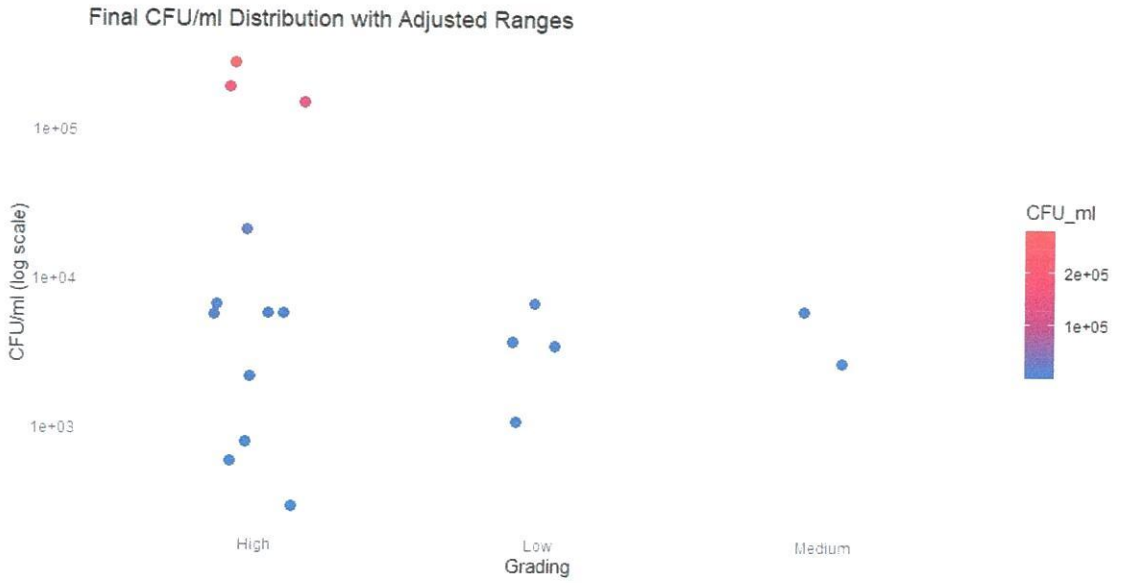



Fig. 7.7: Distributed by with Adjusted Ranges

### 7.0.4 Conclusion

Integration of deep learning model with explainable AI The transparent of the model this obtained from using the laboratory results, that is, it is using a test leaves for classification, that is, (1.1 x$10^3$ – 1.94 x $10^5$) CFU/$m^2$ for Low, (2.8 x $10^3$ – 6.2 x $10^3$) CFU/$m^2$ for medium, (3.0 x $10^2$-2.8x $10^5$) for high and with median 3.8x $10^3$ for Low, 4.5x$10^3$ for medium and 5.85x$10^3$ for high severity of late blight disease in Irish potatoes. The explainable AI is indicated in terms of data transparency by indicating the Phytophthora infestans load amount that is in each prediction done by model.

# CHAPTER 8

# A design of a Deep learning model with (Baseline, Severity and integration of Open weather API) for early prediction and accurate diagnosis of late blight disease in Irish potatoes. A local dataset from Kigezi region-Uganda

Sub-model one is a baseline which is an optimized MobileNetV2 which was optimized by transfer learning and hyperparameter tuning.

Sub model two and contributes to objective two of the study. Various experiments the dataset was tuned to median of median 3.8x $10^3$ for Low, 4.5x$10^3$ for medium and 5.85x$10^3$ for high severity in late blight disease in Irish Potatoes.

The equal datasets were collected purposively 2,000 images for each category, that is, for low, medium and high.

### 8.0.1 Methodology used in development of Sub Model 2 Severity Classification Model

This was done using the deep learning pipeline as demonstrated below in the diagram.

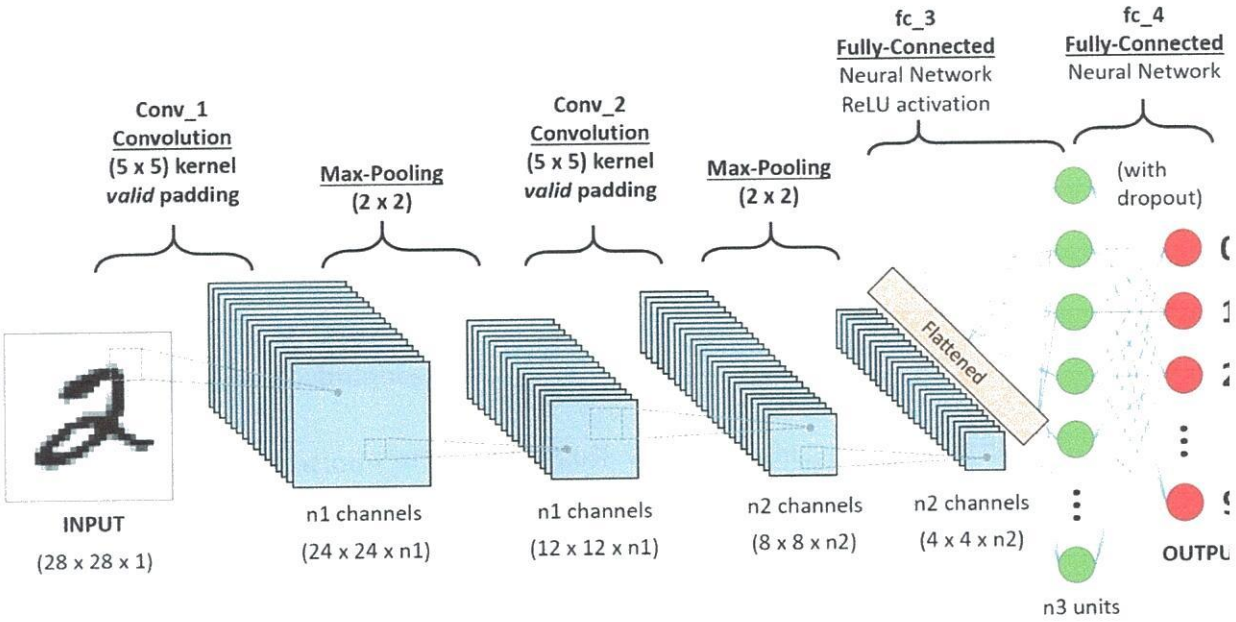



Fig. 8.1: The diagram shows the deep learning pipeline

Step one:Problem Definition Objective: Develop a classification model to categorize images into three classes (Low, Medium, High) based on their tuned median values. Input: 6,000 images (2,000 per class).

Output: Probability distribution over the three classes

### 8.0.2 Data Preparation

- **Dataset Structure**:
  - Images stored in `/late_blight/severity_dataset`.
  - Subdirectories: `low`, `moderate`, `high` (2,000 images per class).
- **Data Splitting**:
  - Training (80%), Validation (20%).

- Stratified splitting to maintain class balance.

### 8.0.3 Data Augmentation & Preprocessing

- **Preprocessing**:
  - Rescale pixel values to $[0, 1]$: `rescale=1./255`.
- **Augmentation Techniques**:
  - Random rotation (20°), shifts (20% width/height), horizontal flip.
  - `fill_mode='nearest'` for padding.
- **Generators**:
  - `flow_from_directory` for batch loading.

### 8.0.4 Model Architecture

- **Base Model**: MobileNetV2 (pretrained on ImageNet).
  - `include_top=False`, input shape $(224, 224, 3)$.
- **Custom Layers**:
  1. Global Average Pooling.
  2. Dense (512 units, ReLU).
  3. Dropout (rate=0.5).
  4. Output (3 units, Softmax).
- **Transfer Learning**:
  - Freeze all MobileNetV2 layers.

### 8.0.5 Training Configuration

- **Optimizer**: Adam (lr $= 1 \times 10^{-4}$).
- **Loss Function**: Categorical cross-entropy.
- **Metrics**: Accuracy.
- **Batch Size**: 32.
- **Epochs**: 20.

### 8.0.6 Model Training

- `model.fit()` with:
  - Training/validation generators.
  - `steps_per_epoch` and `validation_steps`.

## 8.1 Strengths & Improvements

### 8.1.1 Strengths

- Transfer learning with MobileNetV2.
- On-the-fly augmentation for generalization.
- Lightweight (suitable for edge deployment).

### 8.1.2 Recommendations

- Dynamic learning rate scheduling.
- Early stopping.
- Test set evaluation.
- Hyperparameter tuning (unfreezing deeper layers).

The methodology follows a systematic pipeline for image classification, emphasizing reproducibility, scalability, and modularity. The model achieves robust performance with room for further optimization.

### 8.1.3 Results for the model after testing with research adopted a Post –Hoc method of explainable AI called the Local Interpretable model-agnostic explanations

The diagram below shows the metrics of the classification model performance when subjected to 20 high class, 20 medium class and 20 low class.

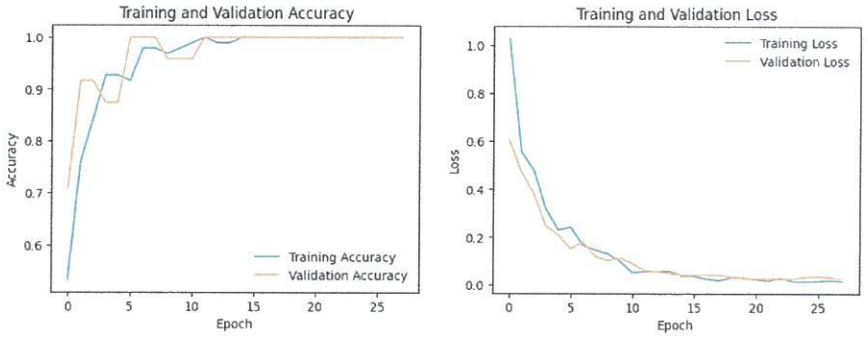



Fig. 8.2: The graphs show the metrics of the Classification model for severity prediction

Discussion The training accuracy of Classification model for severity prediction was 100% and the validation accuracy was 100%. The training loss was 0.0173 and the validation loss 0.0292.The results were obtained after testing with research adopted a Post - Hoc method of explainable AI called the Local Interpretable model-agnostic explanations

## 8.2 Conclusion

The results correctly aligned with laboratory results thus showing high levels of explainable Artificial Intelligence as well as success in classification of low, medium and high.

## 8.3 Integration with the Open Weather API( to predict temperature, humidity and wind speed

The open weather API was customized to the supplies real-time weather data which includes temperature, humidity, and wind speed—which the system's API accesses to enhance predictions and also validated with the environmental weather conditions in Kigezi.

Late blight thrives in temperature, moderate conditions (12-24°C), so this data is critical and humidity raising to more than 90% and a wind speed of 1-5.5 m/s [115].

The API requests this information for the plant's location and forwards it to the Final Prediction Model.

## 8.4 Final Intelligent Late Blight Disease Prediction and Diagnosis Model which was called the Deep Learned Model powered Mini Irish Potato Mini Pathogen Laboratory

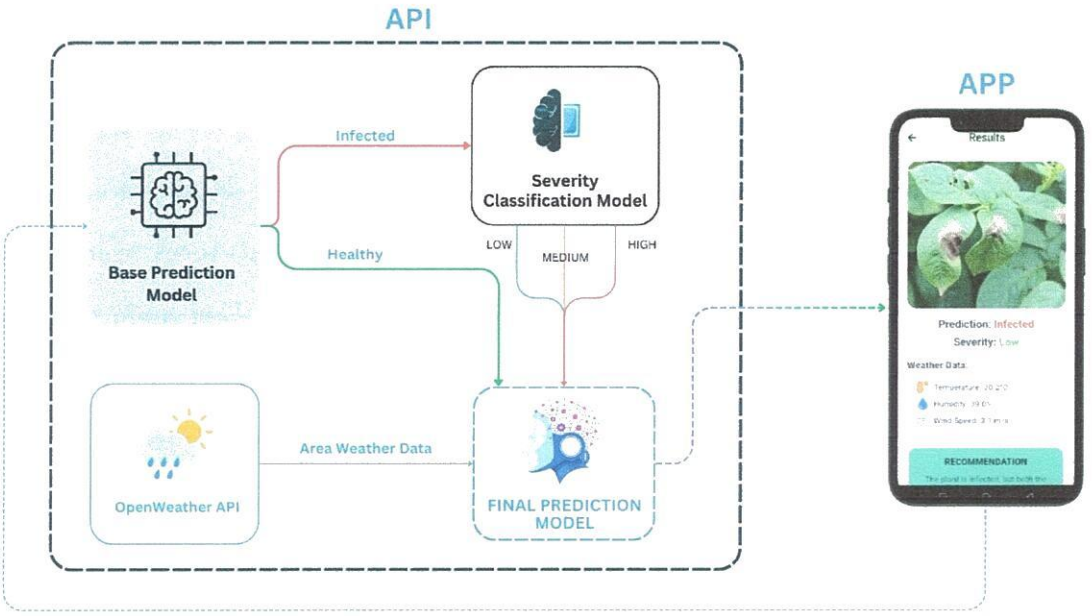



Fig. 8.3: The diagram shows Final Intelligent Late Blight Disease Prediction and Diagnosis Model

### 8.4.1 Overview

The system is built to identify late blight, a destructive disease marked by dark, water-soaked lesions on potato leaves, stems, and tubers, which thrives in cool, humid conditions. It begins with a user uploading an image via the mobile app, which triggers a series of processes managed by the API. This integrated design ensures accurate detection and actionable insights tailored to late blight management.

### 8.4.2 The Mobile App

The mobile app serves as the user interface, allowing farmers to upload images of potato plants and view results. When a user submits an image, the app sends the request to the API. It then displays the response, which includes the prediction, severity, weather data, and a recommendation.

### 8.4.3 API

The API acts as the system's backbone, wrapping the Base Prediction Model, Severity Classification Model, Final Prediction Model, and Open Weather API. It receives the image request from the app and routes it to the Base Prediction Model for initial analysis. If the plant is "Infected," the API forwards the image to the Severity Classification Model. At the same time, it queries the OpenWeather API for weather data, which it then provides to the Final Prediction Model alongside the classification and severity results. Once the Final Prediction Model generates the refined output, the API formats it into JSON and sends it back to the app. This centralized approach ensures efficient data flow, modularity, and the ability to update components without disrupting the user experience.

### 8.4.4 Base Prediction Model (MobileNetV2)

The Base Prediction Model uses the MobileNetV2 architecture, a lightweight and efficient framework ideal for mobile deployment. Trained on potato plant images, it detects late blight symptoms like irregular lesions. The model classifies the plant as "Healthy" or "Infected" and, via the API, passes "Infected" cases to the Severity Classification Model.

#### 8.4.4.1 Severity Classification Model

The Severity Classification Model, a custom CNN, evaluates the extent of late blight infection for Infected cases. It analyzes the image to determine severity levels, such as "Low," "Medium," or "High" based on factors like lesion coverage or intensity. The API directs the image to this model after an "Infected" classification, and the result is forwarded to the final prediction model.

### 8.4.5 Integration with the OpenWeather API

The OpenWeather API supplies real-time weather data which includes temperature, humidity, and wind speed—which the system's API accesses to enhance predictions. Late blight thrives in humid, moderate conditions (10-25°C), so this data is critical. The API requests this information for the plant's location and forwards it to the Final Prediction Model.

### 8.4.6 Final Prediction Model

The Final Prediction Model integrates the Base Prediction Model's classification, the Severity Classification Model's severity assessment, and the OpenWeather API's weather data. This model uses a fusion technique to weigh these inputs, adjusting the prediction based on environmental factors. For example, it might maintain a "Low" severity in dry conditions (39.0% humidity) despite an "Infected" status, recognizing that late blight struggles in such weather. The API then collects this refined prediction for delivery to the app.

## 8.5 The model algorithm and mathematical formulation

The algorithm

**Inputs:**

- InfectionStatus $\in$ {Healthy, Infected}
- WeatherData = $\{T, I, W\}$ Temperature, Humidity, WindSpeed

**Outputs:**

- Severity $\in$ {None, Low, Medium, High}
- RiskScore $\in [0, 1]$
- Recommendations = {Action, Alerts}

PredictInfectionStatus, WeatherData InfectionStatus = Healthy {Severity=None, RiskScore = 0} WeatherRisk $\leftarrow$ ComputeWeatherRisk(WeatherData) DiseaseProb $\leftarrow$ Classifier(WeatherI RiskScore $\leftarrow \alpha \cdot$DiseaseProb+$(1-\alpha) \cdot$WeatherRisk Severity $\leftarrow$ DetermineSeverity(RiskScore) Recommendations $\leftarrow$ GenerateRecommendations(Severity, WeatherRisk) {Severity, RiskScor

ComputeWeatherRisk$\{T, I, W\}$ $T' \leftarrow$ Normalize$(T, [T_{min}, T_{max}])$ $I' \leftarrow I/100$ Convert percentage to [0,1] $W' \leftarrow$ Normalize$(W, [0, W_{max}])$ $\sum w_i \cdot \text{features}_i$ Weighted combination

DetermineSeverityRiskScore RiskScore $< \tau_1$ Low $\tau_1 \leq$ RiskScore $< \tau_2$ Medium High

GenerateRecommendationsSeverity, WeatherRisk Action $\leftarrow$ ActionMap[Severity] Alerts $\leftarrow$ $\emptyset$ WeatherRisk $> \gamma$ Alerts $\leftarrow$ Alerts $\cup$ {WeatherWarning} {Action, Alerts}

The Mathematical Formulation

The core risk calculation follows:

$$\text{RiskScore} = \underbrace{\alpha P(\text{Disease}|\text{Features})}_{\text{Late BlightDisease Risk}} + \underbrace{(1-\alpha)\Psi(\text{Weather})}_{\text{Environmental Risk}} \tag{8.1}$$

Where:

- $P(\cdot)$ represents the disease probability classifier
- $\Psi(\cdot)$ computes the normalized weather risk
- $\alpha$ controls late blight Disease/environmental risk balance

### 8.5.1 Model deployment

After the model is successfully trained, I developed an Application Programming Interface(API) with FastAPI a python library used to create APIs for easy deployment.

The API was used to access the functionalities of our model for inference.

The whole application was wrapped the in a docker container and upload it to a cloud provider , that is, Google Cloud Platform (GCP).

The front end became a mobile application developed using flutter framework which is used to cross platform applications with the same code base.

# CHAPTER 9

# Testing and evaluating the Deep learning model powered Smart mini pathology Lab using a local dataset from Kigezi Uganda

To test and evaluate the developed model for early prediction and accurate diagnosis of Late blight disease.

### 9.0.1 Introduction

Testing and validating the model is one is one of the vital. The confusion matrix was used by extension workers through using the a mobile application that is connected to models in cloud. The samples were later taken to Laboratory for experimental confirmation in Laboratory. This was done to get accurate results for the confirming the performance of the Optimized Mobile V2 Model(Healthy or unhealthy, Severity classification model for confirming if the severity is low, medium or high. And validation of OpenWeather API for the accuracy as compared to real time temperature humidity and wind speed of Kabale, Kisoro and Rubanda. Further more there was need to test the temperature ranges for Late blight. Late blight thrives in temperature, moderate conditions (12-24°C), so this data is critical and humidity raising to more than 90%.and a wind speed of 1-5.5 m/s [116].

### 9.0.2 Methods

The experts were used to test and validate the application. These experts included extension workers (10). The participants above willingly accepted to participate in the study and underwent a successful training for three. The training was facilitated by an Information technologists one from Kabale University. A pathologist from Kachwekano Zonal Agricultural Research and Development Institute. and an expert in extension agriculture and usage of I Cts in Agriculture. The apk was installed on their phones and had a three day training on the use of the application to diagnosis and predict late blight disease. The (10) fifteen trained agricultural experts traversed the districts of Kabale, Rubanda and Kisoro to test and validate the Mobile Application.

To test the app, I used a confusion matrix approach with extension workers validation was used.

Procedure for testing and validating the application.

Step 1:Experiment Sample Selection: Collect crop samples (healthy and infected) in an open environment.

Baseline (Expert Diagnosis): Experts manually classify samples to confirm the ground truth.

App Testing: Run the app on the same samples to get its predictions.

Step 2: Confusion Matrix Analysis Compare the app's results against extension workers judgments.

Step 3: Metrics Calculation

The following performance metrics were calculated from the confusion matrix:

Table 9.1: Confusion Matrix Comparing Extension workers Diagnosis vs. Application Prediction

| | **App Predicts Positive** | **App Predicts Negative** |
|---|---|---|
| **Expert Confirms Positive** | True Positive (TP) | False Negative (FN) |
| **Expert Confirms Negative** | False Positive (FP) | True Negative (TN) |

$$\text{Accuracy} = \frac{TP + TN}{\text{Total}} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall (Sensitivity)} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Where:

- $TP$ = True Positives (Correctly identified late blight cases)
- $TN$ = True Negatives (Correctly identified healthy plants)
- $FP$ = False Positives (Healthy plants misclassified as infected)
- $FN$ = False Negatives (Infected plants misclassified as healthy)

Step 4: Field Testing (Real-World Validation) Deploy the Mobile application in Irish potato gardens for experts to use.

Step 5: Communication The app reduces false negatives by X% compared to manual checks").

Step 6: Publish results:

## 9.1 results

### 9.1.1 Results for the experts in Kabale District

Table 9.2: Evaluation Parameters Results

| E.W | Accuracy | Misclassification | Precision | Recall | F1-Score | Confusion Matrix F | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | TP | FP | FN | |
| 1 | 96% | 4.20% | 93% | 100% | 96% | 25 | 2 | 0 | |
| 2 | 98% | 2.04% | 96.15% | 100% | 98.03% | 25 | 1 | 0 | |
| 3 | 96% | 4.20% | 93% | 100% | 96% | 25 | 2 | 0 | |
| 4 | 100% | 0% | 100% | 100% | 100% | 25 | 0 | 0 | |
| 5 | 95.90% | 6.25% | 92.31% | 96% | 94.12% | 24 | 2 | 1 | |
| 6 | 94% | 6.12% | 95.83% | 92% | 93.87% | 23 | 1 | 2 | |
| 7 | 98% | 2.04% | 96.15% | 100% | 98.03% | 25 | 1 | 0 | |
| 8 | 98% | 2% | 100% | 96% | 97.96% | 24 | 0 | 1 | |
| 9 | 100% | 0% | 100% | 100% | 100% | 25 | 0 | 0 | |
| 10 | 94% | 6.12% | 95.83% | 92% | 93.87% | 23 | 1 | 2 | |

### 9.1.2 Discussion of Evaluation Results from Kabale

The presented results demonstrate the performance of a classification model across 10 experimental trials done by extension workers(E.W) , that is, (E.W 1–10), evaluated using standard metrics: accuracy, Misclassification rate, precision, recall, F1-score, and confusion matrix elements (TP, FP, FN, TN).

#### 9.1.2.1 Accuracy and Misclassification Rate

The model achieves high accuracy, ranging from 94% to 100%, with the lowest accuracy in E.W 5 (95.9%) and E.W 6 & 10 (94%). The Misclassification rate inversely correlates with accuracy, peaking at 6.25% (E.W 5) and dropping to 0% in E.W 4 and 9. This suggests strong overall classification ability, with minor variations.

#### 9.1.2.2 Precision and Recall

Precision (positive predictive value) ranges from 92.31% (E.W 5) to 100% (E.W 4, 8, 9), indicating minimal false positives in most trials.

Recall (sensitivity) is consistently high (92–100%), with perfect recall (100%) in E.W 1–4, 7, and 9, meaning almost all positive cases were correctly identified. Lower recall in E.W 6 and 10 (92%) suggests slight under-detection of true positives.

#### 9.1.2.3 F1-Score (Harmonic Mean of Precision and Recall)

The F1-score, which balances precision and recall, ranges from 93.87% (E.W 6 & 10) to 100% (E.W 4 & 9). The near-perfect scores in E.W 4 and 9 indicate optimal model performance, while lower scores in E.W 6 and 10 reflect minor trade-offs between precision and recall.

#### 9.1.2.4 Confusion Matrix Analysis

True Positives (TP): Consistently high (23–25), with perfect detection in multiple trials.

False Positives (FP): Minimal (0–2), except E.W 5 (FP=2).

False Negatives (FN): Mostly zero, except E.W 5, 6, 8, and 10 (FN=1–2), indicating rare missed detections.

| E.W | Accuracy | Misclassification | Precision | Recall | F1-Score | Confusion Matrix 1 | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | TP | FP | FN | |
| 1 | 94% | 6.12% | 95.83% | 92% | 93.86% | 23 | 01 | 02 | |
| 2 | 98% | 2.04% | 96.15% | 100% | 98.03% | 25 | 1 | 0 | |
| 3 | 96% | 4.20% | 93% | 100% | 96% | 25 | 2 | 0 | |
| 4 | 95.9% | 6.25% | 92.31% | 96% | 94.12% | 25 | 0 | 0 | |
| 5 | 95.90% | 6.25% | 92.31% | 96% | 94.12% | 24 | 2 | 1 | |
| 6 | 94% | 6.12% | 95.83% | 92% | 93.87% | 23 | 1 | 2 | |
| 7 | 98% | 2.04% | 96.15% | 100% | 98.03% | 25 | 1 | 0 | |
| 8 | 98% | 2% | 100% | 96% | 97.96% | 24 | 0 | 1 | |
| 9 | 100% | 0% | 100% | 100% | 100% | 25 | 0 | 0 | |
| 10 | 98% | 2% | 100% | 96% | 97% | 24 | 00 | 01 | |

True Negatives (TN): Stable (23–25), confirming reliable negative-class identification

#### 9.1.2.5 Conclusion

The model demonstrates robustness, with E.W 4 and 9 achieving flawless performance (100% accuracy, precision, recall, F1-score). Slight declines in E.W 5, 6, and 10.Overall, the results validate the model's reliability for practical deployment in late blight detection tasks.

#### 9.1.2.6 Future work

Future work could explore feature optimization or ensemble methods to further reduce misclassifications.

The results from Rubanda

### 9.1.3 Discussion of Evaluation Results from Rubanda

The presented results evaluate a classification model across 10 experimental trials (E.W 1–10) using six key metrics: accuracy, Misclassification rate, precision, recall, F1-score, and confusion matrix components (TP, FP, FN, TN). A comprehensive analysis reveals critical insights into model performance and potential areas for improvement.

#### 9.1.3.1 Accuracy and Misclassification Rate

The model achieves high accuracy (94%–100%), with peak performance in E.W 9 (100%) and near-perfect results in E.W 2, 7, 8, and 10 (98%). The lowest accuracy occurs in E.W 1, 4, 5, and 6 (94%–95.9%), correlating with higher Misclassification rates (6.12%–6.25%). These variations suggest sensitivity to input data distribution or minor overfitting in specific trials.

#### 9.1.3.2 Precision and Recall

Precision (ability to avoid false positives) reaches 100% in E.W 8, 9, and 10, but drops to 92.31% in E.W 4 and 5 due to 2 FP cases.

Recall (ability to detect true positives) is perfect (100%) in E.W 2, 3, 7, and 9, but dips to 92% in E.W 1 and 6, indicating missed positives (FN=2).

#### 9.1.3.3 F1-Score (Harmonic Mean of Precision and Recall)

The harmonic mean of precision and recall (F1-score) ranges from 93.86% (E.W 1) to 100% (E.W 9), reflecting balanced performance. Lower F1-scores (e.g., E.W 1, 5, 6) highlight trials where precision and recall diverge.

#### 9.1.3.4 Confusion Matrix Analysis

True Positives (TP): Consistently high (23–25), with flawless detection in E.W 2, 3, 4, 7, and 9.

False Positives (FP): Minimal (0–2), except E.W 5 (FP=2).

False Negatives (FN): Rare (0–2), with E.W 1 and 6 showing slight under-detection (FN=2).

True Negatives (TN): Stable (23–25), confirming robust negative-class identification.

#### 9.1.3.5 Conclusion

The model demonstrates strong reliability, particularly in E.W 9 (100% across all metrics). Minor declines in E.W 1, 5, and 6 suggest sensitivity to data variability. To enhance robustness:Overall, the results validate the model's reliability for practical deployment in late blight prediction tasks.

#### 9.1.3.6 Future work

Feature Engineering: Address class imbalances or noisy features affecting E.W 5–6. Threshold Tuning: Optimize decision boundaries to reduce FP/FN trade-offs. Cross-Validation: Validate consistency across larger datasets.

The results from Kisoro.

### 9.1.4 Discussion of Evaluation Results from Kisoro

The experimental results from Kisoro present a comprehensive evaluation of a classification model across 10 trials (E.W 1-10), analyzed through standard performance metrics

| E.W | Accuracy | Misclassification | Precision | Recall | F1-Score | Confusion Matrix F | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | TP | FP | FN |
| 1 | 98% | 2.04% | 96.15% | 100% | 98.03% | 25 | 1 | 0 |
| 2 | 98% | 2.04% | 96.15% | 100% | 98.03% | 25 | 1 | 0 |
| 3 | 96% | 4.20% | 93% | 100% | 96% | 25 | 2 | 0 |
| 4 | 98% | 2.04% | 96.15% | 100% | 98.03% | 25 | 01 | 0 |
| 5 | 95.90% | 6.25% | 92.31% | 96% | 94.12% | 24 | 2 | 1 |
| 6 | 94% | 6.12% | 95.83% | 92% | 93.87% | 23 | 1 | 2 |
| 7 | 98% | 2.04% | 96.15% | 100% | 98.03% | 25 | 1 | 0 |
| 8 | 98% | 2% | 100% | 96% | 97.96% | 24 | 0 | 1 |
| 9 | 100% | 0% | 100% | 100% | 100% | 25 | 0 | 0 |
| 10 | 94% | 6.12% | 95.83% | 92% | 93.87% | 23 | 1 | 2 |

and confusion matrix components. This analysis reveals both the model's strengths and areas for potential improvement.

#### 9.1.4.1 Accuracy and Misclassification Rate

The model demonstrates exceptional performance across most trials, with accuracy ranging from 94% to a perfect 100% in E.W 9. The Misclassification rate inversely mirrors this trend, peaking at 6.25% in E.W 5 and reaching 0% in the flawless E.W 9

#### 9.1.4.2 Precision and Recall

Precision values remain consistently high (92.31%-100%), with perfect scores in E.W 8 and 9, indicating minimal false positives. Recall achieves 100% in multiple trials (E.W 1-4,7), though dips to 92% in E.W 6 and 10, suggesting occasional under-detection of positive cases.

#### 9.1.4.3 F1-Score (Harmonic Mean of Precision and Recall)

The F1-score, balancing precision and recall, ranges from 93.87% to 100%, with most trials exceeding 96%.

#### 9.1.4.4 Confusion Matrix Analysis

True Positive (TP) counts remain consistently high (23-25), demonstrating reliable detection of target cases. False Positives (FP) are minimal (0-2), with only E.W 5 showing two instances. False Negatives (FN) appear in just four trials (E.W 5,6,8,10), with a maximum of two occurrences. True Negatives (TN) maintain stable performance (23-25), confirming effective negative case identification.

#### 9.1.4.5 Conclusion

The Kisoro results demonstrate a highly effective classification model, with most trials showing excellent performance metrics. The consistent high accuracy and balanced precision-recall metrics suggest strong potential for practical applications.

#### 9.1.4.6 Future work

Optimize decision boundaries to reduce FP/FN trade-offs.Cross-Validation: Validate consistency across larger datasets.

## 9.2 testing and evaluation of the severity classification model.

testing and evaluation of the severity classification model of the severity classification model majorly look at the conformity of the results with the laboratory experiments.

We random selected 500 samples done by extension works in three districts

### 9.2.1 Selecting the laboratory samples

If n=500

## Step 1: Cochran's Formula for Infinite Populations

First, compute the sample size $n_0$ assuming an infinite population:

$$n_0 = \frac{Z^2 \cdot p \cdot (1-p)}{e^2}$$

where:

- $Z = 1.96$ (Z-score for 95% confidence)
- $p = 0.5$ (maximum variability, conservative estimate)
- $e = 0.05$ (margin of error)

Substituting the values:

$$n_0 = \frac{(1.96)^2 \times 0.5 \times 0.5}{(0.05)^2} = \frac{3.8416 \times 0.25}{0.0025} \approx 385$$

## Step 2: Finite Population Correction

Adjust $n_0$ for the finite population ($N = 500$):

$$n = \frac{n_0}{1 + \frac{n_0 - 1}{N}}$$

$$n = \frac{385}{1 + \frac{385-1}{500}} = \frac{385}{1 + 0.768} \approx 218$$

### Alternative: Yamane's Simplified Formula

For quick estimation, use Yamane's formula:

$$n = \frac{N}{1 + N(e^2)} = \frac{500}{1 + 500(0.0025)} = \frac{500}{2.25} \approx 222$$

## Conclusion

For a population of $N = 500$:

- Cochran's adjusted sample size: $\boxed{218}$
- Yamane's simplified sample size: $\boxed{222}$

A sample size of $\boxed{220}$ (rounded) is recommended for a 95% confidence level and 5% margin of error. Due to constants in resources we did 20 samples for low severity and 20 for medium and 20 for high severity. The sixty samples confirmed with the with

Table 9.3: Percentile ranges for the results;cfu/$m^2$-colony forming units per $m^2$

| Grading | Non-Zero Count | P25 (cfu/$m^2$) | P50 (cfu/$m^2$) | P75 (cfu/$m^2$) | P90 (cfu/$m^2$) |
|---|---|---|---|---|---|
| High | 20 | 1500 | 5850 | 13900 | 151000 |
| Medium | 20 | 3650 | 4500 | 5350 | 5860 |
| Low | 20 | 3600 | 3800 | 6850 | 119140 |

values of used in data collection as shown in the table above.

## 9.3 Evaluation of Open weather API

This was evaluated by comparing the model results with the results of thermometer for temperature, Agronometer for humidity and Anemometer for wind-speed. The Open weather API was adjusted and re-programmed to obtain the real-time results which will be sent to the model for final prediction

The table below shows the comparison of the model results temperature humidity and wind to the atmospheric results of the Kigezi-region Uganda.

Specifications of the equipment used; Thermometer: Liquid-in-Glass Thermometers was used because its of Traditional mercury or alcohol-filled thermometers,used for Basic temperature measurement small-scale farming,and manual weather stations [117] Hygrometer: Digital Hygrometers (Extech RH520) was used in this study because of Range: 10%–99%. [118]

Anemometer Cup Anemometer anemometer was used in this study because of High accuracy and portable. [119]

## 9.4 conclusion

The OpenWeather API results were consistent with the results of the thermometer, Hygrometer and Anemometer.

The results of the temperature, humidity and wind speed are important because they improve the environment factors in prediction for example 10-25 degrees centigrade are favorable for Phytophora infestans, that is if the temperature is below 10 degree centigrade and above 25 degrees centigrade there is less risk as Late Blight disease. Considering humidity when the humidity is less 90% then risk is low and greater than

90 the risk is high. A wind-speed of (1-5.5)m/s for high risk while less 1 m/s and greater than 5.5 is low risk.

Below are the results of one day that show consistency.

Table 9.4: Model and Atmospheric Results in Kigezi

| Days | Model Results in Kigezi | | | Atmospheric Results in Kigezi | | |
|---|---|---|---|---|---|---|
| | Wind speed | Temperature | Humidity | Wind speed | Temperature | Humidity |
| 1 | 2.6 | 31.4 | 30 | 2.6 | 31.4 | 30 |
| 2 | 2.6 | 31.4 | 30 | 2.6 | 31.4 | 30 |
| 3 | 2.6 | 31.4 | 30 | 2.6 | 31.4 | 30 |
| 4 | 2.6 | 31.4 | 30 | 2.6 | 31.4 | 30 |
| 5 | 2.6 | 31.4 | 30 | 2.6 | 31.4 | 30 |
| 6 | 2.6 | 31.4 | 30 | 2.6 | 31.4 | 30 |
| 7 | 2.6 | 31.4 | 30 | 2.6 | 31.4 | 30 |
| 8 | 2.6 | 31.4 | 30 | 2.6 | 31.4 | 30 |
| 9 | 2.6 | 31.4 | 30 | 2.6 | 31.4 | 30 |
| 10 | 2.6 | 31.4 | 30 | 2.6 | 31.4 | 30 |
| 11 | 3.5 | 32.6 | 28 | 3.5 | 32.6 | 28 |
| 12 | 3.5 | 32.6 | 28 | 3.5 | 32.6 | 28 |
| 13 | 3.5 | 32.6 | 28 | 3.5 | 32.6 | 28 |
| 14 | 3.5 | 32.6 | 28 | 3.5 | 32.6 | 28 |
| 15 | 3.5 | 32.6 | 28 | 3.5 | 32.6 | 28 |
| 16 | 3.5 | 32.6 | 28 | 3.5 | 32.6 | 28 |
| 17 | 3.5 | 32.6 | 28 | 3.5 | 32.6 | 28 |
| 18 | 3.5 | 32.6 | 28 | 3.5 | 32.6 | 28 |
| 19 | 3.5 | 32.6 | 28 | 3.5 | 32.6 | 28 |
| 20 | 3.5 | 32.6 | 28 | 3.5 | 32.6 | 28 |
| 21 | 4.6 | 33.0 | 27 | 4.6 | 33.0 | 27 |
| 22 | 5.5 | 30.7 | 33 | 5.5 | 30.7 | 33 |
| 23 | 4.4 | 29.0 | 40 | 4.4 | 29.0 | 40 |
| 24 | 4.4 | 29.0 | 40 | 4.4 | 29.0 | 40 |

# CHAPTER 10

# Research Contributions, Limitations,Conclusion and Future

## 10.1 Chapter Overview

This chapter is composed of conclusion,research contribution, body of knowledge, published papers, Technological Contribution, Limitations and Future Work.

## 10.2 Research Contribution

The study contributed a deep learning powered Mini Irish potato pathology Labo- ratory for extension workers to improve the early prediction and accurate diagnosis of late blight in Irish potatoes.

### 10.2.1 Body of Knowledge

The first manuscript is (A Determination of Sample Size for Plant Leaves in Deep Learning Models for Predicting Late Blight in Irish Potatoes: An experimentation methodology in Kigczi –Uganda) In this manuscript researchers get insights on the how determine sample space for the plant leaf determination and this greatly contributes to the body of knowledge.

The second manuscript is (Exploring Strategies for Optimizing MobileNetV2 Performance in Classification Tasks Through Transfer Learning and Hyperparameter Tuning with A Local Dataset from Kigezi, Uganda). In this manuscript strategies for optimizing MobileNetV2 performance in classification Tasks Through transfer learning and hyperparameter tuning are explored and this greatly contributes to the body of Knowledge.

The third manuscript is (The Application of Explainable AI in a Deep Learning Model for Early Prediction and Diagnosis of Late Blight Disease in Irish Potatoes: A Dataset from Kigezi Region-Uganda). In this manuscript the application of AI is explored and thus contributing to the body of knowledge.

### 10.2.2 Published Papers

1 A Determination of Sample Size for Plant Leaves in Deep Learning Models for Predicting Late Blight in Irish Potatoes: An experimentation methodology in Kigezi –Uganda:https://doi.org/10.33022/ijcs.v14i2.4647

2 Exploring Strategies for Optimizing MobileNetV2 Performance in Classification Tasks Through Transfer Learning and Hyperparameter Tuning with A Local Dataset from Kigezi, Uganda:https://doi.org/10.33022/ijcs.v14i1.4436

3 The Application of Explainable AI in a Deep Learning Model for Early Prediction and Diagnosis of Late Blight Disease in Irish Potatoes: A Dataset from Kigezi Region-Uganda:https://ejsit-journal.com/index.php/ejsit/article/view/661

### 10.2.3 Technological Contribution

The technological contribution of this research is the development of Deep learning powered model mini Irish potato pathology Laboratory to help extension work achieved

early prediction and accurate diagnosis of lab blight disease in Irish potatoes.

This novel innovation has three sub-model which determine if the Irish potato is health or unhealthy.

The first sub-model the baseline model(MobileNetV2) of Deep learning powered Mini Irish potato Pathology Laboratory. This was optimized during transfer learning and hyperparameter tuning and a number unique equation were generated.

### 10.2.4 Equation one is for a complete layer freezing system based on the performance of results from freezing

#### 10.2.4.1 Layer Freezing Model for MobileNetV2

Let:

- $\Theta = \{\theta_1, \theta_2, \ldots, \theta_L\}$ be the parameters of MobileNetV2's $L$ layers
- $k$ = number of unfrozen top layers (control parameter)
- $\eta$ = learning rate
- $\mathcal{L}$ = loss function

## Parameter Update Equations

1. **Layer Activation Function** (determines trainable layers):

$$a_i(k) = \begin{cases} 1 & \text{if } i > L - k \text{ (unfrozen)} \\ 0 & \text{if } i \leq L - k \text{ (frozen)} \end{cases}$$

2. **Parameter Update Rule**:

$$\theta_i^{(t+1)} = \theta_i^{(t)} - \eta \cdot a_i(k) \cdot \nabla_{\theta_i} \mathcal{L}(\Theta^{(t)})$$

3. **Empirical Performance Mapping**:

$$\text{Perf}(k) = \begin{cases} (0.90, 0.85) & \text{for } k = 1 \\ (0.92, 0.88) & \text{for } 2 \leq k \leq 10 \\ (0.95, 0.88) & \text{for } 11 \leq k \leq 20 \\ (0.98, 0.96) & \text{for } k = L \end{cases}$$

**Complete System Description**

$$\Theta^{(t+1)} = \left\{ \theta_i^{(t)} - \eta \cdot \mathbb{I}[i > L - k] \cdot \nabla_{\theta_i} \mathcal{L}(\Theta^{(t)}) \right\}_{i=1}^{L}$$

where $\mathbb{I}[\cdot]$ is the indicator function, and the performance is given by $\text{Perf}(k)$.

### 10.2.5 The logarithmic model for simplicity and interpretability

$$y = 2.34 \cdot \ln(x) + 85.21$$

This equation:

- Quantifies the accuracy gains from layer unfreezing
- Highlights the diminishing returns property of unfreezing additional layers

The model enables computation of optimal layer freezing points through mathematical analysis rather than computational power, making it particularly suitable for resource-constrained environments.

### 10.2.6 Mathematical equation for the optimized model with hyper parameter tuning and layer freezing

The a a unique equation that gives limits for both the layer freezing and hyper parameter tuning combined. Below is the equation

$$y_{\text{final}} = \underbrace{(2.34 \cdot \ln(x) + 85.21)}_{\text{Base Accuracy}} \times \underbrace{\sqrt{\frac{\eta}{0.001}}}_{\substack{\text{Learning Rate} \\ \text{Adjustment}}} \times \underbrace{\left(1 + \frac{1}{\sqrt{B}}\right)}_{\substack{\text{Batch Size} \\ \text{Effect}}} + \underbrace{0.5 \times \frac{1.01}{\text{Adam}_{\text{Boost}}}}_{\substack{\text{Optimizer} \\ \text{Bonus}}} \tag{10.1}$$

## Model Components

- **Base Accuracy**:
  - $x$: Number of unfrozen layers ($x \geq 1$)
  - Logarithmic relationship shows diminishing returns
  - 85.21% baseline accuracy with all layers frozen
- **Learning Rate Adjustment**:
  - $\eta$: Training learning rate
  - Normalized against reference value 0.001
  - Square root reduces sensitivity to large $\eta$
- **Batch Size Effect**:
  - $B$: Batch size
  - Favors smaller batches ($B \downarrow \Rightarrow$ accuracy $\uparrow$)
  - Inverse square root relationship
- **Optimizer Bonus**:

- Adam optimizer with early stopping boost
- Constant scaling factor (0.5)
- 1.01 multiplier represents early stopping benefit

### 10.2.7 The novel architecture and algorithm equation for the Deep learning powered Mini Irish potato Pathology Laboratory

#### 10.2.7.1 The architecture Deep learning powered Mini Irish potato Pathology Laboratory

Below is the architecture;

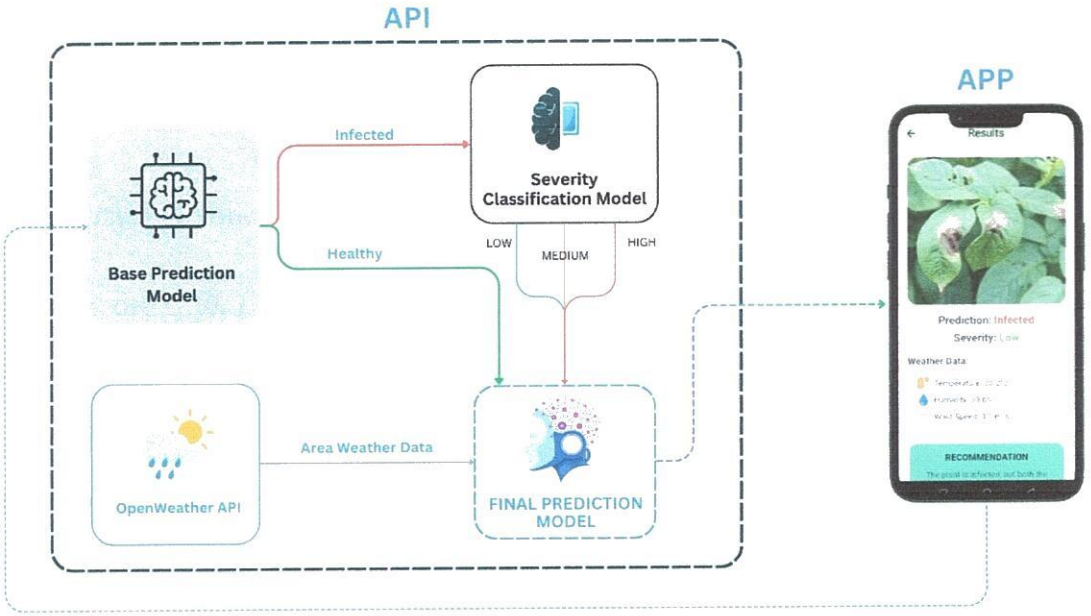



Fig. 10.1: The diagram shows Final Intelligent Late Blight Disease Prediction and Diagnosis Model

The practical implications and scalability of the final model in a real-world agricultural context are as follows; Cheap agricultural diagnosis thus early prediction and diagnosis.

Short turn around time for agriculture lab experiments.

Increase gross domestic production.

Transfer of the pathology laboratory to be used to be used by farmers

#### 10.2.7.2 The novel algorithm and mathematical formulation of severity classification for Deep learning powered Mini Irish potato Pathology Laboratory

The algorithm [1]

**Inputs:**

- InfectionStatus $\in$ {Healthy, Infected}
- WeatherData = $\{T, I, W\}$ Temperature, Humidity, WindSpeed

**Outputs:**

- Severity $\in$ {None, Low, Medium, High}
- RiskScore $\in [0, 1]$
- Recommendations = {Action, Alerts}

PredictInfectionStatus. WeatherData InfectionStatus = Healthy {Severity = None, RiskScore 0} WeatherRisk $\leftarrow$ ComputeWeatherRisk(WeatherData) DiseaseProb $\leftarrow$ Classifier(Weather RiskScore $\leftarrow \alpha \cdot$DiseaseProb$+(1-\alpha) \cdot$WeatherRisk Severity $\leftarrow$ DetermineSeverity(RiskScore) Recommendations $\leftarrow$ GenerateRecommendations(Severity, WeatherRisk) {Severity, RiskSco

ComputeWeatherRisk$\{T, I, W\}$ $T' \leftarrow$ Normalize$(T, [T_{min}, T_{max}])$ $I' \leftarrow I/100$ Convert percentage to [0,1] $W' \leftarrow$ Normalize$(W, [0, W_{max}])$ $\sum w_i \cdot$features$_i$ Weighted combination

DetermineSeverityRiskScore RiskScore $< \tau_1$ Low $\tau_1 \leq$ RiskScore $< \tau_2$ Medium High

GenerateRecommendationsSeverity, WeatherRisk Action $\leftarrow$ ActionMap[Severity] Alerts $\leftarrow$ $\emptyset$ WeatherRisk $> \gamma$ Alerts $\leftarrow$ Alerts $\cup$ {WeatherWarning} {Action, Alerts}

The Mathematical Formulation

The core risk calculation follows:

$$\text{RiskScore} = \underbrace{\alpha P(\text{Disease}|\text{Features})}_{\text{Late BlightDisease Risk}} + \underbrace{(1-\alpha)\Psi(\text{Weather})}_{\text{Environmental Risk}} \tag{10.2}$$

Where:

- $P(\cdot)$ represents the disease probability classifier
- $\Psi(\cdot)$ computes the normalized weather risk
- $\alpha$ controls late blight Disease/environmental risk balance

## 10.3 Limitations

The first limitation was limited funding for this study.

The inability for the Model to communication with The mobile application most especially along the Uganda-Rwanda border due to network challenges

## 10.4 Conclusion

A deep learning model powered Mini Irish potato pathology Laboratory for extension workers to improve the early prediction and accurate diagnosis of late blight in Irish potatoes. This application was developed according to the late blight life cycle and took

into considered prediction of health and unhealthy, it also considered testing the severity of the disease rated as low, medium and high. The model also considered factors like temperature humidity and wind speed.

## 10.5 Future Work

Future research should be done in further crop science to experiment with the model and give recommended on specific herbicides to treat late blight late and proper spraying schedules.

More investigation should be done in unleashing the black-box to make future models more explainable.

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# Appendices

# A Research Ethics Committee Approval

MBARARA UNIVERSITY OF SCIENCE AND TECHNOLOGY
RESEARCH ETHICS COMMITTEE

**20/03/2024**

To: Jack Turihohabwe

Mbarara University of Science and Technology
0788039440

**Type:** Initial Review

**Re: MUST-2023-1308: A deep learning model for early prediction and diagnosis of Late Blight Disease in Irish potatoes: A case of Kigezi Region**

I am pleased to inform you that at the **163rd** convened meeting on **05/01/2024**, the MUST Research Ethics Committee meeting voted to approve the above referenced application.
Approval of the research is for the period of **20/03/2024** to **20/03/2025.**

As Principal Investigator of the research, you are responsible for fulfilling the following requirements of approval:

1. All co-investigators must be kept informed of the status of the research.
2. Changes, amendments, and addenda to the protocol or the consent form must be submitted to the REC for re-review and approval **prior** to the activation of the changes.
3. Reports of unanticipated problems involving risks to participants or any new information which could change the risk benefit: ratio must be submitted to the REC.
4. Only approved consent forms are to be used in the enrollment of participants. All consent forms signed by participants and/or witnesses should be retained on file. The REC may conduct audits of all study records, and consent documentation may be part of such audits.
5. Continuing review application must be submitted to the REC **eight weeks** prior to the expiration date of **20/03/2025** in order to continue the study beyond the approved period. Failure to submit a continuing review application in a timely fashion may result in suspension or termination of the study.
6. The REC application number assigned to the research should be cited in any correspondence with the REC of record.
7. You are required to register the research protocol with the Uganda National Council for Science and Technology (UNCST) for final clearance to undertake the study in Uganda.

The following is the list of all documents approved in this application by MUST Research Ethics Committee:

| No. | Document Title | Language | Version Number | Version Date |
|---|---|---|---|---|
| 1 | Data collection tools | English | Version2 | 2024-02-12 |
| 2 | Informed Consent forms | Runyakore Rukiiga | Runyakore Rukiiga version | 2024-02-12 |
| 3 | Protocol | English | Protocol revised version two. | 2024-02-12 |

Yours Sincerely

Dr. Paul Alele
For: MUST Research Ethics Committee

# B UNCST Approval




**Uganda National Council for Science and Technology**

*(Established by Act of Parliament of the Republic of Uganda)*

**Our Ref: SIR323ES** **5 June 2024**

Jack Turihohabwe
Mountain of the Moon University
**Kabarole**

**Re: Research Approval:** **A deep learning model for early prediction and diagnosis of Late Blight Disease in Irish potatoes: A case of Kigezi Region RefNo:MUST-2023-1308**

I am pleased to inform you that on **05/06/2024**, the Uganda National Council for Science and Technology (UNCST) approved the above referenced research project. The Approval of the research project is for the period of **05/06/2024** to **05/06/2025**.

Your research registration number with the UNCST is **SIR323ES**. Please. cite this number in all your future correspondences with UNCST in respect of the above research project. As the Principal Investigator of the research project, you are responsible for fulfilling the following requirements of approval:

1. Keeping all co-investigators informed of the status of the research.
2. Submitting all changes, amendments, and addenda to the research protocol or the consent form (where applicable) to the designated Research Ethics Committee (REC) or Lead Agency for re-review and approval **prior** to the activation of the changes. UNCST must be notified of the approved changes within five working days.
3. For clinical trials, all serious adverse events must be reported promptly to the designated local REC for review with copies to the National Drug Authority and a notification to the UNCST.
4. Unanticipated problems involving risks to research participants or other must be reported promptly to the UNCST. New information that becomes available which could change the risk/benefit ratio must be submitted promptly for UNCST notification after review by the REC.
5. Only approved study procedures are to be implemented. The UNCST may conduct impromptu audits of all study records.
6. An annual progress report and approval letter of continuation from the REC must be submitted electronically to UNCST. Failure to do so may result in termination of the research project.

Please note that this approval includes all study related tools submitted as part of the application as shown below:

| No. | Document Title | Language | Version Number | Version Date |
|---|---|---|---|---|
| 1 | Data collection Tool | English | 1 | 20 March 2024 |
| 2 | Project Proposal | English | VERSION 1 | |
| 3 | Approval Letter | English | | |
| 3 | Informed consent for farmers | English | 1 | 21 May 2024 |
| 4 | Informed consent for the farmer (RR) | Runyakore Rukiga | 1 | 21 May 2024 |
| 5 | Approved Covid-19 Risk Mitigation Plan for the study | English | 1 | 21 May 2024 |
| 6 | Informed Consent for the extension workers | English | 1 | 21 May 2024 |

Yours sincerely,

Hellen Opolot
For: Executive Secretary
**UGANDA NATIONAL COUNCIL FOR SCIENCE AND TECHNOLOGY**

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# C Letter of authorization from CoVAB Lab Makerere University


**MAKERERE UNIVERSITY**

**COLLEGE OF VETERINARY MEDICINE ANIMAL RESOURCES & BIOSECURITY**
SCHOOL OF BIOSECURITY, BIOTECHNICAL & LABORATORY SCIENCES.

**DEPARTMENT OF BIOTECHNICAL & DIAGNOSTIC SCIENCES**
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**VETERINARY MICROBIOLOGY RESEARCH LABORATORY**

**The Directorate of Research and graduate Training** **Date: 15th/07/2025**
**Mbarara University of science and Technology**

**Dear Sir/Madam,**

**RE: Acknowledgement of Mr. Turihohabwe Jack Conducting Laboratory analyses.**

This is to certify that **Mr. TURIHOHABWE JACK** offering a PhD in Computing at the Mbarara University of science Technology registered under student number **2021/PhD/022/PS** did part of his research objectives from the Veterinary Microbiology Research Laboratory at the College of Veterinary medicine, animal resources and Biosecurity of Makerere University.

Mr. Turihohabwe whose research topic states; **A deep learning model for early prediction and diagnosis of late blight disease. A case of Kigezi-region Uganda** used services of our laboratory to determine the fungal load of *Phytophthora species* on tomato leaves at different infection stages. Laboratory analyses to identify and quantify *Phytophthora species* from tomato leaves were conducted from December, 2024 up to February, 2025 at the Veterinary Microbiology Research Laboratory.

Therefore, I have no reservations in acknowledging that Mr. Turihohabwe Jack conducted his microbial assays at VMRL/CoVAB-Mak

Yours faithfully

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# D List of Publications

1.A Determination of Sample Size for Plant Leaves in Deep Learning Models for Predicting Late Blight in Irish Potatoes: An experimentation methodology in Kigezi–Uganda :https://doi.org/10.33022/ijcs.v14i2.4647

2 Exploring Strategies for Optimizing MobileNetV2 Performance in Classification Tasks Through Transfer Learning and Hyperparameter Tuning with A Local Dataset from Kigezi, Uganda: https://doi.org/10.33022/ijcs.v14i1.4436

3 The Application of Explainable AI in a Deep Learning Model for Early Prediction and Diagnosis of Late Blight Disease in Irish Potatoes: A Dataset from Kigezi Region Uganda:https: //cjsit-journal.com/index.php/cjsit/article/view/661