



ADDIS ABABA SCIENCE AND TECHNOLOGY UNIVERSITY

**DEVELOPING DEEP LEARNING BASED
XANTHOMONAS WILT (BXW) AND SIGATOKA LEAF
SPOT DISEASE DETECTION AND CLASSIFICATION
MODEL ON BANANA CROP**

By

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Declaration

I hereby declare that this thesis entitled "**Developing Deep Learning-Based Xanthomonas Wilt (Bxw) and Sigatoka Leaf Spot Disease Detection and Classification Model on Banana Crop**" was prepared by me, with the guidance of my advisor. The work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted, in whole or in part, for any other degree or professional qualification.

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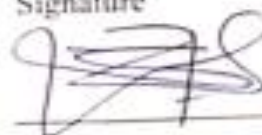
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Abstract

Crop diseases are one of the world's leading causes of famine and food instability. Plant infections are thought to be responsible for up to 16 % of global crop yield losses each year. Banana is a widely cultivating crop and highly consumed fruit in developed and developing countries. Diseases and pests are challenges that affect the productivity of the crop. Xanthomonas wilt and Sigatoka leaf spot diseases are the major problems in the production of banana which can cause up to 100% yield losses. In Ethiopia the diseases are shown widely in South Nation Nationalities and People Region Benchmaji, Gamugofa and Sheka zones banana farms and are affecting huge damage on the banana crop. Once the infection is started, the diseases can destroy the entire farm within a very short period of time. Early detection of the infection of plant diseases prevents the farm from huge damage. Detecting and classifying plant disease by observation with the naked eye has a problem on the accuracy of the classification and identifying severity level of the infection. This research uses deep learning to develop banana plant disease detection and classification model in Convolutional Neural Network. The banana plant leaf image dataset is collected from SNNPR Arbaminch Zuria Woreda Lante kebele and Chano kebele and Gamugofa zone Mierab Abaya Woreda Omolante kebele where banana is produced in vast and xanthomonas wilt and sigatoka leaf spot diseases are common. Since training the model demands a large dataset and there is a shortage of images, data augmentation were performed. The dataset were splits in to 90% for training and 10% for validation and testing the proposed model. A pre-trained model of CNN algorithm were modified and trained and validate using the training images then tested by the test images. From the pre-trained models used, by using evaluation metric the performance of the models were evaluated and VGG16 among the pre-trained models scored 81.53%. The result is promising based on the

amount of data collected. Preparation of large dataset which consists of different plants and their disease types, and integration of the model with drone and IoT technologies can be future words for further studies.

Keywords: *Deep Learning, Convolutional Neural Network, Disease detection and classification, Xanthomonas wilt, Sigatoka leaf spot*

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Abbreviations and Acronyms

ANN	:Artificial Neural Network
API	:Application Program Interface
BXW	:Banana Xanthomonas Wilt
CL	:Convolutional Layer
CNN	:Convolutional Neural Network
DL	:Deep Learning
EIAR	:Ethiopian Institute of Agriculture Research
GLCM	:Gray Level Co-occurrence Matrix
KNN	:K-Nearest Neighbor
LBP	:Local binary pattern
LVQ	:Learning Vector Quantization
ML	:Machine Learning
RGB	:Red, Green and Blue
SVM	:Support Vector Machine
SNNPR	:South Nation Nationalities and People Region
SD	:Sigatoka Disease
VGG16	:the Visual Geometry Group 16
VGG19	:the Visual Geometry Group 19
XVM	:Xanthomonas Vasicola pv. Musacearum

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CHAPTER 1 INTRODUCTION

1.1 Introduction

Agriculture is the backbone of Ethiopia's economy. Nearly 85% of the Ethiopians rely on agriculture as the primary source of livelihood. Agricultural production has become much more important over the last few decades than it has been in previous years, earlier plants were used only for feeding humans and animals. It seems to be an important raw material source for many growing crops industries. Though, crop diseases are one of the world's leading causes of famine and food instability. Plant infections are thought to be responsible for up to 16 % of global crop yield losses each year.

Bananas are a popular fruit crop in both industrialized and developing nations. The production-distribution zone is primarily located between 30° North and 30° South latitudes, with winter temperatures of 60° F or higher and average monthly rainfall of 100 mm. The crop can also be grown in cold, frost-free environments. Following rice, wheat, and maize, bananas are the world's fourth most significant food crop. [1]. As a result, bananas are the world's most important fruit crop in terms of volume and value.

Dessert bananas are the most extensively farmed and consumed fruit crop in Ethiopia [1][2]. It is grown in several locations where the growing circumstances are favorable. It is extremely important socioeconomically, especially in the south and southwest parts of the country, contributing significantly to rural communities' general well-being, including food security, income production, and employment creation. Banana accounts for about 59.64% (53,956.16 hectares) of total fruit area, 68.00 % (478,251.04 tons) of all fruits produced, and 38.30% (2,574,035) of Ethiopia's total fruit-producing farmers. Bananas, on the other hand, cover 68.72 % (37,076.85 hectares) of land, produce 77.53 % (370,784.17 tons), and are home to 22.38 % (1,504,207) of Ethiopia's banana growers in the southern nations nationalities and peoples' national regional state SNNPRS[2]. The SNNPR State's key banana-producing zones include Gamo-Gofa, Bench-Maji, and Sheka, with the Gamo-Gofa zone alone accounting for approximately 70% of the overall banana market share across Ethiopia's major retail outlets [3].

Banana production in the world is estimated to be 104 million tons per year, but only around 10% of it makes it to the commercial market, indicating that the crop is more essential for local consumption than for export. East Africa is the world's largest banana producer and consumer. The bacterium *Xanthomonas campestris* pv *musacearum* causes *Xanthomonas* wilt BXW disease, which threatens the livelihood of millions of farmers in East Africa[4]. Since its discovery in Uganda in 2001, the illness has spread to nearly every major banana-producing country in Africa. The disease has been documented in the Democratic Republic of Congo, Rwanda, Kenya, and Burundi, in addition to the Democratic Republic of Congo, Rwanda, Kenya, and Burundi [5]. BXW was first discovered in Ethiopia more than 30 years ago on *Ensete* species, which are closely related to bananas[4]. BXW disease attacks banana varieties that are regularly grown. Affected banana plants show signs such as leaf yellowing and bendiness, as well as premature fruit growth with distinct yellowish parts and spots in the tissue, and dark brown placental scars. Symptoms on floral parts include wilting of bracts, shrinkage, and rotting of male buds, and yellowing of flower stalks. Infected plants progressively weaken the plant roots as cross-sections of sick pseudo stems reveal yellowish bacterial ooze [1][2][3].

Eventually, infected plants weaken the plant roots. BXW infection can come from a variety of sources. Infected banana plants, plant residues, contaminated soil, and traded products are the main sources of pathogen inoculum. Previous research suggests that insect transmission via moist cushions exposed after male flowers shed from the inflorescence is the predominant mode of disease transmission. Other means for pathogens to spread include diseased plant roots or the usage of contaminated instruments. Absolute yield loss or reduced bunch weights, as well as the death of the mother plant and suckers, which aid in subsequent rate growth on plant production cycles, are all signs of the disease's economic impact [3][4][5].

Sick fields cannot be replanted with bananas for a long period due to the pathogen's soil-borne inoculum. BXW shares characteristics with other *Ralstonia* (formerly *Pseudomonas Solanacearum*, Spp.) bacterial wilts of bananas, such as Moko Blood and Sigatoka sicknesses and creatures. Controlling illnesses once they have established themselves in smallholder banana cropping systems is exceedingly difficult, and eradication is almost impossible, according to experience with these diseases [6].

1.2 Motivation

East Africa in general Ethiopia specific has a good climate and soil for many crop productions. Furthermore, banana is indeed a cash crop and a source of revenue for farmers. In Ethiopia, Banana is a widely cultivated crop and many farmers and their families are dependent on it. However, diseases and pests are challenges that affect the productivity of the crop. *Xanthomonas wilt*/ Bacterial wilt and Sigatoka leaf spot diseases are one of the major problems in the production of bananas. Once the farm is infected by these diseases, farmers are forced to destroy the entire banana tree from their farm and burn the tree and even their farm to kill the bacterial wilt. Re-cultivating the banana farm needs more than a year because the banana tree cannot give the fruit before the tree grows well. In this situation, the farmer loses its income from the banana farm for years. Because of this, farmers become insecure about their food and sending their children to school.

As a result, using an automated approach to detect BXW and Sigatoka leaf spot diseases early, will largely benefit farmers and their communities. The researchers as Software Engineering researchers motivated to work on *Xanthomonas wilt* and Sigatoka leaf spot plant diseases detection and classification system using deep learning. Finally, the proposed effort would assist farmers in detecting if their farm is contaminated with BXW early and taking action before their crop is destroyed by the diseases.

1.3 Statements of the Problem

East Africa in general Ethiopia specific has a good climate and soil for bananas and many other crop productions. Nevertheless, banana is a cash crop and a source of revenue for farmers. The production of banana crops is affected by microorganisms like bacteria, fungus, and viruses. Many banana diseases affect the growth and production of the crop from which *Xanthomonas wilt*, moko disease, Fingertip rot (gumming), and Sigatoka are bacterial diseases.

The major and most distracting disease that severely impacts banana production is *Xanthomonas wilt* and Sigatoka leaf spot diseases. These diseases can destroy the entire farm within a very short period of time once the form is affected. Developing countries like Ethiopia need early detection of *Xanthomonas wilt* and Sigatoka leaf spot disease, to save the banana crop before it

is devastated. Plant disease identification by vision is a more time-consuming and inaccurate task that can only be done in limited locations [7]. Whereas if automatic detection and classification technique is used, it will be more effective, accurate, and take less time to detect and classify.

In the SNNPR of Ethiopia, banana is a widely cultivated crop [8]. However, in the cultivation process, diseases and pests are challenges that affect the productivity of the banana crop. One of the most serious challenges in banana production is Xanthomonas Wilt/bacterial wilt and Sigatoka leaf spot diseases.

BXW and Sigatoka leaf spot diseases are the most devastating disease affecting bananas especially in the southern part of Ethiopia and identifying the infection early is almost impossible by observation. BXW has contributed to decreasing household and national income. The disease shows some symptoms on the crop's leaves, which are the disease's primary indicators in the field[9]. Depending on those symptoms which are directly shown in the crop leaf, we can develop a model that identifies the disease in the crop. Therefore, the development of Xanthomonas wilt and sigatoka leaf spot disease detection is quite useful for the early detection of the infection so that the farmers can detect early if their farm is infected by xanthomonas wilt and or sigatoka leaf spot.

1.4 Research Questions

Below are the research questions for the study.

RQ1: How to develop a banana disease detection and classification model using deep learning?

RQ2: What method could be used to detect and classify Xanthomonas Wilt (BXW) and Sigatoka leaf spot banana diseases.

1.5 Objectives of the Study

1.5.1 General Objective

The general objective of this study is to develop a deep learning-based disease detection and classification model for Xanthomonas Wilt (BXW) and Sigatoka leaf spot banana disease.

1.5.2 Specific Objectives

This study's specific objectives are as follows:

- Examine the literature on computer vision-based work on crop disease detection and classification.
- Collect images of healthy and disease-infected banana leaves directly from the banana farm.
- Choose a suitable methodology and tools to prepare the image dataset.
- Develop a disease detection and classification model using a deep learning algorithm.
- Train and test the proposed model using the prepared dataset.
- Evaluate the proposed model's performance.

1.6 Scope of the Study

The goal of this research is to create and test a BXW detection model for bananas. This is mostly focused on the model, which uses photos of healthy and sick banana leaves obtained from a banana farm. The photos were taken on various farms in the SNNPR Ethiopia region. Using a smartphone camera, the photographs were captured from various fields in SNNPR Ethiopia. The study focuses solely on the detection and classification of BXW and Sigatoka banana disease; other illnesses, such as Moko disease, and other crops are not included. The reason to exclude the other banana leaf disease is, it has a low impact compared to BXW and Sigatoka. Furthermore, it would take a long time to investigate and prepare the image. Finally, the disease detection and classification model do not recommend medical treatment after the disease is found on the crop.

1.7 Significance of the Study

The study will have the following benefits:

- The research result will help the farmers to understand the importance of computer vision in the agricultural sector.

- After the proposed model is integrated with different platforms the research contributes to lowering the cost of production, which causes farmers to make a loss due to the excessive use of pesticides on their crops.
- Integrating the proposed model with different platforms, the proposed model will reduce the cost of experts for continuous monitoring of crops in large farms.
- The research can be used as a reference and guide for further studies.

1.8 Contributions

The study contributes to the area and the following society.

- Preparation of dataset for *BXW* and *Sigatoka* disease detection and classification on a banana plant.
- Farmers who are cultivating banana crops can easily identify whether their crop is infected by BXW disease or Sigatoka banana disease and can take measures to treat the farm.
- The agricultural business will be highly motivated to invest in banana production.
- This research result can be used as input for the researchers and the research community for their further study.

1.9 Structure of the Thesis

The thesis is organized as follows. The first chapter is an introduction that includes a summary of the problem statement, research questions, and the study's significance, the scope of the study, general and specific objectives, and the contribution of the research. The next chapter is talking about the literature review and summary of related works. In general, the literature study gives a summary report on banana sickness, computer vision, machine learning, and deep learning principles.

A list of works produced by other researchers that are highly significant and more closely related to this study subject is given in the same chapter, under the summary of related works. The research approaches are then discussed in Chapter three. The experimentation and its findings are then explained in Chapter four. The experiment's results and discussions are covered in Chapter

five. Finally, the conclusion, recommendation, and contribution of the study are explained in Chapter six.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This chapter mainly emphasizes the review of works of literature within this thesis domain from research papers, journals, books, and conferences. The literature review includes basic concepts of banana production, diseases of banana, machine learning, deep learning, convolutional neural network, tools need to use for image classification, and others. Finally, the chapter is concluded with summaries of related works.

2.2 Banana Production in Ethiopia

In Ethiopia, modern banana production began with the establishment of government farms and various plantations, including large-scale sugarcane plantations. Small plantations in home gardens owned by small farmers, especially in the South-Western and Western provinces; medium-sized plantations of not more than 10 hectares supplying local consumers; and relatively large plantations of more than 20 hectares developed to supply export markets are the main components of the crop production system.

Ethiopia began exporting bananas in 1961, with roughly 5000 tons being exported. However, by 1972, when the country began exporting to various countries in Europe, Asia, and Africa, this amount had climbed to 60,000 tons. In 1975, the country's entire banana production was estimated to be over 100,000 tonnes [14]. The dessert banana is the leading fruit crop in Ethiopia, both in terms of consumption and production, among the country's horticultural crops.

At present, it is believed to cover about 86% (478,251.04 tones) of the total fruit production. The crop grows in various parts of the country in the form of the home garden crop at a household level to large-scale plantations. The SNNPRS of the country is the primary banana producer region which accounts for 37,076.85 hectares area of land coverage by banana production. The Gamo Gofa Bench Maji and Sheka zones in the SNNPR state produce the most bananas, with the Gamo Gofa zone alone accounting for over 70% of the country's total banana market supply. Because of its flavor, the Arba Minch banana is the most popular banana variety in the country, with the highest demand in all of the country's markets at the moment [14].



Figure1: Banana Plant Farm

2.3 Banana Crop Diseases

Bacterial illnesses of bananas have not gotten the same level of attention as other important hazards to banana production, such as fungal diseases, until lately. Bacteria, on the other hand, have a big impact on bananas all over the world, and growers aren't always aware of or follow good management measures.

Many diseases and pests affect bananas, some of which are extremely important for these important food crops. In bananas, there are three types of bacterial infections: *Ralstonia*-related diseases (Moko/Bugtok disease caused by *Ralstonia solanacearum* and banana blood disease caused by *Ralstonia syzygii* subsp. *Celebesensis*); *Xanthomonas* wilt of banana caused by *Xanthomonas campestris* pv. *Musacearum*; *Erwinia*-related diseases (bacterial head rot or tip-over disease *Erwinia caro*[15].

2.3.1 Xanthomonas Wilt

BXW (banana bacterial wilt) is a disease that causes a banana plant to rot from the inside out, and to a lesser extent, BBW (banana bacterial wilt). The bacteria *Xanthomonas vasicola* pv causes the sickness. *Xanthomonas campestris* pv. *Musacearum* (Xvm), originally known as *Xanthomonas campestris* pv. *Musacearum*. These minuscule single-cell creatures grow once inside the plant and generate the slime that is evident when an infected plant is sliced open.

Insects and cutting tools that come into contact with the bacterial slime are the carriers of the disease.

Affected banana trees show signs such as leaf yellowing and wilting, as well as uneven and premature fruit ripening, with portions showing distinctive yellowish blotches in the pulp and dark brown placental scars [8]. Low soil fertility and *Xanthomonas* wilt are currently regarded the two greatest challenges to banana productivity in the East African Great Lakes region [15]. Yield losses, which can reach 100%, depend on cultivar susceptibility, crop growth stage at the time of infection, and weather conditions, with the consequences being more severe during wet seasons [16].



Figure2: Level of Disease Infection from Healthy to Infected

2.3.2 Sigatoka Diseases

On bananas, three Sigatoka leaf diseases have been identified. Yellow Sigatoka, black Sigatoka, and eumusae leaf spot are three types of *Sigatoka*. *Mycosphaerella musicola* causes yellow *Sigatoka*, *Mycosphaerella Fijiensis* causes black Sigatoka, and *Mycosphaerella Eumusae* causes eumusae leaf spot. Yellow *Sigatoka* is the most widespread, while black Sigatoka is rapidly displacing it in many areas. *M. eumusae* has only been found in Nigeria, Mauritius, and South-East Asia, even though its similarity to *M. musicola* and *M. fijiensis* suggests it could be more extensively distributed [17].

Sigatoka disease symptoms can be seen on leaf tissues, with lower photosynthetic capacity affecting fruit size and quantity per bunch. The first noticeable symptoms of Yellow Sigatoka are point-shaped mild discolorations between the secondary veins of the leaves [10]. These points

develop into yellow streaks, brown streaks, and necrotic patches that are oval, elongated, and aligned parallel to the secondary leaf veins over time. These become wounds with depressed centers that are grey in color and encircled by yellow haloes. Within the middle of active incisions, regular lines of sporodochia can be seen.

2.3.3 Moko Disease

Moko disease is a vascular wilt of bananas and plantains caused by phytoplasma. As a result of the bacterial wilt, smallholder plantations have sustained severe losses. The symptoms of Moko disease vary based on the plant's growth stage and infection path. Among them include a conspicuous temporary yellowing, loss of turgor, desiccation, and necrosis. The youngest leaves' lamina stops growing and develops yellowish, then necrotic panels. In mature plants, male blossoms are typically darkened and fading. Daughter suckers can wilt in general, but they can also generate healthy suckers. Internally, the vascular bundles are discolored a reddish-brown color, and the fruits are usually uniformly reddish-brown in color and rotting. Inflorescences are infected, and the illness is spread by insects or infected plant material; the pathogen is likely to survive in soil or plant debris. Because afflicted bunches can appear normal, fruits from sick plants could be a source of infection. Cutting tool cleaning, field sanitation, and the selection of disease-free planting materials are all examples of sanitation methods [11].

2.3.4 Banana Bunchy Top Disease

The most common viral infection in bananas is caused by the banana bunchy top virus, which is disseminated by the banana aphid *Pentalonia nigronervosa*. The illness can result in disastrous plantation losses, which in some places have reached 100%. Infected plants have narrow, erect, and gradually shorter leaves, giving them a rosetted appearance. The leaf edges curl upwards and have a slight yellowing. On the midrib and petiole, dark green streaks extend downward into the pseudostem. After infection, the symptoms develop only on the newly formed leaves. The majority of the diagnostics are short dark green dots and dashes that form hooks as they enter the midrib's edge. The banana bunchy top virus (BBTV) appears to be susceptible to all *Musa* species and cultivars studied, but the incubation period may vary. The elimination of infected plants and the use of virus-free planting material are two methods for controlling BBTV [11].

2.4 Machine Learning

Machine learning (ML) is an artificial intelligence (AI) technique that enables systems to learn and improve without being explicitly programmed. The goal of machine learning is to create computer algorithms that can access data and learn on their own [12][31]. The learning process begins with observations or data, such as examples, direct experience, or teaching, so that we can look for patterns in data and make better decisions in the future based on our examples. The main goal is for computers to be able to learn on their own, without the need for human intervention, and to adapt their behavior accordingly. Traditional ML algorithms, on the other hand, treat the text as a series of keywords; instead, a semantic analysis technique mimics the human ability to decipher the meaning of a document. There are two types of machine learning algorithms: supervised and unsupervised.

2.4.1 Supervised Machine Learning Algorithms

Can use labeled examples to apply what they've learnt in the past to fresh data in order to anticipate future events. The learning algorithm generates an inferred function based on the examination of a particular training dataset to provide predictions about the output values. After proper training, the system may provide targets for any new input. The learning algorithm may also detect faults by comparing its output to the proper, intended result. This allows the model to be tweaked as needed [13][31].

2.4.2 Unsupervised Machine Learning Algorithms

Unsupervised machine learning approaches are used when there is no way to classify or label the training data. The study of how computers may infer a function from unlabeled data in order to explain a hidden structure is known as unsupervised learning. Instead of determining the best output, the system examines the input and used datasets to infer hidden structures from unlabeled data.

2.4.3 Semi-supervised machine learning algorithms

Because they use both labeled and unlabeled data for training (usually a small quantity of labeled data and a big amount of unlabeled data), it falls midway between supervised and unsupervised learning. This strategy can significantly enhance learning accuracy in systems that adopt it.

Semi-supervised learning is typically used when the acquired labeled data necessitates the use of skilled and appropriate resources to train/learn from it. Obtaining unlabeled data, on the other hand, usually does not necessitate additional resources [14][31].

2.4.4 Reinforcement Machine Learning Algorithms

Reinforcement machine learning algorithms are a sort of learning algorithm that generates actions and detects failures or rewards in its environment. Trial and error search and delayed reward are the most crucial aspects of reinforcement learning. This technology allows machines and software agents to autonomously select the proper response in a given environment, increasing their efficiency. For the agent to learn which action is superior, simple reward feedback is required; this is known as the reinforcement signal [14][12][31]. Massive amounts of data can be analyzed using machine learning. While it generally provides faster, more accurate results in identifying profitable possibilities or risky threats, fully training it may take more time and resources. Combining machine learning with artificial intelligence and cognitive technologies can improve its efficiency in processing vast amounts of data [21][19][31].

2.5 Deep Learning

Deep learning (DL) is an AI function that mimics the human brain's processing of data and pattern creation to make decisions. In artificial intelligence, deep learning is a subset of machine learning (ML) that uses networks to learn unsupervised from unstructured or unlabeled data. DL or deep neural network are other terms for the same thing. It's also a machine learning technology that can learn to execute categorization jobs using photos, text, or sound. DL models can achieve cutting-edge accuracy, sometimes even outperforming humans. Models are trained to utilize a huge quantity of labeled data and multilayer neural network architectures [22][23][15].

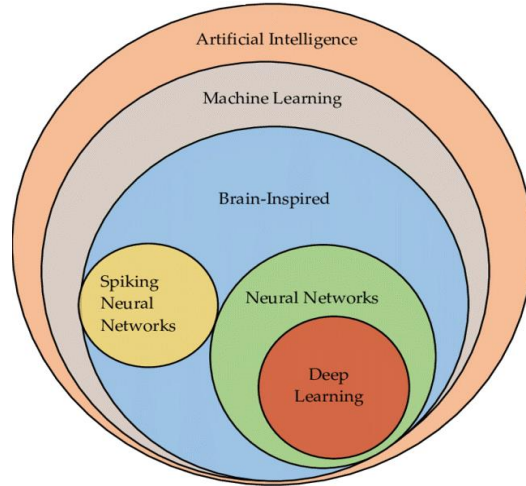


Figure3: The Taxonomy of AI

2.6 Convolutional Neural Network

CNN is considered one of the most widely used Machine Language techniques, especially in vision-related applications. CNN can learn representations from the grid-like data, and recently it has shown substantial performance improvement in various Machine Language applications. Since CNN possesses both good feature generation and discrimination ability, therefore in a typical Machine Language system, CNN capabilities are exploited for feature generation and classification. A neural network is an interconnected system of artificial "neurons" that communicate with one another. Throughout the training phase, the connections are given numerical weights. Convolutional neural networks (ConvNets) are a type of neural network that is frequently used in image processing, image restoration, speech recognition, natural language processing, and bioinformatics to handle problems such as image categorization, object identification, and image recognition. CNN is capable of recognizing and categorizing objects with minimum pre-processing, allowing it to achieve a high level of object analysis and feature separation using multilayered features[16][17][18]. The *convolutional layer*, *pooling layer*, *activation function*, and *fully connected layer* are the main layers of CNN.

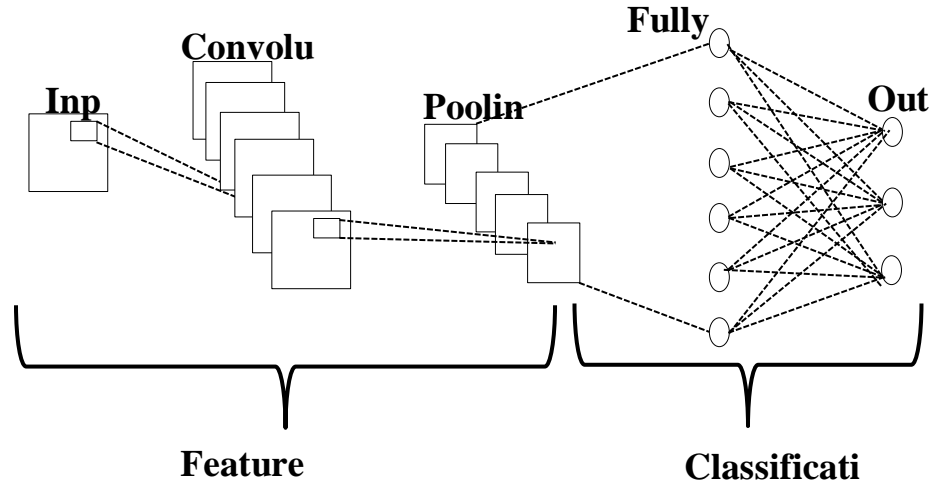


Figure3: Convolutional Neural Networks CNN Architecture

2.6.1 Convolutional Layer

The CNN algorithm took its name from the *convolution layer*. In this layer series of mathematical operations i.e. matrix operation performed to extract a feature map from the input image [19]. The mathematical operation is depicted in Figure 2.4. First, the filter is shifted step by step starting from the upper left corner of the image. At each step, the values in the image are multiplied by the values of the filter (kernel) and the result is summed [20]. A new matrix with a smaller size is created from the input image.

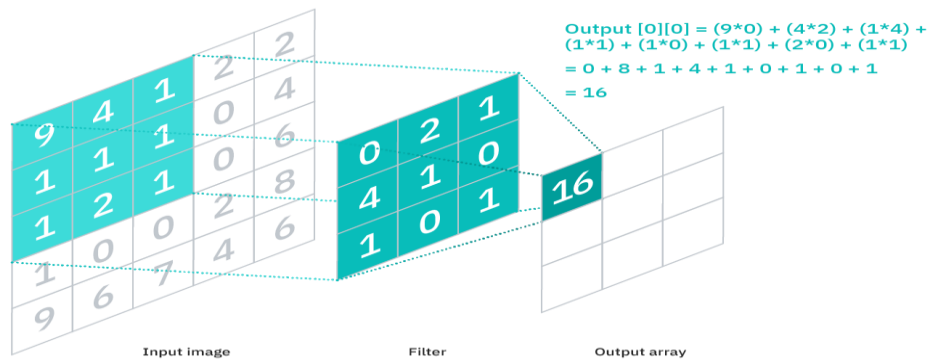


Figure4: Convolutional Layer Operations

2.6.2 Pooling Layer

The pooling layer is the second layer after the convolutional layer operation. This layer provides a typical down sampling operation which reduces the in-plane dimensionality of feature maps to

introduce translation invariance to a small shift and distortion and decrease the number of subsequent learnable parameters[19][20]. After an operation is performed in the convolution layer, a feature map is generated as an output. The output of the Convolutional layer feature map will be reduced in the pooling layer. Different filter sizes are used in the pooling layer. Usually, a 2x2 size filter is used, and also several functions like *max pooling*, *average pooling*, *sum pooling* are used. Max pooling operation is depicted in Figure 2.5, Max pooling is performed by selecting the largest element from the input matrix concerning the filter.

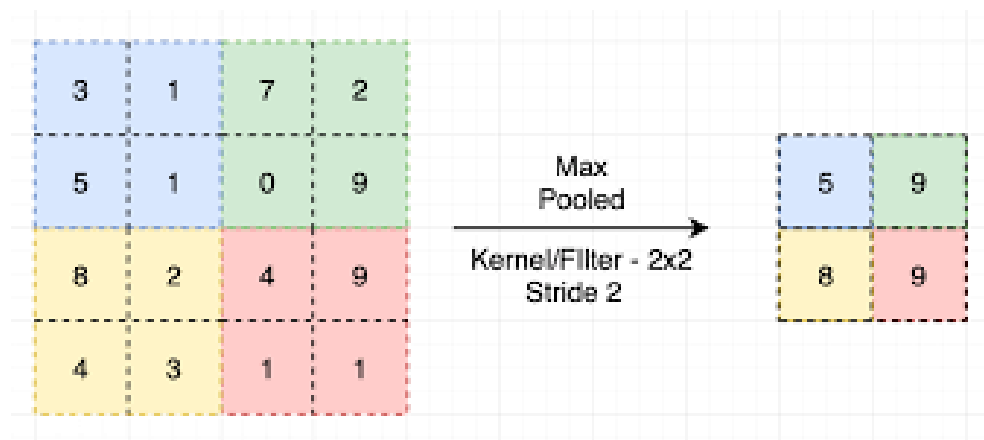


Figure5: Max Pooling With a Stride of 2 With 2x2 Filter

2.6.3 Activation Function

The activation function is a decision-making function that helps in the learning of complex patterns. The use of the right activation function can speed up the learning process. As one of the parameters of CNN architecture, in deep learning (DL), many complex problems like image classification, object recognition, object detection, and others use a non-linear activation function with the neural network [20][21][18]. The task of the function is to decide weighted sum and adding bias to proceed or not its calculation. Sigmoid, Tanh, Maxout (docplayer.net), and other activation functions are only a few examples [19][26][25][30][28]. In a neural network, the activation function handles a distinct complex task, such as image detection and classification. A ReLU and variants of ReLU are recommended among the activation functions described because they overcome the problem of disappearing gradients. MISH is one of the recently proposed activation functions which showed better performance than ReLU. In this study, the MISH activation function is not used because Keras API2 does not support.

2.6.3.1 ReLU (Rectified Linear Unit) Activation Function

It is the most widely used activation function and its value range from 0 to infinity.

2.6.3.2 Sigmoid Activation Function (Logistic Function)

Is a very popular activation function. The function takes an input and transforms between 0 and 1. Similarly, the input value of more than 1 transformed to 1, and a value smaller than 0 snapped to 0.

2.6.3.3 Softmax Activation Function

One of the activation functions used for decision making sigmoid and mostly used for the output layer of DL. It gives value to the input variable according to their weight and the sum of those weights becomes one.

2.6.4 Fully Connected Layer (Dense layer)

Is an essential component of CNN that recognizes and classifies an image in a computer vision successfully. Once the input image feed to the CNN algorithm, after it passes the convolution and pooling layer the image breakdown into a feature and is analyzed independently. This layer flattens the output of the pooling layer to classify an image [20].

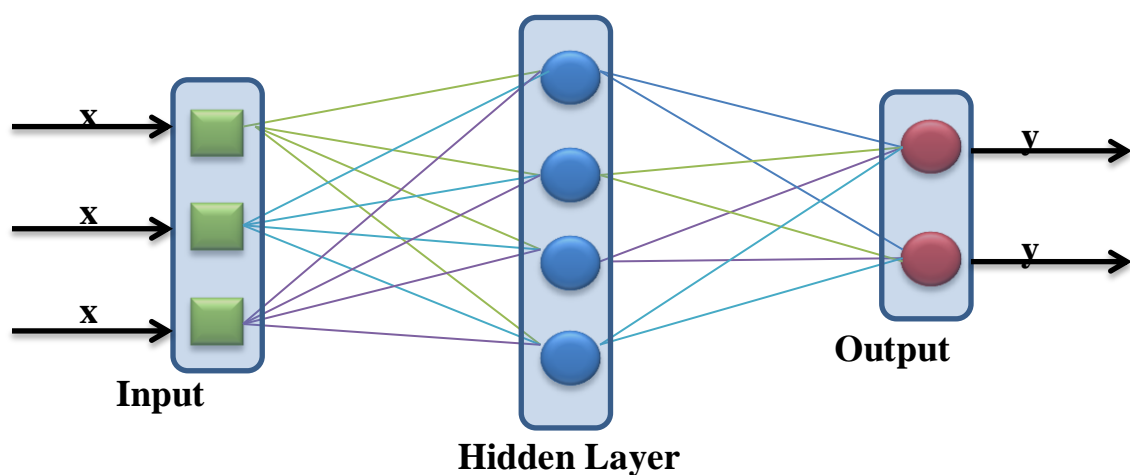


Figure6: Fully Connected Layer

A fully connected layer is a superior way of learning non-linear aspects of the output provided from convolution and pooling layers in addition to classification. Fully Convolutional Networks are convolutional networks that do not have all of their layers connected (FCN).

2.7 Convolutional Neural Network Architectures

The convolution layer, subsampling layer, dense layers, and soft-max layer are all important layer building blocks in the creation of a Convolutional Neural Network. After the design, fully connected and SoftMax layers are frequently added to stacks with several convolutional layers and max-pooling layers. Some examples of such models are LeNet, AlexNet, VGG Net, ResNet, GoogleNet, InceptionNet, and all convolutional (All Conv) models [31].

2.7.1 The LeNet

Despite the fact that LeNet was introduced in the 1990s, the algorithm's poor computing and memory capacity prevented it from being implemented until around 2010. Researchers presented CNNs that used the back-propagation technique to achieve state-of-the-art performance, and then evaluated them on a dataset of handwritten digit accuracy. LeNet-5 [22] is the name for the planned CNN architecture.

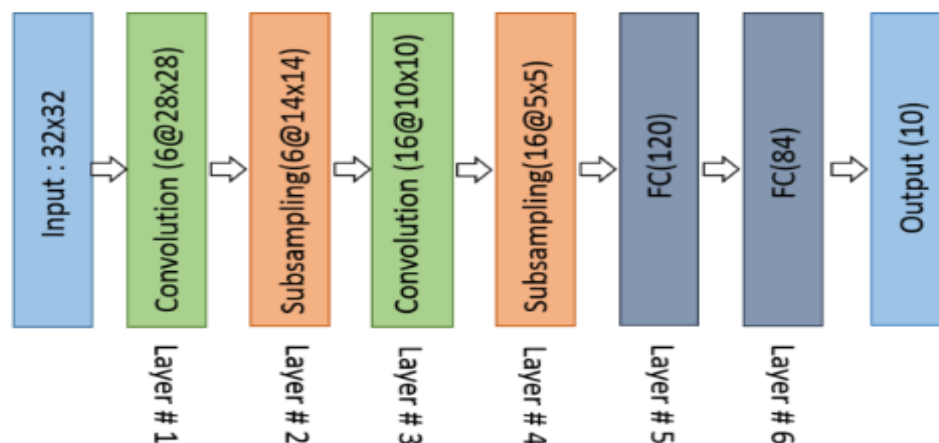


Figure7: Architecture of LeNet

2.7.2 The AlexNet

In contrast to LeNet, Alex Krizhevsky and colleagues introduced a deeper and broader CNN model, which won the most challenging ImageNet challenge for visual object identification, the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), in 2012 [31].

AlexNet outperformed all classic machine learning and computer vision algorithms in terms of recognition accuracy. It was a turning point in the history of machine learning and computer vision for visual recognition and classification tasks, and it ushered in a new era of deep learning interest[32]. The architecture has about 650,000 neurons and 60 million parameters, and the components of the model are arranged as 5 convolution layers, 2 normalization layers, 3 max-pooling layers, 3 fully connected layers, and Softmax in the output. Dropout regularization was applied to decrease the overfitting problem and in each convolution layer, the Relu activation function was used [23].

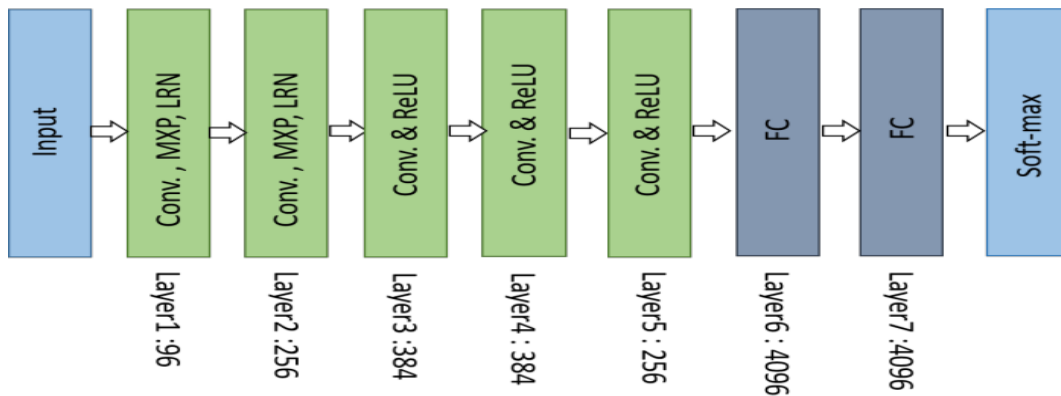


Figure8: Architecture of AlexNet

The convolution window shape of AlexNet's first layer, the second layer, and the third layer is 11 x 11, 5 x 5, and 3 x 3 respectively. The networks add maximum pooling layers with a window shape of 3 x 3 and stride of 2 after the first, second, and fifth convolutional layers. After the last convolutional layer there are two fully-connected layers with 4096 outputs. AlexNet manages the model complexity of the fully connected layer through dropout and image augmentation. This makes the model more stable, essentially reducing overfitting by the greater sample size[22][23].

2.7.3 The VGG Pretrained Model

A Softmax layer for classification is the model's final layer. The convolution filter size in VGG [31] has been adjusted to a 3 3 filter with a stride of 2. Three VGG-E models were proposed, VGG-11, VGG-16, and VGG-19, with 11, 16, and 19 layers, respectively [31].

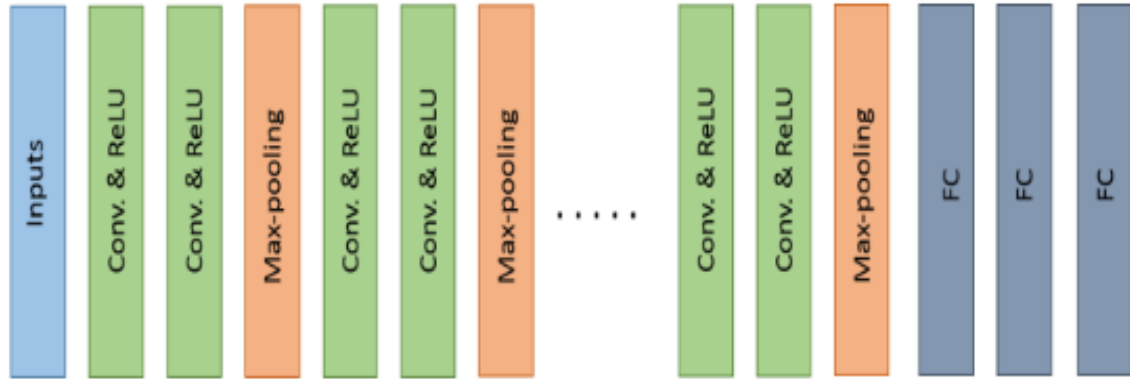


Figure9: The Basic Building Block of the VGG Network

2.7.4 The ResNet Pretrained Model

The Residual Network design, ResNet [31], was the ILSVRC 2015 winner. ResNet is built with a variety of layer counts: 34, 50, 101, 152, and even 1202. The well-known ResNet50 network had 49 convolution layers and one completely connected layer at the end. The total number of weights and MACs in the network is 25.5 million and 3.9 million, respectively.

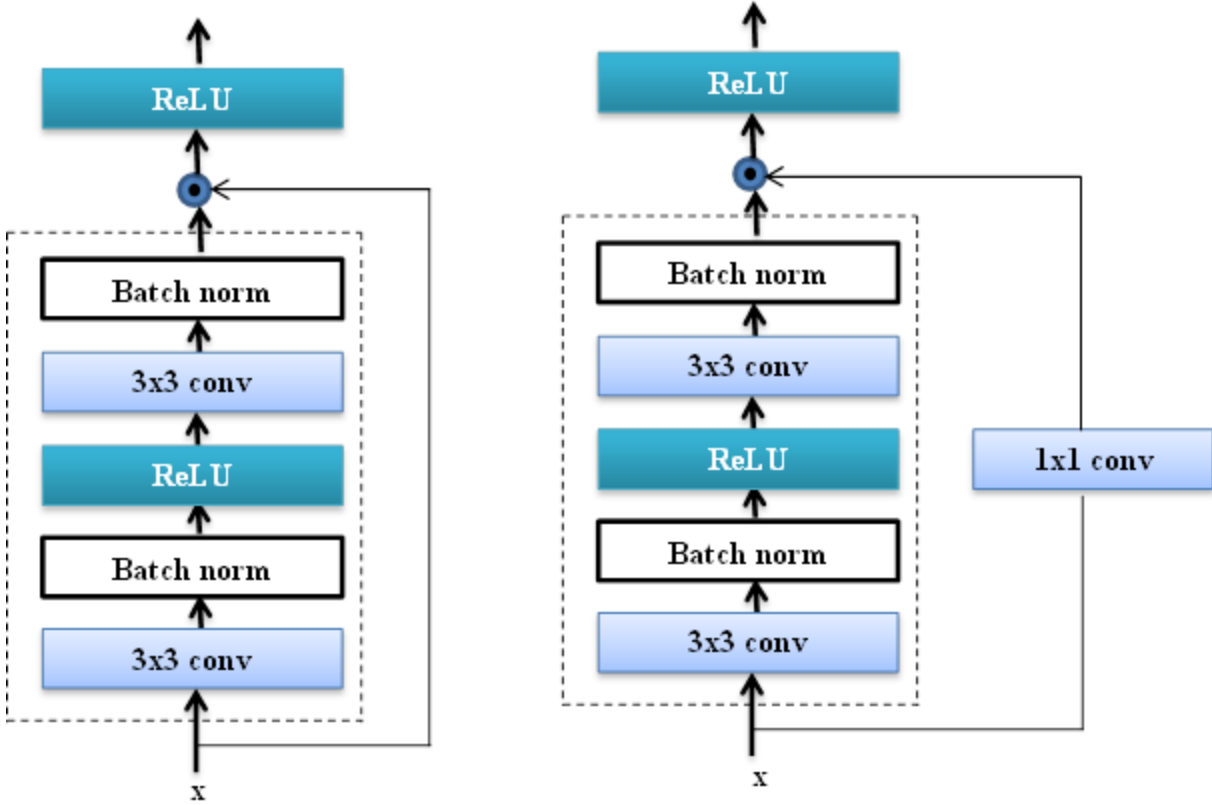


Figure10: Basic Diagram of the Residual Block

2.7.5 GoogleNet

Google produced GoogLeNet, the winner of the ILSVRC 2014 competition. It has a top-five mistake rate of 6.67%, which is very similar to human performance levels. GoogleNet is a search engine that allows you to find information quickly (sometimes called inception V1). It has more complicated routes with parallel convolutions of several filters. The GoogLeNet design has 4 million parameters (smaller than AlexNet) and 22 deep layers. It is based on LeNet, except GoogLeNet uses 11 convolutions in the center of the network to reduce the number of parameters, and there is no fully linked network at the end of the network; instead, global average pooling is used. The inception module [33] is a technique that combines 11 convolutions with global average pooling.

2.7.6 InceptionV3

The aim of the initial module, as defined by ImageNet, is to serve as a "multi-level feature extractor" by computing 1x1, 3 x 3, and 5 x 5 convolutions within the same network module,

then stacking the output of these filters along the channel dimension before being fed into the next layer of the network.

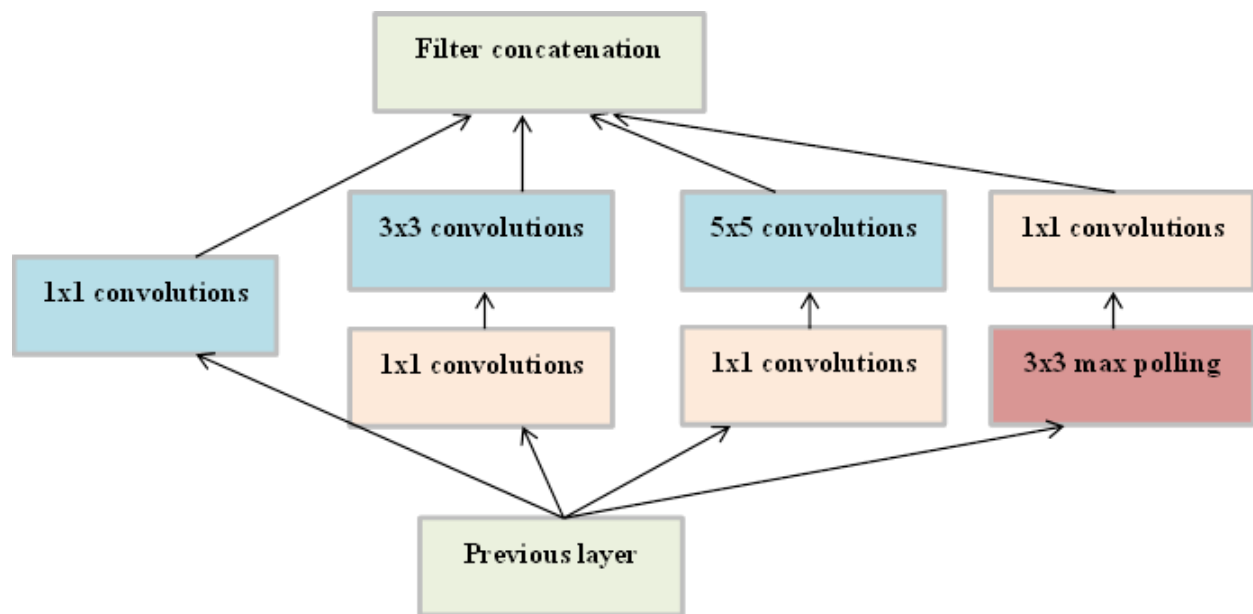


Figure11: Inception Module used in GoogleNet

2.8 Related Works

Plant disease exhibits visual symptoms that aid in the classification and identification of the illness that has afflicted the crop. These visual symptoms are employed as an input for computer vision employing DL algorithms. Furthermore, the primary goal of plant disease detection and classification using CNN is to increase the volume and quality of agricultural produce.

Michael Gomez Selvaraj et al.[24] used CNN to divide banana BXW into eight classes, the first of which is disease-free and the other seven of which are infected. Banana fruits of various varieties, sizes, and illnesses were collected in the databases. The researchers used 30,952 photos from a collection of disease-infected banana fruits in their research. Before training the dataset, data augmentation was used to increase the amount of photographs, and then a different experiment was run on the dataset's data partitioning, with the best result being a 90-10 split between the training and testing sets. Because of their accuracy, the proposed CNN architecture is Faster RCNN with ResNet50 and InceptionV2. Because the Single Shot Multi-box (SSD) model was one of the fastest object identification models available in TensorFlow, it was chosen

with the MobileNetV1. Softmax was utilized as the final activation function, which aids in the classification of images into their respective classes, with a model accuracy of 90%.

According to Y. Min and N. C. Htun, the disease-affected area of the plant leaf is first detected using Gray level co-occurrence matrix (GLCM) and Local binary pattern (doi.org) (LBP) features, followed by the SVM classifier in disease detection. The detection rate is 98.2% accurate. The plant disease type is also classified using GLCM and LBP features and classifiers, such as the k-Nearest Neighbor (k-NN) and Ensemble classifiers. The K-NN classifier has an accuracy rate of 80.2%, whereas the Ensemble classifier has an accuracy rate of 84.6 % [35].

Bipul Neupane et al. used CNN for banana fruit disease detection and classification, picture of the banana tree from the commercial banana farm in Thailand is captured using an Unmanned Aerial Vehicle (UAV). To improve this result, three image processing methods: Linear Contrast Stretch, Synthetic Color Transform, and Triangular Greenness Index were used [25]. Finally, the classification accuracy achieved was 99%.

M. Sardogan et al. employed CNN and learning vector quantization (LVQ) to detect and classify tomato leaves. The dataset contains 500 images of plant leaves divided into five categories: healthy tomato leaves, Late Blight, Septoria Leaf Spot, and yellow curved leaf disease. Out of the whole dataset, 400 photos were utilized to train the model and 100 images were used to test it [26]. The accuracy of the classification was 86%.

A machine learning strategy to detect and categorize banana *Bacterial Wilt* and banana black Sigatoka is described by G. Owomugisha et al. 623 pictures of diseased and healthy banana leaves were used in this study. Color features are retrieved using threshold values from the image's green pixel components, and shape features are extracted using thresholds at a separate level, with connected components extracted and morphological features calculated for each connected component. The authors utilized seven different classifiers to classify the disease: Nearest Neighbor, Decision Tree, Random Forest, Extremely Randomized Trees, Nave Bays, and SVM. Extremely Randomized Trees have a great classification accuracy of 96% for banana Bacterial Wilt and 91% for banana black Sigatoka [37] after testing the seven different classifiers.

According to S. D. Khirade et al., a set of experiments was conducted utilizing a real dataset of banana illnesses acquired from the PlantVillage project [27][28] to validate the performance of the recommended method. The photos are divided into three groups: healthy (1643 images), black Sigatoka (240 images), and black speckle (1817 images), for a total of 3700 images. These photos were taken in a variety of sizes, orientations, positions, backdrops, and lighting. Deeplearning4j is an open-source deep-learning package that uses GPUs to speed up the execution of deep learning algorithms. The goal is to assess the model's ability to anticipate banana disease outbreaks based on previously unreported data. To learn the best set of weights and biases for the neural network that minimizes the loss, the stochastic gradient descent (SGD) technique is utilized[28].

To summarize, the studies show that machine learning and DL have been widely used in the area of Agriculture especially in Banana production. DL architectures and techniques are applied for the detection and classification of banana leaf disease. Since BXW is damaging banana crops promptly, there is a demand to develop a more accurate and efficient model using this state-of-the-art technology. In this work, we have noticed that all the papers that were previously conducted have some problems which we need to overcome in this thesis. For example, most of the papers used publicly available datasets Like Plant Village. The thesis also has the advantage of not requiring any additional typical image processing techniques. As a result, we developed a CNN-based model for the categorization of Banana *Xanthomonas* Wilt (BXW) illness that was both accurate and efficient.

CHAPTER 3 RESEARCH METHODOLOGIES

3.1 Introduction

This chapter describes the approaches that were used to complete this thesis, including methods for implementing the model, data collecting, data preparation, system software and hardware configuration, and revaluation techniques for evaluating the model. The experimental research approach is employed in this thesis, in which one set of variables are kept constant while the other set of variables is measured as the subject of an experiment. Various tests are carried out with various dataset ratios. In addition, numerous experiments involving various activation functions and hyper parameters have been carried out.

3.2 Research Flow

The experimental research method is used in this thesis. The following process flow (Figure 13) is followed to attain the thesis's goal. This thesis is divided into three main phases, as shown in the block diagram below. The first phase entails determining the topic's domain, which entails examining several types of literature to have a better knowledge of the situation. The thesis's goals are then defined, including both broad and specific goals. The thesis design and data preparation are the focus of the second phase. Data is taken from the farm and identified and classified by two pathologists before being divided into three categories: training, validation, and testing. The model is designed after the data has been prepared. The thesis is realized in the third phase, during which the planned model is implemented using relevant tools and methodologies. With the relevant data, the designed model is trained and tested. The performance of the model is evaluated while it is being trained. The model is evaluated with test data after it has been determined to be the best during evaluation. Finally, the model is compared to other models that have already been trained.

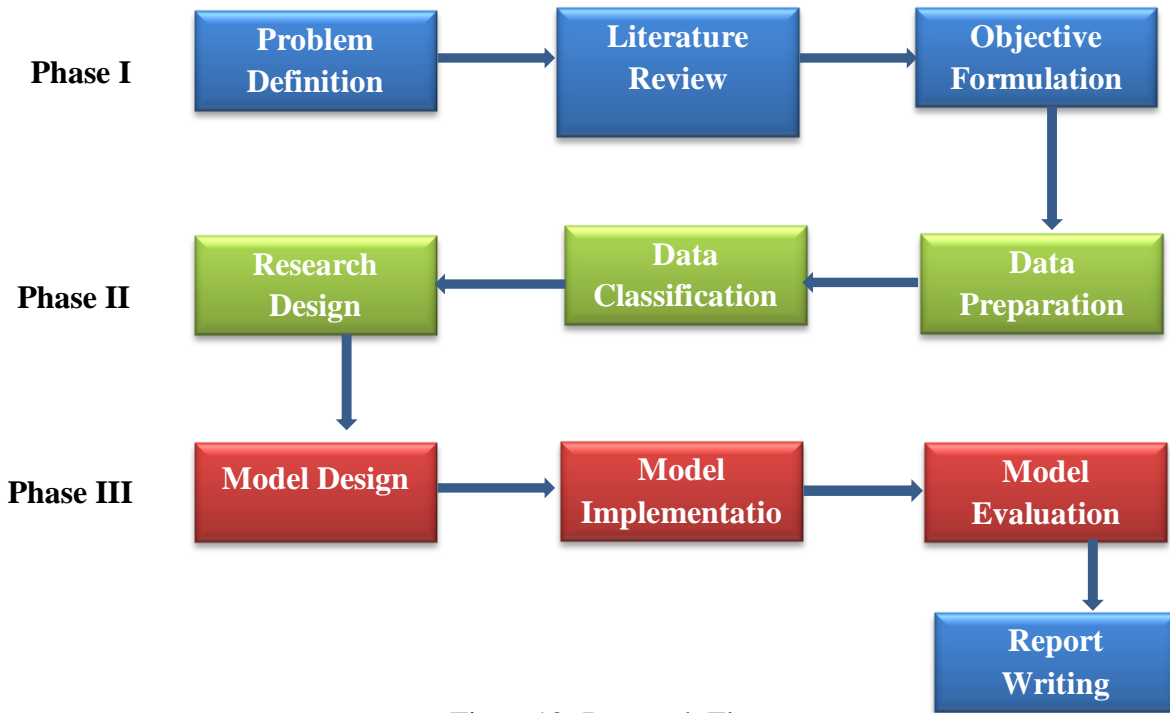


Figure12: Research Flow

To achieve the research's purpose, the basic methods for plant disease detection and classification using image processing include data collecting, data pre-processing, data segmentation, feature extraction in data, and plant disease detection and classification [39].

3.3 Data Collection

Huge data is one of the required resources in deep learning research to train, validate and test CNN models and get better accuracy, prediction, and detection. The banana plant leaf image dataset that is used for this research is collected from SNNPR Arbaminch Zuria Woreda Lante Kebele and Chano Kebele and Gamugofa Zone Mierab Abaya Woreda Omolante Kebele where banana is widely producing area and the infection of *Xanthomonas* wilt and *Sigatoka* disease is highly observed. The image of the leaf of the healthy and infected banana tree is collected using a smartphone. Before the beginning of collecting data, a brief discussion with the two pathologists were conducted on what is the symptom of the infected plant tree and how we can sure about the infection is *Xanthomonas* wilt disease or *Segatoka* infection. The data is collected from four farmers a size of the one-hectare farm each in three *Kebeles*. During the data collection, the daily collected data were identified as healthy or infected by both types of

diseases. The labeled data by the first pathologist is verified and confirmed by the second one to make sure the quality of the collected data. Finally, the collected image was correctly labeled with three classes.

Collecting images of banana plant leaf in thousands is too difficult. The researcher collects 1,288 pictures of banana leaves under three categories as “Health” banana leaf, “Xanthomonas” infected leaves, and “Sigatoka” infected leaves. Data augmentation was also done to increase the amount of data used using different augmentation parameters.

3.3.1 Data Preprocessing

Image preprocessing is the next activity done after image collection. In this stage, removing blurred images, cropping the unnecessary part of the image, and using different image editing techniques like image smoothing and image enhancement.

In general making, the captured image ready for the research like size normalization to get the similar size of all images in the dataset is performed. Furthermore, data normalization help to reduce the computational time required to train the model, because deep learning requires top-performing hardware computation.

3.3.2 Data Partitioning

The training, validation, and testing sets were created from the dataset. The training set is used to teach the model how to recognize different types of images. The validation set is used to evaluate the performance of the model that was built during training and to fine-tune model parameters to choose the best-performing model. Since our dataset is small the data partitioning used is 90%-10%. 1,782 images were used for training and validation, and 200 images were used for testing the proposed model.

3.3.3 Data Augmentation

Deep Learning models require a significant volume of training data to effectively perform well. Data augmentation is the process of creating more data from an existing training sample to increase the amount of training data sets in a dataset. Even though the data collection is

challenging, it is critical to increasing the number of datasets. It allows the neural network to learn more complicated characteristics from the data and avoids the overfitting problem. Various data augmentation techniques were used on the original photos in this thesis to obtain additional images for our data set. Data augmentation can be done either before or after the data is fed into our model. Using Keras libraries, data augmentation is conducted during network training in this thesis.

3.4 Software Tools

Deep learning frameworks such as Keras, TensorFlow, PyTorch, and Blockers are available. The top three deep learning frameworks favored by deep learning beginners to scientists are TensorFlow, Keras, and PyTorch. There is no hard and fast rule for which deep learning frameworks should be used for implementing and solving deep learning problems, but taking into account some of the factors will be efficient and appropriate for our objective. The quality of API, speed, architecture, debugging, dataset, and popularity are some of the characteristics for comparison between these three top deep learning frameworks.

3.4.1 Anaconda

Is a free and open-source version of the Python and R programming languages for data science and machine learning applications that seek to simplify package management and deployment. It includes IDEs like Jupyter Notebook and Spyder, which are used to write the coding part. Because it is simple and runs in a web browser, we utilized Jupyter notebook to develop the coding element. Anaconda Navigator is a desktop graphical user interface (GUI) included in the Anaconda® distribution that allows Conda packages, environments, and channels to be launched and conveniently controlled without using command-line commands. On the Anaconda Cloud or in the local Anaconda Registry, navigators can check for packages. It is available on Windows, Linux, and macOS.

3.4.2 TensorFlow

Is a Google-developed free and open-source deep learning package that is currently the most well-known and fastest. It works on any desktop running Windows, macOS, or Linux, as well as in the cloud as a service and on mobile platforms such as iOS and Android. Tensor Flow

architecture (nadre.ethernet.edu.et) is used for preprocessing data, creating models, training models, and estimating models. Tensors are used in all of TensorFlow operations to represent various types of data. Tensor Flow also makes use of a graph architecture to visualize a series of computations during training.

3.4.3 Keras

Is a python-based high-level neural network API that runs on top of TensorFlow, Theano5, or the Microsoft Cognitive Toolkit (CNTK). It's easy to create a model, it's user-friendly, it's easy to extend with Python, and, most significantly, it includes powerful CNN models like VGG16 and Inception, which we use in the experiment. It supports both CNN and RNN, as well as a combination of the two [41], and enables quick prototyping.

3.4.4 PyTorch

Is an open-source machine learning framework the Python successor of the Torch library and a big competitor for TensorFlow. It was developed by Facebook and is used by Twitter, the Sales force, the University of Oxford, and many others. PyTorch is Used for applications like natural language processing.

3.4.5 Visio

Is a Microsoft Windows-based diagram drawing tool that includes many different symbols and templates which allow users to prepare system development diagrams like use case diagrams and Entity-Relationship diagram. All diagrams found in this thesis are drawn using Vision because it is easy to use, export the final diagram in PNG, JPEG, PDF, and other formats, and also free to download.

3.5 Hardware Tools

3.5.1 System Specification

Table1: System Specification

Computer Type	Operating System	Processor	System Type	Installed RAM:	Storage Disks
Laptop, Lenovo G50	Microsoft Windows 10 Enterprise	Intel(R) Core(TM) i7-4510U CPU@2.00GHz, 2601MHz 2cores, 4 logical processors	64-bit operating system, x64- based PC	8.00 GB (7.9 GB usable)	1 TB

3.5.2 Camera

Samsung Galaxy A9 smart phone with Android 10 operating system, CPU Octa-core(4x2.2 GHz Kyro 260 Gold) GPU Adreno 512, memory, 8GB RAM, 128GB Storage, main camera 24MP, f/1.7, 27mm (wide), 1/2.8", 0.9µm, PDAF was used to capture images from the farm.

3.6 Evaluation Technique

Model evaluation is one of the main tasks how much the proposed model accurately performs the classification is evaluated. To evaluate the proposed model the accuracy, precision, recall, and F1-score evaluation metrics are used. These classification metrics were used and measured based on the confusion matrix with the value TP(True Positive), TN(True Negative), FP(False Positive), FN(False Negative) to test the proposed model. Below the confusion matrix table is shown.

Table2: Confusion Matrix

		Predicted Value	
		Positive	Negative
Actual Value	Positive	True Positive	False Negative
	Negative	False Positive	True Negative

Key:

True Positive: Observation is negative, and expected to be negative.

True Negative: Observation is positive and expected to be positive.

False Positive: Observation negative, but expected positive.

False Negative: Observation is positive, but expected negative.

Accuracy: is defined as the proportion of correctly categorized subjects to the total number of subjects. The one that comes to mind first is accuracy.

Equation1: Accuracy

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{FP} + \text{FN} + \text{TN})$$

Precision: is the proportion of accurately classified items to all items labeled by our program.

Equation2: Precision

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

Recall: is the ratio of the correctly labeled (identified) by our program to all labeled.

Equation3: Recall

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

F1-score: The F1 Score takes precision and recalls into account. It's the precision and recall's harmonic mean (average). The F1 Score is optimal when the system has a good balance of precision (p) and recall (r).

Equation4: F1 Score

$$\text{F1 Score} = 2 * (\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision})$$

Chapter 4 MODEL DESIGN AND EXPERIMENT

4.1 Introduction

This chapter deals with the proposed model, system architecture, and experimental setups, and hyper-parameter configuration for the experiments. The sub-section mentioned will be explained in this chapter. Furthermore, the pre-trained model used and their hyper-parameter experimental value is included.

4.2 Model Selection

CNN derived from deep learning algorithms is widely utilized in computer vision, particularly in picture categorization, according to a large body of literature. It has the best performance in feature extraction, segmentation, object classification and detection, image processing, training, testing, and model accuracy evaluation. Compared to traditional machine learning methods, CNN is more resilient and automated. Developing multiple algorithms for different issues is a need of traditional machine learning techniques. Every challenge necessitates a change in the algorithm employed. Once a Bacterial Wilt Detection Algorithm for Banana Crops has been created at CNN, it can be used to detect other plant diseases. The following are some of the reasons why CCN was chosen for this study.

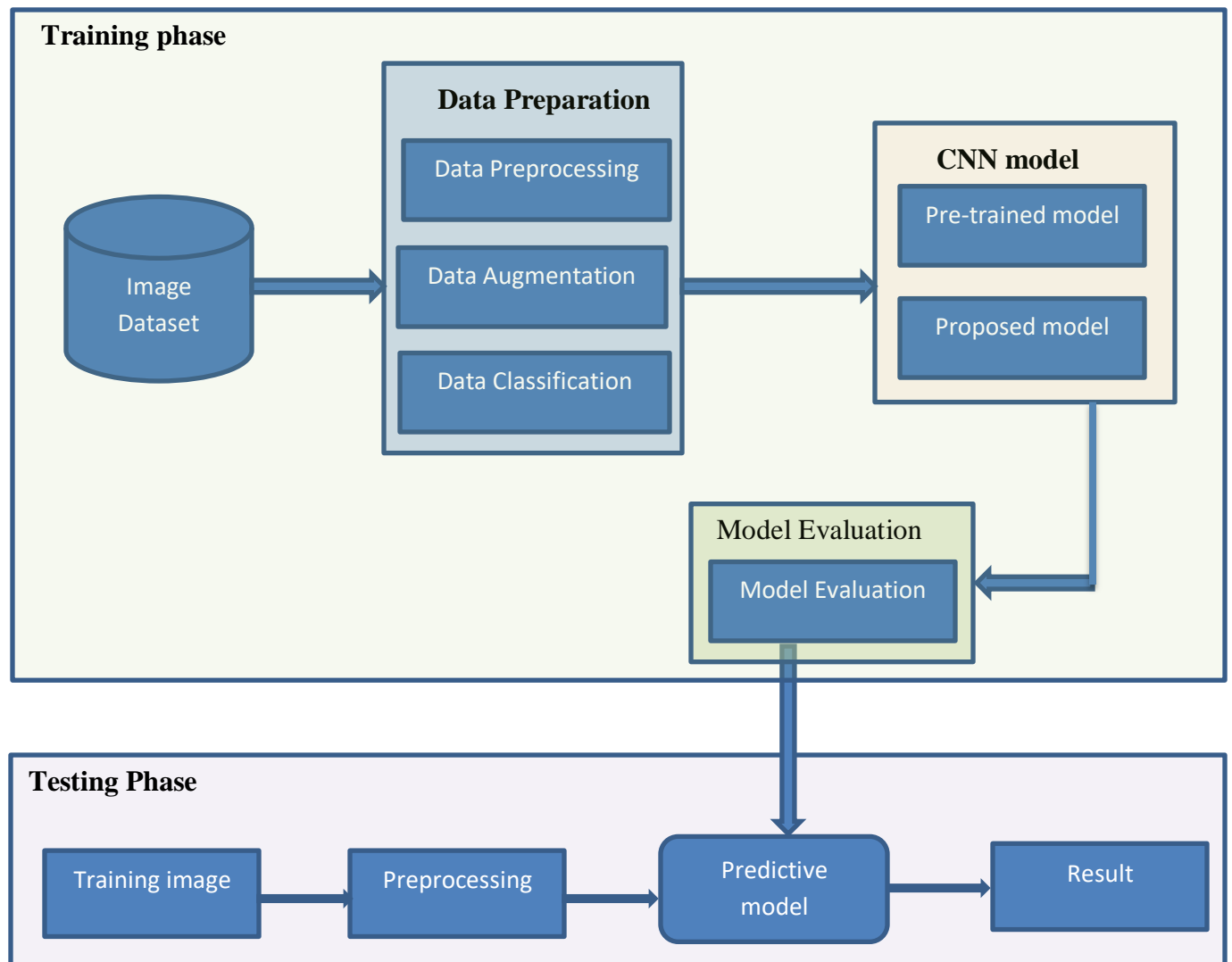
- Many prior studies have demonstrated that CNN outperforms alternative classification algorithms and is state-of-the-art for computer vision applications.
- CNN's are better than other deep learning models for image-related tasks since they are meant to mimic a human's comprehension of vision.
- Before classification and prediction, most traditional machine learning algorithms necessitate the explicit extraction of the features that will be studied from the image.

4.3 Overall System Architecture

This section explains the overall system architecture of Banana's bacterial wilt and fungal disease detection model, the system architecture is shown in the below Figure 15. Processes

shown in the architecture are elaborated below in detail except those explained in the above chapter.

Figure13: System Architecture



The system architecture design shows that it starts with the preparation of training and validation data, which has already been classified and labeled by two plant pathologists by the time the images are collected from the banana farm in Arbaminch. Data preparation is then conducted to make the image data dimension to be 150 *150, cropping and removing the unwanted part of the image. In general, the image is prepared to clearly show the area of infection. Since a huge amount of images is required to train the model and there is a shortage of images, different

parameters of data augmentation are used to escalation the number of images. During training, the model features of the leaf were extracted, and based on the feature extraction the classifier detected *Xanthomonas* wilt or *Sigatoka* infected leaf. While the model is getting trained, its performance will be measured using the validation dataset by which we can get how well the model is performing the model which performs better is saved and used as a predictive model.

In summary, once the image dataset is prepared and feed to the deep CNN algorithm. In the training phase, the algorithm learns the image features, and the validation phase is used to select the best models after the model is trained. The top-performing model will be chosen and saved via model evaluation. Finally, the performance of the model will be tested with unseen data, and the result will classify based on the class result.

4.4 Training Component of the Models

Since the deep learning architecture of the CNN algorithms contains millions of parameters and requires a huge amount of data, thousands of classes take much time to train and test and needs high computational resources, this makes difficult tasks for researchers in this area due to computational resources because a huge amount of parameters and many classes needs adequate resources. The proposed model of CNN architecture is built to run with a limited amount of data, within low computational resources, needs less time to train and test, has fewer parameters, and has only three classes.

In machine learning, the type of problem has dictated the algorithm to be used, and finally, build a model. Many researchers, such as [33][34][35], employed a large enough dataset to experiment. Scholars like [36][37][29], on the other hand, used a less amount of data to develop a deep learning model for plant disease classification. The authors were able to train a model with the help of a pre-trained model, and most of them were able to get a good result with a limited dataset. In this study, a variety of datasets were collected and labeled ‘Healthy’, ‘*Sigatoka*’, and ‘*Xanthomonas*’ classes. Furthermore, the data partitioning employed is 90%-10% meaning 90% of the data used for the training set, and validation set, the reaming 10% used for the testing set to build the neural network.

4.5 Experimental Setups

The study has used multiple scenarios for experimentation, the first scenario building a model from the scratch using CNN deep learning algorithm, the second is using CNN pretrained model to train the neural network. The pretrained model selected is based on the performance in several computer vision competitions and from previous researches papers. To mention the pretrained models, VGG16, VGG19, EfficientNet, MobileNet, and InceptionV3 were used. One of the cases to conduct experimentations is the value of hyperparameters which has a huge impact on the performance of the model. Some of the hyperparameters used in the experimentations are batch-size, epoch, optimization, loss function, and activation functions. Below Table 4 presents the hyperparameters names and values used for experimentation.

To build a robust model, deep CNN algorithms need a high number of parameters, which necessitates a huge amount of data, and one of the challenges with working with small data is overfitting. Using data augmentation [38] is one method to prevent these issues. Data augmentation is a technique for synthesizing artificial data from real data, as discussed in the previous chapters. The number of images in this study is generated utilizing eight augmentation parameters. Here in Table 4, the augmentation parameters with their values were mentioned.

Table3: Augmentation Parameters

Augmentation parameter name	Value
Rescale	1./255
rotation_range	40
width_shift_range	0.2
height_shift_range	0.2
shear_range	0.2
zoom_range	0.2
horizontal_flip	True
fill_mode	nearest
brightness_range	[0.2,1.2]

4.6 Hyper Parameter Tuning

One of the factors which determined the performance of the model is hyperparameters. Its value is configured before starting the training process. Some of the hyperparameters are, Optimization method,

learning rate, loss function, number of the epoch, batch size, and other hyperparameters are among the model's hyperparameters. To find the best value for the hyperparameter variables the study experimented.

There are no particulars for configuring the hyperparameters of a given algorithm [36], as a result, the hyper-parameter setup differs depending on the computing activity. Configuring the hyperparameter value takes time since it requires a lot of experiments or a high-spec machine to execute it several times in a batch [37].

Optimization Algorithm: Choosing the correct optimization method while training a neural network is crucial since it allows the model to learn faster and perform better. Adam and RMSprop, two optimization approaches that were examined at learning rates of 0.0001 and 0.001, respectively, were among the strategies tested.

Learning Rate: is the amount of weight that is updated throughout training is referred to as learning rate. It's a tunable hyperparameter used to train a neural network, with a value that typically ranges from 0 to 1.0. It is one of the most important hyperparameters in terms of neural network performance.

A slow learning rate demands multiple training epochs and weight adjustments, whereas a fast learning rate necessitates a rapid shift in the training epoch. Choosing a learning rate that is neither too high nor too low is one of the most difficult components of developing a neural network model. The learning rate after numerous trials is 0.0001 and 0.001.

Loss Function: Also known as a cost function. Let y = actual output, \hat{y} = predicted output and K = number of classes. Then, $\hat{y} - y$ calculated utilizing a cost function called Cross-Entropy (CE). Problem binary cross-entropy is utilized for binary classification. Binary CE and categorical CE were used in the experiment. Binary CE and multi-class classification are defined mathematically as

Equation5: Binary CE

$$L_{Cross_Entropy}(\hat{y}, y) = -y(\log(\hat{y}) + (1 - y)\log(1 - \hat{y}))$$

Equation6: Multi class CE

$$L_{Cross_Entropy}(\hat{y}, y) = - \sum_{j=0}^k (y_j \log(\hat{y}_j)) \text{ for } j = 1, 2, 3..k$$

Epoch: Count the number of times the neural network has been shown training data. The number of epochs taken during experimentation was 60 as a baseline, and epochs of 30 were employed by interpreting the accuracy validation graph for a suggested model.

Batch Size: Describes the number of subsamples given to the neural network after the parameter update occurred. The default batch size used in much experimentation is 32, 64, and 128. The best value of batch size must be taken via experimentation.

Activation Function: This is a mathematical function that determines the output of the neural network. A computation problem like image detection, image classification, and image recognition requires a non-linear activation to teach the feature given a dataset. In the proposed model the activation function used is ReLU, because the activation function does not suffer the problem called ‘*Vanishing gradient*’ [39]. ReLU is mathematically defined as

$$F(x) = (0, \max)$$

In which gradient with respect to the input is:

Equation7: ReLU activation function

$$\frac{af(x)}{ax} = \begin{cases} 0, & \text{if } x \leq 0 \\ 1, & \text{if } x > 0 \end{cases}$$

The last layer activation function is responsible for doing a task like classification or detection as per the problem. Furthermore, the last layer activation function depends on the type of classification. For instance: a binary classification problem to classify whether a picture is dog or cat uses a *Sigmoid AF*. On the other hand, multi-class classification problems usually use a *Softmax AF*. Mathematically the sigmoid AF is defined as

Equation8: Sigmoid activation function

$$G(Z) = \frac{1}{(1 + e^{-z})}$$

4.7 Disease Detection and Classification via Deep Learning

The rise of artificial intelligence has brought several opportunities in wide areas. One of the sub-area of artificial intelligence is computer vision, and this technology has been studied for past decades

using machine learning algorithms like KNN, SVM, Naïve Base, Random Forest [40]. One of the challenges of the machine learning algorithms is it requires an expert for extraction, takes too much time for image preprocessing. To deal with the problem mention above a new subset of machine learning has emerged and is known as ‘Deep Learning’. In this methodology rather than extracting features via expert, the neural network learns by itself. Besides, it requires minimal image data preprocessing comparing with machine learning. Due to these advantages, a huge application area has emerged in few years, and some of them are enhanced using the methods of the algorithm deep learning provides. One of the application areas is agriculture, to be specific disease detection and classification of crops by collecting data from various parts of the crops.

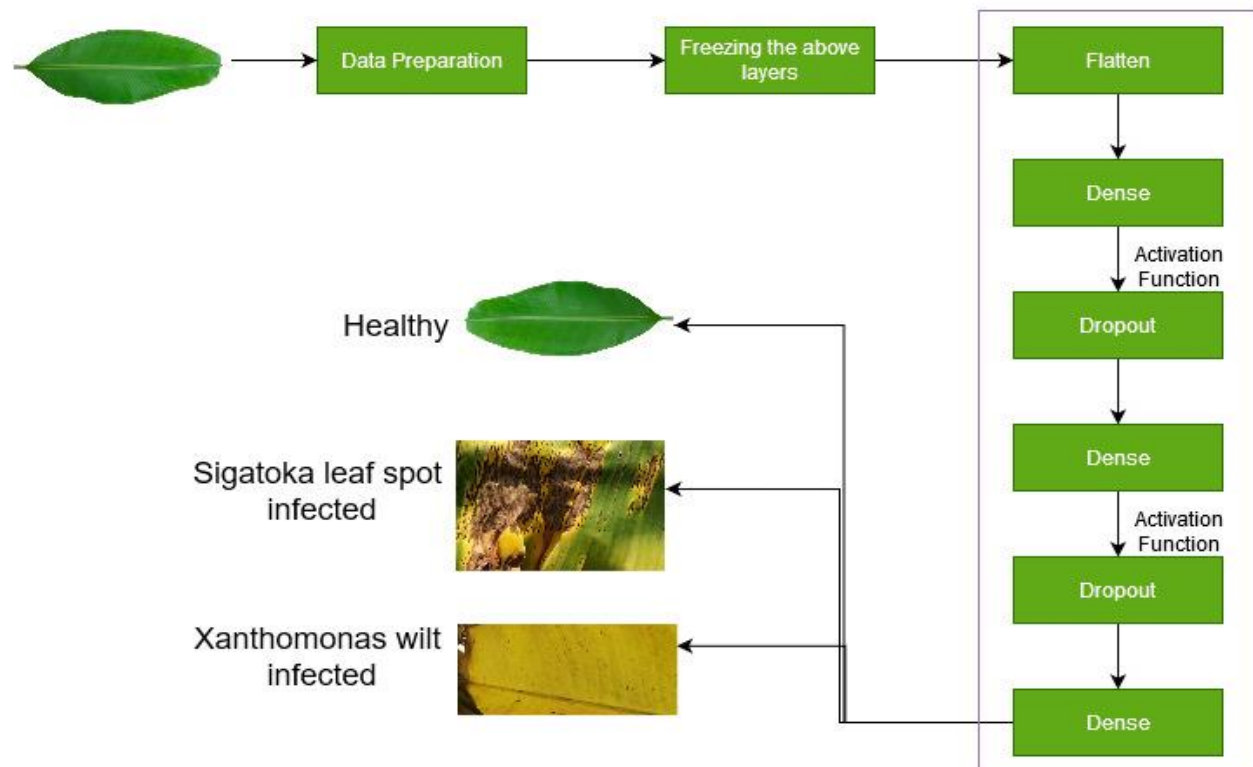


Figure14: Proposed Model

4.8 Detection and Classification of Banana Disease

The proposed model experimented on a pretrained model such as *VGG19*, *VGG16*, *InceptionV3*, *MobileNet*, and *EfficientNet* to identify banana leaf disease. The proposed model can distinguish between three types of disease: healthy, *Xanthomonas*, and *Sigatoka*. As described in the previous section, the pretrained model is utilized as a classifier by freezing the above layers of all

pretrained models and adjusting the activation function, dropout, and other hyperparameters using the model from the flattening layer. The tests conducted imply the VGG16 model has a good performance compared to other pretrained models.

CHAPTER 5 RESULTS AND DISCUSSIONS

The chapter explains the implementation of the banana disease detection and classification model using deep learning. The details of the research, as well as the hyperparameter used for experimentation, are explained in multiple scenarios. Moreover, various deep CNN pretrained models have been tested in a variety of hyperparameters values.

5.1 Experimental Result

As described in section 3.2, the input image for the experiments is an RGB image of a high-quality leaf. The image's RGB characteristic aids the neural network in detecting healthy and disease-infected leaves. Several hyper-parameters were explored with varying values before the model classified the photos into healthy and disease-infected groups.

To develop a neural network, the experimenters used four scenarios. VGG19 is used in the first scenario, InceptionV3 in the second, MobileNet in the third, and the EfficientNet pretrained model in the fourth. Different hyper-parameters, such as the activation function, learning rate, optimization algorithm, loss function, batch size, and epochs, were used to test the models. The data partition utilized for experimentation in all scenarios used 90 %-10.

5.2 CNN Pretrained Model

The CNN algorithm was used to train the neural network in the previous sections, and the algorithm has a pre-trained model that was employed in this investigation. VGG19, InceptionV3, MobileNet, and EfficientNet were the pretrained models used in the trials. The hyperparameter value that was used in the experiment is shown below.

Table4: Hyper-parameter and its value

Hyper-parameters	Values	Pretrained model
Activation Function	Sigmoid, Softmax	<ol style="list-style-type: none"> 1. VGG16 2. VGG19 3. InceptionV3 4. MobileNet 5. EfficientNet
Learning Rate	0.0001, 0.001	
Epoch	30,60	
Drop Out	0.5, 0.25	
Optimization Algorithm	Adam, RMSprop	

5.2.1 The Proposed Model for Banana Disease Detection and Classification

The image was downsampled to 150x150 after the dataset gathering process was completed. Because the photos are high-quality RGB photographs, the downsampling method has no negative impact on the experiment. Taking the raw image for experimentation is also costly in terms of the machine's computational capability. Furthermore, taking the raw image for experimentation is expensive in terms of the computational power of the machine. There are three techniques for using a pre-trained model: (1) training a model from scratch, (2) using a model that has already been trained as a feature extractor, (3) using a model that has already been trained, and (3) using a model that has already been trained with fine-tuning [21]. To put it another way, the first strategy involves using the pre-trained model without any configuration, while the second option involves freezing all of the model's blocks while using the final FC layer as a classifier. Finally, some blocks can be frozen while others are fine-tuned through trial and error. All of the blocks of the pretrained model were frozen in this study, and the models started with the flattening operation and were then sent to the FC classifier, which contains dense layers and dropouts, and lastly, a given image was identified as a healthy or disease-infected banana leaf.

5.2.2 Comparison of the Pretrained Models

As mentioned in the preceding section, four different pretrained models with variable hyper-parameter values were tried to construct a banana leaf disease detection and classification model.

VGG19, InceptionV3, MobileNet, and EfficientNet are only a few of the pre-trained models. We chose the pretrained model by comparing the training and validation set graphs, demonstrating that the suggested model is neither over fitted nor under fitted.

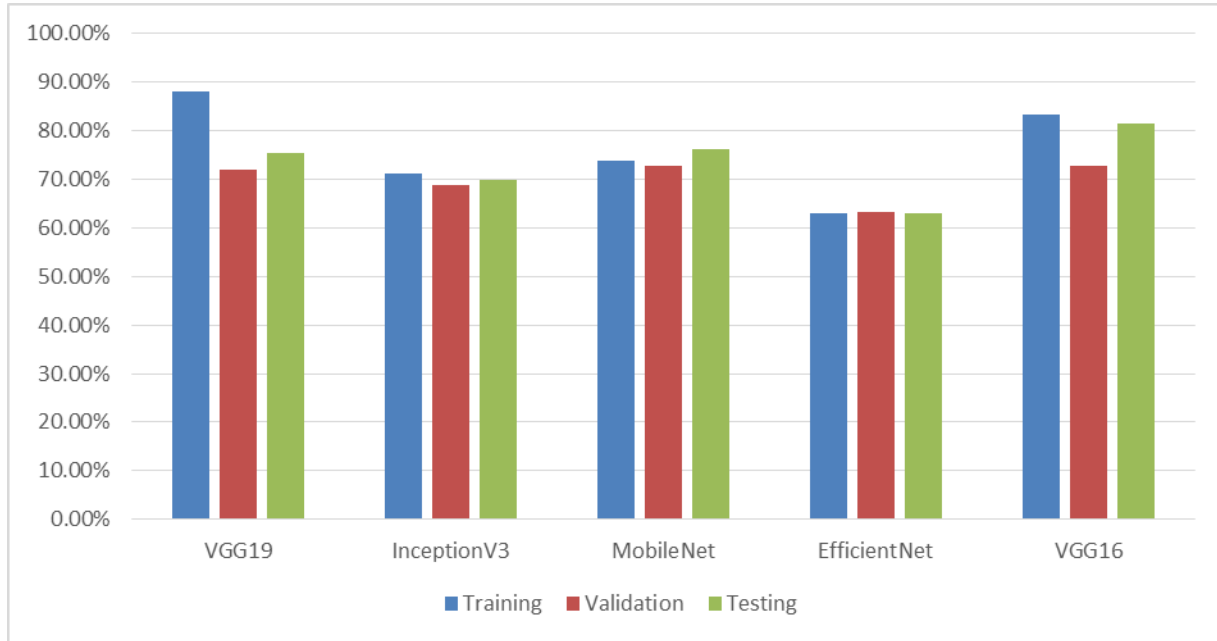


Figure15: Pre-trained Models Comparison

5.2.3 Result of the Proposed Model

Based on the pre-trained model experimentation described in Section 4.2, as well as the hyper-parameter value listed in Table 4, Among VGG19, InceptionV3, MobileNet, and EfficientNet, the VGG16 pre-trained model had the best performance. The pre-trained model has been used as a classifier in all of the models. Image dimension 150X150, learning rate=0.001, batch size=32, loss function categorical CE, RMSprop optimization algorithm, Softmax last layer activation function were the optimal hyper-parameters that produced the desired results.

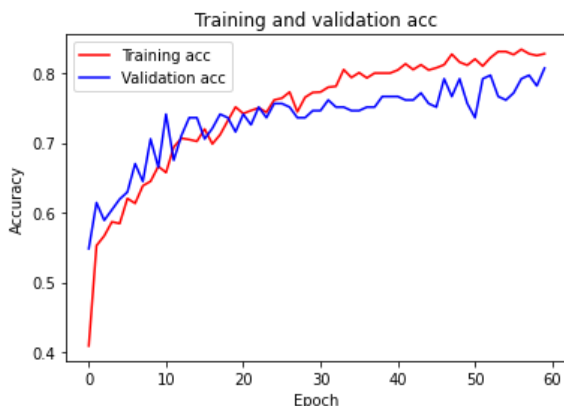


Figure16: Training and validation accuracy

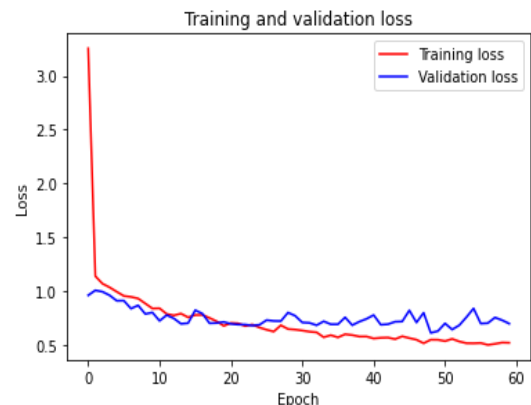


Figure17: Training and validation loss

The training accuracy/validation accuracy and loss of the models were presented above; the data portioning used is 90%-10%, meaning 90% of the total data used for training and validation, the remaining 10% used for the testing set. The difference between training accuracy and validation accuracy became narrower or overlapped with each other as the number of epochs increased until it reached 30. This indicates that the proposed model is not overfitting. Among VGG19, InceptionV3, MobileNet, and EffcientNet, the VGG16 pre-trained model had the best performance. The pre-trained model has been used as a classifier in all of the models. Image dimension 150X150, learning rate=0.001, batch size=32, loss function categorical CE, RMSprop optimization algorithm, Softmax last layer activation function were the optimal hyper-parameters that produced the desired results.

5.2.4 Testing a Proposed Model

After the model was successfully trained, to measure the performance of the proposed model the testing set was used. On the testing set, 10% of the data meaning 200 images were used, the result achieved by VGG16 is 81.53%. There are many reasons to achieving this result. The first and the major reason is the complexity of the image collected. Secondly, the total amount of images are low even though the study used the data augmentation technique. Here below, the figures show the steps for testing a single image with a probability of its class.

Step 1: Reading the image

```
#Testing image on a model

def read_image(file_path):
    print("[INFO] loading and preprocessing image...")
    image = load_img(file_path, target_size=(150, 150))
    image = img_to_array(image)
    image = np.expand_dims(image, axis=0)
    image /= 255.
    return image
```

Figure1918: Image Reading

Step 2: Testing single image function

```
def test_single_image(path):
    images = read_image(path)
    time.sleep(.5)
    bt_prediction = inception.predict(images)
    preds = model.predict(bt_prediction)
    for idx, plant, x in zip(range(0,3), plants , preds[0]):
        print("ID: {}, Label: {} {}".format(idx, plant, round(x*100,2) ))
    print('Final Decision:')
    time.sleep(.5)
    for x in range(3):
        print('.'*(x+1))
        time.sleep(.2)
    class_predicted = model.predict_classes(bt_prediction)
    class_dictionary = generator_top.class_indices
    inv_map = {v: k for k, v in class_dictionary.items()}
    print("ID: {}, Label: {}".format(class_predicted[0], inv_map[class_predicted[0]]))
    return load_img(path)
```

Figure20: Simple Image Function Training

Step 3: Passing the path, detection, and classification of banana disease

```
path1=r'/content/drive/MyDrive/Yordi_Research/output/Banana_Data/test/segatoka/107.jpg'
```

```
test_single_image(path1)
```

```
[INFO] loading and preprocessing image...
ID: 0, Label: Healthy 16.5%
ID: 1, Label: Sigatoka 49.23%
ID: 2, Label: Xanthomonas 34.27%
```

Figure2119: Detection and Classification of Banana Disease

Step 4: Importing libraries for displaying tested image

```
import os

import numpy as np

import matplotlib.pyplot as plt

import tensorflow as tf

from keras.models import load_model
from keras.preprocessing import image

import tensorflow_datasets as tfds
tfds.disable_progress_bar()
```

Figure202: Importing Libraries

Step 5: Loading the exported model and display the image

```
loaded_model=model.load_weights('/content/drive/MyDrive/Yordi_Research/Mobilenet/mobilenet_2.h5')

img_path = '/content/drive/MyDrive/Yordi_Research/output/Banana_Data/test/segatoka/107.jpg'

img = image.load_img(img_path, target_size=(150, 150))
plt.imshow(img)
plt.show()
```

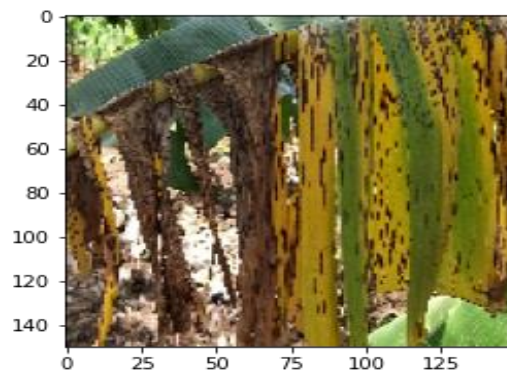


Figure213: Detected and Classified Result Image

CHAPTER 6 CONCLUSION AND RECOMMENDATION

Ethiopia has a huge resource to plant and produce a wide range of crops, but several micro-organisms like viruses, bacteria, and fungus affected the crops. One of the crops affected is the banana, which the study focuses on three classes of bananas. Furthermore, like software engineering students we have to deal with food security problems because if the banana disease is not controlled, it would not only damage the people but also have a significant economic impact on the country. Fortunately, artificial intelligence can recognize plants automatically. In addition, the study developed a deep learning model for detecting banana disease automatically.

The current method for detecting and classifying plant disease is based on professional observation with the naked eye. This method of plant disease detection has several drawbacks, including the fact that the accuracy of the disease identified is dependent on the expert's knowledge and experience, that it is time-consuming, and that it can be unclear at times. The final goal of this research is to use a deep CNN algorithm to develop a banana disease detection model. The deep CNN technique, unlike other classic machine learning algorithms, can extract features from images, making it perfect for experimentation.

A banana leaf disease detection and classification model was built in this study, and it was found to be capable of accurately identifying banana disease. The study concentrated on detecting banana infections because the crop has historically been Ethiopia's main source of food, but it is currently plagued by various diseases. Furthermore, the disease has the potential to take out an entire banana crop in a matter of days. The proposed method assists both the farmer and the country's food safety program in detecting banana disease. Finally, here are the research contributions:

Dataset: With the help of plant pathologists from Arbaminch Agriculture, a real image collection was collected and categorized. The dataset is heterogeneous, which means it contains data from many backgrounds, allowing a neural network to learn a feature in a variety of situations. Finally, the collected dataset will be made available in a dataset repository. As a result, other researchers will be able to contribute more.

Developing a deep CNN model: After that, the data is prepared and trained using a variety of pre-trained models with several experiments utilizing various hyper-parameter settings. The

result is a model for detecting banana disease. The CNN algorithm was employed in the development of the model, which included many pretrained models.

The detection and classification of plant diseases is a vast field of study. To begin with, the study only examined the banana leaf portion. It might be able to investigate the banana's root and fruit. Furthermore, it is preferable if the image has a large number of images because the more data gathered and trained by the neural network, the more robust the model becomes.

The Deep CNN method isn't the only one for detecting plant diseases. Studies should be undertaken to employ many techniques and algorithms, such as Ensemble learning, RCNN, and YOLO, for the identification and classification of plant diseases with a small dataset. Furthermore, hardware resources such as the GPU, high-performance RAM, and CPU significantly help in the reduction of effort and achievement of a good result.

Estimating the disease severity may be useful to farmers and others in the agricultural business because it offers information on how much the plant is affected by the disease and what action should be taken. This gives the agriculture sector accurate information about the disease's stage and the methods needed to effectively manage it. As a result, taking into account an estimate of the disease's severity would be beneficial.

The skill of collaboration is one of the missing elements for many scholars, especially in underdeveloped nations. According to our experience, certain organizations are operating in the agriculture industry to help farmers and the agriculture sector. Working academic research on collaboration would therefore aid researchers and universities in getting a good outcome, as there would be a lot of resources and experts involved.

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