

**IDENTIFICATION OF MAIZE LEAF DISEASES USING SUPPORT VECTOR  
MACHINE AND CONVOLUTIONAL NEURAL NETWORKS ALEXNET AND  
RESNET50**

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Science in Information Technology, Karatina University**

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## DECLARATION

### Declaration by the Candidate

This thesis is my original work and has not been presented for a Conferment of a degree in any other University or for any other award

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## **DEDICATION**

I dedicate this dissertation work to my family. Special appreciation goes to my loving wife and children, whose encouragement and push for tenacity ring in my ears. My parents, Prof. Isaac Micheni and Prof. Elyjoy Micheni are exceptional and never left my side. My siblings, C. Micheni and his family and B. Micheni for always encouraging me.

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## ABBREVIATIONS AND ACRONYMS

ANN	Artificial Neural Network
CLN	Corn Lethal Necrosis
CMOS	Complementary Metal Oxide Semi-conductor
CNN	Convolution Neural Network
DBM	Deep Boltzmann's Machine
DBN	Deep Belief Network
DT	Decision Tree
ELISA	Enzyme Linked Immunosorbent Assays
FAO STAT	Food and Agricultural Organization Statistics
GDP	Gross Domestic Product
GLS	Grey Leaf Spot
GPU	Graphics Processing Unit
ICT	Information and Communication Technology
K-NN	K- Nearest Neighbours
LRN	Local Response Normalization
MATLAB	Matrix Laboratory
MDMV	Maize Dwarf Mosaic Virus
MLN	Maize lethal necrosis Disease

MSV	Maize Streak Virus
NLB	Northern Leaf Blight
RF	Random Forest
Relu	Rectified linear unit
ResNet-50	Residual Network-50
PCR	Polymerase Chain Reaction
SCMV	Sugarcane Mosaic Virus
SVM	Support Vector Machine
VGG-16	Visual Geometry Group-16
WSMV	Wheat Streak Mosaic Virus

## ABSTRACT

Protecting maize crops from devastating plant diseases ensures global food security. Accurate disease identification is essential for implementing effective control measures. However, traditional visual analysis of symptomatic leaves used by maize farmers in Kenya is time-consuming, costly, subjective and prone to errors. Embracing computer vision technologies, such as deep learning and machine learning, offers promising solutions to these challenges, enhancing crop productivity. The general objective of this study was to develop models for maize lethal necrosis (MLN) disease, maize streak disease (MSD) and Gray leaf spot diseases (GLS) detection and classification using AlexNet and ResNet 50 convolutional neural networks (CNN) architectures and machine learning Support Vector Machine (SVM). The specific objectives of this study were to: identify maize leaf disease (MLN, MSD and GLS) using AlexNet, ResNet-0 and SVM models, to evaluate the performance of the AlexNet, ResNet-50 and SVM models in the classification of MLN, MSD and GLS. Digital maize leaf disease images were collected from maize farms in Embu County, resulting in a dataset of 3200 images, with 800 images for each disease category. The results indicate that AlexNet and ResNet50 achieved high accuracy in identifying maize leaf diseases, recording average accuracies of 98.3% and 96.6%, respectively. In contrast, the SVM model exhibited the lowest average accuracy of 85.5%. AlexNet demonstrated exceptional accuracy in classifying Maize Streak Virus (MSV) with a rate of 99.85%, followed by ResNet50 at 99.2%. Conversely, SVM had a lower recall value of 81.7% for Grey Leaf Spot disease. By incorporating these advanced models, farmers and stakeholders in maize crop protection can identify diseases early, allowing for timely interventions and improved disease management strategies. Consequently, this will lead to increased maize productivity and enhanced crop quality. Early disease detection also facilitates the judicious use of pesticides, safeguarding the environment and human health. The findings underscore the importance of leveraging these technologies to enhance food security, optimize agricultural practices, and promote sustainable maize production.

## CHAPTER ONE

### INTRODUCTION

#### 1.1 Background of the Study

Maize (*Zea mays*) is a globally cultivated crop with an annual production of approximately 1137 million metric tons (Erenstein *et al.*, 2022). In Kenya, maize is significant in food security, serving as a vital source of income and employment for small-scale and large-scale farmers. However, despite an increase in the area of maize production in Kenya over the past decade, the total output remains low at 11.7t ha<sup>-1</sup> compared to its potential of 40 t ha<sup>-1</sup> (FAOSTAT, 2021). The significance of maize cultivation transcends mere agricultural pursuits; it constitutes a pillar supporting food security, income generation, and employment opportunities for small-scale and large-scale farming communities across Africa, with Kenya as a notable example (Nosipho & Mpandeli, 2021).

Maize leaf diseases, attributed to viral and fungal agents, represent formidable challenges to maize production (Kitonde *et al.*, 2019). Maize lethal necrosis (MLN) disease and maize streak disease emerge as destructive viral pathogens among these disorders (Bernardo *et al.*, 2021). MLN occurs rapidly and has a devastating impact, causing the yellowing and wilting of leaves, leading to necrosis (Batchelor *et al.*, 2020). Conversely, Maize streak disease results in leaf characteristic streaking and discolouration, significantly impairing photosynthesis and yield (Drechsler *et al.*, 2014).

Furthermore, Grey leaf spot (GLS) disease, triggered by *Cercospora* fungal species (Kibe *et al.*, 2020), contributes to the compounding menace. GLS manifests as small, rectangular lesions with grey centres encircled by a dark border, compromising the plant's

photosynthetic efficiency and weakening its overall vigour (Paul, 2003). This disease often attains its peak severity during high humidity and frequent rainfall (Vines *et al.*, 2020, Paul, 2003).

These disease entities collectively impose substantial yield losses, impacting Kenya's maize production. Reports from Batchelor *et al.*, (2020) and Charles *et al.*, (2019) corroborate that these diseases are responsible for yield reductions ranging from 40% to 100% across the country. These yield losses can lead to dire consequences for both small-scale and large-scale farmers, undermining food security, livelihoods, and economic stability. Effective disease management strategies, therefore, become indispensable to mitigate these losses and bolster maize production in Kenya.

Identifying maize diseases entails various approaches, but the most straightforward and widely adopted method is visualising symptomatic leaves (Natesan *et al.*, 2022). Early crop disease detection is paramount as it empowers farmers to swiftly initiate requisite control measures, including carefully selecting appropriate pesticides. This proactive approach increases crop yield and enhances overall produce quality (Dubois *et al.*, 2021; Rocha *et al.*, 2020).

Farmers commonly scrutinise disease symptoms evident on leaves to recognise and categorise crop diseases (Matinuu Sigit *et al.*, 2022). However, this technique does present inherent limitations. Its subjectivity introduces room for errors, and its time-intensive nature adds to operational complexities. Particularly for resource-constrained rural farmers, its associated costs, which may involve consulting a trained plant pathologist to confirm disease presence, can be a substantial burden (Waheed *et al.*, 2020). This challenge becomes more pronounced in scenarios of multiple infections,

where accurate diagnosis becomes increasingly intricate. The financial implications increase further as the costs associated with engaging trained professionals for disease confirmation add to the already strained resources of farmers. These drawbacks undermine disease identification accuracy. However, the accuracy of disease diagnosis cannot be overstated, as it constitutes the foundation for effective control measures. Selecting the appropriate pesticides, instituting timely interventions, and applying disease containment strategies all hinge on precise disease identification, as explained by Rocha *et al.*, (2020).

Furthermore, the potential for misdiagnosis carries far-reaching repercussions. Erroneous disease identification can result in the inappropriate use of pesticides, not only squandering resources but also potentially endangering environmental contamination through improper disposal. Such contamination can adversely affect humans and non-target organisms, amplifying the ecological toll of disease mismanagement (Gunstone *et al.*, 2021). While the visual analysis of symptomatic leaves serves as a fundamental tool for disease identification, its limitations underscore the need for more advanced and accurate methods in contemporary agricultural practices (Natesan *et al.*, 2022).

Consequently, an apparent necessity arises to enhance the precision, effectiveness, and accessibility of maize leaf disease identification within Kenya. Among the most promising avenues for surmounting the challenges outlined above, computer vision-based automatic systems offer an approach with substantial potential to mitigate losses and augment productivity (Owino, 2023). Recent years have witnessed the dominance of machine learning and deep learning techniques, carving a niche in identifying plant diseases through digital images (Kumar *et al.*, 2022).

In contrast to traditional methods, these modern techniques offer a paradigm shift. While traditional machine-learning approaches necessitate the extraction of features from afflicted plant images such as leaf colour, texture, and shape for training classifiers, contemporary methodologies embrace the inherent richness of image data (Bashir *et al.*, 2019). Machine learning models leverage this data directly, automatically extracting intricate and often imperceptible patterns and features. This, in turn, enables the development of robust and precise models that can discern even subtle indications of disease presence (Bashir *et al.*, 2019).

Furthermore, deep learning techniques, a subset of machine learning, have demonstrated particular prowess in handling image-centric datasets. Their capacity to learn hierarchical representations of data, moving from low-level features like edges to higher-level concepts such as shapes and objects, bolsters their performance in distinguishing between healthy and diseased plants (Purwono *et al.*, 2023). This affords these techniques a distinct advantage over traditional methods, as they can identify even incipient stages of disease development, circumventing the limitations of human-perceptible symptom recognition (Hernández *et al.*, 2021).

In recent applications, these approaches have showcased considerable success in addressing the challenges posed by plant diseases. They enable rapid and accurate disease identification, paving the way for timely interventions (Liu, 2023). Moreover, their adaptability and scalability make them well-suited for various agricultural contexts, from small-scale to large-scale farming operations. Through their automated and data-driven nature, these methods hold great promise in elevating agricultural productivity and fostering sustainable practices by facilitating precise pesticide application, reducing

environmental impact, and ensuring optimal resource utilization (Omkar, 2023). These approaches have been widely employed in identifying diseases like leaf blotch, powdery mildew and rust (Genaev *et al.*, 2021).

Machine learning techniques such as Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbors (K-NN), and Random Forests (RF), have been commonly adopted for crop disease classification due to their established efficacy (Jasrotia *et al.*, 2023). Nevertheless, these techniques encounter inherent limitations when detecting disease in its early stages. Factors like lighting conditions and occlusion can substantially compromise their ability to accurately recognize diseases, thereby undermining their utility in early diagnosis (Yu *et al.*, 2023; Khan *et al.*, 2021).

This is where deep learning methods emerge as a transformative alternative. Their inherent architecture, particularly Convolutional Neural Networks (CNNs), capitalizes on the innate structure of image data, enabling them to automatically identify intricate patterns and features that may elude traditional machine learning techniques. This capability significantly enhances the efficiency of disease recognition (Khan *et al.*, 2021). Furthermore, the adaptability of deep learning models to complex and high-resolution images gives them a distinct advantage. These models can process an extensive array of data inputs, making them particularly suitable for datasets with a rich visual context, as with plant disease images (Bousset *et al.*, 2019). This adaptability positions deep learning models, especially CNNs, as potent tools for addressing the nuances and complexities associated with disease identification in the agricultural domain (Bousset *et al.*, 2019).



Significant efforts have been witnessed in developing automated systems for recognizing crop diseases through adept computer vision techniques. Too *et al.*, (2019) conducted a comparative analysis using diverse pre-trained CNN models. Remarkably, their efforts culminated in an astounding accuracy of 99.75%, achieved by these models in classifying an extensive array of 38 plant disease categories.

Equally noteworthy is the work of Zhang *et al.*, (2022), who demonstrated the impact of CNN architectures by strategically employing data augmentation techniques. By doing so, they classified eight distinct maize leaf diseases, demonstrating the potential of CNNs to refine disease identification within specific agricultural contexts. Alehegn *et al.*, (2019) capitalized on machine learning support vector machines. Their approach was anchored in training a model using leaf colour and coarseness features, which proved effective in categorizing maize leaf diseases on Ethiopian maize farms.

Despite these strides, it is discernible that research in the realm of CNN models' application for maize leaf disease classification, particularly within Kenya's agricultural landscape, remains relatively sparse. We focus on a rigorous evaluation of transfer learning performance, expertly harnessing two potent CNN architectures: AlexNet and ResNet50. Through this endeavour, we aim to chart a course for successfully identifying maize leaf diseases. This area holds immense promise for revolutionizing disease management strategies within the specific context of Kenya's maize production landscape.

## **1.2 Statement of the Problem**

Ensuring crop health is paramount in the broader context of global food security, with plant diseases emerging as a substantial obstacle to maize's sustainable and productive

cultivation (Savary *et al.*, 2017). The identification of diseases affecting maize crops remains predominantly on visual scrutiny of symptomatic leaves, as Natesan *et al.* (2022) highlighted. This conventional practice has inherent shortcomings that impede its efficiency and reliability. Time, a valuable asset, is used excessively, making the process challenging and not financially viable. Additionally, the subjective nature of this method affects diagnosis accuracy, as outcomes can differ significantly depending on the observer's skill and knowledge, a weakness emphasized by Waheed *et al.*, (2020).

Computer vision and machine learning technologies have ushered in a new era of possibilities, offering potent remedies to counter the existing challenges (Owino, 2023). Deep learning and Convolutional Neural Networks (CNNs) are promising among these cutting-edge technologies. CNN models have exhibited their prowess in autonomously assimilating intricate image features and attaining high accuracy levels in disease identification across diverse fields (Kumar *et al.*, 2022). This remarkable capacity to discern complex patterns within images augments their potential to revolutionize disease diagnosis and pave the way for more efficient agricultural practices.

Despite the strides made in CNN technology, their tailored implementation for the unique spectrum of maize leaf diseases prevalent in Kenya has yet to be explored. This presents a novel opportunity to bridge this research gap and unlock the latent benefits of these advanced techniques for better maize farming in the region.

This study aims to bridge this gap by investigating the effectiveness of deep-learning CNN models, such as AlexNet and ResNet-50, in identifying and classifying maize leaf diseases in Kenya. By leveraging these advanced technologies, the research endeavours

to provide farmers with an accurate and efficient tool for early disease detection, enabling timely interventions and improving overall maize crop productivity and quality.

### **1.3 Objectives of the Study**

This research sought to achieve the following objectives:

#### **1.3.1 General Objective**

The general objective of this study was to identify and classify three maize leaf diseases (MLN, MSD and GLS) using CNN architectures (AlexNet and ResNet50) and Support Vector Machine (SVM).

#### **1.3.2. Specific Objectives**

The specific objectives were:

- i. To identify maize leaf diseases (MLN, MSD and GLS) using AlexNet ResNet-50 and SVM models
- ii. To evaluate the performance of the AlexNet, ResNet-50 and SVM models in the classification of MLN, MSD and GLS.

### **1.4 Research Questions**

The research questions were:

- i. What is the efficiency of AlexNet, ResNet 50 and SVM in maize leaf diseases (MLN, MSD and GLS) identification?
- ii. What is the performance of the AlexNet, ResNet 50, and SVM in the classification of MLN, MSD and GLS?

## 1.5 Justification of the Study

Maize is a vital staple crop in Kenya and plays a significant role in ensuring food security, income generation, and employment opportunities for small-scale and large-scale farmers. However, the maize industry faces considerable challenges due to the prevalence of plant diseases such as MLN, MSV, and GLS. These diseases cause substantial yield losses and impact the country's overall productivity and sustainability of maize farming.

The current methods for disease identification in maize crops heavily rely on visual analysis of symptomatic leaves by trained personnel and diagnostic techniques such as enzyme-linked immunosorbent assays (ELISA) and polymerase chain reaction (PCR) methods. However, these traditional approaches are time-consuming, subjective and costly (Zhou *et al.*, 2022). The accuracy and efficiency of disease identification are crucial for implementing appropriate disease control measures, selecting suitable pesticides, and implementing timely interventions. Unfortunately, the limitations of visual analysis impede the effective and efficient identification of maize leaf diseases, leading to suboptimal disease management strategies.

In recent years, computer vision and machine learning technologies, particularly deep learning and Convolutional Neural Networks (CNNs) have shown promising potential in disease identification and classification across various domains. These advanced technologies can automatically learn image features and achieve high levels of accuracy. However, their specific application for maize leaf disease identification in Kenya remains understudied, with limited research available.

Therefore, this study aims to address these gaps and provide a comprehensive investigation into the efficacy of deep learning CNN models, specifically AlexNet and ResNet-50, for identifying and classifying maize leaf diseases in Kenya. By leveraging these advanced technologies, the research seeks to develop an accurate, efficient, and automated tool for early disease detection in maize crops. This tool will provide timely and reliable information to farmers and other stakeholders involved in maize crop protection/ production. It will enable them to implement appropriate disease control strategies, minimize yield losses, protect the environment, and ensure sustainable maize production.

Therefore, this study aims to address the current understanding and knowledge gaps systematically. This entails conducting an in-depth investigation into the effectiveness and capacity of deep learning CNN models, emphasising the AlexNet and ResNet-50 architectures in particular. The main goal is to determine these advanced models' applicability and effectiveness in identifying and classifying native Kenyan maize leaf diseases.

This research seeks to open the path for designing a creative and automated solution by utilising these cutting-edge technological innovations. This method is intended to be a precise and effective technique for the early identification and classification of diseases within maize crops. The strength of deep learning and CNNs support it. This innovative technology aims to provide timely, accurate, and reliable information to farmers and other stakeholders involved in maize crop security. This knowledge will be a crucial advantage, enabling them to rapidly implement accurate disease control measures and effectively mitigate possible yield losses.

The effects of this work transcend beyond its direct agricultural advantages, too. Once developed, the automated tool can promote disease management strategies that are environmentally friendly. It has the potential to dramatically minimise the ecological footprint associated with excessive pesticide application by permitting rapid responses and the wise use of resources. This strategy supports a larger vision of environmental protection and sustaining a healthy balance between crop yield and ecological well-being while enhancing agricultural sustainability.

Cultivating sustainable maize in Kenya is the study's primary goal; this is how it is ultimately expected to be completed. The study seeks to promote a change in disease identification by providing stakeholders with cutting-edge technology tools and knowledge, enabling preventive measures that protect both crop yields and the sustainability of the environment.

## **1.6 Scope of the study**

This study primarily analyses maize leaf image features and their significance in identifying and categorizing maize leaf diseases. The research compares two Convolutional Neural Network (CNN) architectures, AlexNet and ResNet50, with Support Vector Machine (SVM), a machine learning technique applied to computer digital images.

This study justifies its scope by emphasizing the critical importance of understanding maize leaf image features for identifying and classifying maize leaf diseases. It highlights the relevance of this research to agriculture, especially in regions where maize is crucial for food security and economic stability. The study's focus on advanced technologies like Convolutional Neural Networks (CNNs) and the comparison with traditional methods like Support Vector Machine (SVM) underscores its contemporary significance. Furthermore, it addresses the research gap in applying CNNs to maize leaf diseases, particularly in specific geographical contexts like Kenya. The practical implications of this research extend to both small and large-scale maize farming, offering the potential for improved disease management and enhanced crop quality. Lastly, the study's contribution to the broader fields of computer vision and agricultural technology is emphasised, emphasising its potential to advance disease management strategies and support sustainable maize production for the benefit of farmers and the agricultural sector.

## **1.7 Limitations of the Study**

An in-depth examination of the variety of characteristics found in photographs of maize leaves and their essential role in accurately detecting and categorizing maize leaf diseases i.e. maize lethal necrosis (MLN), maize streak virus (MSV) and grey leaf spot (GLS)

forms the basis of this study. To achieve this goal, the research compares and contrasts the performance of two cutting-edge Convolutional Neural Network (CNN) designs, AlexNet and ResNet50. The performance of Support Vector Machine (SVM), a widely utilized machine learning method capable of processing digital images, is added to this comparison analysis.

In the design of this study, the SVM model is carefully trained by including essential information collected from pictures of maize leaves. These cover three characteristics: leaf colour, texture, and shape. By aligning with the strategy suggested by (Pujari *et al.*, 2016), this cutting-edge feature extraction method gives the research a strong basis based on tried-and-true approaches.

Nevertheless, it is critical to acknowledge and openly discuss the limitations of this study. Although carefully detailed within its stated goal, this research is limited to the diseases (MLN, MSV and GLS) and does not broaden its investigation to include the wide range of potential plant diseases or other agricultural crops. Therefore, even though the knowledge gained from this study provides an invaluable understanding of the complexities of the three maize diseases and their detection through cutting-edge technology, it is still prudent to recognize that the findings may not directly apply to other plant species or diseases. When attempting to apply the findings of this study to more general agricultural contexts, some caution is required because the precise symptoms and traits that define diseases in different plants or crops can differ. The work intentionally focuses on the specific area of the maize leaf diseases, deepening our understanding within this field and highlighting the necessity for more focused research to examine similar characteristics across various plant species and diseases.



The photographs used in this study, which came only from maize farms in Embu County, served as a boundary for its scope. Although careful efforts were made to collect a wide variety of photos of infected maize leaves, it is important to recognize that the results might not fully capture the full range of maize leaf diseases present in many other geographic regions.

Although the photos from Embu County serve as a useful starting point for the study's inquiry of the maize leaf diseases in that particular area, the intrinsic levels of the diseases, in terms of severities, could potentially present differently in other locations. Different symptoms of the diseases may occur in various geographical regions due to variations in climate, conditions of the soil, agronomic practices, and the presence of associated diseases.

As a result, even while the study's findings provide important new information, it is prudent to acknowledge that they may not be universally extended to reflect the whole spectrum of the three leaf diseases across other geographies. When attempting to generalize the study's findings to larger maize-growing regions, one must take into account the study's sample size and geographic focus because research into plant diseases consequently takes into account the complex interplay of various ecological factors.

Furthermore, it's critical to note that various factors may potentially impact the effectiveness and application of the generated models. The complex interactions between variables, including changes in lighting, differences in image quality, and the potential occurrence of occlusions or instances of overlapping symptoms within the images, may adversely affect the accuracy and adaptability of the disease identification and classification process.

For instance, various colours and intensities of light can be put upon the images, changing how colour and texture are perceived. The capacity of the models to distinguish between healthy and diseased leaves may be subject to errors due to this variability. Similarly, differences in image quality, including elements like resolution and focus, may significantly impact how well the models can detect and interpret minute visual clues suggestive of the presence of disease. Additionally, due to the complexities of real-world conditions, it is possible for leaves to display many disease symptoms at once or to get partially veiled, resulting in obstructions. Due to the possibility of inaccurate isolation or classification of overlapping symptoms, this occurrence could potentially disrupt the models' recognition process.

Finally, it's critical to point out that the primary goal of this study was to apply computer vision and machine learning approaches solely to identifying maize leaf diseases. Although these methods have great potential to transform disease recognition, it's important to remember that the bigger picture of disease management involves intricate aspects beyond simple identification.

The selection and implementation of the best disease control strategies, for example, fall outside the realm of this study. Factors that go far beyond the scope of identification are required to select the appropriate actions to reduce disease outbreaks and the subsequent impact of these strategies on crop yield. These characteristics include the local climate, socioeconomic circumstances, and the success rate of various interventions in different scenarios. It is important to understand that while this study offers a fundamental cornerstone in identifying maize leaf diseases, the full domain of disease management contains an array of factors that call for independent scientific proposals.

## **CHAPTER TWO**

### **LITERATURE REVIEW**

#### **2.1 Introduction**

This chapter aims to comprehensively review the literature on maize production, constraints in maize cultivation, maize diseases, their causative agents, and the symptoms exhibited upon infection. Additionally, this chapter will focus on both traditional and digital image processing techniques and classification algorithms that have been employed to aid in identifying maize diseases. A comprehensive understanding of the current knowledge and research gaps can be established by reviewing the existing literature in this field.

#### **2.2 Maize Production in Kenya**

Maize is a globally significant cereal food crop, ranking third after wheat and rice (FAOSTAT, 2021). In sub-Saharan Africa, it holds paramount importance as a crucial food and income source for over 300 million smallholder households (Oyewale *et al.*, 2020). Consequently, the national food security of Kenya heavily relies on the production of an adequate maize supply to meet the ever-increasing national demand (FAOSTAT, 2021).

The total land area dedicated to maize cultivation in Kenya amounts to approximately 1.5 million hectares, with around 70-80% of maize being produced by small-scale farmers who achieve an average on-farm production of 1.5-2.6 tons per hectare (Kiponda *et al.*, 2023). However, maize production in the country faces numerous constraints, including the presence of insect pests, weeds, diseases, and various abiotic factors that limit its

growth and yield potential (Simtowe *et al.*, 2021). These factors collectively pose significant challenges to the productivity and sustainability of maize farming in Kenya.

### **2.3 Plant Diseases as a Threat to Maize Production**

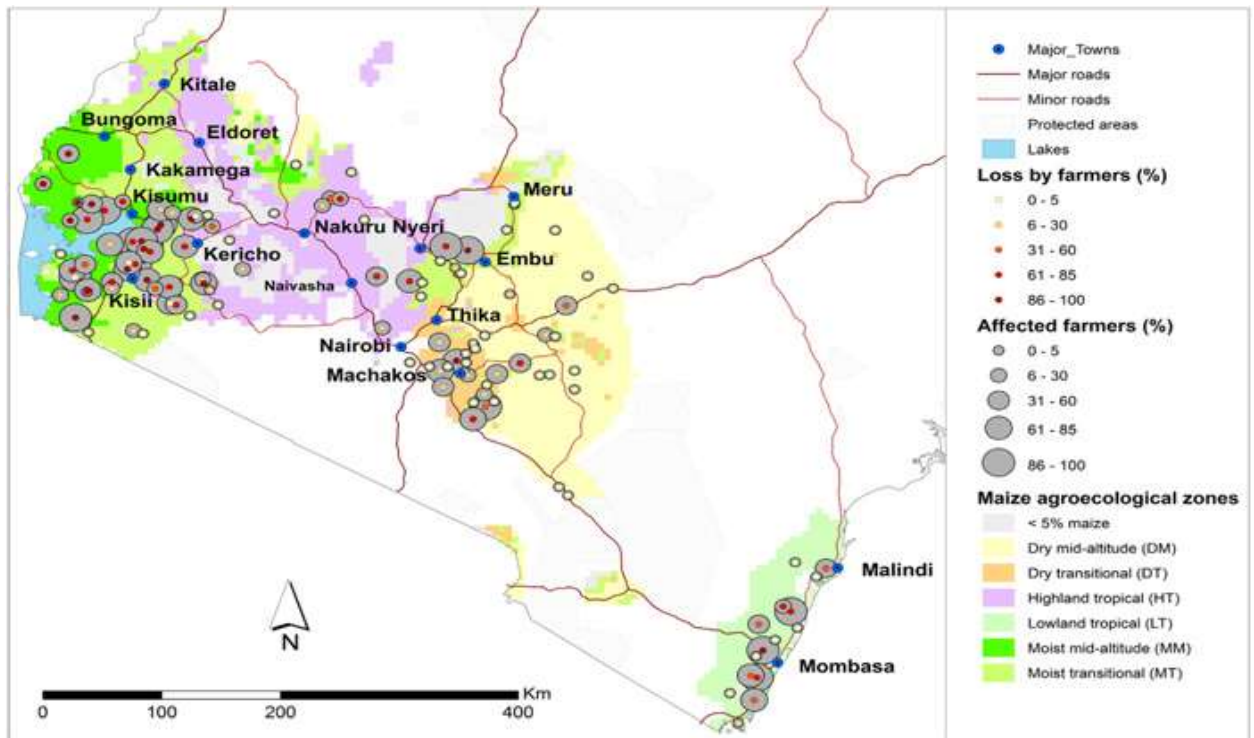
Significant threats to maize crops include grey leaf spot (GLS), maize lethal necrosis (MLN), maize streak virus (MSV), and ear rots. Various pathogens, including bacteria, fungi, and viruses, cause these diseases. They pose a significant challenge to the farming of maize. The most dangerous viruses among them are MLN and MSV, which cause severe damage to maize crops. They have a significant negative impact on the plant's health and yield. Additionally, fungi infections like GLS worsen the situation by reducing a plant's capacity to produce food through photosynthesis.

Real-world consequences of all of these problems include decreased maize production and quality. It is evident that these diseases have negative impacts on more than just agriculture; they also have negative effects on many people's ability to obtain food. Finding solutions to these diseases is therefore urgent. This entails correctly identifying them, controlling their spread, and developing solutions that mitigate their effects. By taking these measures, maize farming is protected from these harmful diseases and is more sustainable, ensuring enough food for everyone.

#### **2.3.1 Maize Lethal Necrosis (MLN) Disease**

The emergence of maize lethal necrosis (MLN) disease was initially documented in Bomet County, Kenya, in 2011 (Wangai *et al.*, 2012) and has since spread into other maize-growing areas of Kenya (Fig 2.1). MLN is the result of multiple infections in maize plants by maize chlorotic mottle virus (MCMV) along with any of the potyviruses such as Sugarcane mosaic virus (SCMV), Maize dwarf mosaic virus (MDMV), or Wheat

streak mosaic virus (WSMV) (Bernardo *et al.*, 2021). The co-infection of these two viruses leads to the development of MLN, also known as Corn Lethal Necrosis (CLN) (Wamaitha *et al.*, 2018). The transmission of MLN occurs through various insect vectors, including maize thrips (*Frankliniella williamsi* Hood), while aphids have been reported to contribute to the proliferation of SCMV (Mwando *et al.*, 2018). Although the transmission rate of MLN through contaminated maize seeds is low (Bernardo *et al.*, 2023), it remains a potential transmission route. MLN poses a significant threat to maize crops, causing severe yield losses and impacting farmers' livelihoods.



**Figure 2.1** Distribution and losses affiliated by MLN in Kenya. Source De Groote *et al.*, 2016

Maize crops in Kenya have been reported to suffer yield losses of up to 100% (Awata *et al.*, 2021), while in Peru, losses of 59% and in the Democratic Republic of Congo, losses ranging from 40% to 80% have been observed (De Groote *et al.*, 2016). Maize plants

infected with maize lethal necrosis (MLN) exhibit various characteristic symptoms. These include chlorotic mottling on the leaves, initially affecting young leaves at the whorl stage (Karanja *et al.*, 2018). The mottling can range from mild to severe, accompanied by stunting of the plants and premature ageing (Awata *et al.*, 2019). Necrotic lesions develop from the leaf margins towards the midrib, and young leaves in the whorl can experience necrosis, leading to the distinct 'dead heart' symptom. Ultimately, the entire plant may dry up (Awata *et al.*, 2019). Severely affected plants often exhibit reduced cob size or fail to set grain (Figure 2.2). These symptoms collectively contribute to significant yield reductions and seriously threaten maize production. Understanding the symptoms of MLN is essential for early detection and effective management of the disease. Several control measures have been implemented to reduce the impact and spread of MLN disease in Kenya. These include quarantining maize from infected regions to prevent the movement of infected seeds, plants, or soil (Mudde *et al.*, 2019). Crop rotation with non-host crops such as beans, cowpeas, or sorghum breaks the disease cycle and reduces the inoculum load (Xu *et al.*, 2022). Use certified, clean seeds and hybrid, tolerant plants screened and tested for MLN resistance (Awata *et al.*, 2022). Stringent monitoring and surveillance of MLN occurrence and distribution using rapid diagnostic kits and remote sensing (Richard *et al.*, 2021; Biswal *et al.*, 2022). Insecticide application to reduce the transmission of MLN by insect vectors such as thrips, aphids and leaf beetles (Wamonje *et al.*, 2020). These control measures have contributed to the recent decline of MLN disease in Kenya. However, there is still a need for continuous research and development of more effective and sustainable strategies to combat MLN, such as genetic engineering, gene editing, biological control, and integrated pest management (Alemu, 2020).

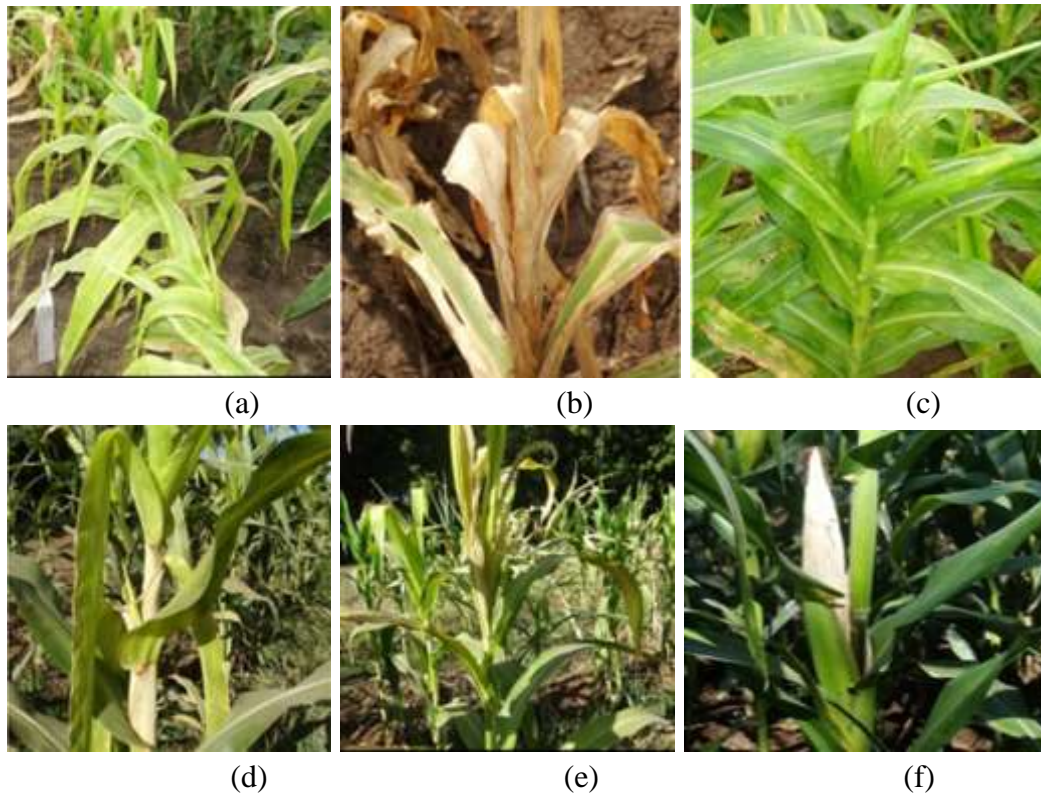


Figure 2.2. Disease symptoms of MLN.(a) Mosaic and Mottling (b) Dead Heart (c) Shortened Internodes (d) Premature drying of the leaf sheath (e) Sterile Tassel (f) Premature drying husk. Source De Groote *et al.*, 2016

### 2.3.2 Maize Streak Disease (MSD)

Maize streak virus (MSV) is considered one of the most severe viral diseases affecting maize crops, leading to significant yield reductions and threatening african food security (Tembo *et al.*, 2020). The first reported case of MSV occurred in central Kenya, and since then, the disease has spread to other maize-growing regions in mid-altitude ecological zones (Charles, 2019). Under natural infection conditions, yield losses due to MSV in sub-Saharan Africa can reach up to 100% (Ketsela *et al.*, 2022).

Symptoms of MSV are characterized by chlorotic stripes on maize leaves, which ultimately reduce the leaf's photosynthetic area, depending on the severity of the disease (Drechsler *et al.*, 2014). To effectively control and manage MSV, it is essential to have

robust and sensitive diagnostic tests capable of rapidly detecting the presence of MSV (Tembo *et al.*, 2020). Rapid and accurate detection methods enable early intervention and implementation of appropriate disease management strategies to minimize yield losses and protect maize crops (Paliwal & Joshi, 2022).

Several control measures have been implemented to reduce the impact and spread of MSV disease in Africa. These include quarantining maize from infected regions to prevent the movement of infected seeds, plants, or soil. Crop rotation with non-host crops such as legumes, cereals, or vegetables to break the disease cycle and reduce the whitefly population (Karavina, 2014). Field hygiene and early planting to avoid overlapping crops and reduce infection chances 24. Use of certified, clean seeds and tolerant or resistant maize varieties that have been screened and tested for MSV resistance (Martin & Shepherd, 2009). Insecticide application to reduce the transmission of MSV by whiteflies, especially during the early stages of crop growth (Karavina, 2014). These control measures have contributed to the management of MSV disease in Africa in recent years. However, there is still a need for continuous research and development of more effective and sustainable strategies to combat MSV, such as genetic engineering, biological control, and integrated pest management (Alemu *et al.*, 2020).

The prevalence of MSD and its detrimental impact on maize production highlight the urgent need for improved disease management approaches. Developing effective strategies for MSD control requires a comprehensive understanding of the disease's epidemiology, transmission dynamics, and host-pathogen interactions. Furthermore, developing reliable detection tools will aid in the early detection and timely implementation of control measures, contributing to enhanced food security and sustainable maize production in affected regions (Stutsel *et al.*, 2021).



### 2.3.3 Grey Leaf Spot Disease

Grey leaf spot disease is a fungal infection caused by *Cercospora zae-maydis* and is one of the most destructive diseases affecting maize crops (Yu *et al.*, 2018, Kinyua *et al.*, 2011). The first report of GLS in sub-Saharan Africa was documented in South Africa in 1990, leading to significant losses of up to 60% (Paul *et al.*, 2003). The disease spread to other regions, including Uganda in 1994 and Zimbabwe in 1995 (Dunkle and Levy, 2000). In Kenya, GLS has been reported to cause maize yield losses of up to 37% (Kinyua *et al.*, 2011).

The characteristic symptoms of GLS manifest as lesions on older maize leaves, exhibiting a colour change to pale brown or grey-tan, mainly concentrated along the veins (Paul, 2003). Severe outbreaks of GLS can result in considerable losses due to reduced photosynthesis and impaired grain fill. The severity of the disease is heavily influenced by favourable environmental conditions, such as warm temperatures and high humidity (Vines *et al.*, 2020, Paul, 2003).

Several control measures have been implemented to reduce the impact and spread of GLS disease in Kenya. These include destroying plant debris after harvest to eliminate the primary source of inoculum. Crop rotation with non-host crops such as legumes, cereals, or vegetables to break the disease cycle and reduce the fungal population (Kaya, 2022). Using certified, clean seeds and more tolerant or resistant maize varieties screened and tested for GLS resistance (Chung *et al.*, 2011). Applying fungicides, especially during the early stages of crop growth, protects the plants from infection and reduces the transmission of GLS by wind or rain (Aguado *et al.*, 2018). These control measures have contributed to the management of GLS disease in Kenya in recent years. However, there is still a need for continuous research and development of more effective and sustainable

strategies to combat GLS, such as biological control, integrated pest management, and genetic engineering (Alemu et al., 2020).

To mitigate the yield losses caused by GLS and other similar diseases, the accurate and efficient identification of the disease is of utmost importance. Early detection is crucial for implementing timely and effective disease management strategies, including fungicides and other control measures. By promptly identifying and addressing the presence of GLS, maize farmers can minimize the impact of the disease on crop yield and overall agricultural productivity (Ma *et al.*, 2022)

#### **2.4 Traditional Approaches for Identification Maize Leaf Disease**

Conventional techniques for identifying maize leaf diseases have historically employed diverse methodologies, including visual assessments conducted by seasoned pathologists and serological methods like Enzyme-Linked Immunosorbent Assay (ELISA) and Polymerase Chain Reaction (PCR)-based techniques. However, these well-established methods have limitations that hinder their practicality in routine disease management (Elfatimi *et al.*, 2022).

The main drawbacks include time-consuming procedures that demand a significant amount of time. Furthermore, these techniques frequently call for destroying plant samples, damaging the plant and making it unsuitable for future growth. Another issue is the lack of real-time monitoring capabilities, which prevents the prompt intervention necessary for disease control. Additionally, these methods are unlikely to be effective when a single plant may be affected by multiple diseases, which could result in incorrect diagnoses (Khakimov et al., 2022).

Therefore, it is crucial to develop a simple, unobtrusive framework that can quickly identify and categorize maize leaf diseases (Owino, 2023). A paradigm shift of this nature might usher in innovative disease monitoring, providing real-time insights that enable prompt and focused interventions, and effectively reducing the disease's impact on maize crop yield (Khakimov et al., 2022).

The significance of early disease detection cannot be overstated, as it bestows farmers with the power of foresight. This timely awareness empowers them to enact measures with surgical precision, such as judiciously deploying fungicides and insecticides, thereby averting excessive usage and resultant economic losses (Dubois *et al.*, 2021; Rocha *et al.*, 2020). The financial ramifications extend beyond the immediate - resource efficiency and contribute to substantial cost savings while aligning with sustainable agricultural practices.

Beyond the realm of economics, this paradigm shift holds I each crop dientrinsic ecological value. Adopting such a model by reducing unnecessary chemical applications aligns with a broader commitment to environmental protection. This virtuous cycle safeguards not only the health of the environment but also the well-being of humans and the diversity of life, curtailing the inadvertent consequences of overzealous chemical usage (Gunstone *et al.*, 2021).

## **2.5 Computer Based Vision Digital Images in Crop Diseases Identification**

Adopting affordable and powerful digital computing solutions has gained much popularity due to the weaknesses in manual disease identification methods (Xie *et al.*, 2020). The transformational power of digital image processing ushers in an era where visual information is enhanced and harnessed for human interpretation and machine

comprehension, improving image data storage, transmission, and representation (Singh *et al.*, 2012).

The journey through the landscape of digital image processing follows a structured path involving a sequence of well-defined stages. Commencing with image acquisition, where the digital realm captures real-world visual data, the process advances into pre-processing, a critical phase to refine and enhance raw image inputs. Subsequently, image segmentation dissects these enhanced images into distinct, meaningful components. Feature extraction follows, where relevant attributes are distilled from the segmented image, paving the way for the heart of the process - recognition and classification. Here, the extracted features are employed to differentiate and categorize the image in line with predefined classes (Too *et al.*, 2019). In this digital milieu, two dominant methodologies stand tall: machine learning and deep learning techniques (Stančić *et al.*, 2022). Machine learning is a versatile approach where algorithms learn from patterns within data and adapt their response accordingly. On the other hand, deep learning, a subset of machine learning, uses layers of interconnected nodes to interpret data hierarchically, grasping intricate patterns and nuances that might evade traditional approaches (Stančić *et al.*, 2022).

## **2.6 Machine Learning Techniques in Plant Diseases Detection and Classification**

In digital agriculture, machine-learning techniques have swiftly emerged as potent tools for precise and efficient plant disease detection through the analysis of digital images (Kini *et al.*, 2023). This innovative approach hinges on extracting and interpreting a multitude of digital image attributes, ranging from leaf colour to shape and texture, all intricately woven together to create a comprehensive profile (Liu & Wang, 2021; Khan *et al.*, 2021).

The underlying mechanics of this technique are rooted in pattern recognition and learning from data. By systematically feeding the machine with an extensive array of digital images encompassing healthy and diseased plant samples, a robust algorithm learns to decipher the minute variations that set them apart (Genaev *et al.*, 2021). Each image helps build a mental library of indicators that can indicate the presence of a disease.

The beauty of machine learning lies in its capacity to rapidly process an immense volume of images, quickly identifying those nuanced features that elude human eyes. Once trained, the algorithm becomes a reliable classifier capable of independently assessing new images and delivering a verdict with remarkable accuracy (Yavuzer & Kose, 2022). This technology reduces the time required for disease identification and opens new avenues for large-scale monitoring and detection, heralding a transformative shift in how we safeguard agricultural productivity.

However, it is crucial to recognize that while machine learning techniques offer remarkable capabilities, they have certain limitations that warrant consideration. For instance, these techniques might not be sensitive to detecting disease images in their initial stages of infection, which is a critical aspect of disease management (Khan *et al.*, 2021; Liu & Wang, 2021).

Additionally, external factors can influence machine learning models' effectiveness. Variations in lighting conditions, for instance, can cast shadows or distort colours, potentially leading to erroneous assessments (Shoaib *et al.*, 2023). Similarly, occlusion – when parts of the plant or image are obstructed can confound the model's ability to accurately perceive the image (Shoaib *et al.*, 2023). These issues can collectively contribute to reducing the overall accuracy of disease recognition.

Understanding these limitations is essential to avoid overreliance on machine learning techniques without a comprehensive grasp of their intricacies. Moreover, it underscores the importance of holistic approaches that integrate these tools with complementary methods, creating a more robust and reliable disease detection framework that can effectively tackle various challenges.

Various models serve as machine learning classifiers, with Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbors (K-NN), and Random Forests (RF) being among the commonly employed ones (Jasrotia *et al.*, 2023).

### **2.6.1 Support Vector Machine – a Machine Learning Model**

Support Vector Machines (SVM) are powerful tools within supervised machine learning, renowned for their adeptness in data analysis and pattern recognition (Yu & Kim, 2012). These models operate on robust learning algorithms meticulously crafted to dissect complex datasets and unveil discernible patterns that may not be readily apparent to the human eye. This remarkable trait makes them valuable assets for various analytical tasks, including classification and regression analysis (Kim *et al.*, 2018).

The true prowess of SVM is in its capacity to tackle diverse data scenarios. Not limited to linear data distributions, SVM can also proficiently navigate the intricacies of nonlinear data structures. This exceptional adaptability allows it to address the multifaceted complexities inherent in real-world datasets. Whether the data exhibits linear relationships or is characterized by intricate nonlinear correlations, SVM can aptly capture and distinguish these underlying patterns (Yu & Kim, 2012).

Support Vector Machines employ a strategic approach that elevates the original training data to a higher-dimensional space in classification. Within this augmented space, SVM meticulously constructs what is known as a hyperplane—a precise mathematical portrayal of a decision boundary that demarcates different data groups. This hyperplane plays a pivotal role as it effectively distinguishes one set of data from another, guiding the classification process (Spence & Fokas, 2010).

SVM's skill is especially evident when data relationships are not linear. In such instances, SVM adopts a technique by mapping the data into a higher-dimensional realm. This mapping involves intricate transformations that unveil subtle patterns that may be obscured in the original data dimensions. SVM crafts the optimal hyperplane within this transformed space that effectively separates the distinct classes. This higher-dimensional hyperplane serves as a dynamic bridge between different data clusters, allowing for precision in classification (Han & Kamber, 2012).

The key to SVM's effectiveness is its ability to identify support vectors and important data points that significantly impact where the decision boundary is placed. These vectors play a dual role: they define the decision boundary and maximize the gap between the data classes, enhancing the robustness of the classification. This concept is crucial as it not only aids in accurate classification but also bolsters the model's ability to handle new, unseen data with reliability (Bahari *et al.*, 2014).

By maximizing the margin distance between classes in the decision plane, SVM enhances the model's generalization capabilities and reduces the risk of overfitting (Prajapati & Patle, 2010).

## 2.7 Deep Learning Techniques in Plant Diseases Identification

Deep learning techniques have arisen as a beacon of promise in surmounting the hurdles that conventional machine learning models encounter in plant disease identification (Liu & Wang, 2021). These innovative methods have demonstrated a remarkable capacity for achieving specificity and accuracy in discerning plant diseases (Drenkow *et al.*, 2021). This prowess largely stems from their unique ability to extract intricate image features without laborious manual feature engineering autonomously (Xie *et al.*, 2020).

What sets deep learning apart is its innate capability to fathom complex patterns and relationships embedded within images. Unlike traditional methods that often necessitate a thorough process of hand-crafting features to suit the problem, deep learning models autonomously learn and refine these features from the data. This intrinsic aptitude enables them to capture even the subtlest cues that signify disease presence, culminating in heightened accuracy (He *et al.*, 2022).

The flexibility of deep learning models extends to their ability to handle vast amounts of data. This trait aligns perfectly with the demands of large-scale plant disease detection endeavours. In scenarios where datasets burgeon in size and complexity, these models remain unfazed, seamlessly scaling their processing capabilities to accommodate the abundance of information (Too *et al.*, 2019; Khan *et al.*, 2021).

Recognition of plant diseases has seen widespread use of deep learning models, demonstrating the field's rapid development. Boltzmann's Deep Machine (DBM) (Hess *et al.*, 2016), Deep Belief Networks (DBN) (Hasan *et al.*, 2020), and Deep Convolutional Neural Networks (CNN) (Mushtaq *et al.*, 2022) are a few examples of these models. Deep CNNs have attracted interest for their remarkable performance in plant disease



identification and classification, with precision rates of 99-99.2% (Lin *et al.*, 2020; Stani *et al.*, 2022).

Deep CNNs are distinguished by their capacity to seamlessly combine the strength of convolutional neural networks with the fundamental principles of deep learning. These models can recognize even the most subtle signs of disease due to this combination's outstanding ability to recognize intricate patterns within images. Through this inherent ability, they can achieve remarkably high levels of accuracy in differentiating between healthy and diseased plants (Purwono *et al.*, 2023).

However, it's prudent to note that these acknowledged methods have prerequisites. Deep learning models, particularly Deep CNNs, utilize large training datasets and require a great deal of accurately labelled data to optimize their performance. When faced with diseases they had not encountered during their training, their effectiveness can diminish, making them less skilled at spotting new or emerging conditions (Ren *et al.*, 2019).

Numerous Convolutional Neural Network (CNN) architectures have been used to identify plant diseases, including AlexNet, ResNet, GoogleNet, and imageNet (Maeda-Gutierrez *et al.*, 2021). Among these architectures, AlexNet and ResNet50 have demonstrated remarkable accuracy rates of up to 99% in plant disease recognition (Stančić *et al.*, 2022).

### **2.7.1 AlexNet CNN Architectures**

AlexNet is a Convolutional Neural Network (CNN) architecture developed in 2012 (Antonellis *et al.*, 2015). This model is well-known for its high specificity, speed, and accuracy in identifying plant diseases (Too *et al.*, 2019). The input layer of AlexNet consists of a 227x227x3 colour image. The network comprises five convolutional layers, three pooling layers, three fully connected layers, and one activation layer (Stančić *et al.*, 2022).

AlexNet uses a dynamic approach to augment image data to strengthen its discernment capabilities. It carefully enters the image field and blends randomness into capturing a 224x224 region. This foray carefully uses various transformative operations, such as flipping and mirroring. In addition to expanding the training data pool, this orchestration of manipulations also acts as a safeguard against the risk of overfitting that might otherwise impair the convolutional neural network's learning process (Ren et al., 2019).

This augmentation technique is similar to giving the model access to various viewpoints, each revealing new aspects of the image. This multifaceted understanding promotes adaptability and allows the network to spot even the most minute patterns across multiple scenarios. The model has developed a greater generalization capacity, enabling it to navigate previously unknown images effectively (Li *et al.*, 2022).

The method AlexNet uses for image down-sampling, which is crucial for controlling computational complexity while preserving essential features, further sets it apart from competitors. In contrast to the usual average pooling, the model chooses a maximum pooling approach for this endeavour. This method avoids the dangers of image blurring that average pooling may unintentionally introduce, maintaining the image's essential characteristics (Too *et al.*, 2019).

In addition, a meticulous overlap and coverage strategy distinguishes AlexNet's approach to pooling. This process is designed with smaller step sizes than the pooling core's dimensions. This calculated manoeuvre orchestrates a planned overlap between the pooling layer's outputs, creating a diverse array of features that enhance the understanding of the model as a whole. This carefully organized coverage effectively

increases the network's accuracy because features are captured using a precision that mirrors the image's complex details (Stančić *et al.*, 2022).

In the network structure, an improvement over traditional CNNs is the addition of the Local Response Normalization (LRN) layer, which introduces a competition mechanism for the activity of local neurons (Du *et al.*, 2016). The LRN layer increases the influence of more significant values in the image and reduces less influential parts, enhancing the model's generalisation ability. There are two more enhancements in the back-end part of the neural network (Wu, Guo & Yang, 2021). First, the Rectified Linear Unit (ReLU) is chosen as the activation function of the network. This piecewise linear function makes the forward calculation simple and efficient without requiring complex index calculations (Du *et al.*, 2016). Second, dropout is used in the last few fully connected layers to randomly ignore some neurons, thus preventing the over fitting of the neural network model (Too *et al.*, 2019).

AlexNet efficiently utilises Graphics Processing Unit (GPU) acceleration to train deep convolutional networks, significantly improving the speed of network training and enhancing its overall performance (Zhang *et al.*, 2019). Combining these features and improvements has made AlexNet a powerful tool for accurate and fast disease identification in plant health assessment.

### **2.7.2 ResNet50 CNN Architectures**

ResNet50 is a deep convolutional neural network architecture introduced by Microsoft Research in 2015. It has since been widely used in various computer vision applications, such as picture classification, object recognition, and image segmentation (Rahman *et al.*, 2023). The "50" in ResNet50 denotes the number of layers in the network, which

includes convolutional layers, pooling layers, fully connected layers, and shortcut connections (Jiang *et al.*, 2022).

The integration of residual connections, also known as skip connections, is at the core of ResNet50, a significant advancement that has completely changed the field of convolutional neural networks. The network's information flow has undergone a paradigm shift due to this intelligent architectural addition, which has given the network a remarkable resilience and depth that distinguishes it from others (Jiang *et al.*, 2022).

Consider this invention as a collection of connected bridges that cross the layers of the neural network. Traditionally, moving from one layer to another requires navigating a series of complicated pathways, and each layer may weaken the signal, similar to the echo of a distant voice. The diminishing gradient challenge caused by this signal attenuation can make it difficult to train deep neural networks. ResNet50 effectively overcomes this obstacle by including these bypass bridges. These connections serve as conduits, enabling the information to skip over certain network layers and vault straight to deeper levels. The data travels these direct routes without being hindered by the potential dampening effects of intermediary layers. This critical architectural development effectively "short-circuits" the vanishing gradient problem by incorporating these skip connections, significantly reducing signal distortion (Jiang *et al.*, 2022).

This architectural feat has profound implications. The network can delve into unprecedented depths without sacrificing performance by enabling information to flow unimpeded through these bypass bridges. This is a monumental departure from the traditional notion that increasing network depth might lead to diminishing returns in terms of accuracy. ResNet50 defies this conventional constraint, achieving both depth

and performance, effectively rewriting the rulebook for deep convolutional neural networks (Rahman *et al.*, 2023).

The fundamental building block of ResNet50 is the residual block, which comprises two or more convolutional layers followed by a shortcut connection (Chou *et al.*, 2023). The shortcut connection adds the original input of the block to the output of the block, enabling the network to learn residual mappings instead of directly learning the desired mappings (Rahman *et al.*, 2023). This characteristic empowers ResNet50 to efficiently train deep networks and achieve state-of-the-art performance on various image recognition tasks (Chou *et al.*, 2023).

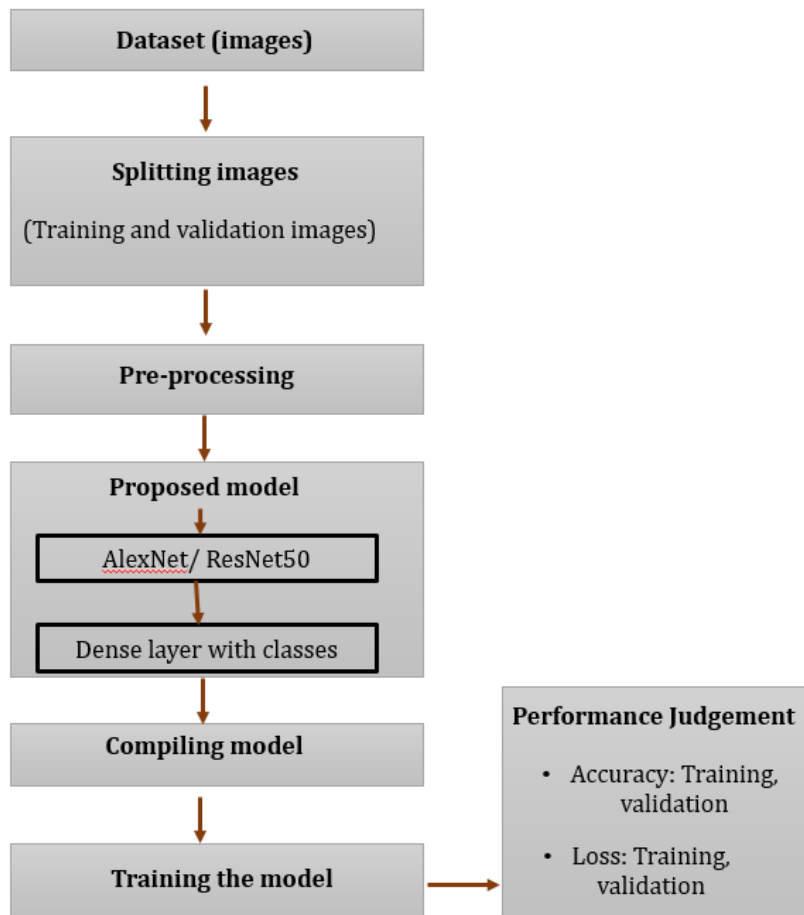
ResNet50 is often pre-trained on large-scale image datasets, where it learns to recognize a wide range of visual concepts. After pre-training, the network can be fine-tuned or used as a feature extractor for specific tasks (Jiang *et al.*, 2022). By leveraging the learned representations from the lower layers, ResNet50 can effectively capture high-level features and generalize well to new images (Shafiq & Guet, 2022). Its ability to learn complex features and adapt to different tasks makes ResNet50 a powerful and versatile tool for plant disease identification and classification.

## **2.8 Conceptual framework of the CNN Architectures: AlexNet and ResNet50**

A conceptual framework serves as a visual representation of how a researcher envisions the relationships between variables within a study. This model is typically presented graphically or diagrammatically. The researcher posits that a conceptual framework is essentially a hypothesized model that identifies the key concepts or variables under consideration within a study, elucidating their interrelationships.

Convolutional Neural Networks (CNNs) consist of two main components: feature extraction and classification. The feature extraction segment comprises an input layer, convolutional layer with stride and padding, rectified linear unit (ReLU), pooling layer, and batch normalization layer. The classification part includes a fully connected layer, softmax activation, and output layer (Ramanjaneyulu *et al.*, 2020). In this study, two CNN architectures, namely AlexNet and ResNet50, were utilized (Fig 3.2).

AlexNet consists of an input layer, five convolutional layers with various filter sizes (e.g., 11x11, 5x5, and 3x3), seven ReLU layers, two normalization layers, three max-pooling layers, three fully connected layers, two dropout layers with a rate of 0.5, softmax activation, and an output layer (Purwono *et al.*, 2023). On the other hand, ResNet50 addresses the challenges posed by the increasing number of layers in CNNs, which can make learning more difficult and decrease accuracy. Residual Network (ResNet) tackles this issue by incorporating skip connections between layers. ResNet50 is a CNN architecture with 50 layers (Ganesan & Chinnapan, 2022).



**Figure 2.3:** Conceptual framework of the proposed model using AlexNet/ ResNet50

## CHAPTER THREE

### MATERIALS AND METHODS

#### 3.1 Introduction

This section dealt with the methodology that was used in carrying out the research. It describes the data sets, the pre-processing phase, the training phase, the description of the CNN and SVM architectures, and the evaluation of the CNN and SVM performance.

#### 3.2 Data Sets

Maize leaf images of size 256x256 pixels were captured using a digital camera around farms within Embu County i.e KALRO Embu, and farms within Mutunduri Center, Kirigi Center, Manyatta Center, Kavutiri Center, Kianjakoma Center, Kivwe Center, Gatunduri Center, Kawanjara and ENA Area. The camera used to capture the images in this study was the Canon EOS 250D (Canon, UK). This camera is equipped with a range of advanced features that proved instrumental in obtaining high-quality images for disease classification. Notably, the Canon EOS 250D boasts a 24.1-megapixel advanced photo-system complementary metal oxide semi-conductor (CMOS) sensor, providing exceptional image resolution. It offers versatile shooting capabilities, including the ability to capture images in RAW format, which is crucial for preserving image quality during post-processing. The camera's DIGIC 8 processor ensures fast and efficient image processing, and its Dual Pixel CMOS Auto Focus system allows for accurate and rapid focusing, even in challenging lighting conditions. These features collectively contributed to the successful acquisition of the dataset used for disease classification.

The images were captured in August and September. This period typically falls within the country's dry season, with relatively lower humidity and minimal rainfall. These months



are characterised by abundant sunshine, with the days being generally warm and clear. The weather is often stable and predictable, making it an ideal time for capturing images for analysis. The reduced cloud cover and diminished intensity of sunlight in the mornings and evenings during this season were advantageous for minimizing challenges associated with image reflections in the classification process. These climatic conditions provided an optimal environment for the research, allowing for collecting high-quality data for the CNN and SVM analysis of maize leaf diseases.

The total number of images was 3200, with each category having 800 images as suggested by Wagle and R, (2021). A plant pathologist classified the diseased leaves to limit the number of images with multiple diseases. The study identified and classified three maize leaf diseases: Maize lethal necrosis, Maize streak virus and Grey leaf spot. Healthy leaves were used as a control in training our model (Table 3.1).

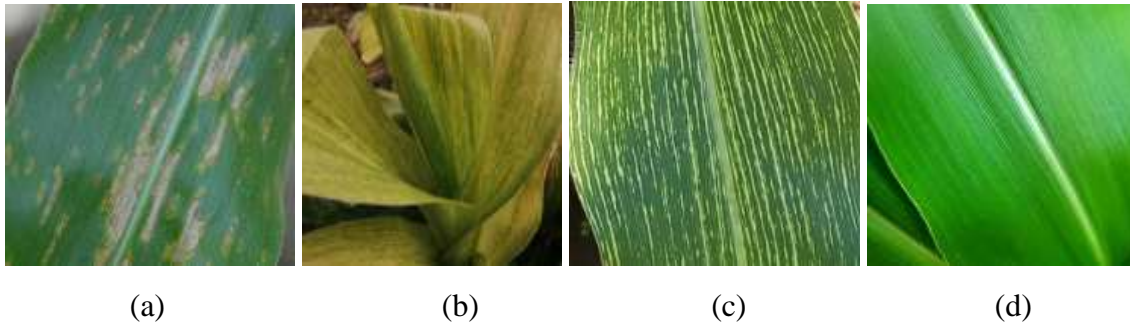
The dataset was split into three parts for deep neural network classification. The first part was the training set, i.e., a collection of images to be used by the network to learn its hidden parameters (weights and biases) automatically. The second dataset was the validation set that manually adjusted parameters that could not be automatically learned during training. We evaluated the trained model using the validation dataset at the end of each epoch. This allowed us to monitor the training process and detect overfitting instances. The third part of the data was used after the model training to test the model's accuracy.

**Table 3.1:** Distribution of data sources and division of images used in training validation and testing per disease

Maize leaf disease	Total data set	Training data set	Validation	Testing data set
Maize leaf necrosis	800	640	240	160

Maize streak disease	800	640	240	160
Grey leaf spot	800	640	240	160
Healthy control	800	640	240	160

Some Maize leaves showing various diseases identified and classified in this study are shown in Figure 3.1



**Figure 3.1:** A sample of maize leaf images representing crop disease used: (a) Grey leaf spot, (b) Maize lethal necrosis disease, (c) Maize streak disease, (d) Healthy maize leaf

### 3.3 Pre-processing Phase

The captured data images, initially sized at 256x256 pixels, were resized to match the default size of each CNN architecture. For the ResNet50 network, the images were adjusted to 224x224x3 pixels, while for AlexNet, the images were resized to 227x227x3 pixels.

### 3.4 Training Phase

In the training phase, we employed pre-trained ResNet-50 and AlexNet networks, utilizing transfer learning to adapt the output layers for our specific classification task. For ResNet-50, the final three layers of the original network were retrained to generate new layers: a fully connected layer, a softmax layer, and a classification output layer. Similarly, transfer learning was applied to AlexNet, following a comparative approach. The training parameters for AlexNet were configured as follows: The number of

iterations was set to 162, with 27 iterations per epoch. The base learning rate was set to 0.0001, and the training process was conducted for six epochs.

### **3.5 Evaluation of Performance of AlexNet, ResNet50 and SVM in Maize Leaf**

#### **Diseases Classification**

The performance of AlexNet, ResNet50 and SVM in classifying the maize leaf disease was determined by considering four values generated during the testing phase. The values were:

- a) True Positive (TP): The number of values of the principal class that the model predicts right.
- b) False Positive (FP): The number of values of the principal class that the model predicts is wrong.
- c) True Negative (TN): The number of values of the secondary class that the model predicts right.
- d) False Negative (FN): The number of values of the secondary class that the model predicts is wrong.

Based on the above values, four evaluation metrics were scored: Precision, Recall, Accuracy, and F1 score as described below:

- i) *Accuracy*: Accuracy was the most common metric used in many studies. It is used to find out how much a model is right. It is calculated as the sum of TP and TN divided by the total number of predictions, as shown below:

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}}$$

*Recall* is a measure of the number of accurately predicted true positives to the total number of positive predictions.

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive} + \text{False Negative}}$$

ii) *Precision* was metric defines how many cases classified as TP actually are TP, and is calculated as the number of TP divided by the sum of TP and FP, as shown.

$$\text{Precision} = \frac{\text{True positive}}{\text{True positive} + \text{False Positive}}$$

iii) *The F1-score* is the harmonic mean between two metrics: precision and recall. It is used when the objective is to seek a balance between these two metrics. The F1 score balances both the prediction and recall metric and was calculated as presented below:

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

Additionally, the model's performance was assessed by determining Model loss and Model accuracy. Model accuracy refers to the proportion of correctly classified instances. It is typically used for classification tasks, whereas model loss, on the other hand, is a measure of how well the model can predict the target output for a given input instance. The loss function represents the discrepancy between the predicted and actual output and is used to update the model parameters during training to minimize this discrepancy. A lower loss indicates that the model is better able to predict the target

output for a given input instance (Montalbo & Hernandez, 2020). Model accuracy and model loss are important metrics that provide different information about the performance of the model.

## CHAPTER FOUR

### RESULTS FINDINGS AND INTERPRETATIONS

#### 4.1 Introduction

This chapter presents the analysed data. It highlights the findings according to the study objectives. The objectives of the study were to: Identify maize leaf disease (MLN, MSD and GLS) using AlexNet ResNet-50 and SVM models and evaluate the performance of the AlexNet, ResNet-50 and SVM models in the classification of MLN, MSD and GLS.

#### 4.2 Identification of Maize Leaf Diseases Using AlexNet, ResNet50 and SVM

##### Architectures

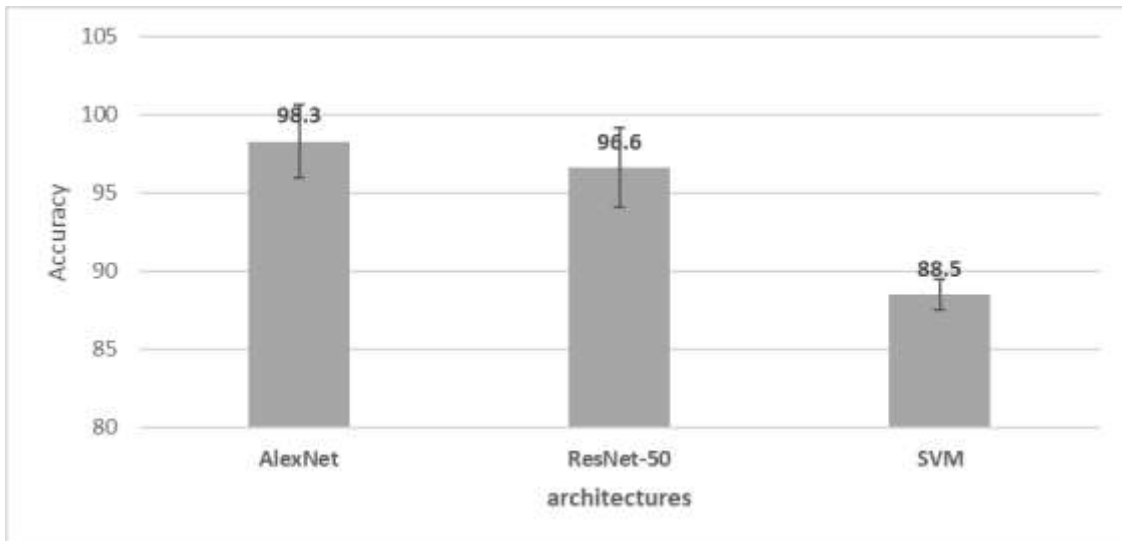
The results of the maize leaf disease identification using AlexNet, ResNet-50, and SVM models are presented in Table 4.1. All models achieved relatively high accuracies in identifying the three maize leaf diseases. The deep learning convolutional neural network models, AlexNet and ResNet50, exhibited higher accuracy than the machine learning SVM model.

AlexNet demonstrated the highest accuracy across the diseases, achieving 99.9% accuracy for Maize Streak Disease (MSD) and a slightly lower accuracy of 95.9% for Maize Lethal Necrosis (MLN). ResNet-50, on the other hand, achieved the highest accuracy of 99% for MSD recognition and 94% for MLN. In contrast, the SVM model exhibited lower accuracy in disease detection, with accuracies of 89% for MSD and 78% for Grey Leaf Spot (GLS). For the classification of healthy maize images, AlexNet achieved a perfect accuracy of 100%, while SVM showed the lowest accuracy of 90%.

**Table 4.1:** Percentage accuracy in detection of maize leaf diseases by AlexNet, ResNet50 and SVM models

<b>Disease</b>	<b>Model</b>	<b>Accuracy (%)</b>
Maze lethal necrosis	AlexNet	95.9
	ResNet50	94.0
	SVM	88.0
Maize Streak Disease	AlexNet	99.9
	ResNet50	99.0
	SVM	89.0
Grey leaf spot	AlexNet	97.4
	ResNet50	96.0
	SVM	87.0
Healthy	AlexNet	100
	ResNet50	97.9
	SVM	90

On average, both CNN architectures demonstrated higher accuracy in maize leaf disease detection than the machine learning SVM model. AlexNet exhibited the highest average accuracy of 98.3%, followed by ResNet-50, and lastly, the machine learning SVM model with an average accuracy of 88.5% (Figure 4.1). Based on these findings, we can conclude that the CNN algorithms, specifically AlexNet and ResNet-50, outperformed the machine learning SVM model in maize leaf disease recognition.



**Figure 4.1:** Average accuracy in identification of the three maize leaf diseases by AlexNet, ResNet50 and SVM

### 4.3 Performance of AlexNet, ResNet50 and SVM in Classification of Maize Leaf

#### Diseases

In the Maize Lethal Necrosis (MLN) disease classification, the AlexNet architecture demonstrated the best performance, achieving a precision, recall, and accuracy of 93.7%, 96.4%, and 95%, respectively. ResNet-50 closely followed with slightly lower precision, recall, and accuracy percentages of 94.0%, 89.1%, and 92.9%. The machine learning model SVM exhibited the lowest precision, recall, and accuracy percentages of 88.0%, 83.8%, and 88.4%, respectively (Table 4.2).

**Table 4.2:** Confusion matrix and performance of AlexNet, ResNet50 and SVM in recognition of MLN disease

Model	TP	TN	FP	FN	Precision	Recall	F1-Score	Accuracy
AlexNet	239	236	16	9	93.7	96.4	95.0	95.0
ResNet50	188	273	12	23	94.0	89.1	91.5	92.9
SVM	176	266	24	34	88.0	83.8	85.9	88.4

Where TP represent true positive, TN- true negative, FP-false positive and FN- false negative



Similarly, for the classification of Maize Streak Disease, AlexNet outperformed all other models and achieved the highest recall of 100%. ResNet50 followed closely behind. In contrast, the SVM model recorded the lowest precision (89.0%), recall (85.6%), and accuracy (89.6%) for MSD classification (Table 4.3).

**Table 4.3:** Confusion matrix and performance of AlexNet, ResNet50 and SVM in recognition of MSD

Model	TP	TN	FP	FN	Precision	Recall	F1-Score	Accuracy
AlexNet	249	250	1	0	99.6	100.0	99.8	99.8
ResNet50	197	299	3	1	98.5	99.5	99.0	99.2
SVM	178	270	22	30	89.0	85.6	87.3	89.6

Where TP represent true positive, TN- true negative, FP-false positive and FN- false negative

For Grey Leaf Spot fungal disease classification, AlexNet demonstrated the highest precision, recall, F1-score, and accuracy of 98.8%. ResNet-50 followed with slightly lower performance. The SVM model exhibited the lowest recall value of 81.7% for GLS classification (Table 4.4).

**Table 4.4:** Confusion matrix and performance of AlexNet, ResNet50 and SVM in recognition of GLS disease

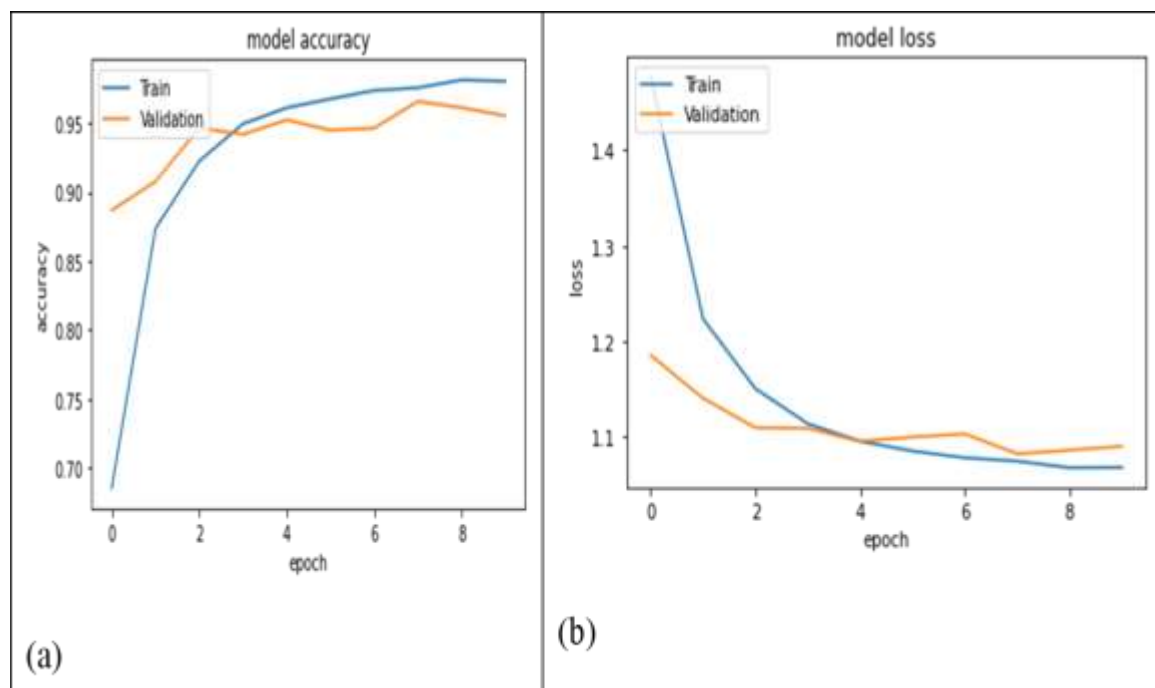
Model	TP	TN	FP	FN	Precision	Recall	F1-Score	Accuracy
AlexNet	247	243	3	7	98.8	97.2	98.0	98.0
ResNet50	192	283	8	17	96.0	91.9	93.9	95.0
SVM	174	261	26	39	87.0	81.7	84.3	87.0

Where TP represent true positive, TN- true negative, FP-false positive and FN- false negative

## 4.4 Model Accuracy and Loss Curves for CNN (Alexnet and Resnet50)

### Architectures

The accuracy of a model provides insights into its overall performance by indicating the correct classification rate, while the loss of a model reflects the quality of its predictions. Ideally, a model should exhibit high accuracy and low loss. During the validation of AlexNet architecture, high model accuracy (Fig. 4.2 a) and low model loss (Fig. 4.2 b) were observed. The model's accuracy increased with each epoch while the loss function decreased (Figure 4.2 a, b). Similarly, ResNet-50 demonstrated high model accuracy (Fig. 4.3 c) and low model loss (Fig. 4.3 d). These findings highlight the exceptional performance, accuracy, and specificity of both AlexNet and ResNet50 in identifying and classifying maize leaf diseases. Additionally, the low model loss indicates that the predictions generated by these two CNN architectures were of high quality.



**Figure 4.2:** Model accuracy (a) and model loss (b) curves for the proposed models for AlexNet.

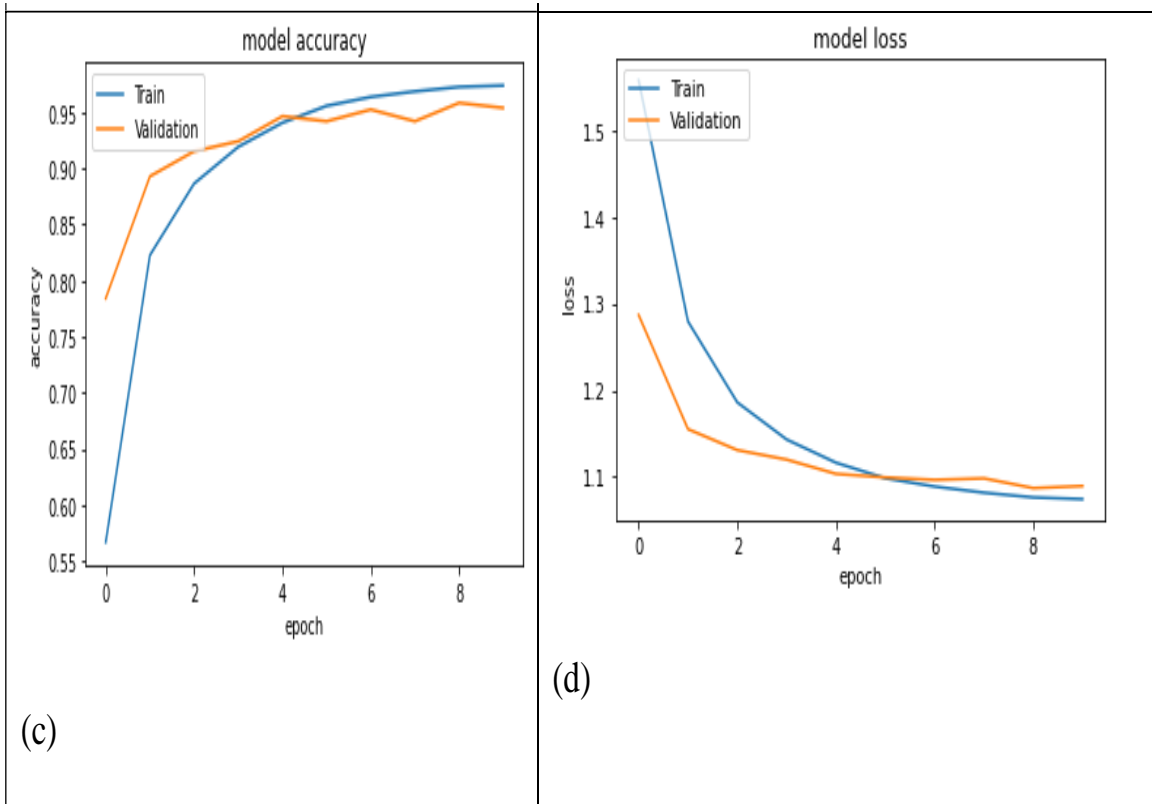


Figure 4.3: Model accuracy (c) and model loss curves (d) for ResNet50

## CHAPTER FIVE

### SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

#### 5.1 Introduction

The discussion section delves into the compelling outcomes of this study, revealing the remarkable efficacy of the AlexNet and ResNet50 architectures in the realm of maize leaf disease identification. These architectures demonstrated outstanding average accuracies of 98.3% and 96.6%, respectively, underscoring their prowess in accurate classification. On the other hand, the machine learning SVM model, with an accuracy of 88.5%, showcased comparatively lesser performance.

#### 5.2 Summary of Findings

The difference in disease identification accuracy between AlexNet and ResNet50 in this study can be attributed to their distinct designs. AlexNet, with its fewer layers, exhibits faster training speed and lower susceptibility to overfitting. This aligns with findings from previous research by Chow *et al.* (2023), who utilized a "dropout" regularization technique to mitigate overfitting and expedite model training. In contrast, ResNet-50, being a deeper and more intricate model compared to AlexNet, can capture more complex features within the data. However, this complexity also makes ResNet50 more prone to overfitting, particularly when dealing with small or noisy datasets. This observation is in line with the results reported by Sood and Singh (2020), who compared ResNet50 and VGG16 for detecting leaf rust in wheat and found that ResNet50 achieved a validation accuracy of 60% with datasets containing fewer than 300 samples, while VGG16 achieved an accuracy of 93.33%.

Furthermore, the lower accuracy of the support vector machine in maize leaf disease identification compared to the CNN models (AlexNet and ResNet-50) can be explained by the nature of CNNs designed explicitly for image data, which is typically high-dimensional and complex. CNNs can automatically learn relevant features from images, such as textures, shapes, and patterns, without manual feature extraction. In contrast, SVMs require explicit feature definitions, which can be time-consuming and less effective at capturing relevant features. CNNs also have the advantage of learning hierarchical representations, allowing them to capture low-level and high-level features important for plant disease classification. SVMs, on the other hand, are typically limited to linear or kernel-based models, which may not capture complex and non-linear relationships in the data as effectively.

The high performance of AlexNet and ResNet50 in terms of accuracy, precision, and recall can be attributed to the adoption of transfer learning in this study. This finding is consistent with earlier research by Chen *et al.* (2020), who reported increased accuracy in identifying rice lesion images in complex scenarios through transfer learning, achieving an average accuracy of 94%, surpassing standard training accuracy.

### **5.3 Conclusion**

The results of this study demonstrate the effectiveness of AlexNet and ResNet50 architectures in the identification of maize leaf diseases, achieving average accuracies of 98.3% and 96.6%, respectively. The machine learning SVM model yielded the lowest accuracy of 88.5%. These findings highlight the superior performance of the convolutional neural networks, particularly AlexNet and ResNet50, in feature extraction and accurate classification of maize leaf diseases. Evaluation parameters presented in Table 4.2 further support the superiority of AlexNet and ResNet50 over SVM. AlexNet

consistently outperformed the other models, followed by ResNet50, while SVM obtained the lowest scores. These findings reinforce the significance of employing AlexNet and ResNet50 for classifying maize leaf diseases. By leveraging these advanced CNN models, farmers and stakeholders involved in maize crop protection can benefit from enhanced accuracy and specificity in disease detection, surpassing the limitations of traditional visual analysis methods commonly used in the field. Adopting the two CNN models offers the advantage of early disease identification, enabling prompt intervention measures to prevent the spread of diseases before they cause significant economic damage. This proactive approach can reduce crop yield losses and maintain overall crop quality. By integrating state-of-the-art technology like AlexNet and ResNet50 into maize disease management practices, farmers can make informed decisions regarding disease control strategies and ultimately improve their crop production and profitability.

#### **5.4 Recommendations**

Based on the findings of this study, the following recommendations are made for future research:

- i. This study focused on specific maize leaf diseases, such as Grey Leaf Spot, Maize Lethal Necrosis, and Maize Streak Disease. Future research could explore other economically significant maize diseases, such as Northern Leaf Blight (NLB), to broaden our understanding of the various threats to maize production. These models could also be used to classify and identify other diseases in various crops in Kenya.
- ii. While the current research utilized a computer-based model for disease identification, it is recommended to develop a mobile-based model. A mobile application would enable farmers and stakeholders to access the disease

identification system on their smartphones or tablets, facilitating real-time disease detection and prompt interventions.

- iii. To further enhance disease classification accuracy, ensemble methods are suggested. The overall performance and robustness of the disease identification system can be improved by combining different classifiers, such as Support Vector Machine (SVM), with other machine learning models.
- iv. The availability of comprehensive and diverse datasets is crucial for effectively training Convolutional Neural Networks models. Therefore, there is a need to create more extensive databases containing a wide variety of maize leaf disease images. This will enable CNN models to learn from more diverse examples and enhance their accuracy and generalization capabilities.

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