DESIGN AND IMPLEMENTATION OF A SMART SYSTEM FOR MAIZE CROP DISEASE DETECTION IN PRECISION AGRICULTURE

BY

TEMILOLUWA FOLORUNSO

CSC/2019/071

A THESIS SUBMITTED TO THE DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING, FACULTY OF TECHNOLOGY, OBAFEMI AWOLOWO UNIVERSITY, ILE-IFE, OSUN STATE, NIGERIA

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF BACHELOR OF SCIENCE (B.SC) HONORS DEGREE IN COMPUTER ENGINEERING

OCTOBER, 2025

CERTIFICATION

This is to certify that this research work carried out by TEMILOLUWA FOLORUNSO with registration number CSC/2019/071 in partial fulfilment of the requirements for the award of Bachelor of Science (B.Sc.) degree in Computer Science and Engineering Department, Faculty of Technology, Obafemi Awolowo University, Ile-Ife, Osun State.

______________________ ______________________

Prof. A.I Oluwaranti **Date**

(Project Supervisor)

______________________ ______________________

Prof. A. O. Oluwatope **Date**

(Head of Department)

DEDICATION

This project is dedicated to God for His never-ending love and my beloved family, whose unwavering support and encouragement have been the cornerstone of my academic and professional journey.

ACKNOWLEDGEMENT

First and foremost, I thank God Almighty for His unfailing love, His greatness, and for the grace to be called His child. I would like to express my heartfelt appreciation to my parents for their constant love, sacrifices, affection, support and faith in me. I am truly grateful to be called their child, and I promise to always make them proud.

I would also like to thank my supervisor, Prof. A. I. Oluwaranti, and my co-supervisor, Engr. Sobowale, for their firm principles, guidance, and insightful contributions throughout the course of this project. Thank you for making this project a success.

My sincere appreciation also goes to my family members, from my grandma, aunts, and uncles, for their love, prayers, and continuous support throughout this journey. Thank you for everything.

Lastly, to my friends Mercy, Divine, Richard, Olubiyi, Stephen, Ibukun, Sanmi, Ayobami and Samson, thank you for being my partners, motivators, and friends throughout my university journey. To all my other friends and colleagues whose names are not mentioned, please know that you each hold a special place in my heart. Thank you all for making this journey memorable and fulfilling.

TABLE OF CONTENTS

ABSTRACT

Agriculture remains one of Nigeria's main drivers of economic growth, yet maize farming continues to experience enormous yield loss due to late or inaccurate disease diagnosis. The project's objective is to design and deploy a Smart System for Maize Disease Detection using Artificial Intelligence (AI) and Internet of Things (IoT) for real-time disease detection and environmental monitoring. The system aims to enable farmers to identify diseases of maize leaves at an early stage and hence prevent losses while increasing productivity through the application of data-driven farming methods.

The system implemented uses an ESP32-S3 microcontroller, OV2640 camera module, DHT11 sensor, and a self-built Convolutional Neural Network (CNN) model. The training data were drawn from PlantVillage and PlantDoc datasets with 4,188 images of maize leaves distributed across four classes: Blight (1,146), Common Rust (1,306), Gray Leaf Spot (574), and Healthy (1,162). The dataset was pre-processed, augmented, and split into training (80%), validation (10%), and test (10%) sets in order to present a balanced dataset, including the less-represented Gray Leaf Spot class (Sulaniishara, 2024). A web application developed with Flask was designed to facilitate users to upload or take a picture of a maize leaf, visualize classification results, monitor temperature and humidity, and receive treatment suggestions using an interactive dashboard.

The trained CNN model had an overall accuracy of 96% and 11% loss, showing strong classification performance on all target classes. The integrated system demonstrated genuine real-time behaviour, effectively communicating acquired images and environmental information to the web interface. Minor misclassifications between Blight and Gray Leaf Spot were due to their visual similarity, but overall performance remained reliable and accurate. Hardware performed as anticipated, with a response time of 3–5 seconds, making it field-ready.

The project successfully demonstrated the feasibility of combining AI-driven image analysis and IoT-enabled sensing to enhance the detection of disease in precision agriculture. The cost-effectiveness, scalability, and responsiveness of the system make it an effective tool for application by farm-level smallholder farmers. Future developments can be made through real-time model deployment on the ESP32-S3 with TensorFlow Lite, solar-based operations, and expansion to other crops to maximize its contribution to food security and sustainable agriculture.

LIST OF FIGURES

LIST OF TABLES

CHAPTER ONE

INTRODUCTION

1.1 Background

Crop diseases are harmful conditions that affect the structure, growth, function, and yield of a plant. Crop diseases are caused by pathogenic factors such as bacteria, viruses, and fungi or non-pathogenic factors such as temperature and nutritional deficiency. Crop diseases are a major threat to agricultural yield and food safety because they can lead to enormous losses in crops if managed poorly. (Gai and Wang, 2024).

Previously, the farmers relied on visual examination to detect the disease in crops through color, texture, and shape of leaves. Although it is widely applied, it is ineffective, error-prone, and generally non-productive (Dementievgeopard, 2023). It is even worse in Nigeria because nearly 90% of its output is handled by smallholder farmers who have no access to new diagnostic technologies and extension services. Therefore, over 40% of the crops are lost annually due to disease (Abdulmalik, 2023).

Maize (*Zea mays L.*) is one of the most important staple crops in Nigeria and Sub-Saharan Africa, and is used both as human food and animal feed (Wossen *et al.*, 2023). Despite this, maize is very susceptible to pests and diseases that most commonly go undetected until they have resulted in considerable yield loss. The most prevalent maize diseases in Nigeria include Maize Streak Virus (MSV), Rust (Common and Southern Rust), Northern Leaf Blight, and Gray Leaf Spot, whose prevention and control at the must be carried out early to prevent severe yield loss.

To combat these challenges, there is a need for technology-driven solutions for enhanced crop disease management. Precision Agriculture (PA) is a data-driven method that uses Artificial Intelligence (AI) and the Internet of Things (IoT) to improve farming efficiency and productivity.

IoT sensors then monitor environmental factors such as temperature and humidity levels, and AI algorithms based on these inputs to detect early stages of the disease, predict yields, and enable intervention at the right time.

Therefore, there is a need to develop an IoT-based AI system for the detection of maize disease to curb maize diseases, increase yield, productivity, and the welfare of Nigerian smallholder farmers. This study focuses on the design and implementation of the system's prototype.

1.2 Statement of the Problem

The identification of crop disease is significant because it significantly affects crop yields and world food availability. Traditional techniques of disease detection are based on time-consuming field surveys and manual observation for visible symptoms like leaf spots, discoloration, wilting, or unusual growth patterns. These methods are as labor-intensive as they are prone to human error.

Plants account for more than 80% of the human diet and are therefore important for food security. Since about 40% or more of crop loss is registered every year (Alabi *et al.*, 2006), accurate and timely crop disease estimates are required to attain control of plant diseases and crop productivity.

In Nigeria, where maize (Zea *mays L.*) is an important staple and cash crop, this constraint is an important challenge. The average maize yield nationally is approximately 2.0 tonnes per ha, which is significantly lower than potential levels and consequently leaves no space for farmers to incur further losses (United States Department of Agriculture [USDA], 2024).

Although advances in Artificial Intelligence (AI) and the Internet of Things (IoT) hold potential for early detection and precise control of disease, adoption is still limited among smallholder maize farmers in Nigeria. The absence of affordable, real-time, easy-to-use disease diagnostic systems for crops, especially for staple crops like maize, creates a significant gap in disease management capability.

With the aid of computer vision-based AI models for disease identification with IoT sensors for environmental monitoring, farmers can detect diseases early, maize crop diseases, provide insights, and recommend better curing methods to safeguard their crops, make well-informed farming decisions.

1.3 Aim and Objectives

This project aims to develop a comprehensive solution that leverages machine learning and data analysis to help farmers detect maize crop diseases early, provide insights, and recommend better curing methods to help safeguard their crops, leading to better informed farming decisions, increasing crop yield.

The specific objectives are to:

i. collect data from existing maize crop disease datasets for model training,
ii. design an AI-enabled maize disease detection model using the collected data for maize disease classification,
iii. design a user-friendly system that presents the collected data, AI analysis, and recommendations; implement a hardware system for image acquisition, and;
iv. evaluate the performance of the system in (iii).

1. 4 Scope of Study

This work is limited to the design and implementation of an IoT-enabled AI analytics platform for detecting diseases in maize crops. The system integrates three core components: an ESP32-S3 microcontroller with an OV2640 camera module for image acquisition, a Convolutional Neural Network (CNN) model for image-based disease classification, and a web application for real-time disease detection, information and recommendations.

The focus is on developing a functional prototype that demonstrates the feasibility of combining IoT and AI techniques for early maize disease detection, rather than a full-scale deployment.

1.5 Justification of Study

Maize (*Zea mays L.*) is one of the key staple crops of Sub-Saharan Africa and Nigeria, with millions of households receiving food, animal fodder, and income from its production. Nigerian farmers alone produce over 60% of West African maize (FAO,2023). The maize production is, however, greatly limited by pathogens, including the Maize Streak Virus (MSV), rusts, and leaf blights that can induce a loss of yield of between 30% to 100% through infection by their pathogens if not effectively checked and contained (Oyekanmi *et al.*,2024).

Traditional disease detection approaches, such as visual observation and field surveys, remain the widely practised approaches among smallholder farmers. They are labour-intensive, inconsistent and unreliable for early detection (Adejumo *et al.*, 2018). High percentages of future yield, therefore, are lost annually. In Nigeria, maize productivity is about 2.0 tonnes per hectare, which is significantly below the potential yield of 5–6 tonnes with improved management (United States Department of Agriculture [USDA], 2024).

Under such limitations, tech-based innovations come into play to fill the gap. Internet of Things (IoT) with Artificial Intelligence (AI)–image classification can potentially attain real-time monitoring, early detection, and decision-making support to farmers (Gai and Wang, 2024). Such innovations can potentially prevent crop losses and cope with future global trends of precision agriculture and sustainable agriculture (Okorie *et al*., 2025).

Therefore, this study is justified by the necessity to close the gap between inefficient, conventional detection models and innovative, data-driven solutions. It contributes to the theoretical understanding of smart farms and informs applied solutions that can improve farmer livelihood and food security in Nigeria and other developing nations.

1.6 Methodology Overview

The methodology of the study involved several key stages to achieve the outlined objectives.

i. An extensive review of existing works on maize disease detection, IoT-based agricultural systems, and AI image classification was conducted to gather insights and establish a foundation for system design and identify suitable approaches.
ii. Existing maize disease image datasets were obtained from publicly available sources. Images were pre-processed through resizing, normalization, and augmentation to improve model training and generalization.
iii. A Convolutional Neural Network (CNN) was designed and trained using the processed datasets for the classification of maize leaf diseases into healthy or diseased categories.
iv. The OV2640 camera module was interconnected with the ESP32-S3 to capture maize leaf images and transmit them via Wi-Fi to a web application. The trained CNN model was then deployed locally within the web application to perform image-based disease classification, visualize detection results, display AI analysis, and provide actionable recommendations to users.
v. The performance of the developed system was evaluated based on classification accuracy, responsiveness, and feasibility as a prototype for early maize disease detection.

Through this methodology, the study aims to design and implement a smart system that combines IoT and AI for timely, accessible, and effective maize crop disease detection.

1.7 Organisation of Thesis

This thesis is organized into five chapters, covering different aspects of the study. Chapter One introduces the study by introducing the background, the problem statement, the aim and objectives, scope, significance, justification, as well as the general methodology that was used. Chapter Two reviews existing literature related to diseases in the maize crop, IoT-based agricultural systems, and artificial intelligence approaches to disease diagnosis. Chapter Three describes the methodology employed, including dataset acquisition and preprocessing, CNN model development, system design, and implementation steps. Chapter Four presents the results obtained from system implementation and testing, followed by analysis and discussion of performance. Chapter Five provides the summary, conclusion, and recommendations for future work.

CHAPTER TWO

LITERATURE REVIEW

2.1 Overview

This chapter provides an overview of the literature concerning disease detection in maize and the application of Internet of Things (IoT) and Artificial Intelligence (AI) technologies in precision agriculture. Disease in crops continues to pose one of the greatest risks to agricultural productivity and global food security, as it lowers yields, quality, and increases production expenses. Methods for detecting crop diseases have progressed from manual visual inspection to the application of sophisticated computational methods over the years. Though the conventional methods are still prevalent, they are often limited by time-consuming procedures and late detection.

Precision agriculture has been advocated in recent times by using digital technologies to enhance disease management. IoT devices now enable real-time monitoring of environmental and crop conditions, while AI, particularly machine learning and deep learning, has been employed for image-based recognition and classification. The integration of these technologies has tremendous potential to improve early detection, generate insights, and minimise yield losses, especially for smallholder farmers who have limited access to modern agricultural innovations.

The review in this chapter is organized into key sections that progressively build towards the research problem. Section 2.2 highlights the History & Evolution of Crop Disease Detection. Section 2.3 delves into Precision Agriculture and its role in agricultural development,

presents common maize diseases and their impacts. Section 2.4 explores traditional disease detection techniques and their limitations, and Section 2.5 explores the history of precision agriculture. Sections 2.6 and 2.7 address IoT and AI-based crop disease detection with embedded vision and machine learning algorithms. Section 2.8 explores the fusion of IoT and AI, describing benefits and limitations. Finally, Section 2.9 gives an overview of pertinent studies and indicates available research gaps, on which this study relies methodology-wise.

2.2 History and Evolution of Crop Disease Detection

Plant pathology entails the scientific study of diseases in plants that occur due to both abiotic and biotic factors. Plant pathology is the study of identifying what leads to diseases in plants and what mechanisms plants use for survival and for them to actualize their full genotypic potential (Haq and Ijaz, 2020). Besides the reduction of crop yield, disease in plants also reduces quality and reduces resource use efficiency for the farmer. The study of disease in crops is a branch within plant pathology that entails the study of diseases that happen in food and commercially grown plants for human consumption.

In early civilization, disease explanations for plants were mythological and superstitious, as the scientific principle of pathogens did not yet apply. The Romans associated rust diseases on cereal crops with Robigus's wrath as a god. To avoid it, they observed the Robigalia celebration and sacrificed animals, hoping this would prevent the disease's progression (Yuen, 2019). Archaeological and fossil evidence suggest that plants have suffered from disease for over 250 million years, even before written history existed (Pelczer, 2025). Ancient literature, such as the Bible, identifies crop diseases such as blights, mildews, and rusts that have also caused famine and economic collapses over time.

Some notable epidemics show the destructive impact of plant diseases on the availability of food and trade. Among these epidemics are the Irish potato late blight from 1845 to 1860, which killed on a massive scale; French grape powdery and downy mildew from 1851 and 1878; Ceylonese (Sri Lankan) coffee rust from the 1870s; and the wheat black stem rust in the middle of the 20th century (Pelczer, 2025). All these epidemics have repeatedly brought into focus the significance of better monitoring and early detection methods in crops because they caused economic losses, a decrease in agricultural production, and increased food prices.

Farmers formerly used visual examination and customary know-how to spot plant diseases. Leaf discoloration, wilting, and marking were some of the key symptoms of infections. They were extremely time-consuming and labour-intensive and often error-ridden, so heavy losses of crops occurred. The need for more efficient and accurate detection methods became evident as agriculture intensified.

The integration of image recognition and classification with machine learning has transformed crop disease detection. These technologies, along with machine learning algorithms, facilitate automatic detection and classification of plant diseases with accuracy. Singh, Sharma, and Singh (2020), in their comprehensive review, highlighted the success of various imaging techniques and computer vision methods in the detection and classification of plant diseases, citing their potential in enhancing early detection and control strategies.

Advancements in deep learning methods have also revolutionized crop disease diagnosis. Deep learning models such as Convolutional Neural Networks and others have been used for the classification and detection of complicated image patterns with notable increases in efficiency and accuracy. Ngugi *et al.* (2024) documented that the detection and classification of crop diseases with deep learning models have surpassed feature-based approaches, with the ability for faster and more accurate results. The developments have produced real-time systems based on the utilisation of IoT that possess the ability to track crops via the utilisation of smartphones and low-cost sensors.

Therefore, the evolution of crop disease detection methods shows a change from manual, error-prone practices to high-technology driven methods. The integration of imaging technologies and machine learning has greatly improved the accuracy and efficiency in disease detection, through the provision of highly promising avenues for enhancing crop health monitoring and management. Further research and development in this field are crucial to overcome current limitations and exploit the potential of these technologies to achieve global food security.

Figure 2.1 illustrates a generalized architecture for a leaf disease detection system, representing the workflow that has been followed in general in recent research studies. It starts with the acquisition of images from crop fields, and then a dataset of images of leaves is created. The images are pre-processed for quality enhancement and noise removal before they are processed through segmentation, feature extraction, and classification algorithms. The final output provides a diagnosis indicating whether a leaf is healthy or diseased. This architecture provides a foundation for understanding how image-based crop disease detection systems have evolved in the past decade (Orchi, *et al*, 2021).

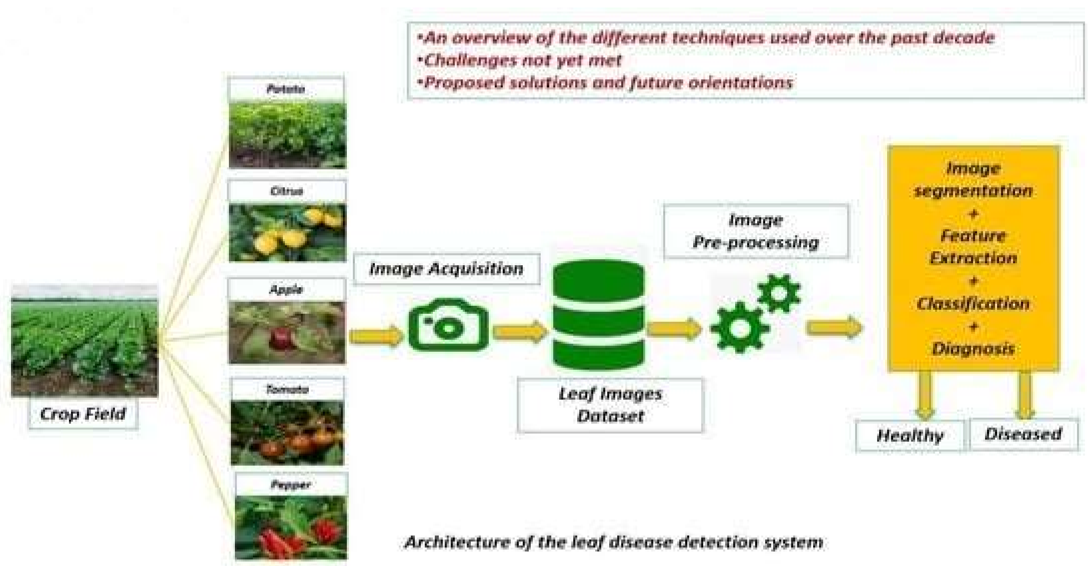

Figure 2.1: Graphical abstract showing the existing architecture of a leaf disease detection system. *Source: Modified from Orchi et al. (2021).*

2.3 Precision Agriculture

Precision agriculture (PA) came as a new approach to farming that involved technology, data, and analysis to maximize crop yield and the utilization of resources (Padhiary *et al.*, 2025). PA involved advanced sensing, monitoring and analytical tools to achieve precise information on soil, crop, and environmental properties, which directed site-specific and timely management practices to achieve peak efficiency, productivity, and sustainability.

Bwambale (2025) defines precision agriculture as the technology of improving crop yields and decisions using sensor-based technology to enable one to control irrigation, fertilization, and other inputs to minimize waste and labour. The concept relies heavily on vast data gathering, real-time analysis, and processing to improve agricultural operations in terms of efficiency, productivity, and environmental sustainability.

PA, over time, has experienced increased use of Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML). IoT sensors monitor key parameters like soil moisture content, nutrients, temperature, and plant health and send data to analyze (Abu *et al.,* 2022). AI and ML models learn data to produce predictive data, anomaly detection, and decision-making systems (Singh *et al.,* 2025). For example, AI-ML-based precision agriculture solutions have been employed to detect early indicators of crop stress, predict yields, and propose variable-rate fertilizer application (Gupta and Pal, 2025). IoT-AI integration is viewed as a key to revolutionizing PA by combining sensing, connectivity, and smart analytics.

This notwithstanding, PA adoption is still low in most developing nations owing to numerous challenges. Among these, the challenges are high up-front investments, insufficient digital infrastructure, weak rural connectivity, and few technical-savvy farmers (Nawaz and Babar, 2025). Added to these are interoperability problems in heterogeneous devices, data security, and data governance, which make implementation a daunting process (Miller *et al.*, 2025). In response to these issues, recent research has been working towards affordable, modular, and straightforward PA solutions that are more suited to smallholder agricultural production systems.

As a whole, precision farming has continued to convert conventional farming into a data-oriented practice, on which intelligent solutions like IoT-based AI platforms for crop disease monitoring rely. The coming together of sensing, connectivity, and information analysis has the potential to make agriculture more productive, frugal, and resilient in the event of environmental circumstances.

2.4 IoT in Crop Disease Detection

The term "Internet of Things" (IoT) was first used by Kevin Ashton in 1999 to refer to a collection of physical devices such as sensors, actuators, and embedded systems that are capable of gathering, sharing, and processing information on their own (Tzounis *et al*., 2017). In agriculture, IoT is one of the key drivers of monitoring, automation, and decision-making based on data.

IoT sensors are one of the most widely used technologies in PA, due to their efficiency, ease of installation and affordability. A standard wireless monitoring system must include several sensors linked to an installed node in each zone, with sensors and nodes communicating via radio frequency. IoT-based monitoring systems use a smart network to collect data on different environmental parameters like temperature, humidity, soil moisture, and light intensity. The data collected are subsequently sent to centralized platforms where they are processed, leading to early detection of conditions favourable for disease development. (Orchi *et al*., 2021b) further explains that IoT applications can assist farmers at any time during their farming activities and keep them up to date with the latest crop and weather information to monitor their fields, detect crop diseases at an early stage to curb the spread of disease, and save their yield.

The latest technologies now integrate IoT with image classification. For instance, low-cost microcontrollers like the ESP32-S3 with a camera module can provide on-site image acquisition and early disease detection via wireless communication (Sharma and Shivandu, 2024). Recent low-cost IoT applications have demonstrated the feasibility of integrating image-based disease detection in field settings. For example, Mohtasim *et al.* (2023) implemented an Arduino UNO-based robotic monitoring system incorporating an ESP32-CAM. Images and real-time video were then sent to a central server, where OpenCV-based image processing detected suspicious color changes in plant leaves, showing possible early disease detection (Mohtasim *et al.*, 2023).

These systems allow farmers to remotely observe crop conditions and take precise, data-informed decisions.

2.5 Integration of Artificial Intelligence and IoT in Crop Disease Detection

The study of artificial intelligence (AI) focuses on the development of theories and computer systems capable of carrying out tasks requiring human intelligence, such as sensorial perception and decision making. Kaplan and Haenlein (2018) defined AI as "…a system's ability to properly interpret external data, to learn from such data, and to apply the learning to achieve specific goals and tasks through flexible adaptation.".

AI in smart farming is combined with the Internet of Things (IoT) as an infrastructure of networking sensors, devices, and communication technologies that collect, analyze, and act on environmental and crop information. Misra *et al.* (2020) emphasized that AI uses external information sourced from IoT and other big data sources, using knowledge-based rules (given by developers) or identifies the underlying rules and patterns using machine learning, to discover concealed patterns, make predictions, and enable autonomous decision-making. This type of integration allows intelligent systems to learn, generalize, store knowledge, and optimize farm-level decisions such as irrigation planning, disease prediction, and pest control.

As evident in Figure 2.2, the integration of AI and IoT in the agri-food industry is a multilayer architecture in which sensors capture environmental or crop data, transmit the data wirelessly to cloud or edge servers, and AI-based analytics processes the data to gain insights. The results are either in the form of suggested actions or real-time alerts, which are sent back to the field through the same communication channels. This feedback loop supports continual monitoring and crop health management.

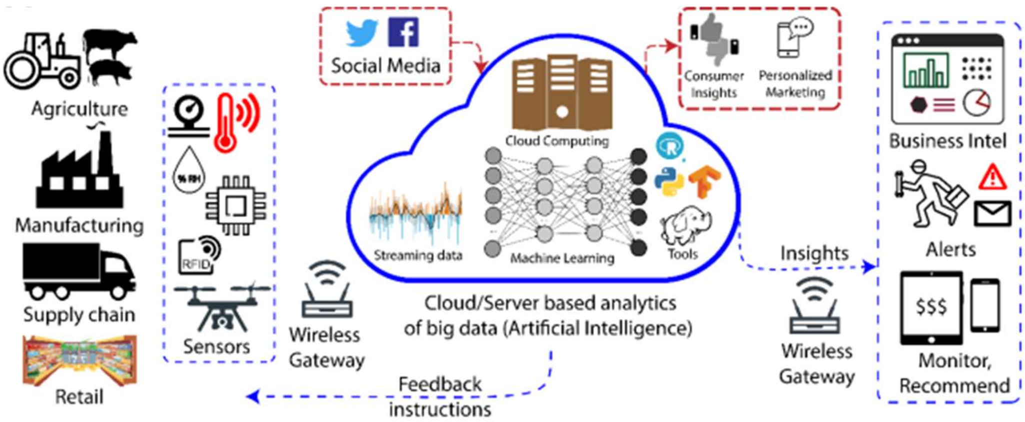

Figure 2.2 *IoT–AI integration framework in agri-food systems. Source: Modified from Misra et al. (2020).*

The successful integration of these technologies has greatly improved data-driven decision-making and automation in farming, especially for early disease detection and crop yield.

2.5.1 Benefits of the Integration

a) Early and Accurate Disease Detection: IoT sensors can collect data such as temperature, humidity, soil moisture, etc., which can be analyzed with AI to aid in detecting signs and diseases in crops early. With the current technological developments, agricultural IoT applications can be of substantial importance in improving crop production and minimizing losses from disease early detection (Orchi *et al*., 2021). The collected data of the crops is then analyzed to detect patterns and symptoms of disease to guide the farmer to predict possible diseases in an effort to take preventive steps (Delfani *et al.,* 2024).

b) Improved crop monitoring and management: conditions can be monitored with the help of IoT sensors and Wireless Sensor Networks (WSNs), allowing for better decision-making. This leads to improved data coverage and reduced latency, enhancing overall performance.

2.5.2 Challenges of the Integration

While the integration of AI analytics and IoT systems in crop disease detection offers groundbreaking potential, it also presents several challenges that may limit its deployment, scalability, and effectiveness.

a. Data Quality and Incompleteness: Data quality and completeness have a great influence on AI-based disease detection accuracy. In healthcare applications, missing or incomplete data in certain attributes reduces the accuracy of analysis. This issue translates quite well in agriculture, where sensor or IoT data can be incomplete or inconsistent due to weather conditions or hardware limitations (Hwang and Chen, 2017).

b. Data Preprocessing Requirements: Data from IoT devices needs a lot of preprocessing, such as cleaning, integration, and transformation, before it becomes usable for AI analysis. This process is time-consuming and resource-intensive (Hwang and Chen, 2017).

c. Technical Limitations of IoT Devices: Most IoT sensors used in fields, e.g. farms, are limited by low power, memory, and communication capabilities. This limits the quantity and frequency of the data they transmit, which could impact real-time analysis.

Data Privacy and Security: The integration of AI and IoT, especially in cloud-assisted environments, raises concerns for data privacy. Hence, there is a need for adequate protection and secure communication protocols between IoT nodes and cloud servers to prevent data breaches and ensure the confidentiality and integrity of agricultural information.

2.6 Maize and Its Importance in Nigeria

Maize (*Zea mays L.*) is one of Nigeria's major staple crops, playing a key role in food security, income, and industrial supply chains. Maize has shifted from being a subsistence to a major commercial crop sustaining both rural livelihoods and national agricultural growth (Onumah *et* *al*., 2021). Producing over 10 million metric tons annually, Nigeria is one of Africa's major maize producers.

Its applications cut right across most sectors, with maize serving as food, animal feed, and raw material. In Nigeria, a massive amount of Nigerian production is taken up by the poultry sector alone, accounting for a significant percentage of maize consumption.

However, despite all its importance, maize production in Nigeria is relatively low, which is often less than 2 tonnes per hectare when compared to potential production in more developed production systems (e.g., 4–5 t/ha in South Africa or Ethiopia). This gap highlights its inefficiencies, low access to inputs (better seed, fertilizer), pests, disease, and infrastructural constraints.

The increase in the demand for maize is driven by Nigeria's growing population, emphasizing the importance of maize productivity improvement. With maize's contribution to both food and feed security, any decrease in yield directly affects household nutrition and industrial value chains. Hence, maize crop yield, its disease detection and conditions are important in Nigeria.

2.6.1 Common Maize Diseases and Their Impact

Maize production in Nigeria is often limited by several diseases that negatively affect photosynthesis, growth, and overall yield. In this study, four classes of maize leaf conditions were considered, which are Healthy, Common Rust, Turcicum Leaf Blight, and Gray Leaf Spot, representing the four major classifications commonly observed in maize farms across the country. These diseases are among the most damaging to maize production and have been extensively reported in both tropical and temperate regions.

Common rust caused by *Puccinia sorghi* is among the most prevalent leaf diseases of maize. Its symptoms begin as small, chlorotic spots that eventually develop into powdery, reddish-brown pustules on both top and bottom sides of the leaves. As the disease progresses, pustules may darken to cause surrounding tissue necrosis, hence reducing the efficiency of the maize to photosynthesize. According to the Crop Protection Network, severe infections can weaken the maize and cause reduced grain filling and poor kernel development ("Common Rust of Corn," 2019). Yield losses due to common rust depend on the degree of susceptibility of the maize variety, but under favourable environmental conditions for disease progression, yield losses are typically moderate (Wise, 2010). The disease may be managed through the use of resistant hybrids, early fungicide application, and the removal of alternate host plants that provide shelter to rust spores.

Turcicum Leaf Blight (also called Northern Leaf Blight), caused by *Exserohilum turcicum*, is another widespread disease known by long, cigar-shaped lesions of blight along the veins on the leaves, which are grey-green to tan. These lesions usually begin on the lower leaves and spread upward under favourable conditions. Research has shown that Turcicum Leaf Blight accounts for more than 10% yield loss and, in some severe cases, up to 60% for highly vulnerable maize types (Nsibo *et al.,* 2024). The disease thrives in humid conditions, particularly during the rainy season in the tropics. Control measures include planting resistant types, rotating maize with non-host crops, and fungicide application at the appropriate time before disease spreads.

Gray Leaf Spot, caused by *Cercospora zeae-maydis*, has also become one of the most serious maize diseases globally and is responsible for considerable yield losses. The disease begins as small, rectangular, tan-to-brown lesions restricted by leaf veins, which gradually enlarge and turn grey as the disease advances. Under severe infections, lesions coalesce, leading to blighting of the entire leaf surface. Gray Leaf Spot significantly reduces the photosynthetic area of the plant and can predispose maize stalks to lodging and secondary infections. Yield reductions caused by this disease have been reported to range between 10% and 50%, and in extreme cases, near-total crop failure has been observed (Bayer Crop Science, 2023). Management strategies focus on the use of resistant hybrids, residue destruction, and crop rotation to minimize the build-up of fungal inoculum.

Other maize diseases not covered in this study, such as Maize Streak Virus (MSV), also contribute to production losses in Nigeria. MSV is particularly damaging under early planting and is characterized by chlorotic streaks, leaf stunting, and inadequate ear formation. However, because MSV symptoms are viral and not primarily leaf-spot in character, it is not covered in this image-based detection system.

In summary, MSV, Common Rust, Turcicum Leaf Blight, and Gray Leaf Spot are some of the most economically important maize leaf diseases in Nigeria, with their visual symptoms on leaves making them suitable for detection using image-based machine learning models. Therefore, early and accurate disease detection of these diseases is essential for timely intervention, improved crop management, and higher maize productivity in Nigeria's major maize-producing regions.

2.6.2 Crop Disease Detection in Maize

Early detection of maize diseases is key to improving crop yield and reducing losses caused by pathogens. Traditional methods of detection are based to a great extent on visual inspection and field observation by plant specialists. While effective, it is time-consuming, prone to human error, and unsuitable for commercial-sized farm operations. Furthermore, rural access to plant pathologists in most parts of Nigeria is not good, hence delaying disease diagnosis and intervention control.

To address these limitations, the application of computer vision and machine learning (ML) techniques to the autonomous detection and classification of maize leaf diseases is required. The techniques are employed to analyze digital images of maize leaves for discoloration, lesions, and blight patterns corresponding to specific diseases. Sladojevic *et al.* (2016) proposed a convolutional neural network (CNN) system to classify several crop diseases, demonstrating the effectiveness of deep learning in processing agricultural images. Similarly, Mohanty *et al.* (2016) applied deep CNNs in identifying 26 plant diseases across 14 crops with over 99% accuracy on test sets, including maize leaf diseases.

New trends have integrated Internet of Things (IoT) and Artificial Intelligence (AI) analytics-driven solutions for real-time disease monitoring and automatic alarm triggering for farmers. IoT-enabled devices with low-cost sensors and camera modules (e.g., ESP32-CAM) can continuously capture images of maize leaves and environmental conditions such as humidity, soil moisture, and temperature. These streams of data are then relayed to cloud servers, which feed AI models through them to detect diseases, predict possible outbreaks, and suggest protective measures (Orchi *et al.,* 2021).

In Sub-Saharan Africa and Nigeria, respectively, these kinds of systems prove especially valuable to smallholder farmers who face inadequate extension services and weak disease reporting networks. AI-driven disease detection models trained using locally relevant datasets, such as those containing maize leaf images of the classes Healthy, Common Rust, Blight (Turcicum Leaf Blight), and Gray Leaf Spot, can be applied to support farmers' decisions via mobile or web applications. These models not only improve detection accuracy but also allow precision agriculture by supporting accurate pesticide use and resource management.

Also, emerging research focuses on increasing model generalizability and robustness by incorporating hybrid AI models that have convolutional layers for feature extraction and attention mechanisms to improve classification performance under tricky field conditions. Such techniques are necessary when dealing with changes in lightning, background noise, and leaf orientation that are prevalent under real farm settings (Zeng *et al.,* 2025).

In summary, computer vision maize disease diagnosis has evolved from basic image classification tasks to intelligent IoT-AI-based systems capable of real-time monitoring and data-driven decision making. Integration of these technologies has the capability of revolutionizing disease control methods in maize farming to achieve yield increase, reduce chemical misuse, and ensure sustainable farm production in Nigeria and beyond.

2.7 Computer Vision and IoT for Crop Disease Detection

The Internet of Things (IoT) has added new possibilities to modern farming by connecting devices, sensors, and systems to collect and share data in real-time. With IoT, farmers can now monitor soil conditions, temperature, humidity, and crop growth easily, improving decision-making and resource management (Duguma and Bai, 2024). This has made it possible to move from traditional farming practices to more data-driven methods.

Computer vision thus enables computers to "see" and understand images with cameras and image-processing software. When combined with agricultural devices, computer vision allows for real-time analysis of crop health, early disease detection, and automated field monitoring (Dolatabadian *et al.,* 2024). This technology removes the limitations of manual observation and increases the accuracy of the crop performance.

When IoT and computer vision are combined, they form a strong system for crop disease detection. IoT devices collect environmental data such as humidity and temperature, while computer vision tools capture and analyze images of the plants. For example, in maize farms, a device with a small camera can take pictures of maize leaves, analyze them using trained models, and send results to the farmer's phone or computer for early action (Nkuna *et al.,* 2025).

In this project, the ESP32-S3 CAM microcontroller is used because it combines both IoT and computer vision features in one device. It has an in-built Wi-Fi for data transmission, a Camera Slot for a Camera Module for image capturing, and an AI accelerator for image processing tasks. The ESP32-S3 captures images of maize leaves, analyzes them to check if there are diseases, and sends the results wirelessly. Overall, the combination of computer vision and IoT offers a practical and technological approach to improve early disease detection and promote smart agriculture in Nigeria.

As shown in Figure 2.3, the proposed IoT-based framework integrates environmental sensors, an embedded camera module, and cloud-based analytics for real-time plant disease monitoring and management (Nandhini *et al.,* 2022).

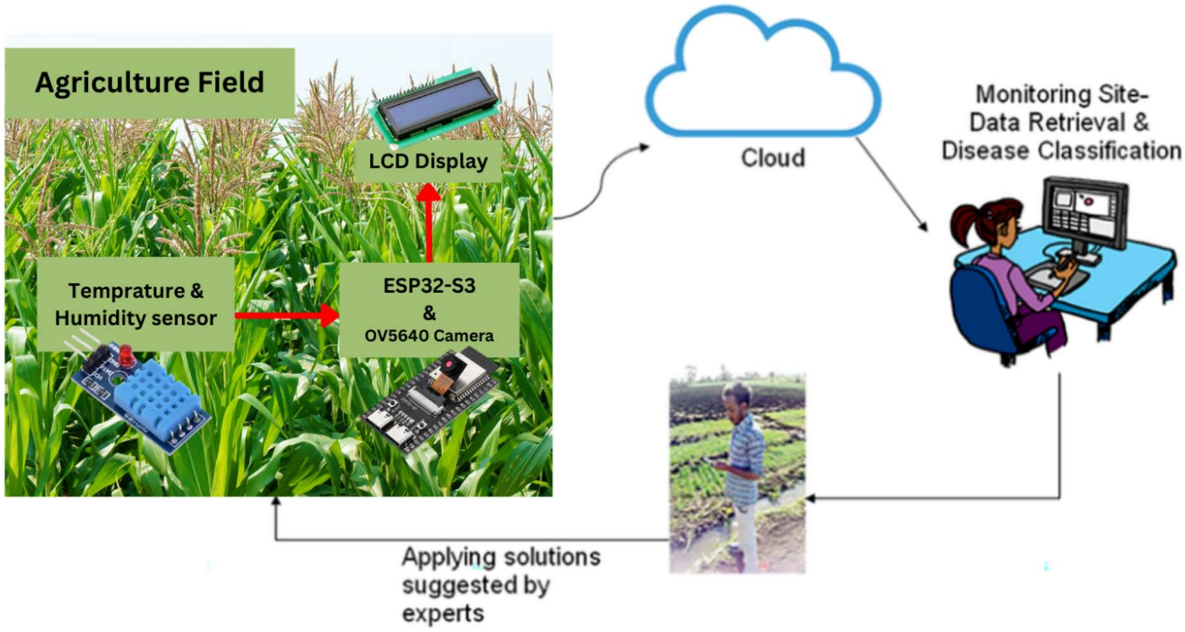

Figure 2.3. *Overview of the proposed IOT based plant disease detection framework. Source modified from (Nandhini et al., 2022).*

2.8 AI Techniques for Image-Based Disease Detection

Artificial Intelligence (AI) is now an important component of modern agriculture, particularly in the early diagnosis and distinction of crop diseases based on images. Farmers can now detect crop diseases such as maize at early stages, thereby preventing loss by early intervention.

In previous years, Traditional machine learning (ML) techniques were used to identify plant diseases by manually extracting features such as color, texture, and shape from leaf images. These features are used to train classifiers like Support Vector Machines (SVM), k-Nearest Neighbours (k-NN), and Decision Trees to classify healthy and diseased plants.

Modern agriculture now depends significantly on artificial intelligence (AI), especially when it comes to the early detection and classification of crop diseases using image analysis. Farmers can detect diseases in crops like maize early on by using AI, allowing quick interventions and reducing yield losses. Still, these methods rely so much on manual feature extraction and do not generalize easily across various environmental and disease contexts (Shoaib *et al.,* 2023).

The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has completely changed image-based disease detection by using automatic feature learning from raw images. CNNs excel in recognizing visual patterns such as spots, edges, and changes in color, which are common indicators of plant diseases without any human-aided feature engineering (Toda *et al.*, 2019). Models such as VGGNet, ResNet, and Inception have achieved high accuracy in the detection of crop diseases like maize leaf blight, rust, and other leaf infections (Abade *et al.,* 2020; El Sakka *et al.,* 2025). Therefore, these CNN-based approaches have been the foundation of many computer vision-based applications for precision agriculture and smart farming systems (El Sakka *et al.*, 2025).

2.9. Related Works

This section explores a significant contribution to the design of a smart system for crop disease detection in precision agriculture. The progression of automated image-based plant disease detection over the last decade has risen rapidly with the advancement of convolutional neural networks (CNNs) and the availability of large, labelled leaf image datasets. Based on the study "Using Deep Learning for Image-Based Plant Disease Detection" by Mohanty *et al.* (2016), one of the earliest and most influential demonstrations showed that deep CNNs trained on the PlantVillage dataset could achieve near-perfect accuracy on a multi-crop, multi-disease classification task, placing CNNs as the top approach for image-based plant pathology tasks. Later studies show that CNNs, such as well-known architectures like VGG, ResNet and Inception, tend to surpass traditional handcrafted-feature approaches, i.e. older machine learning methods that required researchers to manually decide which features or characteristics from an image should be used by the model to detect diseases (Ngugi *et al.,* 2024) (Wang *et al.,* 2022).

Maize leaf disease detection has moved from proof-of-concept to more application-oriented systems by developing and applying CNN models on specifically maize datasets, with Qian *et al.* 2022 reporting better performance under controlled or semi-controlled imaging conditions. Newer CNN models have shown improved robustness to background clutter, varying light conditions, and partial leaf occlusion, rivalling real-world scenarios (Albahli and Masood, 2022).

The integration of IoT sensors and connectivity with AI models to create end-to-end disease monitoring systems highlights architectures that combine environmental sensors, edge image capture (ESP32-CAM and similar hardware), and cloud or edge analytics pipelines to issue near-real-time disease alerts and management recommendations (Orchi *et al*, 2021; Ngugi *et al.,* 2024). These reviews focus on the benefits of fusion of images and environmental sensors for improving early detection and reducing false positives, but they also identify the challenges of integrating different types of data, privacy, and the cost of deployment in resource-limited settings.

A survey by Orchi *et al* (2021) identifies several important gaps, such as models being trained on datasets collected under controlled or laboratory conditions (uniform backgrounds, clear lighting), which inflates accuracy compared with performance in real-world field environments. Also, dataset imbalance and limited diversity (few crop varieties, geographic regions, or growth stages) reduce the model's generalizability across regions and seasons. Few studies also demonstrate fully integrated, end-to-end deployed systems that combine lightweight CNN inference on edge devices with robust sensor networking and practical farmer interfaces; when such systems are reported, they often lack long-term field trials (Ngugi *et al.*, 2024).

The study "Design and Implementation of a Smart System for Maize Crop Disease Detection in Precision Agriculture" focuses on a practical part of the problem by classifying maize leaves into four classes (Healthy, Common Rust, Turcicum Leaf Blight, and Gray Leaf Spot) using CNN. The images in the dataset used depict field variability and a way to IoT deployment. This addresses two of the common gaps identified above. First, by restricting the classification task to a small, well-defined set of economically significant maize leaf diseases and prioritizing model robustness (via data augmentation, realistic image sampling, and lightweight CNN architectures suitable for edge inference), the study aims to achieve practical use and lead to better field decision making.

For Nigerian maize growers. Second, by prioritizing model robustness (via data augmentation, realistic image sampling, and lightweight CNN architectures suitable for edge inference), the work aims to bridge the gap between high laboratory accuracies and usable in-field performance. Therefore, this study complements larger multi-crop studies and IoT–AI frameworks by providing a focused, implementable maize detection system that can be integrated into broader AI-IoT platforms in future work.

CHAPTER 3

METHODOLOGY

3.1 Overview

This chapter presents the system architecture, hardware and software components, workflow, model training process, deployment strategy, and evaluation metrics, illustrating how the proposed solution improved upon traditional approaches to maize disease detection.

The IoT-enabled computer vision system integrated both hardware and software components to facilitate automated image acquisition, environmental sensing, data transmission, and intelligent disease analysis.

Furthermore, the chapter discussed the implementation of the system, including the system description, the computer vision model used for maize leaf classification and disease detection, as well as the suggested management strategies displayed through the web application interface. Finally, the chapter concluded with the evaluation, performance analysis, and implementation details of the developed prototype.

3.2 System Design

The design of a smart system for maize disease detection in precision agriculture was developed to provide a smart and automated solution for detecting maize leaf diseases using IoT and computer vision technologies. The design was integrated with hardware and software components to execute smooth interaction between image acquisition, environmental data acquisition, data processing, and result display. The system was structured to capture images of maize leaves, process them through a trained Convolutional Neural Network (CNN) model for classification, and transmit the results via a web-based interface.

The proposed design, as shown in Figure 3.1, illustrates the system architecture of the proposed IoT-enabled computer vision maize disease detection system. The system architecture consisted of five main functional stages. The first stage was the Image Acquisition Unit, in which the OV2640 camera module and ESP32-S3 board took images of maize leaves. The second stage was Data Preprocessing and AI Analysis, in which the images were cleaned and resized, and prepared for analysis. The third stage was Disease Classification and Detection, in which the CNN model classified the images into one of four classes: Healthy, Common Rust, Blight, or Gray Leaf Spot.

The fourth step, Results Visualization on Web Application, was where the detection result, confidence rate, and brief disease descriptions were displayed on a Flask-based web application. Finally, in the Feedback and Alerts step, the users were provided with brief suggestions or suggested management practices based on the detected disease type.

This modular design makes the system easy to maintain and flexible for future improvements, such as including more disease types, other crops, the addition of mobile alerts, or adding other environmental sensors.

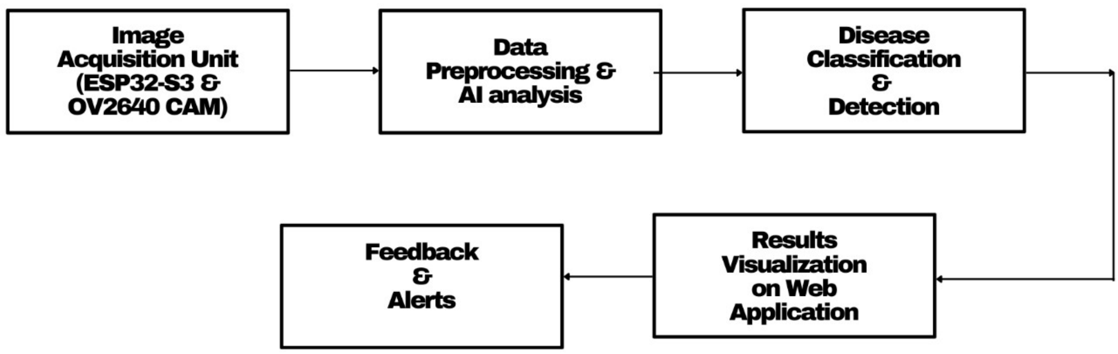

Figure 3.1: System Architecture of the IoT-Enabled Maize Disease Detection System

3.3 System Architecture and Workflow

The system architecture, as presented in Figure 3.1 above, is composed of five modules coordinated to facilitate efficient disease detection and feedback. These include the image acquisition unit, pre-processing unit, AI inference module, results visualization, and feedback system.

The image acquisition unit consists of the ESP32-S3 microcontroller interfaced with an OV2640 camera module. This microcontroller captures the images of maize leaves in real-time and sends them via Wi-Fi to the Flask-based server for processing.

At the pre-processing stage, the Flask backend preprocesses the captured images by resizing and normalizing them to match the model input requirements. This makes sure that the data fed into the model is consistent with the dataset used during training, improving accuracy as well as stability during inference.

The AI inference module is a fine-tuned Convolutional Neural Network (CNN) model trained to classify maize leaf images into four categories: *Healthy*, *Common Rust*, *Blight*, and *Gray Leaf Spot*. To address dataset imbalance, data augmentation and class weighting techniques were applied in training to ensure enhanced model generalization, especially for less dense classes.

The result and visualization module consists of a straightforward web interface coded with the Flask framework for testing locally and hosted on Vercel for production. The user can, through the interface, upload or capture an image of a maize leaf, view the class of predicted disease and its confidence level, and receive management recommendations. Aggregations like average confidence of the model, number of diseases recognized, and the option to print the prediction history for records are also included on the dashboard.

The feedback system ensures real-time warning and user interaction. Classification results are displayed on an I²C LCD, while a buzzer is triggered whenever a disease is detected to notify the farmer or user to take immediate corrective action.

Overall, the architecture provides a seamless workflow from image capture to disease detection and visualization, supporting real-time monitoring and decision-making in precision agriculture.

3.4 System Core Components

This section details the core hardware and software components that formed the backbone of the proposed IoT-based computer vision system for maize disease detection. The system was structured in two major layers: the hardware layer, which took charge of physical acquisition of data, control, and feedback, and the software layer, which dealt with computational processing, AI inference, and visualization of output. Both layers were designed such that they could cooperate to deliver an effective, reliable, and cost-efficient operation suited for precision farming applications.

3.4.1 Hardware Components

The hardware layer consisted of various integrated components that work together to capture images, provide environmental sensing, and provide feedback.

At the core of the system is the ESP32-S3CAM microcontroller, shown in Figure 3.2, which serves as the central processing and control unit. The ESP32-S3CAM contains a dual-core Xtensa LX7 processor up to 240 MHz with built-in Wi-Fi and Bluetooth capabilities. It also contains a dedicated camera slot designed for direct integration with the OV2640 module. This on-device integration can effectively capture images and wirelessly transmit data to the server. Its computational power, low power consumption, and inexpensiveness made it highly feasible to be utilized in precision agriculture embedded computer vision systems.

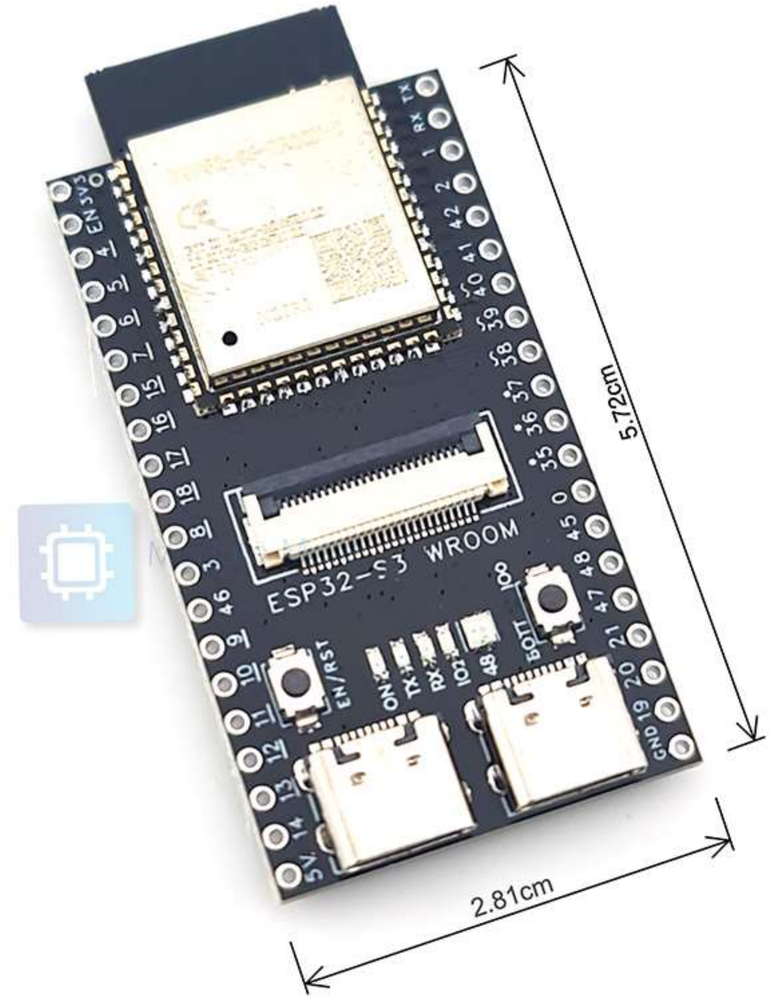

Figure 3.2: ESP32-S3 Development Board (with camera slot) microcontroller

The OV2640 camera module, shown in Figure 3.3, was responsible for image acquisition. It is a 2-megapixel CMOS sensor that can capture images in JPEG format, providing clear visual inputs of maize leaves for disease classification. The camera module's compact design and compatibility with the ESP32-S3CAM made it ideal for field deployment and real-time monitoring.

Figure 3.3 Showing the OV2640 camera module

In addition to the image data, a temperature and humidity sensor DHT11 (Figure 3.4) was included to monitor temperature and relative humidity environmental factors. Such measurements are relevant, as certain maize diseases tend to thrive under specific environmental conditions. Using the DHT11 sensor provides additional data that correlates environmental factors with the possibility of maize diseases.

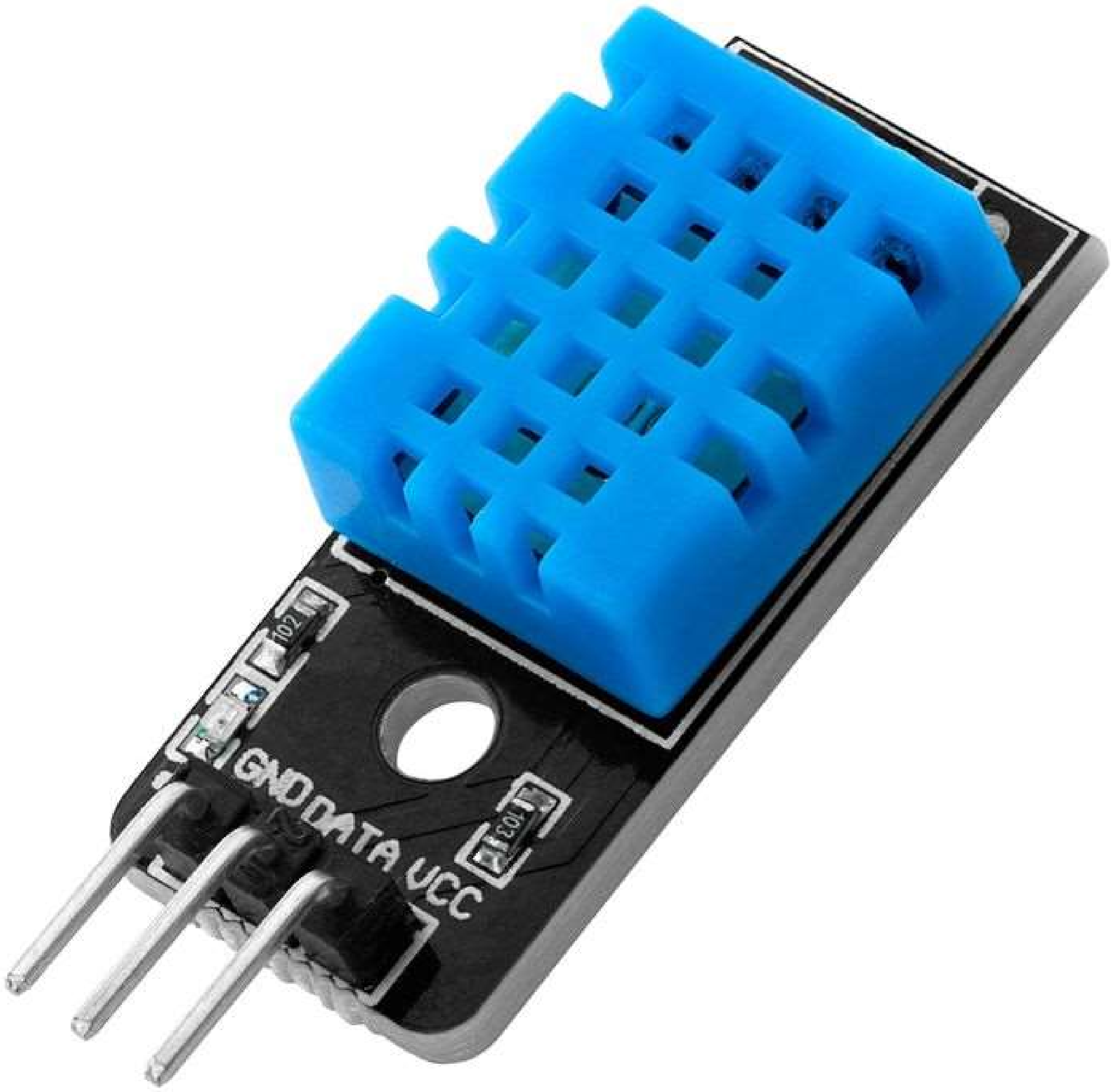

Figure 3.4 DHT 11 Temperature & Humidity Sensor

For user feedback and interaction, a 16×2 I²C Liquid Crystal Display (Figure 3.5) was used to present basic real-time output messages, such as “Healthy” or “Leaf Blight Detected.” This allowed immediate visual feedback on the field without requiring a connected web interface.

Figure 3.5: 16x2 I2C LCD

The system was powered using a portable power supply module, as indicated in Figure 3.6. Power was provided via a USB-C connection connected to a power bank with 5V DC output. This ensured stable operation of the ESP32-S3CAM and its peripherals. The arrangement enabled mobility and ease when performing field testing.

Figure 3.6: Power bank via USB-C interface (5V USB) for power supply

For circuit prototyping, a breadboard and jumper wires Figure 3.7 were used for connections among the components. This setup facilitated testing, debugging, and iterative design without the need for soldering, making the development process flexible and efficient. The entire assembly was housed within a protective casing to ensure durability during field use. The enclosure shielded the components from dust, moisture, and insects, for better portability of the device.

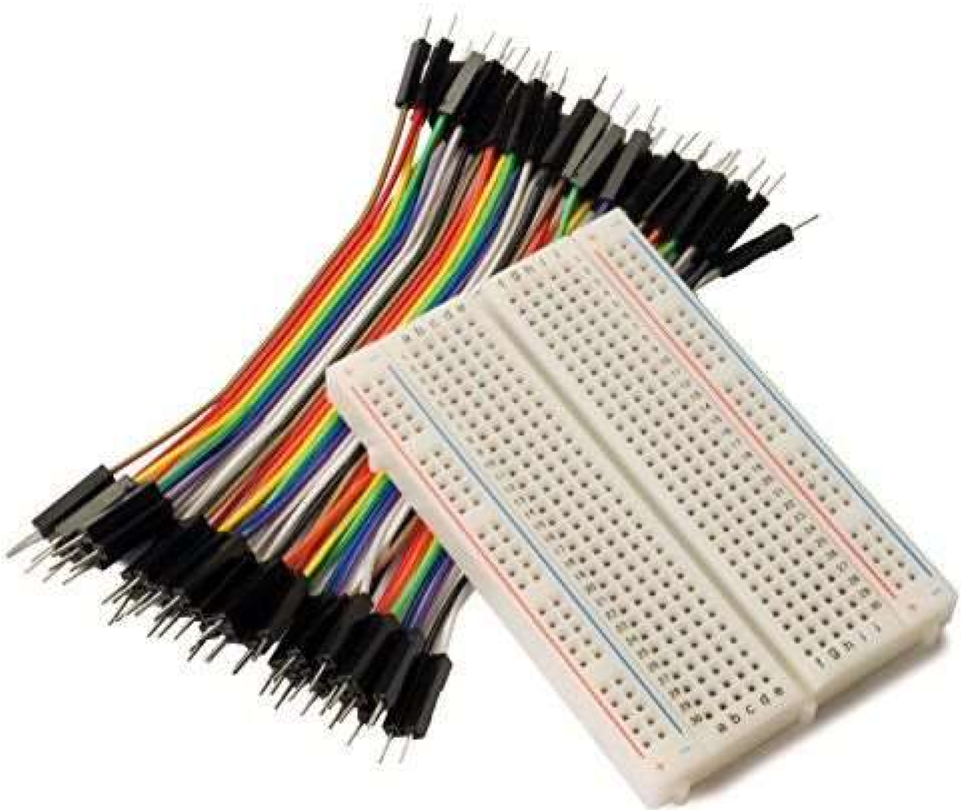

Figure 3.7: Showing breadboard and Jumper wire for solderless connection

Each of these components together created a compact, efficient, and reliable embedded system capable of capturing, transmitting, and analyzing maize leaf images under real-world conditions. They played a critical role in the overall functionality of the system.

3.4.2 Software Components

The software layer forms the smart and interactive part of the proposed maize disease detection system. It integrates artificial intelligence, web-based visualization, and IoT connectivity to enable end-to-end disease detection, data processing, and user feedback.

At the core of the software design is a Flask-based web application developed using HTML, CSS, and Bootstrap for responsive user interaction. This web interface served as the primary medium for uploading maize leaf images captured by the ESP32-S3CAM and for visualizing the disease detection results. This web application deployed both the web frontend and backend inference engine, allowing for interaction with the system in real time, whether locally or over a network connection.

Image preprocessing was done within the web application, which is an important stage in the system. Each uploaded image underwent a sequence of transformations to ensure that the images were consistent with the trained model's expected input type. These transformations included image resizing, normalization, and augmentation to reduce model bias and improve detection accuracy. This preprocessing pipeline helped maintain uniformity across different maize images, preventing errors that could arise from feeding the model with incompatible image dimensions or wrong pixel distributions.

The AI model used for inference was a custom Convolutional Neural Network (CNN), designed and trained specifically for maize leaf disease classification. The model was trained on a dataset of maize leaf images grouped into four classes, namely Healthy, Common Rust, Blight, and Gray Leaf Spot. Data augmentation and class weighting techniques were used during training to address class imbalance and enhance model generalization. The CNN architecture was implemented using TensorFlow and Keras, leveraging their high-level APIs for efficient model building, training, and deployment.

To support these processes, several essential Python libraries and frameworks were also used. OpenCV handled image processing tasks such as reading, resizing, and color space conversion. TensorFlow and Keras were used for developing and fine-tuning the deep learning model, while Flask served as the application framework connecting the model to the user interface. The application was further styled using HTML, CSS, and Bootstrap to ensure a responsive layout across devices. For cloud or remote deployment, the system could be hosted on Vercel, allowing online accessibility to users and field operators.

Model training and validation were done in the Google Colab environment, which uses GPU acceleration for faster computation and integrates with Google Drive for dataset storage. The use of Colab made it possible to train the CNN model efficiently without needing high-end local hardware resources.

Finally, the result visualization and recommendation engine formed the decision management part of the system. After inference, the detected class and corresponding confidence score were displayed to the user with a short description of the disease and suggested management recommendations. The combination of real-time detection and insights increased the system's practical value to farmers and agricultural researchers, which is the goal of precision agriculture.

3.5 System Process Flow

The system flow chart process illustrated in Figure 3.8 describes the sequential operations carried out by the IoT-enabled computer vision maize disease detection system. The process began with image capture and concluded with disease classification and feedback generation through both the LCD and the web application interface.

The system started when the ESP32-S3-CAM module captured an image of a maize leaf in real time. The captured image was then sent to the processing unit, where image preprocessing was performed to ensure compatibility with the trained CNN model. Preprocessing operations included resizing, normalization, and augmentation to improve the model's generalization and reduce input variation.

After preprocessing, the image was passed to the trained Convolutional Neural Network (CNN) for inference. The model analyzed the image and determined whether a disease symptom was present. If no disease was detected, the system displayed "Healthy" on both the LCD screen and the web application.

If a disease symptom is detected, the model further classifies the image into one of the trained classes: Blight, Common Rust, or Gray Leaf Spot. The corresponding class label is displayed on the LCD screen and on the web interface. The web platform provides the confidence score of the disease, information about the disease detected, including a brief description and recommended management strategies. Finally, the LCD screen and web interface communicate the results to the user, while the buzzer produces an alert signal whenever a diseased leaf is detected. The process then returns to the initial stage, allowing for continuous image acquisition and monitoring of maize leaves in real time.

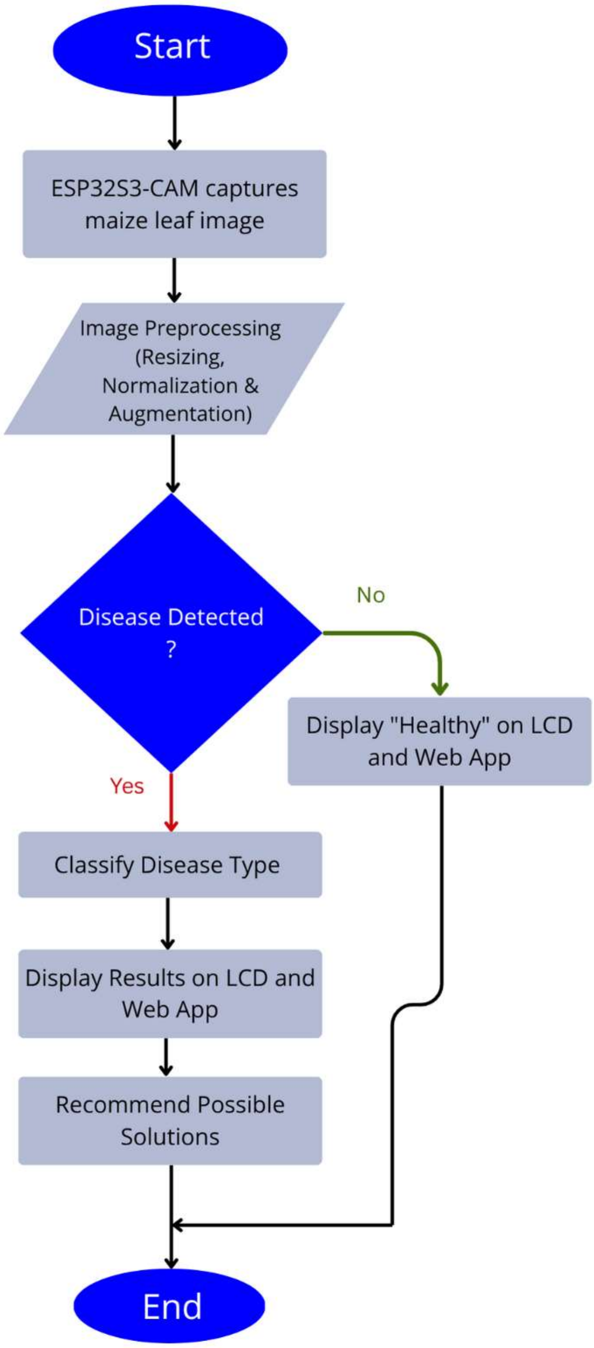

Figure 3.8: System Flowchart of the IoT-Enabled Computer Vision Maize Disease Detection System.

As shown in Figure 3.8 above, the flowchart of the system:

- ❖ Start System
- ❖ ESP32-S3 CAM captures maize leaf image.
- ❖ Pre-process (resize, normalise, augmentation)
    - o Load processed images to trained AI model (CNN) for inference
- ❖ If disease is detected:
    - o Classify the type of disease
    - o Display results on web app and confidence level.
    - o Provide disease information and suggested solutions
    - o Send Alert to Notify farmer via web app
    - o Buzzer makes an alert and result is displayed on LCD
- ❖ If no disease is detected:
    - o Display healthy status and confidence on dashboard and LCD
- ❖ Terminate all processes and connections.

3.6 System Interfacing and Configuration

The implementation of the IoT-enabled computer vision maize disease detection system involves the integration and configuration of both hardware and software components for effective data acquisition, processing, and feedback. This section describes how the components work together and are configured to detect maize diseases and the communication between the hardware components and the web-based analytical platform.

3.6.1 Hardware Interfacing and Configuration

The implementation of the IoT-enabled computer vision maize disease detection system involves the integration and configuration of both hardware and software components for effective data acquisition, processing, and feedback. This section describes how the components work together and are configured. The hardware setup describes the connection between the ESP32-S3 microcontroller, OV2640 camera module, DHT11 temperature and humidity sensor, I^2C LCD display, and buzzer.

The ESP32-S3 served as the central processing and communication unit, coordinating the input from peripheral devices and transmitting data to the web application via Wi-Fi. The OV2640 camera module was interfaced directly through the camera slot on the ESP32-S3-CAM board to capture images of maize leaves. These images were resized to 224 × 224 pixels before they were sent to the AI model, where the trained CNN model analyzed them for disease detection and classification.

The DHT11 sensor was connected through GPIO pin 14 of the ESP32-S3 to record temperature and humidity values, which are vital environmental parameters that can affect the presence and spread of maize leaf diseases, complementing the image-based disease detection, giving additional context for decision-making.

An I2C 16×2 LCD display provided real-time visual feedback by displaying classification results such as *Healthy*, *Blight Detected*, or *Rust Detected*. Giving the farmer the results immediately, even without accessing the web interface. A buzzer was also configured to sound when a disease is detected to raise an alert.

The system was powered by a portable USB-C power bank, ensuring stability, portability, and flexibility for on-field use.

The overall hardware interfacing of the system is illustrated in Figure 3.9, which shows the communication pathways between the ESP32-S3-CAM development board, peripheral modules, and the web application to detect maize diseases, showing the communication between the hardware components and the web-based analytical platform.

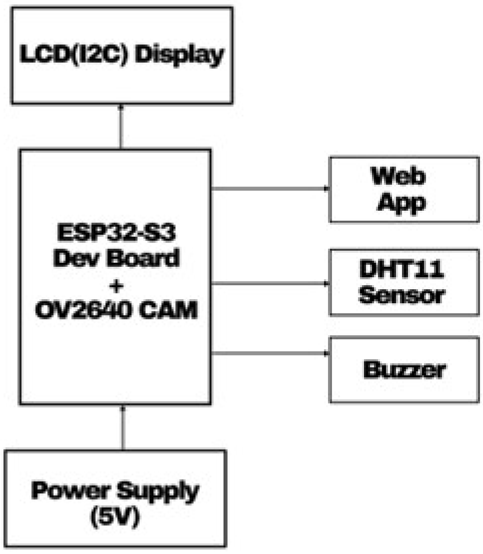

Figure 3.9: Block diagram showing system interfacing between the ESP32-S3, OV2640 camera, DHT11 sensor, LCD, buzzer, and web application.

3.6.2 Software Configuration and Integration

The software comprises a Flask-based web application which serves as the backend for communication between the hardware and the AI model. The ESP32-S3 transmitted captured images via HTTP POST requests to the Flask server, which handled image preprocessing, including resizing, normalisation, and augmentation, before passing them to the CNN model for detection.

The CNN model was deployed locally and optionally through a cloud-hosted inference API. The detection results were then sent back to the web interface to view the disease class, confidence score, and suggested management recommendations.

3.7 Model Training and Implementation Process

The maize disease detection model was developed based on a custom Convolutional Neural Network (CNN) model trained on the PlantVillage dataset that contains images of healthy and diseased maize leaves, including Blight, Common Rust, and Gray Leaf Spot. The dataset was selected due to its diversity and suitability for agricultural image classification research.

The data was normalized and pre-processed before training to promote model generalization and for normalization. The pre-processing of images included resizing to 224 × 224 pixels, normalization to set pixel values between 0 and 1, and data augmentation via rotation, flipping, and zooming to prevent class imbalance and improve robustness to leaf orientation and illumination conditions. The model architecture comprised a few convolutional and pooling layers for abstracting features in a hierarchical manner, followed by ReLU-activated fully connected layers and a Softmax output layer for multiclass classification. The network was trained using the Adam optimizer and categorical cross-entropy loss function. The model was trained on Google Colab to leverage its GPU acceleration for quicker computation.

The model was also validated during training on an independent validation set to monitor performance and prevent overfitting. The final model that was trained with 96% accuracy and 11% validation loss had good learning convergence and feature discrimination. Very minimal overfitting was also demonstrated by the training and validation curves, confirming the validity of the model for generalization.

Although the CNN model performed well across all classes, there were minor misclassifications between Blight and Grey Leaf Spot due to their physical similarity in lesion appearance. Also, since the dataset was derived from publicly available data repositories such as PlantVillage and PlantDoc, it may not capture field-specific variations like differences in lighting conditions, leaf overlap, or cluttered backgrounds prevalent in natural farm environments.

After training, the CNN model was saved as an HDF5 (.h5) file and was passed into the Flask web application, where it was used for real-time inference. Images from the ESP32-S3 +

OV2640 camera module were transmitted to the Flask backend, pre-processed, and input to the trained CNN model for disease classification. The result, confidence level, and recommendation were displayed on the web interface.

3.6 Summary

This chapter presented the methodology pursued in designing and developing the IoT-based computer vision maize disease detection system. The system combined hardware devices such as the ESP32-S3-CAM, DHT11 sensor, LCD, and buzzer with software elements such as a Flask-based backend and a custom CNN model for smart disease detection.

The chapter detailed the system architecture, design, and workflow intended, demonstrating how data was transferred from image acquisition through to processing and inference, then visualized and sent back. It also discussed interfacing and setup of the hardware and software components and how they interact and are integrated to work effectively.

CHAPTER 4

IMPLEMENTATION AND RESULTS

4.1 Overview

This chapter discusses the practical implementation of the IoT-enabled computer vision maize disease detection system. It provides a detailed description of how the system design proposed in Chapter Three was realized in both hardware and software. The implementation covers the setup of the ESP32-S3-CAM-based IoT module, software integration through the Flask web application, and deployment of the trained CNN model for maize disease detection.

Additionally, this chapter presents the experimental results obtained during system testing, highlighting the performance metrics of the CNN model, system response, and overall functionality. The results demonstrate the effectiveness of integrating IoT and AI for precision agriculture, specifically for real-time maize disease detection, and environmental monitoring.

4.2 System Implementation

The implementation of the IoT-enabled computer vision maize disease detection system involved the integration of hardware and software components described in Chapter Three.

This includes the setup of the ESP32-S3CAM to the IoT sensor, the sensor configuration, loading of the CNN model, and the integration of a web-based analytics platform to assemble, configure, and test the hardware and software components.

The hardware implementation starts with gathering all the necessary components shown in Figure 4.1, which includes the ESP32-S3CAM microcontroller, the OV2640 camera module, DHT11 sensor, I2C LCD, buzzer, and enclosure. These components were carefully assembled into the enclosure, ensuring proper wiring between the communication module, microcontroller, sensors, and alerting systems.

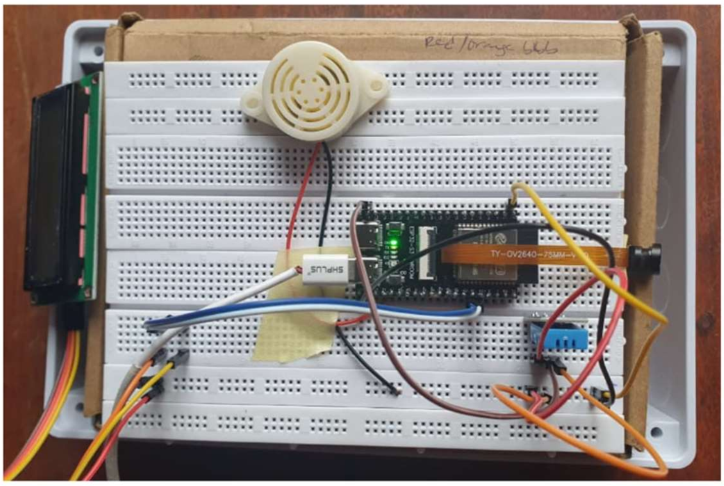

Figure 4.1: *System Hardware Setup*

The ESP32-S3CAM acts as the central communication and processing unit. The OV2640 camera module was accessed directly via the ESP32-S3CAM slot for the capturing of images of maize leaves. The captured images were pre-processed and wirelessly sent via Wi-Fi to the Flask-based web server for processing.

The DHT11 sensor was connected to GPIO pin 14 of the ESP32-S3 to measure environmental parameters such as temperature and humidity, which complement the disease detection process by providing contextual data on environmental conditions.

An I2C 16×2 LCD was used to display disease detection outcomes such as *"Healthy," "Leaf Blight Detected,"* or *"Common Rust Detected."* A buzzer is also used to an alert each time a disease was found, helping farmers detect infected crops even without the use of the web interface.

The entire system was powered through a 5V USB-C power bank, ensuring portability and field usability. The setup was tested on a breadboard before being enclosed in a protective casing for stability and safety during operation.

The software implementation was carried out in two stages: web application setup and model integration.

The web application was developed using the Flask framework, serving as the interface between the IoT device and the machine learning model. Captured images were transmitted to the server via HTTP POST requests from the ESP32-S3, where they were processed by the backend for disease prediction.

The Flask backend handled image preprocessing operations such as resizing, normalization, and augmentation before forwarding the processed images to the trained CNN model for inference. The CNN model, trained in Google Colab, was deployed locally within the Flask server and optionally hosted through a cloud API for remote access.

The web interface was designed to allow users to either upload maize leaf images directly or capture live images from the ESP32-S3CAM. Once analyzed, the interface displayed the detected disease type, prediction confidence level, and management recommendations.

An example of the implemented web interface showing the image upload section and detection result page is presented in Figure 4.2.

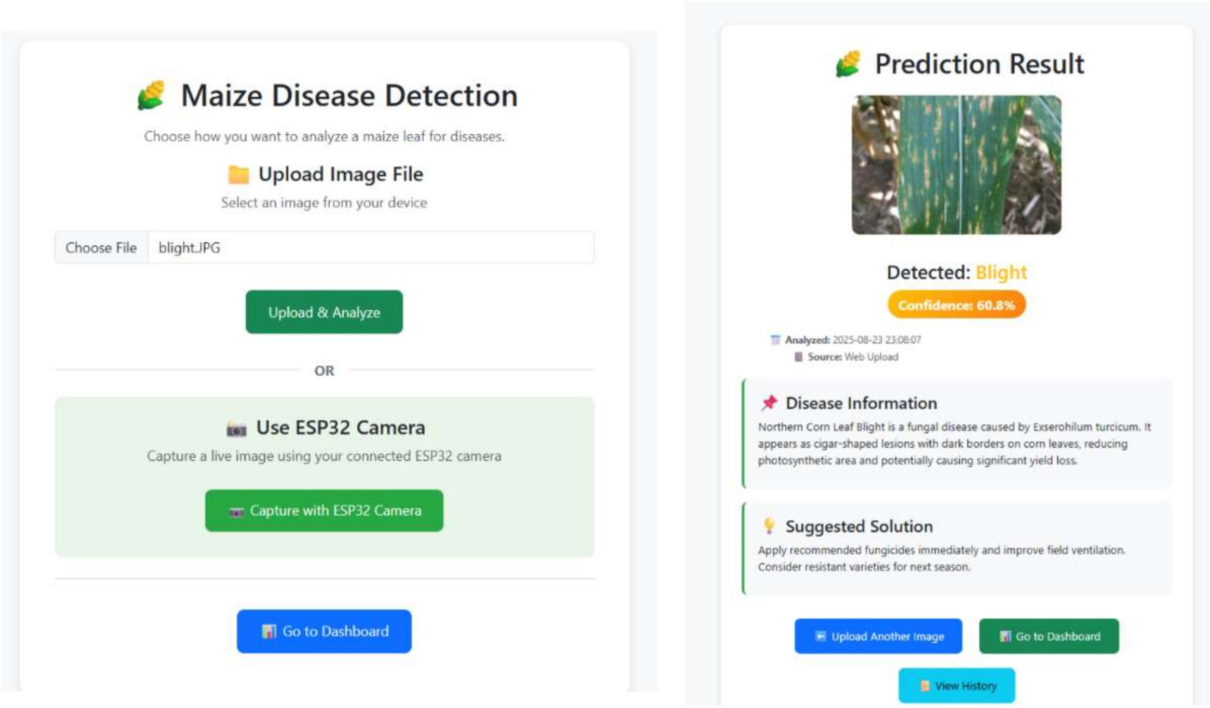

Figure 4.2: *Maize Disease Detection Web Homepage.*

4.3 System Testing

System testing was carried out to verify the proper functioning and reliability of both the hardware and software components of the IoT-enabled maize disease detection system. The goal was to ensure that all integrated modules operated as intended and that the overall system met its design requirements in terms of accuracy, communication, and usability.

4.3.1 Hardware Testing

The hardware components were tested individually and as an integrated system to confirm seamless operation and communication between devices.

The ESP32-S3 and OV2640 Camera module were tested for proper image capturing and transmission. Remote camera triggering via the web application was also tested to ensure reliable connectivity.

The DHT11 sensor was tested in temperature and humidity sensing and was compared with reference values to check for accuracy. The sensor successfully transmitted data through the ESP32-S3 for real-time tracking and synchronization with the web interface.

OLED display (16×2 I²C LCD) was tested to ensure that it would show results of classification in Healthy, Blight Detected, or Rust Detected format. The display is updated constantly after each prediction, and immediate feedback is provided to the user.

The buzzer was confirmed to make a beep sound whenever a photo was taken and provided audio signals when diseased leaves were detected, serving as a notification system.

The rechargeable USB-C power bank, which served as the power supply, was tested for system stability and endurance for extended periods under field-like conditions. There was no significant performance degradation, confirming that the power is reliable.

4.3.2 Software Testing

The software components were tested to ensure efficient image classification, data handling, and seamless user interaction through the web interface.

The custom-built CNN model was tested using the prepared maize disease dataset obtained from PlantVillage. Testing focused on evaluating accuracy, loss, and classification performance across the four target classes. The model achieved an overall accuracy of 96% with a loss of 11%. The confusion matrix analysis revealed slight misclassifications between *Blight* and *Gray Leaf Spot*, likely due to visual similarities in lesion patterns.

Performance metrics such as precision, recall, and F1-score were determined to check the classification reliability for all classes. Precision remained high for each class, recall values were balanced, and the F1-score showed consistent performance and good handling of dataset imbalance after augmentation.

The web application was intensively tested with uploaded images and live camera feeds. It consistently processed images, made model inference, and displayed classification output along with corresponding disease description and management recommendations.

The dashboard testing confirmed that the history of previous classifications was properly logged and retrieved from the database for future reference.

Lastly, response time testing showed the average time for image upload to display the results was between 3 and 5 seconds, which is virtually real-time and suitable for field usage.

4.4 Results

The implementation and testing of the IoT-enabled maize disease detection system produced significant results across both the hardware setup and the software model. This section presents the outcomes of system operation, model performance, and interface outputs using tables, charts, and figures for clarity.

4.4.1 CNN Model Performance Results

The performance of the custom convolutional neural network (CNN) model was evaluated using the test dataset derived from PlantVillage, with a class distribution of Blight: 1,146 images, Common Rust: 1,306 images, Gray Leaf Spot: 574 images, and Healthy: 1,162 images, with all the classes being a total of 4,188 images. The dataset was then split into a training set of 80%, a Validation set of 10%, and a Test set of 10%. This balanced dataset preparation ensured effective model training and good performance across all classes, including the underrepresented *Gray Leaf Spot* (Sulaniishara, 2024). The model achieved an overall accuracy of 96% with a loss of 11%, indicating strong classification performance across the four target classes.

i. Training and Validation Performance: Figure 4.3 presents the training and validation accuracy and loss curves, showing consistent learning with minimal overfitting throughout the epochs.

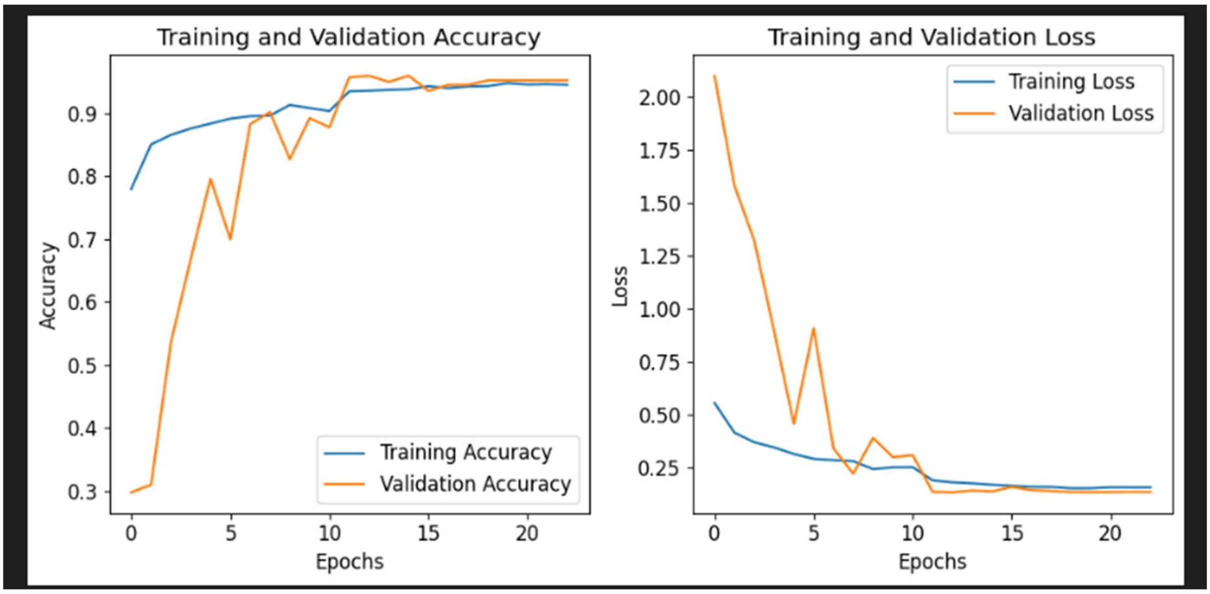

Figure 4.3: Training and Validation Accuracy and Loss Curves

ii. Confusion Matrix: Figure 4.4 shows the confusion matrix, highlighting the distribution of correct and misclassified predictions. The model performed strongly across all classes, with minor misclassifications observed between *Blight* and *Gray Leaf Spot*, likely due to visual similarities in lesion patterns.

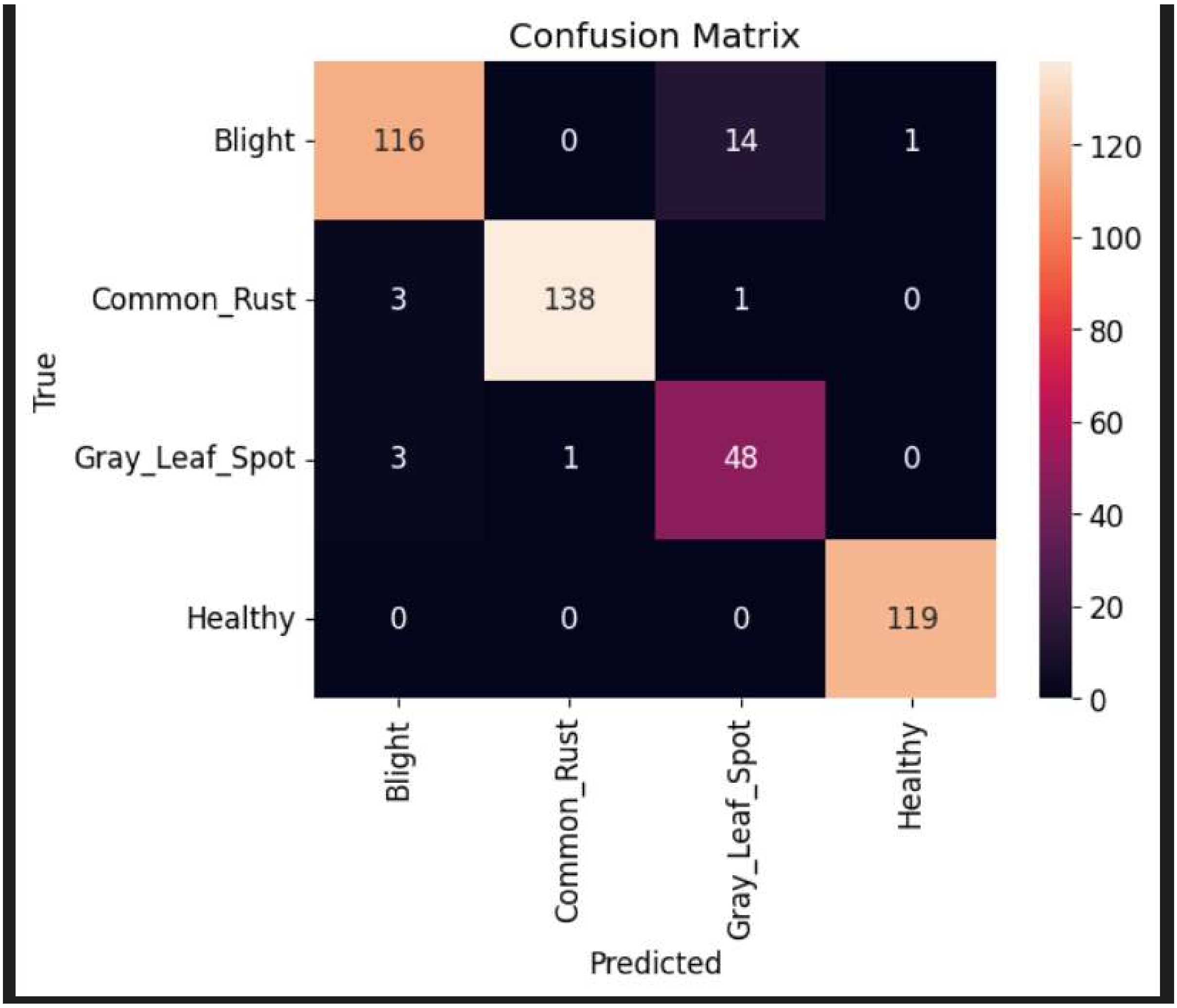

Figure 4.4: Confusion Matrix of Classification Results

iii. Classification Results and Performance Metrics: Table 4.1 summarizes the precision, recall, and F1-score for each class, confirming the robustness of the CNN model.

Table 4.1: Classification Performance Metrics

Class	Precision	Recall	F1-Score	Support
Blight	**0.95**	**0.89**	**0.92**	**131**
Common Rust	**0.99**	**0.97**	**0.98**	**142**
Gray Leaf Spot	**0.76**	**0.92**	**0.83**	**52**
Healthy	**0.99**	**1.00**	**1.00**	**119**
Accuracy			**0.95**	**444**
Macro Avg	**0.92**	**0.95**	**0.93**	**444**
Weighted Avg	**0.95**	**0.95**	**0.95**	**444**

From Table 4.1, the model performed exceptionally well on *Common Rust* and *Healthy* leaves, with precision and recall values close to 1.0. *Gray Leaf Spot* was the most challenging class, with lower precision (0.76) but relatively high recall (0.92), indicating a tendency to over-predict this class. Overall, the weighted metrics align with the 95% accuracy, confirming the CNN model's reliability.

4.4.2 Sample Classification Outputs

The system was tested using both images uploaded through the web interface and images captured via the ESP32-S3 + OV2640 camera. The CNN model correctly classified disease conditions in real time. In Figure 4.5, the sample classifications for all the classes with healthy maize leaf correctly classified as *Healthy*, maize leaf with rust correctly classified as *Common Rust* and maize leaf with blight correctly classified, though occasionally misclassified as *Gray Leaf Spot* in rare cases.

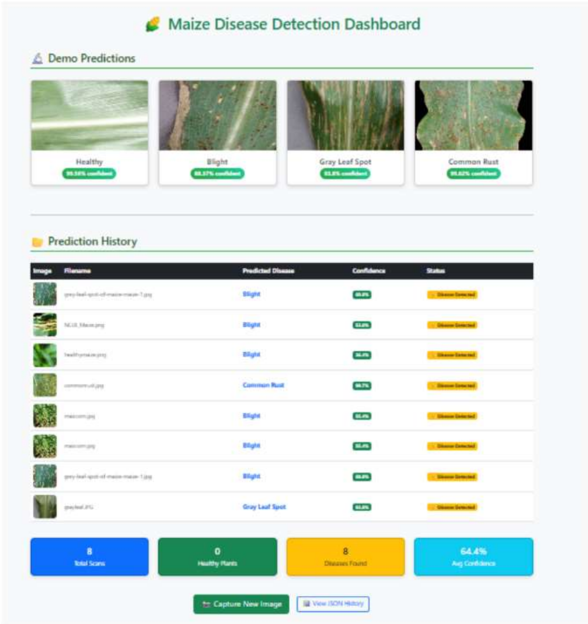

Figure 4.5: Sample Classification Outputs from the Web Application

4.4.3 Integrated System Results

The integrated system demonstrated successful communication between the IoT hardware and the AI-powered backend.

The OLED Display provided real-time feedback by displaying classification results such as "Healthy" or "Diseased," while the buzzer alerted users each time an image was captured or a disease was detected.

The web dashboard Figure 4.6 recorded and displayed the history of detections, allowing users to monitor crop health over time and reference past classification outcomes.

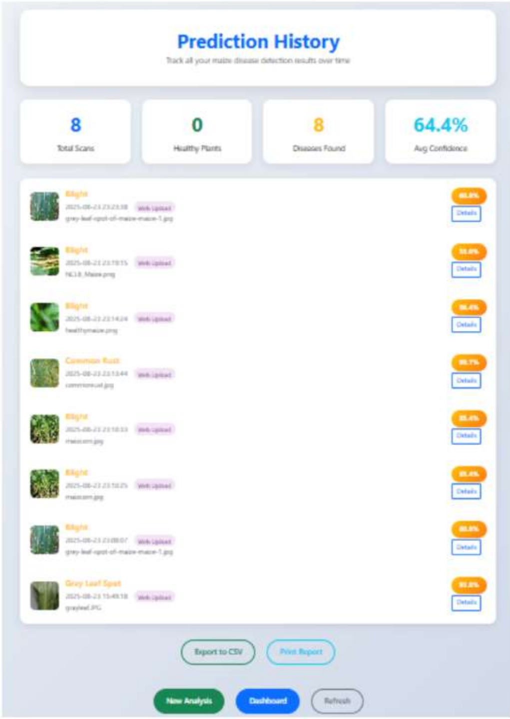

Figure 4.6: Web Application Dashboard Showing Detection History

4.5 Discussion of Results

The developed smart system for maize disease detection successfully integrated both hardware and software components to offer real-time and accurate disease diagnosis. The IoT-based system demonstrated that incorporating image-based classification along with environmental sensing significantly enhances precision in crop health monitoring in precision agriculture.

The results obtained from system testing confirmed that each hardware component functioned as expected. The ESP32-S3 and OV2640 camera module captured clear images of maize leaves, while the DHT11 sensor yielded correct readings of temperature and humidity conforming to standard values. The LCD correctly indicated disease types such as Healthy, Blight, Common Rust, or Gray Leaf Spot, and the buzzer showed immediate alerts with the detection of infected leaves. The power supply unit also proved to supply system stability when the system was continuously run, making it appropriate for use in the field.

The software test indicated strong classification capability of the convolutional neural network (CNN). With 96 per cent test accuracy and 11 per cent loss, the model could effectively classify between the four conditions of maize leaves. A few misclassification cases observed between Blight and Gray Leaf Spot were attributed to the visual similarity of symptom patterns and class imbalance in the data. Nevertheless, precision, recall, and F1-score metrics for each class confirmed that the model led to good generalization and valid inference power.

The web application's interface was smooth and responsive, with image upload or direct capture using the ESP32 camera to be analyzed. The average response time of 3–5 seconds was found to be near real-time and acceptable for deployment in games. Disease descriptions and treatment recommendations were displayed correctly for each diagnosis, with previous results successfully logged on the dashboard for record keeping and future analysis.

Generally, the discussion of results indicates that the system, in its designed form, met its intended objectives through the establishment of an affordable, accessible, and efficient solution for maize disease diagnosis. The integration of AI-based image analysis with IoT-driven data collection proved effective in improving the accuracy and timeliness of crop disease surveillance, thereby enabling smart and sustainable agriculture.

CHAPTER 5

SUMMARY, CONCLUSION, AND RECOMMENDATIONS

5.1 Summary

This project involved the design and implementation of a Smart System for Maize Disease Detection using an ESP32-S3 microcontroller, OV2640 camera module, DHT11 sensor, and a Convolutional Neural Network (CNN) model.

The hardware unit of the system comprised the ESP32-S3CAM for image capture and transmission, DHT11 sensor for monitoring environmental conditions (humidity and temperature), an OLED display for real-time feedback, and a buzzer for alert notifications. The software module was a CNN model that was trained based on maize leaf disease datasets to classify captured images as Healthy, Blight, Common Rust, or Gray Leaf Spot.

Captured images and sensor data were wirelessly transmitted via Wi-Fi to a web-based dashboard for disease analysis, environmental monitoring, and presentation of treatment recommendations. The maize disease detection system was tested, showing that the CNN model attained approximately 95% training accuracy and 93% validation accuracy with little loss, which indicates good generalization and classification performance.

During hardware testing, the ESP32-S3CAM successfully captured and transmitted images, while the DHT11 sensor successfully sensed environmental data. The LCD provided classification outputs, while the buzzer provided sounds when diseased maize leaves are detected.

Overall, the project was successful in the early detection of maize diseases, recording environmental data, and providing timely feedback to farmers. The project showed how IoT and AI analytics can provide a scalable and efficient way to identify crop disease in developing countries like Nigeria by reducing constant crop checking and providing farmers with early identification of diseases, which ends up reducing crop loss and boosting yield.

5.2 Conclusion

The project successfully developed a functional prototype of an IoT-enabled smart maize disease detection system, effectively integrating AI-driven analytics with IoT hardware components. By leveraging the CNN model for image classification and the ESP32-S3 platform for environmental sensing and wireless data transmission, the system provided a low-cost, practical solution for precision agriculture.

The system achieved its objective effectively by identifying maize leaf diseases and correlating these to environmental factors. This improves data-driven decision-making and reduces the need for laborious manual inspection, is time-consuming and error-prone.

Despite this, some challenges were encountered during the project. Blight was misclassified to some extent with Gray Leaf Spot, which was likely due to the visual similarity of the look of their leaf lesions. In addition, the dataset used was derived from publicly shared data sources (PlantVillage and PlantDoc) and cannot reflect real-field conditions such as light variation, background noise, or leaf orientations. These factors show that future work should focus on dataset diversity and image acquisition in real-field environments for increased accuracy and robustness.

This project shows how the integration of artificial intelligence and IoT technologies can increase crop yield and address agricultural issues such as disease outbreaks in crops. This provides a window for future innovations aimed at improving food security and promoting digitalization in agriculture in Nigeria and globally.

5.3 Recommendations

Although the Smart Maize Disease Detection System in this project has proven to be highly reliable and has promising performance in identifying maize leaf diseases, there are various areas that can be improved further to enhance its robustness, scalability, and practical usability. The following recommendations are made based on the limitations encountered and lessons learned from system development and experimentation.

Future studies would involve expanding the dataset used for training the model by obtaining more and larger maize leaf images from other farms under different environmental conditions. This would improve the ability of the convolutional neural network (CNN) model to generalize across a wide range of real-world conditions. A larger dataset would also help minimize misclassifications especially between visually similar diseases such as Blight and Gray Leaf Spot and improve the diagnostic reliability and precision of the model.

The CNN model can also be optimized for on-device, real-time inference using low-weight deployment platforms such as TensorFlow Lite or PyTorch Mobile. This would enable the model to run directly on the ESP32-S3 microcontroller or embedded systems without having to constantly rely on a web server. This would reduce latency, power, and costs of operation while enhancing system autonomy and usability in rural farming applications.

Also, the sustainability of the system can be increased through the addition of renewable power sources like solar charging modules. Integrating this would provide seamless functionality even in off-grid or rural locations, where reliable electricity and internet connectivity are among the biggest challenges smallholder farmers face.

In addition to this, developing a custom mobile application is strongly advised. Through the application, farmers can receive real-time disease detection alerts, see farm-level insights, and receive offline recommendations. This can also aid in user-centered interfaces and remove language barriers among diverse user groups.

The system framework can also be extended to other economically valuable crops such as cassava, rice, and yams. Using transfer learning and multi-crop datasets, the model can be a generalized platform for crop health monitoring that can serve precision agriculture for different types of crops and geographies.

Last of all, large-scale pilot deployments and field testing with farmers and agricultural officers are necessary for feedback on the system's performance under real-world conditions to determine if it meets the needs of the users and if there are other areas for improvement.

With these recommendations, the Smart Maize Disease Detection System can be made a more responsive, power-efficient, and farmer-friendly system. These would make it far more sustainable in the long run, scalable, and beneficial to national efforts in scaling up precision agriculture, reducing crop losses, and improving food security in Nigeria and around the world.

REFERENCES

Abade, A. S., Ferreira, P. A., & De Barros Vidal, F. (2020). Plant diseases recognition on images using convolutional neural networks: A systematic review. *arXiv*. https://doi.org/10.48550/arxiv.2009.04365

Abdulmalik, A. (2023, January 19). The problem of food security in Nigeria. *Plantae*. https://plantae.org/the-problem-of-food-security-in-nigeria-a-plant-pathologists-view/

Abu, N. S., Bukhari, W. M., Ong, C. H., Kassim, A. M., Izzuddin, T. A., Sukhaimie, M. N., Norasikin, M. A., & Rasid, A. F. A. (2022). Internet of Things Applications in Precision Agriculture: a review. *Journal of Robotics and Control (JRC)*, *3*(3), 338–347. https://doi.org/10.18196/jrc.v3i3.14159

Adejumo, S. A., Ezeh, O. S., & Adebiyi, O. A. (2018). Assessment of maize farmers' knowledge of pests and diseases in Oyo State, Nigeria. *Journal of Agricultural Extension*, *22*(1), 94–105.

Alabi, O., Banwo, O. O., & Alabi, S. O. (2006). Crop pest management and food security in Nigerian agriculture. *Archives of Phytopathology and Plant Protection*, *39*(6), 457–464. https://doi.org/10.1080/03235400500383693

Albahli, S., & Masood, M. (2022). Efficient attention-based CNN network (EANet) for multi-class maize crop disease classification. *Frontiers in Plant Science*, *13*. https://doi.org/10.3389/fpls.2022.1003152

Bayer Crop Science. (2023, July 11). Gray leaf spot in corn. Retrieved October 7, 2025, from https://www.cropscience.bayer.us/articles/bayer/gray-leaf-spot-in-corn

Bwambale, E., Wanyama, J., Adongo, T. A., Umukiza, E., Ntole, R., Chikavumbwa, S. R., Sibale, D., & Jeremaih, Z. (2024). A review of model predictive control in precision agriculture. *Smart Agricultural Technology*, Article 100716. https://doi.org/10.1016/j.atech.2024.100716

Common Rust of Corn. (2019, March 19). Retrieved October 7, 2025, from https://cropprotectionnetwork.org/encyclopedia/common-rust-of-corn

Delfani, P., Thuraga, V., Banerjee, B., & Chawade, A. (2024). Integrative approaches in modern agriculture: IoT, ML and AI for disease forecasting amidst climate change. *Precision Agriculture*, *25*(5), 2589–2613. https://doi.org/10.1007/s11119-024-10164-7

Dementievgeopard. (2023, August 11). How to control crop diseases with smart agriculture. *Geopard*. https://geopard.tech/blog/how-to-control-crop-diseases-with-smart-agriculture/

Dolatabadian, A., Neik, T. X., Danilevicz, M. F., Upadhyaya, S. R., Batley, J., & Edwards, D. (2024). Image-based crop disease detection using machine learning. *Plant Pathology*. https://doi.org/10.1111/ppa.14006

Duguma, A. L., & Bai, X. (2024). How the internet of things technology improves agricultural efficiency. *Artificial Intelligence Review*, *58*(2). https://doi.org/10.1007/s10462-024-11046-0

El Sakka, H., Qureshi, A., & Thoma, G. (2025). Deep learning models for plant disease detection. *Computer Vision and Pattern Recognition*, *15*(2), 145–162.

FAO. (2023). *FAOSTAT: Crops and livestock data*. Food and Agriculture Organization of the United Nations. https://openknowledge.fao.org/server/api/core/bitstreams/6e04f2b4-82fc-4740-8cd5-9b66f5335239/content

Gai, J., & Wang, L. (2024). Crop disease detection using deep learning and IoT: A comprehensive review. *Smart Agriculture*, *6*(3), 234–248.

Gupta, G., & Pal, S. K. (2025). Applications of AI in precision agriculture. *Discover Agriculture*, *3*(1). https://doi.org/10.1007/s44279-025-00220-9

Haq, I. U., & Ijaz, S. (2020). History and recent trends in plant disease control: An overview. In *Sustainability in plant and crop protection* (pp. 1–13). Springer. https://doi.org/10.1007/978-3-030-35955-3_1

Hwang, K., & Chen, M. (2017). *Big-data analytics for cloud, IoT and cognitive computing*. John Wiley & Sons.

Kaplan, A., & Haenlein, M. (2018). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Miller, T., Mikiciuk, G., Durlik, I., Mikiciuk, M., Łobodzińska, A., & Śnieg, M. (2025). The IoT and AI in Agriculture: The Time Is Now—A Systematic Review of Smart Sensing Technologies. *Sensors*, *25*(12), 3583. https://doi.org/10.3390/s25123583

Misra, N. N., Dixit, Y., Al-Mallahi, A., Bhullar, M. S., Upadhyay, R., & Martynenko, A. (2020). IoT, big data, and artificial intelligence in agriculture and food industry. *IEEE Internet of Things Journal*, *9*(9), 6305–6324. https://doi.org/10.1109/jiot.2020.2998584

Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for Image-Based plant disease detection. *Frontiers in Plant Science*, *7*. https://doi.org/10.3389/fpls.2016.01419

Mohtasim, S. N., Khan, J. J., Islam, M. M., Sarker, M. K., Uddin, R., & Hasan, M. (2023). IoT-based crop monitoring and disease detection. *2023 5th International Conference on*

Sustainable Technologies for Industry 5.0 (STI). DOI:10.1109/STI59863.2023.10464923

Nandhini, A., R, H., S, R., G, S., & R, S. (2022). A Smart Agriculturing IoT System for Banana Plants Disease Detection through Inbuilt Compressed Sensing Devices. *Research Square (Research Square)*. https://doi.org/10.21203/rs.3.rs-2182006/v1

Nawaz, M., & Babar, M. I. K. (2025). IoT and AI for smart agriculture in resource-constrained environments: challenges, opportunities and solutions. *Discover Internet of Things*, *5*(1). https://doi.org/10.1007/s43926-025-00119-3

Ngugi, H. N., Ezugwu, A. E., Akinyelu, A. A., & Abualigah, L. (2024). Revolutionizing crop disease detection with computational deep learning: a comprehensive review. *Environmental Monitoring and Assessment*, *196*(3). https://doi.org/10.1007/s10661-024-12454-z

Nkuna, B. L., Abutaleb, K., Chirima, J. G., Newete, S. W., Van Der Walt, A., & Nyamugama, A. (2025). Identification of maize leaf diseases using red, green, blue-based images with convolutional neural network (CNN) and Residual network (ResNet50) models. *Smart Agricultural Technology*, 101226. https://doi.org/10.1016/j.atech.2025.101226

Nsibo, D. L., Barnes, I., & Berger, D. K. (2024). Recent advances in the population biology and management of maize foliar fungal pathogens Exserohilum turcicum, Cercospora zeina and Bipolaris maydis in Africa. *Frontiers in Plant Science*, *15*. https://doi.org/10.3389/fpls.2024.1404483

Okorie, V., Nwosu, C., & Okonkwo, E. (2025). Precision agriculture technologies for sustainable farming in Nigeria. *African Journal of Agricultural Technology*, *10*(1), 45–58.

Onumah, G., Dhamankar, M., Ponsioen, T., & Bello, M. (2021). Maize value chain analysis in Nigeria. *Report for the European Union, INTPA F*, *3*.

Orchi, H., Sadik, M., & Khaldoun, M. (2021). On using artificial intelligence and the internet of things for crop disease detection: A Contemporary survey. *Agriculture*, *12*(1), 9. https://doi.org/10.3390/agriculture12010009

Oyekanmi, A. A., Alabi, O. J., & Oladipo, F. O. (2024). Plant-parasitic nematodes and viral diseases of cereals in sub-Saharan Africa: Implications for maize production. *Cereal Research Communications*, *52*(1), 45–58. https://doi.org/10.1007/s44279-024-00040-3

Padhiary, M., Kumar, A., & Sethi, L. N. (2025). Emerging technologies for smart and sustainable precision agriculture. *Discover Robotics*, *1*(1). https://doi.org/10.1007/s44430-025-00006-0

Pelczar, J. M., Shurtleff, C. M., Kelman, A., & Pelczar, R. M. (2025, March 17). Plant disease: Importance, types, transmission, & control. *Encyclopedia Britannica*. https://www.britannica.com/science/plant-disease

Qian, X., Zhang, C., Chen, L., & Li, K. (2022). Deep Learning-Based identification of maize leaf diseases is improved by an attention mechanism: Self-Attention. *Frontiers in Plant Science*, *13*. https://doi.org/10.3389/fpls.2022.864486

Sharma, K., & Shivandu, S. K. (2024). Integrating artificial intelligence and Internet of Things (IoT) for enhanced crop monitoring and management in precision agriculture. *Sensors International*, *5*, Article 100292. https://doi.org/10.1016/j.sintl.2024.100292

Shoaib, M., Shah, B., Ei-Sappagh, S., Ali, A., Ullah, A., Alenezi, F., Gechev, T., Hussain, T., & Ali, F. (2023). An advanced deep learning models-based plant disease detection: A review of recent research. *Frontiers in Plant Science*, *14*. https://doi.org/10.3389/fpls.2023.1158933

Singh, V., Sharma, N., & Singh, S. (2020). A review of imaging techniques for plant disease detection. *Artificial Intelligence in Agriculture*, *4*, 229–242. https://doi.org/10.1016/j.aiia.2020.10.002

Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). Deep neural networks based recognition of plant diseases by leaf image classification. *Computational Intelligence and Neuroscience*, *2016*, 1–11. https://doi.org/10.1155/2016/3289801

Sulaniishara. (2024, December 28). 🌽 *LeafHealth: Diagnose corn Diseases Fast!* 🚀. Kaggle. https://www.kaggle.com/code/sulaniishara/leafhealth-diagnose-corn-diseases-fast/notebook

Toda, Y., Okura, F., Ito, J., & Okada, S. (2019). Deep learning for plant classification and disease detection. *Journal of Agricultural Informatics*, *8*(3), 23–35.

Tzounis, A., Katsoulas, N., Bartzanas, T., & Kittas, C. (2017). Internet of Things in agriculture, recent advances and future challenges. *Biosystems Engineering*, *164*, 31–48. https://doi.org/10.1016/j.biosystemseng.2017.09.007

United States Department of Agriculture (USDA). (2024). *Nigeria: Corn production summary*. Foreign Agricultural Service. https://ipad.fas.usda.gov/countrysummary/Default.aspx?crop=Corn&id=NI

Wang, H., Shang, S., Wang, D., He, X., Feng, K., & Zhu, H. (2022). Plant Disease Detection and Classification Method based on the optimized lightweight YOLOV5 model. *Agriculture*, *12*(7), 931. https://doi.org/10.3390/agriculture12070931

Wise, K. (2010). *Diseases of corn* (BP-82-W). Retrieved from https://www.extension.purdue.edu/extmedia/bp/bp-82-w.pdf

Wossen, T., Menkir, A., Alene, A., Abdoulaye, T., Ajala, S., Badu-Apraku, B., Gedil, M., Mengesha, W., & Meseka, S. (2023). Drivers of transformation of the maize sector in Nigeria. *Global Food Security*, *38*, 100713. https://doi.org/10.1016/j.gfs.2023.100713

Yuen, J. (2019). The evolution of plant pathology over two millennia. *Plant Disease*, *103*(4), 615–622.

Zeng, Z., Mahmood, T., Wang, Y., Rehman, A., & Mujahid, M. A. (2025). AI-driven smart agriculture using hybrid transformer-CNN for real time disease detection in sustainable farming. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-10537-6

APPENDICES

Appendix A: Arduino Code for ESP32S3 Data Receival and Transmittal to Web Application

Appendix B: Code Snippet of Web Application

```
from flask import Flask, render_template, request, jsonify, redirect, url_for, flash, send_from_directory
import os
import json
from datetime import datetime
from werkzeug.utils import secure_filename
import sqlite3
from PIL import Image
import numpy as np
import tensorflow as tf
import io
import base64
from pathlib import Path

app = Flask(__name__)
app.config['SECRET_KEY'] = 'your-secret-key-change-this'
app.config['UPLOAD_FOLDER'] = 'static/uploads'
app.config['MAX_CONTENT_LENGTH'] = 16 * 1024 * 1024  # 16MB max file size

# Ensure upload directory exists
os.makedirs(app.config['UPLOAD_FOLDER'], exist_ok=True)

# Disease classes
DISEASE_CLASSES = {
    0: 'Healthy',
    1: 'Common Rust',
    2: 'Blight',
    3: 'Gray Leaf Spot'
}

DISEASE_INFO = {
    'Healthy': {
        'description': 'The plant appears healthy with no visible signs of disease.',
        'action': 'Continue regular monitoring and maintain good agricultural practices.',
        'severity': 'None',
        'color': 'success'
```

```
    },
    'Common Rust': {
        'description': 'Fungal disease characterized by small, circular to oval rust pustules on leaves.',
        'action': 'Apply fungicide treatment and improve air circulation around plants.',
        'severity': 'Moderate',
        'color': 'warning'
    },
    'Blight': {
        'description': 'Serious fungal infection causing large lesions and potential yield loss.',
        'action': 'Immediate fungicide application and removal of infected plant material.',
        'severity': 'High',
        'color': 'danger'
    },
    'Gray Leaf Spot': {
        'description': 'Fungal disease creating rectangular gray spots parallel to leaf veins.',
        'action': 'Apply appropriate fungicide and practice crop rotation.',
        'severity': 'Moderate to High',
        'color': 'warning'
    }
}
```

Appendix C: Code Snippet of Model Training Notebook

```
# Import libraries
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.applications import EfficientNetB0
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLROnPlateau
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import categorical_crossentropy
from tensorflow.keras.utils import to_categorical

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.utils.class_weight import compute_class_weight
from imblearn.over_sampling import RandomOverSampler
import cv2
import os
import zipfile
from google.colab import drive, files
from PIL import Image
import json
import warnings
warnings.filterwarnings('ignore')

# Check GPU availability
print("GPU Available: ", tf.config.list_physical_devices('GPU'))
print("TensorFlow Version: ", tf.__version__)
```

```python
# Set memory growth for GPU
gpus = tf.config.experimental.list_physical_devices('GPU')
if gpus:
    try:
        for gpu in gpus:
            tf.config.experimental.set_memory_growth(gpu, True)
    except RuntimeError as e:
        print(e)

# ========================================
# 2. MOUNT GOOGLE DRIVE AND DATA SETUP
# ========================================

# Mount Google Drive
drive.mount('/content/drive')

# Create project directory in Google Drive
project_dir = '/content/drive/MyDrive/Maize_Disease_Classification'
os.makedirs(project_dir, exist_ok=True)
os.makedirs(f'{project_dir}/models', exist_ok=True)
os.makedirs(f'{project_dir}/results', exist_ok=True)

print(f"Project directory created: {project_dir}")

# ========================================
# 3. DATA LOADING AND PREPARATION
# ========================================

def upload_and_extract_data():
    """
    Upload and extract dataset from zip file
    Expected structure after extraction:
    /content/maize_data/
    ├── Healthy/
    ├── Common_Rust/
```