DEVELOPMENT OF DEEP LEARNING MODELS TO IMPROVE PLANT BIOSECURITY FOR SUSTAINABLE AGRICULTURE

A Thesis Submitted
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CANDIDATE'S DECLARATION

I, **Parul Sharma (enrollment no. 2K20/PHDCO/504)**, hereby declare that the work which is being presented in the thesis entitled **"Development of Deep Learning Models to Improve Plant Biosecurity for Sustainable Agriculture"** in the partial fulfillment of the requirements for the award of the Degree of Doctor of Philosophy, submitted in the **Department of Software Engineering**, Delhi Technological University is an authentic record of my own work carried out during the period from **2021** to **2025** under the supervision of **Dr. Abhilasha Sharma**.
The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

Candidate's Signature

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

Signature of Supervisor(s) **Signature of External Examiner**

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CERTIFICATE BY THE SUPERVISOR

Certified that **Parul Sharma** (enrollment no. 2K20/PHDCO/504) has carried out her research work presented in this thesis entitled **"Development of Deep Learning Models to Improve Plant Biosecurity for Sustainable Agriculture"** for the award of **Doctor of Philosophy** from Department of Software Engineering, Delhi Technological University, Delhi, under my supervision. The thesis embodies results of original work, and studies are carried out by the student herself and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

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Abstract

Agriculture is the golden thread that fastens all the sustainable development goals globally. Its profound relationship to the global economy, biodiversity, and human history is unquestionable. The increasing environmental concerns have transitioned agriculture from conventional to sustainable practices. This transformation prioritizes ecological balance, long-term agriculture productivity, and natural resource conservation. However, plant stress and indiscriminate use of chemicals significantly threaten agricultural productivity and quality, undermining the pillars of agricultural sustainability. In this context, plant biosecurity becomes a crucial element of sustainable agriculture, focusing on monitoring, preventing, and managing pests, diseases, and invasive species that endanger crop health. Achieving plant biosecurity begins with identifying plant stress, which requires continuous monitoring of the agricultural landscape. However, traditional techniques and manual inspection are time-consuming and require domain expertise, making automated monitoring solutions crucial for effectively identifying biotic stress and strengthening crop protection and food security.

Digitalization, particularly deep learning, has emerged as a powerful tool for data analysis in many areas, including agriculture. Researchers from various disciplines leverage deep learning for stress monitoring and propose innovative solutions to address plant resilience, sustainability, and biosecurity issues. However, they face challenges in deploying proposed solutions in real-world settings. To address this, a systematic literature review was conducted to identify key research gaps. The identified challenges include the lack of available datasets, an over-reliance on supervised learning, high costs associated with data labelling, neglect of computational efficiency metrics, limited generalizability of models, and regional disparities in research output.

This work also comprehensively evaluates the strengths, weaknesses, opportunities, and threats of employing deep learning in the field of monitoring plant biotic stress. By examining internal and external factors influencing technology development and implementation, the analysis highlights advantages that can drive progress while addressing challenges that may hinder adoption. Ultimately, this evaluation offers a balanced perspective on the potential impacts of deep learning applications on the future of plant biosecurity, considering both opportunities and risks.

Considering the challenges identified through literature review and motivated by the *Digital Agriculture Mission*, the authors propose a new framework using semi-supervised and ensemble learning. This framework utilizes unlabelled data, reduces annotation costs and efforts, and enhances classification and detection models for monitoring plant disease. The proposed framework was rigorously validated with benchmark datasets, a crucial process as it provides reassurance of the framework's effectiveness and potential for practical application. The testing process, which demonstrated significant performance improvements in classifying plant diseases and outperforming existing methods, ensures that the proposed framework is reliable and effective.

Additionally, this study explores the potential of integrating sustainable computing with deep learning to maintain the ecological facet and balance the three pillars of sustainable agriculture practices: social, economic and environmental. Consequently, the *Comprehensive Sustainable Smart Agriculture Framework* is introduced to address the often-neglected environmental aspect of agriculture sustainability. This framework incorporates two crucial facets of sustainable computing: software and deployment optimization, aimed at improving model efficiency to reduce energy consumption and computational demands. To validate the Comprehensive *Comprehensive Sustainable Smart Agriculture Framework*, we propose and test a novel model, *Sustainable Smart Agriculture Model* , specifically designed for plant disease classification in Indian crops. The Sustainable Smart Agriculture Model surpasses existing state-of-the-art models, showcasing outstanding performance while requiring fewer resources.

This research further advances plant biosecurity by exploring the feasibility of popular deep learning object detection models for accurately locating weeds in Indian cotton farms. This approach addresses a major challenge encountered by cotton farmers in India, who often struggle with the effective management of weeds. By providing accurate and timely identification of weed species, the proposed model empowers farmers to implement targeted interventions.

This thesis presents deep learning models to enhance plant biosecurity for sustainable agriculture, thereby supporting the three pillars of sustainability—social, economic, and environmental—and fostering their synergistic interaction. This comprehensive contribution emphasizes the critical role of integrating advanced technologies to attain long-term sustainable agricultural practices.

List of Publications

This thesis is mainly based on the following peer-reviewed articles:

Papers Published in International Journals

- **Journal 1: Sharma, P.**, & Sharma, A. (2024). "A novel plant disease diagnosis framework by integrating semi-supervised and ensemble learning". *Journal of Plant Diseases and Protection*, 131(1), 177-198. `https://doi.org/10.1007/s41348-023-00803-y` (**SCIE Journal, Impact Factor: 2.2, Publisher: Springer**)

- **Journal 2:** Sharma, A., & **Sharma, P.** (2024). "S^2AM: a sustainable smart agriculture model for crop protection based on deep learning". *Journal of Plant Diseases and Protection*, 1-25. `https://doi.org/10.1007/s41348-024-00934-w` (**SCIE Indexed Journal, Impact Factor: 2.2, Publisher: Springer**)

- **Journal 3: Parul, S.**, & Abhilasha, S. (2025). "Deep learning to improve plant biosecurity and agriculture sustainability: A systematic literature review". *CABI Reviews*, 20(1), 0009. `https://www.cabidigitallibrary.org/doi/abs/10.1079/cabireviews.2025.0009` (**Scopus Indexed Journal, CiteScore: 2.2, Publisher: Centre for Agriculture & Bioscience International**)

Papers Published in International Conferences

- **Conference 1:** Sharma, A., & **Sharma, P.** (2024, July). "Weed Detection in Indian Cotton Farms Using Deep Learning" *International Conference on Artificial Intelligence and Information Technologies (ICAIIT 2023)*, India, pp 8-14. `https://doi.org/10.1201/9781032700502-2` (**Scopus Indexed Conference**)

- **Conference 2:** Sharma, A., & **Sharma, P.** (2024, July). "Integration of deep learning and plant biosecurity toward sustainable agriculture: A SWOT analysis". In AIP Conference Proceedings (Vol. 3168, No. 1). AIP Publishing. Presented in *International Conference on Recent Advancements in Computing Technologies & Engineering (RACTE 2023)*,India `https://doi.org/10.1063/5.0219003` (**Scopus Indexed Conference**)

Paper(s) Under Review

- **Journal 1: Sharma, P.**, & Sharma, A. "HINDIPESTBERT: Sustaining Human Health and Agriculture Yields with NLP Driven Solution using Hindi Textual Data", *ACM Transactions on Asian and Low-Resource Language Information Processing*, Submitted in August, 2024 (**SCIE Journal, Impact Factor: 1.8, Publisher:Association for Computing Machinery**)

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List of Abbreviations

DL Deep Learning

ML Machine Learning

NLP Natural Language Processing

CNN Convolutional Neural Network

RNN Recurrent Neural Network

LSTM Long Short-Term Memory

ViT Vision Transformers

GAN Generative Adversarial Network

FAO Food and Agriculture Organization

GFSI Global Food Security Index

GHI Global Hunger Index

DAM Digital Agriculture Mission

SLR Systematic Literature Review

SWOT Strengths, Weaknesses, Opportunities, and Threats

CV Computer Vision

GHG Greenhouse Gas

GPU Graphics Processing Unit

IoT Internet of Things

UAV Unmanned Aerial Vehicles

TL Tranfer Learning

S^{2}AM Sustainable Smart Agriculture Model

S^{2}A Comprehensive Sustainable Smart Agriculture Framework

AI Artificial Intelligence

MHSA Multi-Head Self-Attention

MLP Multi-Layer Perceptrons

FLOPs Floating-point operations

CPU Central Processing Unit

CAM Class Activation Map

NRCWS National Research Council of India

SSD Single Shot Detector

YOLO You Only Look Once

DETR DEtection TRansformer

mAP mean Average Precision

IoU Intersection over Union

MS COCO Microsoft Common Objects in Context

R-CNN Region-based Convolutional Neural Network

RQ Research Question

IC Inclusion Criteria

EC Exclusion Criteria

PRISMA Preferred Reporting Items for Systematic reviews and Meta-Analyses

ACM Association for Computing Machinery

IEEE Institute of Electrical and Electronics Engineers

Q1 Quartile 1

ANN Artificial neural network

VGG Visual Geometry Group

SDGs Sustainable Development Goals

GELU Gaussian error linear unit

ReLU Rectified linear unit

GDP Gross domestic product

JPEG Joint Photographic Experts Group

LLMs Large Language Models

Chapter 1

Introduction

Food is an essential component for survival and an integral part of life. Agriculture, the principal food production sector, is crucial in meeting this essential need. It serves vital nutrition to individuals and families, ensuring access to crucial vitamins and minerals. Moreover, it is a foundation of employment, economic growth, and sustainability [1]. However, pests, diseases, and weeds threaten agriculture and sustainability by reducing crop yields, lowering produce quality, and increasing production costs [2, 3]. These biotic stressors lead to widespread crop failures, disrupt food security, and mandate the overuse of chemicals, which can be detrimental to the environment.Furthermore, their resistance to control measures and climate-driven expansion into new areas worsen the problem, making sustainable agriculture harder to maintain.

Given the above-mentioned challenges, plant biosecurity is crucial in safeguarding agriculture from the disastrous impact of biotic stressors. By implementing stringent measures for early detection, prevention, and control, plant biosecurity helps to mitigate the risks to crop health and ensures the sustainability of agricultural practices [4, 5, 6]. It is crucial for improving food security, lowering reliance on poisonous chemicals, and advancing resilient farming practices against evolving biotic threats.

Recently, Deep Learning (DL) has emerged as a powerful tool for enhancing plant biosecurity through precise and efficient monitoring of diseases, pests, and weeds. Through advanced image recognition and pattern analysis, DL models can detect early signs of biotic stress in crops with high precision, even in large-scale agricultural environments [7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19]. This allows for timely interventions, reducing the spread of pathogens, pests weeds and minimizing crop losses. By automating monitoring, DL supports proactive management, strengthening plant biosecurity and promoting sustainable agriculture. It enhances decision-making by providing early, accurate insights into plant health conditions.

Building on the significant potential of DL in enhancing the plant biosecurity—by enabling precise and efficient monitoring of diseases, pests, and weeds, this chapter offers a comprehensive overview of the domain under study. It begins with a problem statement identifying key issues and challenges in applying DL to automate biotic stress monitoring. Further, this chapter outlines the research objectives guiding this investigation, detailing the study's goals and intended outcomes. Additionally, it delves into the significance of the research, highlighting its relevance in advancing sustainable agricultural practices and enhancing plant biosecurity measures. By addressing these critical areas, the chapter lays the groundwork for the detailed exploration and analysis presented in subsequent chapters.

1.1 Background

This section delves into the elementary concepts intrinsic to the research title, namely sustainable agriculture, plant biosecurity, and deep learning. By analyzing these components, the author aims to inaugurate a basic understanding of how plant biosecurity measures can reinforce sustainable agriculture practices and how advancements in DL technology are revolutionizing the monitoring of biotic stressors. This discussion sets the stage for understanding the intersection of these fields and their collective importance in promoting resilient agricultural systems.

1.1.1 Sustainable Agriculture

Sustainable agriculture refers to the farming practices that aim to fulfil society's current food and textile needs without endangering future generations to meet their needs [20, 21]. Sustainable agriculture is grounded on three main pillars, as presented in Figure 1.1, environmental health, economic profitability, and social equity [22]. These pillars ensures that agricultural practices are productive, environmentally friendly, and beneficial to society. A comprehensive examination of each of these pillars is given below:

- **Environmental Health**: This pillar is dedicated to mitigating farming's environmental impact and bolstering agriculture's reliance on natural resources. Its primary components encompass soil management, water conservation, pest management, and biodiversity preservation.
- **Economic Profitability**: This pillar affirms that agricultural systems must be economically profitable for both small-scale farmers and large agribusinesses. The

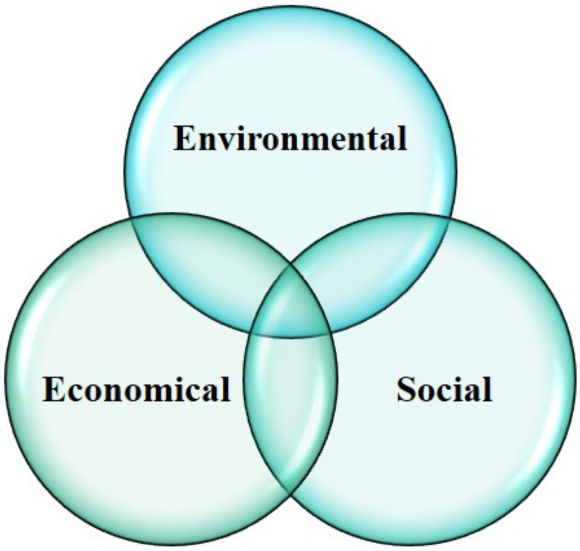


Figure 1.1: Three Pillars of Sustainable Agriculture

main elements of this pillar include efficiency and productivity, market opportunities, cost and risk management.

- **Social Equity**: This pillar ensures that agriculture's benefits are equitably distributed and that it contributes positively to the community. The primary components of this pillar include fair labour practices, community engagement and development, access to resources, gender equality, education and capacity building, health and nutrition, and cultural respect.

1.1.2 Plant Biosecurity

Plant biosecurity comprises a set of actions intended to prevent the entry and transmission of harmful organisms, pests, diseases, and invasive species that pose serious risks to agriculture, horticulture, and ecosystems [4, 23]. It is pivotal for ensuring food safety, food security, trade, market access, and development, significantly influencing the profitability and sustainability of the agriculture sector [6]. Various biotic factors, including pathogens, pests, and weeds, pose significant threats to plant security, as detailed below:

- **Pathogens**: Pathogens are biological organisms, such as fungi, bacteria, nematodes, and viruses, that can cause plant disease symptoms. These organisms have the potential to significantly reduce the productivity and quality of crops and, in severe cases, can lead to the destruction of entire crops. Pathogens spread very quickly and cause massive damage to plant health and agricultural systems [24].

- **Pests**: Pests interfere with crop production by feeding on various parts of plants, including leaves, stems, fruits, and roots. Pests in agricultural fields can lead to substantial losses in crop yield and quality. Pests can also act as vectors for diseases, further exacerbating their detrimental effects on plant health. Effective pest management is essential to mitigate these risks and protect agricultural productivity [25].

- **Weeds**: Weeds are unwanted, persistent plants that compete with crops for essential resources such as light, water, and nutrients. The presence of weeds in agricultural fields can significantly impede the growth of crop plants, leading to reduced yields and lower-quality produce. Weeds adaptability to burgeon in varied surroundings and their defiance to control actions drive them as a perpetual challenge in plant biosecurity [26].

Given the pervasive impact of these biotic threats on agricultural productivity, it is imperative to develop effective strategies to combat them. Addressing the threats mentioned above requires comprehensive strategies, as illustrated in Figure 1.2, to ensure the sustainability and profitability of plant industries, and explained below:

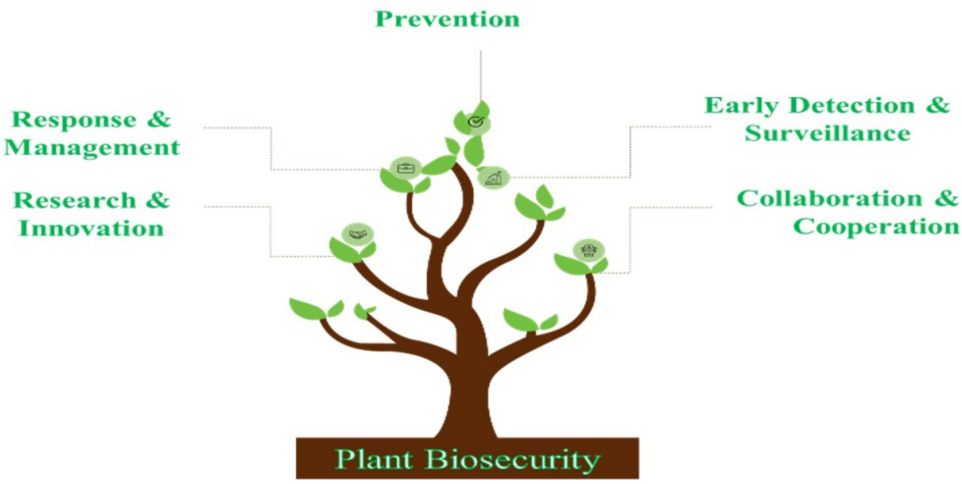


Figure 1.2: Elements of Plant Biosecurity

- **Prevention**: This element focuses on averting the introduction of exotic diseases, pests, and weeds into new regions. This can be achieved through stringent biosecurity measures at borders and points of entry, ensuring that harmful organisms do not infiltrate and establish themselves in non-native environments. By implementing rigorous inspection protocols and quarantine regulations, the spread of invasive species can be effectively minimized [27].

- **Early detection and surveillance**: This involves continuous monitoring and surveillance activities to identify the presence of pests, diseases, and weeds at the earliest possible stage. Advanced detection technologies and regular field inspections provide timely information that enables swift and effective responses to potential stress. This helps curb the proliferation of threats before they become widespread [28].
- **Response and management**: This element includes different approaches to regulate and lessen the effects of identified threats. Various methods to manage and reduce the impact of pathogens, pests and weeds include chemical treatments, biological control agents, and mechanical removal of stressors [29].
- **Research and innovation**: This pillar focuses on advancing the scientific understanding and technological capabilities for managing agricultural threats. It aims to develop improved decision-making and risk analysis tools, enhancing the ability to predict, prevent, and manage biological invasions. Continuous research contributes to the innovation of more effective and sustainable management practices [29].
- **Collaboration and cooperation**: Effective biosecurity requires robust communication and coordination among various stakeholders, including government agencies, research institutions, industry bodies, and the farming community. By fostering collaborative efforts and information sharing, it is possible to build a comprehensive and unified approach to managing biosecurity risks, ensuring that socio-economic drivers are aligned with environmental protection goals [29].

1.1.3 Deep Learning

DL is a specialized branch of Machine Learning (ML) distinguished by its use of deep networks that learn from data in a manner akin to human brain functions. This advanced technology uses deep neural networks with many layers as illustrated in Figure 1.3, leveraging enhanced computing power and sophisticated training techniques to analyze complex patterns in large data sets [30, 31]. DL models are particularly skilled at automatically and adaptively learning rich, hierarchical data representations. This makes them exceptionally suited for managing complex, unstructured inputs in tasks like image recognition [32], Natural Language Processing (NLP) [33], audio synthesis [34] and many more.

In contrast to traditional ML models, which are highly dependent on manual feature engineering and domain expertise to select pertinent data features, DL models excel at independently identifying and learning essential features for classification directly from raw data. This inherent capability enhances their scalability as data volume and complexity increase—areas where traditional models might falter—and boosts flexibility and performance [35, 36]. DL models can be readily adapted to new tasks with minimal architectural modifications, and they consistently outperform traditional models in complex, high-dimensional tasks across various domains, such as speech recognition and image classification [37, 38, 39].

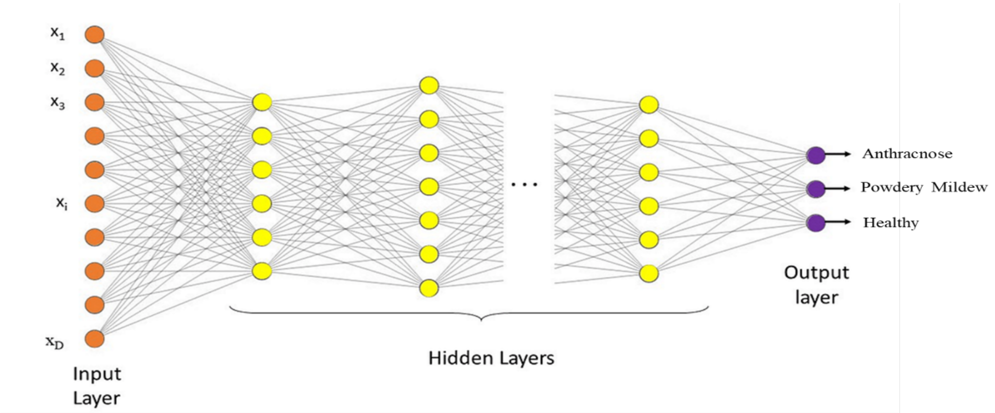


Figure 1.3: Basic Neural Network

Among the leading techniques in plant biotic stress monitoring, Convolutional Neural Network (CNN) [40] stand out for their exceptional performance in image-based stress monitoring, effectively identifying patterns and anomalies in plant health. Recurrent Neural Network (RNN)[41] and Long Short-Term Memory (LSTM) [42] networks effectively analyse time-series data, capturing temporal dependencies in environmental conditions affecting plant health. Further, transformers [43], initially developed for NLP, are powerful for handling sequential data, enabling the model to focus on different parts of the sequence for better prediction. Vision Transformers (ViT) [44] extend the concept of transformers to image analysis by dividing images into patches and processing them similarly to sequences of text, resulting in high accuracy and efficiency in visual tasks. Additionally, Generative Adversarial Network (GAN) [45] are increasingly used for data augmentation, creating synthetic images to enhance model training and robustness.

1.2 Motivation

The pressing challenges of ensuring food security are becoming more critical as global demand continues to rise. The Food and Agriculture Organization (FAO) projects that food production must increase by at least 50% to meet the needs of a population expected to reach 9 billion by 2050, emphasizing the urgency for sustainable solutions [46]. Despite this necessity, up to 40% of global crop yields are lost annually due to plant biotic stresses such as pests, diseases, and weeds [47]. Additionally, the 96% increase in global pesticide usage from 1990 to 2021 has raised significant environmental and health concerns [48, 49, 50]. These alarming statistics underscore the critical need for developing DL models to enhance plant biosecurity. Such models can facilitate early detection and efficient monitoring of biotic stressors. By doing so, they can reduce reliance on pesticides while ensuring agricultural productivity and sustainability.

While global issues demand attention, addressing local challenges is equally critical to bolstering food security and sustainability. In India, which has the world's largest cropland area at 168.91 million hectares, agricultural yields significantly trail behind those of countries with smaller croplands [51]. This disparity is reflected in India's fluctuating rank on the Global Food Security Index (GFSI)—68th out of 113 countries in 2022—and its ranking of 107th out of 121 on the Global Hunger Index (GHI) in the "serious" category [52, 53], underscores the urgency for effective interventions.

The introduction of Digital Agriculture Mission (DAM) is poised to revolutionize agricultural practices by enhancing productivity, efficiency, and sustainability. This initiative aligns with the need for robust plant biosecurity measures in India, where agricultural yields are underperforming, and food security remains a significant concern [54]. By leveraging digital technologies, such as DL, this mission offers a pathway to more effective monitoring of plant biotic stress, reducing reliance on harmful chemicals and enabling early detection and monitoring of pests, diseases, and weeds. Improving plant biosecurity through digital innovations is essential for tackling local issues in India as well as supporting global initiatives to promote sustainable farming practices and achieve food security. Thus, to ensure agriculture sustainability on a local and global scale, DL must be incorporated into plant biosecurity strategies.

1.3 Problem Statement

The growing threat posed by plant biotic stresses to agricultural sustainability and global food security is a vital concern, yet prevailing DL models for plant biosecurity, specifically monitoring biotic stress have a number of unresolved issues.

Current DL models rely heavily on supervised learning, which requires large amounts of labeled data that are often scarce, particularly in diverse environments. Moreover, most studies focus predominantly on leaf datasets, neglecting other crucial plant parts such as roots, stems, and fruits. While hybrid models show promise, they are frequently overlooked, and many existing models struggle to generalize across varying conditions. Additionally, the limited understanding and explainability of these models create trust issues among practitioners, while computational inefficiency hampers large-scale applications.

Furthermore, research often overlooks regional disparities and the simultaneous occurrence of abiotic and biotic stresses, such as nutrient deficiencies and diseases. Therefore, to enhance plant biosecurity and advance sustainable agriculture, there is a critical need for more reliable, scalable, and effective models.

1.4 Research Objectives

This thesis aims to leverage DL technology to advance plant biosecurity and sustainable agriculture. It offers innovative solutions that improve agricultural yields, quality and sustainability by filling critical research gaps founded by a systematic literature review. The main objective is to align with the DAM and promote digital tools in agriculture for ecological balance, food security, and long-term sustainability. To achieve the above-mentioned goals, this thesis is centred around three primary objectives:

- **Research Objective 1**: To seek the convergence of Deep Learning and Plant Biosecurity as a step towards the Digital Agriculture Mission.
- **Research Objective 2**: To explore the existing data sources and bridge the gap of limited datasets to train the plant disease identification models.
- **Research Objective 3**: To propose a novel model for Plant Biosecurity to strengthen the pillars of sustainable agriculture.

The first research objective aims to comprehensively review the current literature on the application of DL in plant biosecurity. This analysis will identify strengths, research gaps, and opportunities to effectively apply DL in this field, contributing to sustainable agriculture. The second objective focuses on developing a novel framework inspired by semi-supervised learning and optimized through ensemble learning to address the challenge of limited labelled data in this domain. By utilizing labelled and unlabeled data, this objective aims to address the problems like data scarcity and over-reliance on labelled data. The third research objective aims to design a lightweight model to overcome the limitations of existing heavy and resource-intensive models, thus improving computational efficiency. This thesis seeks to bridge the gaps in current DL approaches to advance plant biosecurity for sustainable agriculture by achieving these objectives.

1.5 Contributions of Thesis

Agriculture is the fundamental thread that intertwines all global sustainable development goals. However, the rapid growth of the population and the degradation of ecosystems have placed significant stress on the pillars of sustainable agriculture, food security, and crop protection. Inspired by the DAM, this research explores the integration of DL in crop protection, with a particular focus on plant biosecurity. Despite the potential of DL, the Systematic Literature Review (SLR) revealed that existing automated solutions for monitoring biotic stresses in agriculture are insufficient. The SLR identified critical challenges in applying DL to biotic stress monitoring, leading to the developing and validating of two novel frameworks for plant disease identification. These frameworks, validated through innovative models, demonstrated high efficiency in aligning with the DAM's goals, promoting plant biosecurity and agriculture sustainability by reducing excessive chemical usage.

Additionally, the research proposed a model to enhance weed detection in Indian cotton farms, contributing to improved crop yields and economic benefits while minimizing the indiscriminate use of herbicides. This research introduces sustainable and innovative solutions that contribute to preserving agricultural yields, improving crop quality, and minimizing pesticide use through efficient resource management. These approaches support sustainability by enhancing livelihoods and promoting safer farming practices. Moreover, the study provides essential insights beneficial to diverse agricultural stakeholders. Farmers can apply these insights to refine their cultivation and stress management strategies. At the same time, researchers can use these findings to investigate further novel solutions and methodologies, potentially catalyzing significant advancements in plant pathology.

Table 1.1 illustrates the mapping between the research objectives and the corresponding research publications that fulfil each objective's requirements.

1.6 Thesis Organization

This thesis is structured to provide an overview of work done during the Ph.D. Each chapter is meticulously crafted to build upon the preceding sections, ensuring a logical flow and coherence throughout the thesis. The organization of the thesis is as follows:

- Chapter 1: **Introduction**

  This chapter provides a comprehensive overview of the thesis, starting with the problem statement and identifying the key issues and challenges in achieving plant biosecurity and agricultural sustainability. It outlines the specific research objectives that guide the investigation, detailing the study's goals and intended outcomes. Furthermore, the chapter delves into the significance of the research, explaining its

Table 1.1: Mapping of Research Objectives with the Corresponding Publications

Research Objective(s)	Publication(s)
RO1: To seek the convergence of Deep Learning and Plant Biosecurity as a step towards the Digital Agriculture Mission	1. Sharma, A., & **Sharma, P.** (2024, July). "Integration of deep learning and plant biosecurity toward sustainable agriculture: A SWOT analysis". In AIP Conference Proceedings (Vol. 3168, No. 1). AIP Publishing. Presented in *International Conference on Recent Advancements in Computing Technologies & Engineering (RACTE 2023)*, India. `https://doi.org/10.1063/5.0219003` (**Scopus Indexed Conference**) 2. **Parul, S.**, & Abhilasha, S. (2025). "Deep learning to improve plant biosecurity and agriculture sustainability: A systematic literature review". *CABI Reviews*, 20(1), 0009. `https://www.cabidigitallibrary.org/doi/abs/10.1079/cabireviews.2025.0009` (**Scopus Indexed Journal, CiteScore: 2.2, Publisher: Centre for Agriculture & Bioscience International**) 3. **Sharma, P.**, & Sharma, A. "HINDIPESTBERT: Sustaining Human Health and Agriculture Yields with NLP Driven Solution using Hindi Textual Data", *ACM Transactions on Asian and Low-Resource Language Information Processing*, Submitted in August, 2024 (**SCIE Journal, Impact Factor: 1.8, Publisher:Association for Computing Machinery**)-Under Review
RO2: To explore the existing data sources and bridge the gap of limited datasets to train the plant disease identification models.	1. **Sharma, P.**, & Sharma, A. (2024). "A novel plant disease diagnosis framework by integrating semi-supervised and ensemble learning". *Journal of Plant Diseases and Protection*, 131(1), 177-198. `https://doi.org/10.1007/s41348-023-00803-y` (**SCIE Journal, Impact Factor: 2.2, Publisher: Springer**)
RO3: To propose a novel model for Plant Biosecurity to strengthen the pillars of sustainable agriculture	1. Sharma, A., & **Sharma, P.** (2024). "S^{2}AM: a sustainable smart agriculture model for crop protection based on deep learning". *Journal of Plant Diseases and Protection*, 1-25. `https://doi.org/10.1007/s41348-024-00934-w` (**SCIE Indexed Journal, Impact Factor: 2.2, Publisher: Springer**) 2. Sharma, A., & **Sharma, P.** (2024, July). "Weed Detection in Indian Cotton Farms Using Deep Learning" *International Conference on Artificial Intelligence and Information Technologies (ICAIIT 2023)*, India, pp 8-14. `https://doi.org/10.1201/9781032700502-2` (**Scopus Indexed Conference**)

relevance and importance in advancing sustainable agricultural practices and enhancing plant biosecurity measures. By addressing these critical areas, the chapter sets the stage for the detailed exploration and analysis in subsequent chapters.

- Chapter 2: **Systematic Literature Review**

  This chapter presents the current trends, gaps, and advancements in this area by systematically reviewing the existing research. The SLR synthesizes the knowledge accumulated in these domains and establishes a solid foundation for the subsequent research presented in this study. It highlights the significance of ongoing innovation and progress in sustainable agriculture and plant biosecurity by providing the required context and explanation for the selected research area.

- Chapter 3: **Integration of Deep Learning and Plant Biosecurity: Strengths, Weaknesses, Opportunities, and Threats (SWOT) Analysis**

  This chapter examines the strategic integration of DL with plant biosecurity to promote sustainable agriculture, using a SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis. This SWOT analysis provides a balanced overview of the current landscape and the future potential of DL in enhancing plant biosecurity and achieving sustainable agriculture.

- Chapter 4: **A Novel Plant Disease Diagnosis Framework to Overcome Data Scarcity**

  This chapter addresses a significant gap in existing research on plant disease diagnosis, focusing on issues such as the unavailability of comprehensive datasets, high annotation costs, and the non-conformity of existing models. A novel framework utilizing semi-supervised and ensemble learning techniques has been proposed in this chapter.

- Chapter 5: **S^2AM: A Model for Sustainable Crop Protection**

  This chapter introduces a novel model utilizing the potential of sustainable computing and DL to tackle critical agricultural challenges, reduce resource expenditure, and promote sustainable agricultural practices. The chapter details the architecture and functionality of the proposed model, explaining how it integrates various DL techniques to achieve high accuracy in identifying and classifying plant diseases.

- Chapter 6: **Effective Weed Detection to Enhance Cotton Yield in India**

  This chapter examines various DL algorithms to create a robust weed detection model specifically designed for effective management in Indian cotton fields. The optimal model was identified and presented as the preferred solution for improving weed control strategies through thorough experimentation and analysis.

- Chapter 7: **Conclusion, Future Scope and Social Impact**

  This chapter presents a comprehensive summary of the research work done. Further, the chapter discusses the research work's future directions, how it will benefit societal implications, and how it will assist the next scholars in the field.

1.7 Chapter Summary

This chapter outlines the foundation for this thesis. It explains the necessity and driving forces behind the selected study subject and draws attention to the research gaps, problem statement, and objectives. Additionally, the organization of the thesis is also presented.

Chapter 2

Systematic Literature Review

This chapter presents a comprehensive overview of plant biotic stress identification using deep learning, focusing on monitoring pests, diseases, and weeds. Since its emergence in 2016, this field has seen remarkable growth, with deep learning demonstrating significant potential for plant stress monitoring and improving plant biosecurity. This promise has drawn widespread attention from scholars and researchers globally, resulting in a vast body of literature that explores diverse methodologies and approaches. Given this rapid expansion, a thorough review is essential to showcase the advancements in the domain while critically evaluating the trends and challenges. Thus, this chapter, a systematic literature review, is structured to provide a detailed analysis of plant stress identification using deep learning. This chapter aims to offer a comprehensive state-of-the-art review, identifying research gaps, emerging trends, and challenges in plant biotic stress monitoring using deep learning-based solutions.

2.1 Plant Stress: A Brief Overview

Plant stress is a complex and multifaceted phenomenon that exerts a negative influence on a plant's overall health by interfering with its normal growth, development, and productivity. This stress disrupts vital physiological processes such as photosynthesis, respiration, and nutrient uptake, ultimately leading to reduced yields, stunted growth, or even plant death. Plant stress can be broadly categorized into two main types: biotic and abiotic stress, as presented in Figure 2.1, each having distinct sources and impacts on plant health and productivity [55]. These categories encapsulate various stress factors that plants encounter during their life cycle, and understanding the distinction between them is crucial for effective management and intervention strategies.

2.1.1 Biotic Stress

Biotic stress refers to the challenges induced on plants by living organisms, including pathogens, pests, and weeds. Pathogens, such as bacteria, fungi, viruses, and nematodes, can invade plant tissues, leading to diseases that disrupt normal physiological processes. Similarly, pests, ranging from insects to rodents, can inflict significant damage on plants by feeding on leaves, stems, fruits, and roots. Additionally, weeds compete with the host plants for nutrients, water, and sunlight, frequently leading to stunted development and lower harvests [56].

2.1.2 Abiotic Stress

The detrimental effects of non-living elements on plant growth and development, such as severe temperatures, droughts, salt, and nutrient shortages, are called abiotic plant stress. These stresses interfere with vital physiological functions, obstruct photosynthesis, and lower crop yields and quality. The general health and production of plants can be seriously compromised by such environmental stressors, which presents a significant obstacle to sustainable agricultural practices and food security [57].

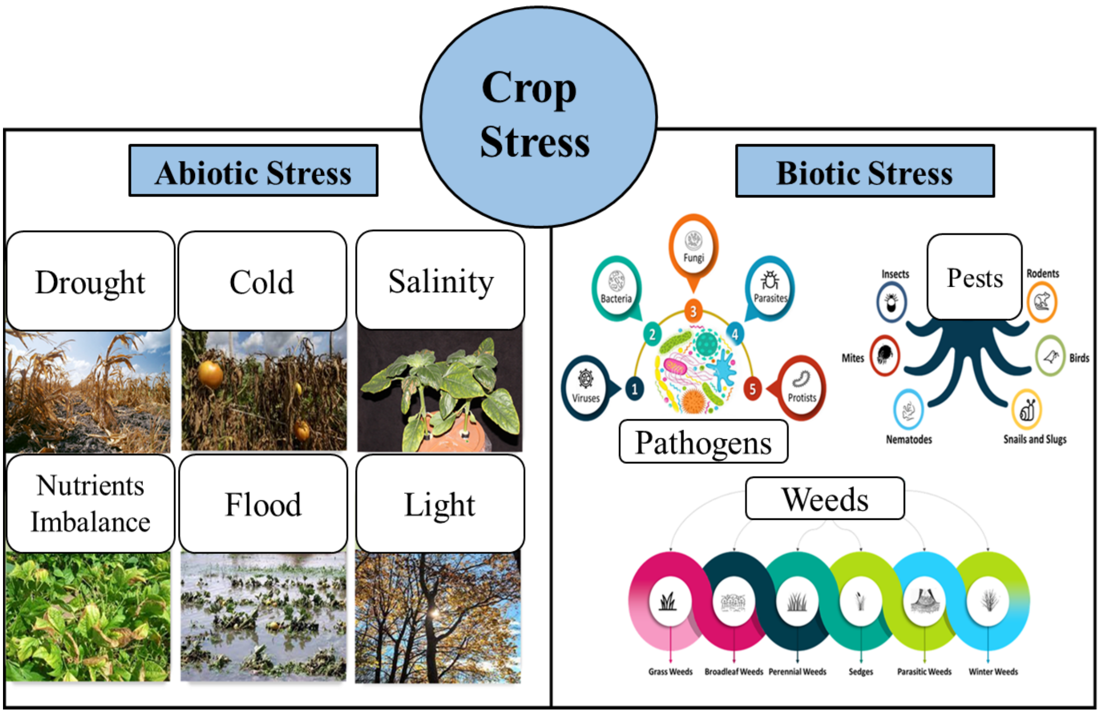


Figure 2.1: Classification of Plant Stress: Distinguishing Between Abiotic and Biotic Stress Factors

Despite the distinct origins of biotic and abiotic stress, their consequences intertwine, exacerbating the challenges faced by plants and agricultural systems. Unlike abiotic stress, where plants can sometimes adapt, biotic stress often requires immediate intervention to prevent significant yield losses and economic damage. Furthermore, biotic stress can result in long-term problems with the health of the soil and secondary diseases, therefore prompt and efficient management is crucial for sustainable agriculture [58] .

2.2 Key Operations for Plant Biotic Stress Monitoring Using Deep Learning

DL-based plant biotic stress monitoring is a cutting-edge approach that leverages advanced Artificial Intelligence (AI) techniques to improve the identification and management of biotic stressors affecting plants. This methodology encompasses several sophisticated processes, including classification, segmentation, and detection, each playing a critical role in effectively monitoring plant health [59]. These operations significantly enhance the accuracy and efficiency of monitoring pests, disease, and weeds. These key operations are elaborated upon below and visually presented in Figure 2.2

Classification assigns a categorical label to an input based on its inherent features by training a model to identify and recognize underlying patterns. In comparison *Detection* identifies and locates objects within an image or video frame by predicting their bounding boxes and associated class labels. Whereas *Segmentation* partition an image into distinct regions or segments, typically by classifying each pixel into a specific category, to understand the image's detailed structure and content comprehensively.

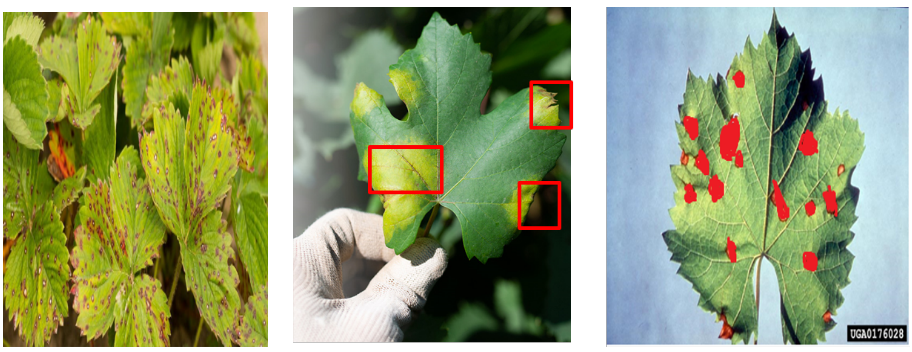


Figure 2.2: Core Operations for Plant Biotic Stress Monitoring Using Deep Learning

2.3 Systematic Mapping Methodology

In this systematic investigation, the authors carefully review DL-based primary studies relying on textual and/or image data to monitor plant biotic stress. These data modalities are generally less computationally and storage-intensive than others, making them advantageous for deployment in real-world agricultural settings. This analysis includes an extensive exploration of DL operations tailored to segment, classify, and detect diseases, pests, and weeds. Adopting the systematic review framework outlined in the literature [60], this methodological approach is structured around three fundamental phases: planning, execution, and summarization. In the planning phase, detailed protocols are established for formulating research questions, gathering relevant literature, and defining selection criteria. In the execution phase, articles are carefully selected using keyword searches across prominent scholarly publication platforms. Finally, the summarization phase critically evaluates existing methodologies and elucidates their strengths, limitations, and potential implications.

2.3.1 Research Questions

The primary objective of this study is to elucidate the current advancements and challenges in DL based plant biotic stress monitoring, thereby constructing an extensive body of knowledge. This research is centred around the questions formulated and presented below:

- **RQ1:** What patterns have emerged in applying deep learning to address biotic stresses in plants since 2016?
- **RQ2:** Which primary biotic stresses in plants have been addressed using deep learning technology?
- **RQ3:** How is deep learning revolutionizing in-situ biotic stress recognition?
- **RQ4:** Which deep learning algorithms are employed for monitoring biotic stress, and how are they revolutionizing biotic stress monitoring?
- **RQ5:** To what extent has deep learning been implemented in proposed solutions?
- **RQ6:** What are the key characteristics of the datasets used for training and evaluating deep learning models in plant stress monitoring?
- **RQ7:** What performance metrics are employed to evaluate the effectiveness of deep learning models in monitoring biotic stress?

- **RQ8:** To what extent are the explainability and interpretability of deep learning models considered in plant biotic stress monitoring?

2.3.2 Search Strategy

In the next step, the search strategy for this SLR was scrupulously crafted to answer the specified research questions framed, ensuring a comprehensive coverage of relevant literature. To frame the search strategy, the following steps were performed following well-known guidelines in the literature.

A. Keyword Identification

After selecting the databases, relevant keywords were identified based on the research questions, objectives, and existing studies in the field. Synonyms and related terms are also considered to ensure comprehensive coverage. The specific terms used in the search strategy are listed in Table 2.1

Table 2.1: Comprehensive Overview of Keywords and Synonyms Considered in the Systematic Literature Review

Thematic Areas	Keywords
Biotic Stress	Disease / Pest / Insect/ Weed / Biotic / Stress / Pathology / Infection / Contamination/ Phenotyping / Pathogen
Technology	Deep Learning / DL / Convolutional Neural Network / CNN / Vision Transformer / ViT / Transformer / Computer Vision / DNN
Operation	Identification / Classification / Detection / Localization /Prediction / Monitoring / Recognition / Count / Segmentation
Domain	Agriculture / Crop / Plant / Leaf / Vegetable/ Fruit

B. Search Query Formulation

The identified keywords were carefully combined in a complicated search query. This approach minimized extraneous results while ensuring a comprehensive and accurate search that included all pertinent studies. The search string was created using the boolean operators AND and OR: the boolean operator "OR" was used to combine synonyms, while the boolean operator "AND" was used to connect significant phrases. The resulting search string is presented as follows:

(Disease OR pest* OR Insect* OR weed* OR Biotic OR stress* OR Patholog* OR Infection* OR Contamination OR phenotyp* OR pathogen*) AND ("Deep Learning" OR DL OR "Convolutional neural network" OR CNN OR "Vision Transformer" OR ViT OR Transformer OR "Computer Vision" OR DNN) AND (Identification OR Classification OR Detection OR Localization OR Prediction OR Monitoring OR Recognition OR Count* OR Segmentation) AND (Agriculture OR Crop* OR Plant* OR leaf OR Vegetable* OR Fruit*)*

It is essential to mention that the search string was slightly modified for the IEEE Xplore database, as it does not support many keywords.

C. Inclusion and Exclusion Criteria

In the subsequent step, rigorous inclusion and exclusion criteria were applied to ensure the relevance and quality of the literature incorporated in the SLR. These criteria were meticulously designed to filter studies based on their focus, publication type, date, and language, ensuring the selection of high-quality and pertinent research articles. The selection process was conducted according to the study selection criteria presented in Table 2.2.

Table 2.2: Inclusion and Exclusion Criteria for Selected Studies in the Systematic Literarure Review

Inclusion Criteria (IC)	Exclusion Criteria (EC)
IC1: Empirical studies published in quartile 1 journals	**EC1:** The title, abstract, or content were closely related to our search string but lacked any meaningful semantic connection.
IC2:: Articles published in peer-reviewed journals	**EC2:** Studies published in conferences, book chapters, review articles, thesis, short surveys, and patents
IC3: Studies published from January 2016 until 9 April 2024	**EC3:** Studies without full-text availability
IC4: Studies written, published, or disseminated in English	**EC4:** Duplicate publications from multiple sources
IC5: Studies strictly based on RGB images, text data, video, or any combination thereof	**EC5:** Studies exclusively related to gas, acoustic, and environmental data.
	EC6: Studies based on grey literature or perspective papers.

2.3.3 Data Extraction

The data extraction process in the SLR follows a structured approach, illustrated step by step in the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) flow diagram in Figure 2.3. Initially (July 13, 2023), records were identified from six databases: *Scopus* (2,347 records), *Engineering Village* (1,484 records), *Institute of Electrical and Electronics Engineers (IEEE) Xplore* (157 records), *Springer Link* (3,807 records), *Wiley* (175 records), and *Association for Computing Machinery (ACM)* (15 records), accumulating a total of 7,985 records. It is important to note that SpringerLink initially yielded 32,853 articles. To narrow this down, authors filtered for content relevant to the computer science discipline, resulting in 3,807 articles. This set includes surveys and may contain conference papers, book chapters, etc., which need to be manually excluded, as there is no way to select journal articles only in Springer Link. Table II.1 presents the various fields for selecting primary studies from the respective databases.

In the screening phase, 996 duplicate records were removed, resulting in 6,479 unique records. These records underwent title and abstract screening, leading to the exclusion of 5,003 records. During the eligibility phase, 1,476 records were assessed through full-text evaluation based on predefined inclusion and exclusion criteria. This assessment resulted in the exclusion of 919 full-text articles due to reasons such as being outside of quartile 1, exclusively related to gas, acoustic, and environmental data, focusing solely on ML, Computer Vision (CV), fuzzy logic, or image processing, not being fully accessible, being retracted, or not utilizing DL. Ultimately, 557 articles met the inclusion criteria and were incorporated into the systematic review. Further, 188 new studies were included through snowballing and performing the search again to account for new articles published between July 14, 2023, and April 9, 2024. A complete and reliable study of the pertinent literature was ensured by the 745 papers that made up the final evaluation as a result of this exhaustive procedure.

2.4 Results and Discussions

In this section, the author precisely synthesize the data from 745 primary studies, a testament to the thoroughness and rigour of the research process. This level of detail and care supports formulating answers to the eight research questions, instilling confidence in the reliability of this study's findings.

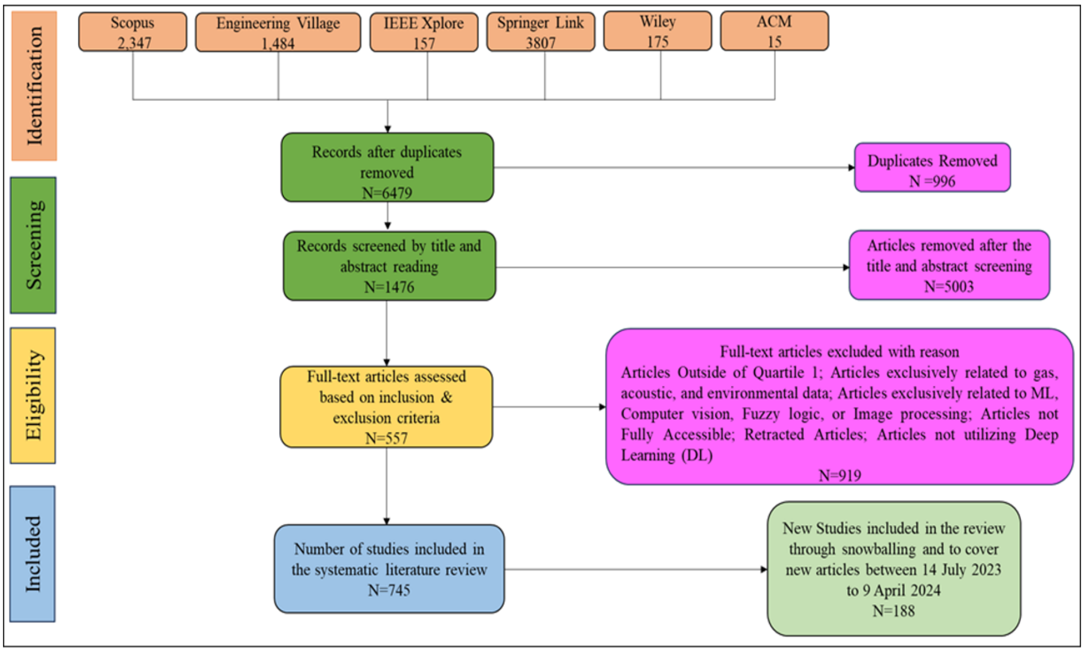


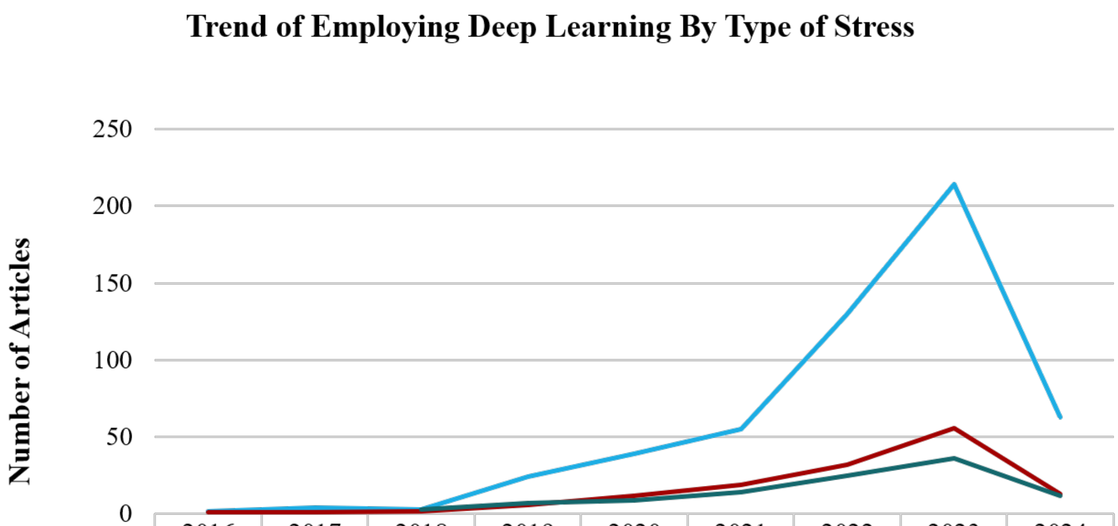
Figure 2.3: PRISMA Flow Diagram Detailing the Selection Process of 745 Studies Included in the Systematic Literature Review

2.4.1 RQ1: What Patterns Have Emerged in Applying Deep Learning to Address Biotic Stresses in Plants Over the Last Few Years?

Research Question (RQ)1 seeks to examine the emerging trends in applying DL to monitor biotic stresses in plants over recent years. To address this inquiry comprehensively, this RQ is subdivided into the following components: Year-wise trend of publications and venues/sources of publications.

A. The Year-Wise Trend of Publications

Upon examining the primary studies, the author identified significant trends in using DL technology to monitor biotic stresses in plants, specifically in pests, weeds, and diseases, spanning 2016 to 2024. Figure 2.4, shows a consistent increase in research publications over the years, indicating a growing interest and investment in applying DL to plant health monitoring. This upward trend reflects technological advancements and the recognition of the potential of DL to solve complex agricultural problems. From 2016 to 2019, publications on DL applications for biotic stresses in plants remained relatively low and stable, indicating an initial exploration phase. However, from 2020 to 2022, there was a noticeable upward trend, with a steady increase in publications each year, suggesting early explorations were promising and spurred further research and development. The year 2023 saw a dramatic spike in research activity across all categories, particularly in disease monitoring, likely due to technological advancements, increased funding, and successful applications of DL models. Although 2024 shows a decline in publications, this is likely because the data only includes articles up to April, and the entire year's trend may be higher once all publications are accounted for.



	2016	2017	2018	2019	2020	2021	2022	2023	2024
Disease	2	4	3	24	39	55	130	214	63
Pest	1	1	2	6	12	19	32	56	13
Weed			3	7	9	14	25	36	12

*Note**: Although 745 articles have been included in this review, the figure represents 781 articles to account for those addressing multiple stresses.*

Figure 2.4: Year-wise Trend in Employing Deep Learning by The Type of Biotic Stress

B. Venues of Publications

Figure 2.5 and Table II.2 presents the number of articles published in various academic journals Quartile 1 (Q1), highlighting the venues where research on applying DL to monitor biotic stresses in plants has been disseminated."Frontiers in Plant Science" leads with 157 articles, indicating its prominence in this research area. Other significant sources include "IEEE Access" with 119 articles, and "Multimedia Tools and Applications" with 82 articles. Several journals, such as "Agronomy," "Remote Sensing," and "Plants," have also contributed a substantial number of publications. Additionally, numerous journals with fewer articles reflect a broad interest across various scientific fields. This distribution showcases the interdisciplinary nature of the research, encompassing fields like agriculture, computer science, and environmental studies.

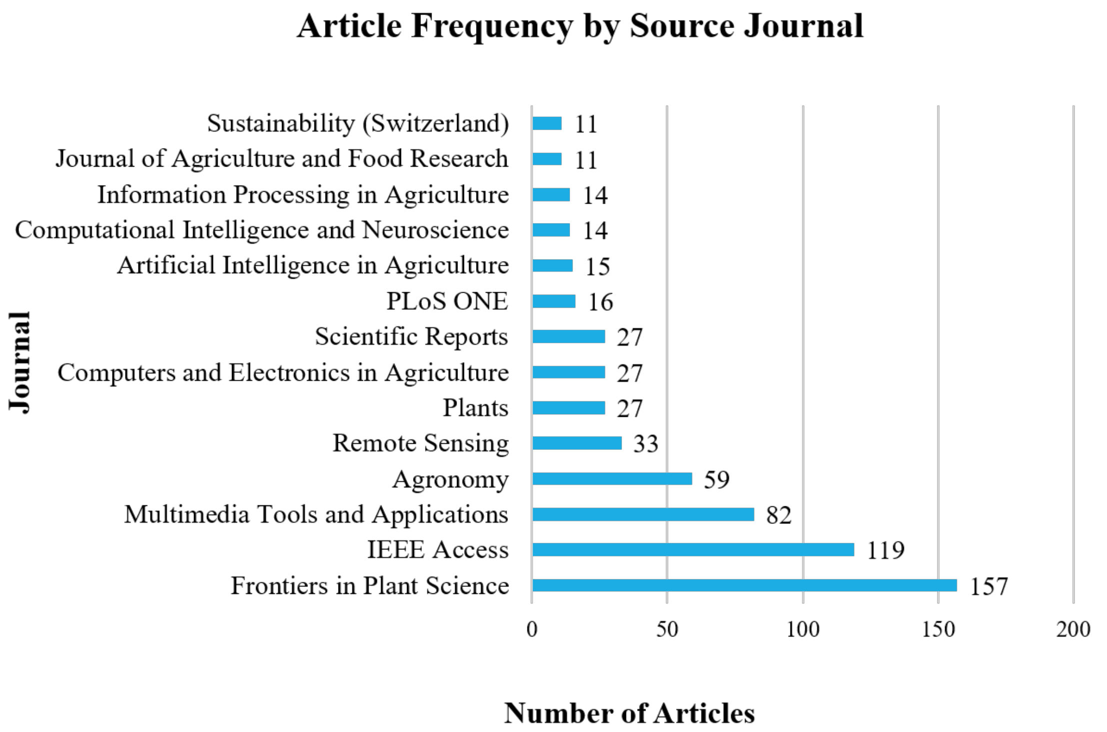


Figure 2.5: Distribution of Primary Studies Considered in the Systematic Literature Review Across Various Sources

2.4.2 RQ2: Which Primary Biotic Stresses in Plants Have Been Addressed Using Deep Learning Technology?

RQ2 investigates which biotic stress in plants has been most frequently targeted using DL. To answer this, Figure 2.6 presents a chart that analyzes the data collected from the primary studies, as detailed in Appendix I. The data indicates that *disease* has been the most frequently targeted biotic stress, with a significant number of 484 articles dedicated to this area. This highlights the critical impact of plant diseases on agricultural productivity and the extensive research efforts to mitigate this stress using advanced computational methods. The prominence of disease-related studies underscored the importance of understanding and controlling plant diseases through DL.

Weeds represent the second most addressed biotic stressors following diseases, with 104 articles. Because weeds can negatively impact crop development and productivity, weed control is an important topic for research. Furthermore, the volume of research on *pest* monitoring—103 articles—reflects the seriousness of pest infestations on crops and the interest in using DL to develop efficient pest monitoring solutions. Maintaining crop health and avoiding significant production losses require this effort. Furthermore, 14 publications devoted to research on combined biotic and abiotic stresses have shown that

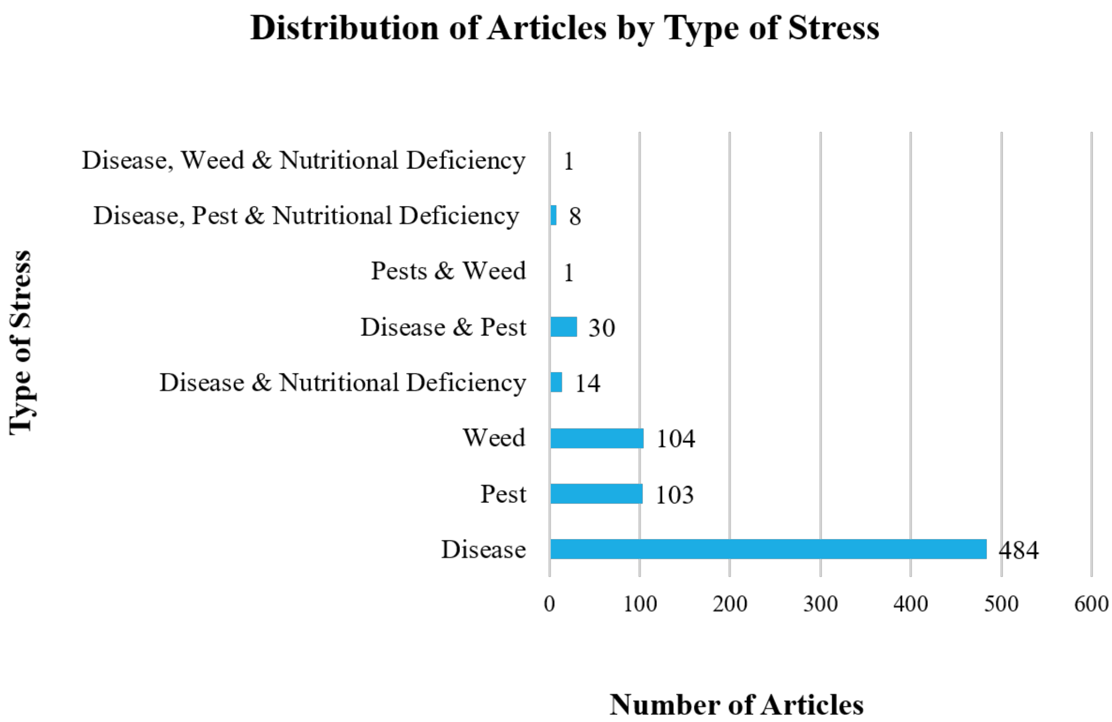


Figure 2.6: Distribution of Primary Studies Considered in the Systematic Literature Review by Type of Stress

the combination of *disease & nutritional deficiency* stands out. This shows increasing interest in learning how biotic and abiotic (nutritional deficit) elements interact and affect plant health.

Additionally, the ability to address multiple stresses simultaneously is essential for developing comprehensive biotic stress monitoring solutions, considering this *disease & pest* category have been explored in 30 articles, showing efforts to tackle more complex scenarios where plants are affected by multiple biotic stressors. However, other combinations, such as *pests & weeds*, and *disease, weed & nutritional deficiency*, have received minimal attention, with only one article each. This suggests potential gaps in research and opportunities for further exploration in these areas. The combined stressor of *disease, pest & nutritional deficiency* has been addressed in 8 articles, reflecting an emerging interest in studying the multifaceted nature of plant stress and developing integrated solutions using DL.

2.4.3 RQ3: How is Deep Learning Revolutionizing in-situ Biotic Stress Recognition?

Figure 2.7 provides a comprehensive analysis of the operational approaches adopted in primary studies to examine innovations in plant biotic stress monitoring using DL. The chart's X-axis categorizes different operations/tasks performed, such as classification, detection, segmentation, and their combinations, while the Y-axis indicates the number of articles for each operation.

The figure reveals that *classification* is the most frequently documented task, with 458 articles as presented in Appendix I (D2; D3; D4; D&P1; D5; P3; D6; D7; P4; D8; D9; W6; P5; D&P3; D12; D13; P7; P8; D16; D17; D18; D19; D22; D23; D24; D25; W7; P13; D&P4; P15; D29; D30; W9; D32; D33; P17; D39; D41; D42; D44; D46; P20; D48; D49; D50; D53; D55; D57; D59; D60; D61; D63; W18; D66; D67; D68; D69; D71; W22; D73; D74; D76; D77; D79; D82; D84; D85; D86; D88; D89; D90; D91; P28; W26; D94; D&P7; D96; D99; D100; D101; D,P&ND2; W28; D103; D105; D106; D107; D108; D109; D111; D112; D116; D&ND3; D117; P37; D118; W30; D120; W32; D121; D122; D123; D124; D125; D126; D127; D128; D129; W33; D,P&ND3; D130; P40; D131; D132; D133; D134; D135; P41; D136; D137; D138; D139; D140; D&P10; D141; D142; D143; D144; W34; D145; D146; D147; D&P12; D148; D149; D150; D152; D156; P42; D157; D158; W37; D&P13; D159; D160; D161; D163; P45; D164; D167; W40; W41; P48; D168; W43; D&P14; D171; D172; D173; D175; D176; P49; P50; D179; W44; W46; D182; D&P15; D183; D184; D186; D187; D,W&ND1; W50; D190; D191; D192; D193; P53; D194; D195; D196; D197; D199; D201; W54; W55; W57;D202; D&P16; D203; D204; D&ND6; D&P18; D207; D208; D211; D,P&ND6; D213; D214; D215; D216; D217; D221; D223; D224; D225; D226; W59; D228; D229; D230; D231; D235; D236; D&ND8; W62; D237; D238; D,P&ND8; D&P19; D239; D240; D241; P65; P66; D243; D244; P61D247; P68; D248; D249; D250; W67; P69; D251; D252; D253; D255; D257; D258; D259; D260; D261; D262; D263; D264; D265; D267; D268; D270; D271; D272; D273; D274; D276; D277; D278; D279; D280; D281; D283; D285; D&P20; D287; D288; D289; D290; D291; D292; D293; D296; D297; D298; D300; D301; D302; D303; D304; D305; D306; P70; P71; D307; D308; D309; D310; D311; D313; D314; D315; D316; D317; D318; D319; D320; D321; D322; W71; D323; D325; D326; D327; W72; P74; D328; D329; D331; D333; W73; D334; D335; D336; D337; D338; D339; D340; D341; D343; D345; D346; D348; D349; D350; D351; D352; D353; P77; W78; D&P22; W79; D355; D357; D358; D359; P78; D360; W82; W84; D362; D363; D364; D365; D366; D367; D&P23; D368; D369; D371; D373; D374; P80; D376; D377; D378; D379; D380; D381; D382; D383; D&P24; P84; D385;

D386; D&P25; D388; D390; D391; D392; D393; D394; D395; D&ND9; D396; D398; P86; D401; D402; D403; D405; D406; D&P26; D&P27; D407; D408; D409; D410; P88; D411; D412; D413; D414; D416; D418; D419; D420; D&ND10; D&P28; D423; D&ND11; D425; D426; D427; D431; D432; P89; D433; D&P29; D435; D436; P102; D437; D438; D439; D440; P92; D442; D443; D444; D445; D446; D447; D448; D449; D450; D451; W97; P96; W98; D452; D453; D454; D455; D456; D457; D460; D462; D463; W100; D464; D466; P100; P103; D467; D468; D469; D472; D473; D474; D475; D476; D477; D&P30; D479; D480; D&ND14; D482; D483; D484) emphasizing its importance in categorizing plant health conditions. This task involves assigning predefined labels to the images/text, making it fundamental in biotic stress recognition. *Detection*, the second most common task with 162 articles (P1; D1; P2; P6; D& D20; P2; D10; W5; P9; D&ND1; P11; W8; P14; D28; P16; D31; D34; P18; D38; D40; D45; W10; W11; W13; D&P5; D&P6; D&ND2; D&ND12; P21; D52; D54; D56; W15; D,P&ND1; W17; P23; D62; D64; D70; D75; W20; W21; P24; W23; D81; D83; W24; P26; D87; P27; D93; D95; P30; D97; P31; D98; W27; P32; D110; D104; D&P9; P33; W29; P34; P35; D115; P36; P38; P39; D&P11; D,P&ND4; D,P&ND5; D,P&ND7; D151; W36; D162; W38; P43; P44; D165; P46; P47; D169; D174; D181; P51; D185; W45; W49; P52; D198; P54; D200; W56; D205; D&P17; P56; D206; P58; P59; D212; P60; D220; D222; D227; W35; D232; D242; D245; W65; P67; D254; W68; D256; D269; D295; D299; P72; D324; P73; D&P21; P75; W74; D347; P76; W77; P&W1; D356; W81; W83; D370;D372; P79; D375; W86; P81; P82; P83;D389; P85; W88; D404; P87; D421; D422; W92; W93; P90; P91; W95; P94; P95; P97; D458; W99; P98; P99; P101; W102; W103; W104; D471), focuses on identifying and localizing specific instances of biotic stress, such as pests, weeds, or plant disease spots. This task is crucial for precise intervention and management. *Segmentation* in 60 articles (D36; D37; D51; P22; W16; W19; D72; P25; W25; D119; W31; P61; D153; D154; D155; D166; D177; D180; W48; W52; W53; D209; D219; W58; W60; W61; P63; D233; D234; P64; W63; W64; W66; D282; D294; D312; W70; D330; D332; W76; D344; D354; D361; W85; W87; D397; D399; W89; D415; W90; W91; D424; D429; D434; W94; D441; W96; D459; W101; D482) involves partitioning an image into segments to isolate regions affected by biotic stress. This task provides detailed spatial information on the extent and distribution of stress, facilitating targeted treatment. Several tasks combine multiple operations to enhance the accuracy and comprehensiveness of biotic stress monitoring. *Segmentation & classification*, performed in 17 articles (W4; D11; D14; D15; D21; P10; D47; D58; D78; D80; P29; D178; D218; D284; W80; D428; D479), combines segmenting the image to identify stress regions and classifying these regions to determine the type of stress. *Data generation/augmentation & classification*, implemented in 11 articles (D35; P19; D114;

D170; D188; D189; P55; D&ND7; D210; D387; D472), generates synthetic data to augment datasets and improve classification models' robustness. Other notable combinations include tasks integrating *dataset curation, segmentation, classification, & detection*. *Segmentation & detection*, undertaken in 10 articles (W1; W2; W3; P12; D26; D&P8; D102; W39; W69; D286), for identifying different plant parts and stress signs, allowing precise targeting of affected areas. *Data generation/augmentation & detection*, performed in 3 articles (W14; P62; D384), enhances detection models by generating synthetic data to simulate stress conditions. Similarly, *improving resolution & classification* (P57; D246; D275), also executed in 3 articles, improves image clarity for accurate stress type classification. *Segmentation, classification & detection* (D92; D462), implemented in 2 articles, integrates these operations for a holistic monitoring approach. Data augmentation combined with these techniques, also executed in 2 articles (D&ND4; W75), to train models on diverse data.

The other category addresses specific stress monitoring operations, showcasing how DL revolutionize in-situ biotic stress recognition. It includes the following tasks, each documented in one article: 1) *Classification, segmentation & remedy suggestion* (D266): This operation involves classifying the biotic stress, segmenting the affected areas within the plant, and suggesting appropriate remedies. It provides a comprehensive approach that identifies and localizes stress and offers actionable solutions for the detected issues. 2) *Not applicable* (D&ND13): This study represents a task that does not fit into conventional categories or is irrelevant to the context, as the study only proposed data without performing any operation. 3) *Detection and tracking of insects' behaviour, movement, size, and habits* (P93): This specialized task involves detecting insects and tracking their behaviour, movement, size, and habits. It is crucial for understanding pest dynamics, developing effective pest management strategies, and providing detailed information about pest activity for targeted interventions. 4) *Classification and caption generation* (D430): This task combines the classification of biotic stress with generating descriptive captions. It enhances interpretability by providing detailed descriptions of the identified stress conditions, facilitating better understanding and communication of the findings. 5) *Data generation/augmentation* (D417): This task involves generating synthetic data to augment existing datasets, which helps improve the robustness and accuracy of DL models. This approach reduces issues related to limited or imbalanced datasets by creating additional training data. 6) *Classification, detection, and caption generation* (D400): An integrated approach that includes classifying stress types, detecting specific stress factors within the plant, and generating descriptive captions. This combination provides a comprehensive biotic stress analysis, offering detailed identification and explanatory context. 7) *Detection and spread distance* (D342): This task detects biotic stress and estimates the spread distance within the affected area. Understanding the spatial extent of the stress is vital for effective management and containment strategies. 8) *Segmentation, classification, and plant survival* (D43): This combined task involves segmenting and classifying stress areas while assessing the plant's survival chances. It provides insights into the impact of stress on plant health and potential outcomes, guiding more informed decision-making. 9) *Data generation/augmentation and segmentation* (D65): This approach uses data generation/augmentation techniques to enhance segmentation models, improving their performance in identifying and isolating stress regions within the plant. 10) *Classification and localization* (D27): This task combines classifying the type of biotic stress with localizing it within the plant. It is essential for targeted intervention, as precise localization allows for more effective treatment applications. 11) *Classification and biomass estimation* (W12): This combined task classifies biotic stress and estimates the biomass of the affected plants. It provides a measure of the impact of stress on plant growth, which is crucial for evaluating the overall health and productivity of the crops. 12) *Segmentation & weed density estimation* (W47): This task involves segmenting the image to identify weeds and estimating their density. It is essential for weed management, as understanding weed density helps plan and execute effective control measures. 13) *Classification and economic loss estimation* (D&ND5): This approach classifies biotic stress and estimates its potential economic loss. Assessing the financial impact of stress helps prioritize management efforts and allocate resources effectively. 14) *Detection and fresh weight prediction* (W42): This task detects biotic stress and predicts the fresh weight of the plants. Providing an estimate of the yield impact helps in understanding the severity of the stress and its potential effects on crop productivity. 15) *Detection and biomass estimation* (W51): This task focuses on detecting biotic stress and estimating the biomass. It highlights the importance of quantifying the impact of stress on plant growth and health. 16) *Detection and crop loss estimation* (D113): This approach detects biotic stress and estimates crop loss. Understanding the potential yield loss is essential for planning mitigation strategies and ensuring food security. 17) *Segmentation, improving resolution, and classification* (D466): The task includes image segmentation, improving its resolution, and classifying the type of biotic stress. Enhancing the resolution improves the accuracy and detail of stress recognition, facilitating more precise management actions. Classification, detection, and segmentation tasks are common, which emphasizes their essential roles in efficient in-situ biotic stress recognition. Combined tasks demonstrate how various procedures can be integrated into a single task, highlighting the growing intricacy and sophistication of DL models. More precise and thorough stress recognition, necessary for efficient plant health monitoring, can be obtained from these advanced activities.

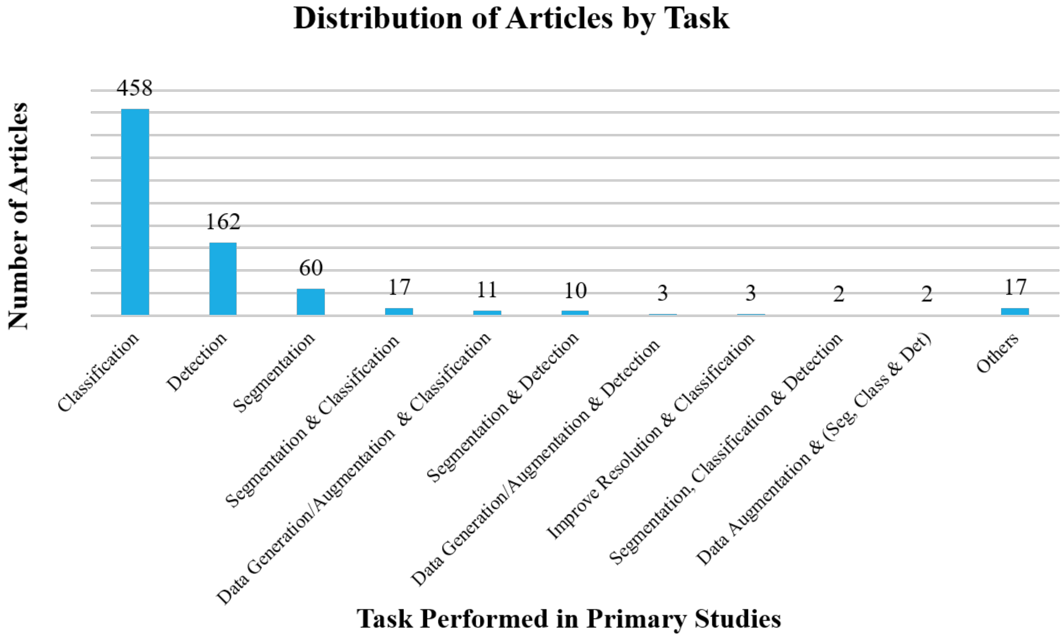


Figure 2.7: Breakdown of Deep Learning Tasks/Operations Employed in Primary Studies Considered in the Systematic Literature Review

2.4.4 RQ4: Which Deep Learning Algorithms are Employed for Monitoring Biotic Stress, and How are They Revolutionizing Biotic Stress Monitoring?

A comprehensive overview of the various DL algorithms used for monitoring biotic stress and their transformative impact on recognition methods is presented in Figure 2.8 to address research question 4. The authors of this study classify the different algorithms employed in 745 primary studies into 12 categories, indicating the number of articles documenting their application in biotic stress monitoring 1) *CNN*: CNNs dominate the list with 635 articles (P1; W1; D1; D2; D3; P2; D&P1; D6; D7; P4; D8; D&P2; D9; W3; W4; D10; W5; W6; P5; D11; D13; D14; P7; D15; P8; P9; D16; D17; D&ND1; D20; P10; D22; D23; P11; P12; D25; W7; W8; D26; D&P4; D27; P14; P15; D28; P16; D30; D31; D33; P17; D34; P18; P19; D37; D38; W10; D39; D40; W11; D41; W12; D42; D43; D44; D45; D46; W13; D&P5; D47; P20; D48; D49; W14; D50; D51; D52; D&ND2; P21; D53; P22; D54; D56; D58; W15; D59; D60; D,P&ND1; D61; W17; P23; D62; D63; W18; D64; W19; D66; D67; W20; W21; D68; P24; D69; D70; D71; D72; W22; D73; W23; D74; D75; D76; D77; D79; D80; D81; D82; P25; D83; D84; W24; P26; W25; D86; D87; D88; D90; P27; D91; P28; P29; D92; W26; D93; D94; D95; D&P7; D96; P30; D97; P31; D&P8; D99; D100; W27; D101; P32; D102; W28; D103; D&P9; P33; D107; D108; W29; D109; D110; D111; D112; P35; D113; D115; D116; P36; D&ND3;

D117; P37; D118; D119; D&ND4; W31; D120; P38; W32; D121; D122; D123; D124; D125; D126; D127; P39; W33; D,P&ND3; D130; P40; D131; D132; D133; D134; D135; P41; D136; D137; D138; D139; D140; D&P10; D141; D142; D143; D144; W34; D145; D146; D147; D&P11; W35; D,P&ND4; D,P&ND5; D148; D149; D150; D151; W36; D152; D&P12; D153; D154; D155; D156; P42; D157; D158; W37; D&P13; D159; D160; D161; D162; W38; P43; P44; D163; P45; D164; D165; W39; D166; D167; W40; P46; P47; W41; P48; D168; D169; W42; D&ND5; D&P14; D170; D171; D172; D173; D174; D175; D176; P49; P50; D178; D179; W44; D180; W45; W46; D181; P51; D182; D&P15; D183; D184; D185; W47; D186; D187; D,W&ND1; W48; W49; P52; W50; D190; W51; D192; D193; P53; D194; D195; W52; D196; D197; D198; P54; D199; P55; D200; W53; D201; W54; W55; D202; W56; D&P16; D203; D204; D205; D&ND6; D&P17; D&P18; D206; D207; P58; D208; D209; P59; D,P&ND6; D212; D214; D215; D216; D217; W57; P60; D219; W58; D220; D221; D222; D223; D224; D225; P61; D226; W59; W60; D227; D228; W61; D229; P62; P63; D230; D231; D232; D233; D234; D235; P64; D236; D&ND8; W62; W63; D237; D238; D,P&ND8; W64; D&P19; D239; D240; D241; P65; P66; D242; D243; D245; W65; P67; D247; P68; D248; W66; D249; D250; W67; P69; D251; D252; D253; D254; W68; D255; D256; D257; W69; D258; D260; D262; D263; D264; D266; D267; D268; D269; D270; D271; P70; D272; D273; D274; D276; D277; D278; D279; D280; D281; D282; D283; D284; D285; D286; D&P20; D287; D288; D289; D290; D291; D292; D293; D294; D295; D296; D297; D299; D300; D301; D303; D304; D305; D306; P71; D307; D309; D310; D311; D313; D314; D315; D316; D318; D319; D321; D322; W71; D323; P72; D324; P73; D325; W72; P75; D329; D330; D331; D332; D333; D334; W74; D335; W75; D336; W76; D338; D339; D340; D341; D342; D343; D344; D346; P76; D349; D350; D351; D352; W77; D353; P77; W78; D354; D&P22; P&W1; W79; D355; D356; D357; D358; D359; W81; P78; D360; W82; D362; D363; W83; D365; W84; D366; D367; D&P23; W85; D368; D369; D370; D371; D372; P79; D373; D374; P80; D375; W86; D376; D377; P81; P82; D378; D379; D380; D381; P83; W87; D382; D383; D&P24; D386; D&P25; D388; D389; D390; D391; D392; D393; D395; D&ND9; D396; D397; P85; D398; W88; P86; D401; D402; D404; P87; D405; D406; D&P26; D&P27; D407; D408; D409; D410; P88; D411; D412; D413; D415; D416; D418; D420; D421; D&P28; D&ND11; D424; D425; D427; D429; D431; D432; P89; W92; D433; W93; P90; D&P29; D435; D436; W104; D437; W94; D438; D439; D440; P91; P92; D442; D&ND12; D443; P93; D445; D446; W95; W96; D449; D450; D451; P94; P95; P96; D452; D455; D457; D458; D459; D460; D461; W99; D462; P98; D463; W100; P99; D464; D466; P100; P101; P102; P103; D467; D468; D469; D470; D472; D474; D476; D477; D&P30; D478; W101; D479; D480; W102; D&ND14; D481; D482; W103; D483; D484), highlighting their widespread use in biotic stress recognition. CNN are particularly effective in image-based tasks, making them highly suitable for detecting visual symptoms of biotic stress, such as diseases, pests, and weeds. Their ability to automatically extract and learn features from images has significantly transformed plant stress recognition methods by enhancing accuracy and efficiency. 2) *CNN & GAN:* This combination has been employed in 23 articles (D18; D32; D35; D104; D114; W43; D188; D189; P57; D&ND7; D210; D211; D213; D218; D246; D261; D275; D384; D387; W97; D466; D472; D417) to leverages the strengths of both CNN and newly proposed GAN. GAN generate synthetic data to augment datasets, thereby improving the robustness and accuracy of CNN. This approach addresses data scarcity issues and enhances the training DL models, particularly in scenarios with limited annotated data. It is important to note that only studies specifically proposing a new GAN for biotic stress monitoring are considered here; studies using existing GAN (for general purposes) solely for data augmentation are not included in these 23 articles. 3) *CNN & Transformer:* Integrating CNN with transformers combines the feature extraction capabilities of CNN with the transformer model's advanced sequence modelling and attention mechanisms. This hybrid approach has been applied to 30 articles (P6; D12; D24; D29; D36; D57; W16; D89; D, P&ND2; D244; D337; D347; D361; W89; D403; D422; D430; D434; D448; D456; W2; D&P6; D105; D317; D326; W73; D345; W80; D428; D441), enhances the ability to capture complex patterns and dependencies in the data, improving biotic stress monitoring. It is important to note that the authors omitted ViT in the transformer categories and considered them an independent identity because ViT is specifically designed for image processing tasks, leveraging self-attention mechanisms to handle the spatial structure of images. This distinct focus on visual data processing differentiates them from traditional transformers originally developed for NLP tasks. Therefore, their unique application and design rationale justify treating ViT as a separate category. 4) *ViT*: Vision Transformers apply transformer models directly to image data. They are known for their powerful attention mechanisms, which helps to understand the global context in images. This algorithm has shown promise in improving the accuracy of recognition of biotic stresses and has been employed in 13 articles (D55; W30; D320; D327; P74; P84; D423; D444; D447; D453; D454; D474; D476.). 5) *CNN & RNN:* The combination of CNN with RNN has been exercised in 12 articles (D19; D21; P56; D,P&ND7; D298; D302; D308; D328; D348; D364; D394; D400) to leverage the strengths of both architectures: CNN for spatial feature extraction and RNN for temporal sequence modelling. This combination is beneficial for monitoring the progression of biotic stress over the time. 6)*Transformer:* Transformers, known for their superior sequence modelling capabilities, have been used in 17 articles (W9; D65; D78; D106; P34; D129; D399; D419; D426; W98; P97; D98; D259; W70; W90;

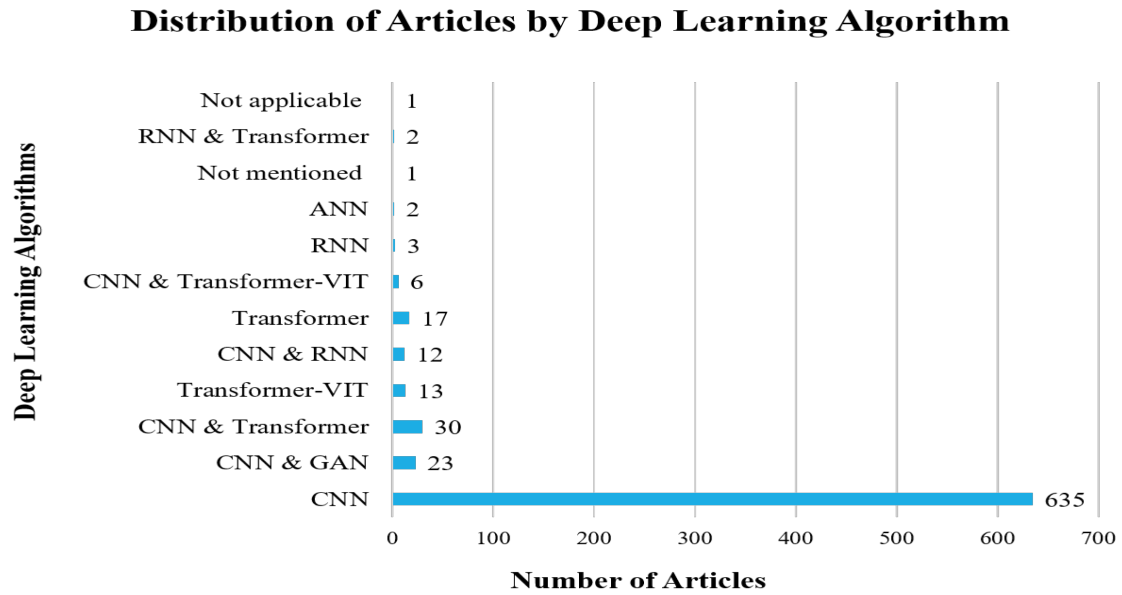


Figure 2.8: Distribution of Various Deep Learning Algorithms Used in the Primary Studies Examined in the Systematic Literature Review

W91; D177), capturing the complex dependencies and patterns in the data. They are particularly effective in scenarios where understanding the temporal progression of stress is crucial; 7) *CNN & ViT:* This combination uses CNN for initial feature extraction and ViT for capturing global context in images, enhancing the overall recognition performance in plant biotic stress identification, six articles (D5; P3; P13; D85; D128; D&P21) have been implemented using this combination. 8) *RNN:* RNN are effective for sequential data processing, making them suitable for monitoring temporal changes in biotic stress, and have been utilized in 3 articles (D191; D265; D385). They help in understanding the progression and dynamics of plant stress over time. 9) *Artificial neural network (ANN):* ANN are foundational neural network models for various tasks and applied to 2 articles (D4; D312) for basic classification and detection tasks in biotic stress monitoring 10) *Not mentioned:* This entry indicates an algorithm not specified in the documentation, suggesting the need for clarity in reporting methodologies (D&ND10). 11) *RNN & Transformer*: Combining RNN and Transformers in 2 articles (D&P3; D414) leverages the temporal sequence modelling capabilities of RNN with the powerful attention mechanisms of Transformers, providing a robust approach for monitoring biotic stress. 12) *Not applicable:* This entry indicates a non-standard or irrelevant approach that does not fit the conventional categories listed (D&ND13).

2.4.5 RQ5: To What Extent Has Deep Learning Been Implemented in Proposed Solutions?

RQ5 aims to analyze the contributions of primary studies in terms of their proposed solutions. The authors of the SLR have classified these contributions into the following categories: algorithm, data acquisition system/dataset, framework, method, metric, model, and tool/application. Figure 2.9 illustrates the correlation between plant stress and the proposed DL solution in the 745 primary studies considered in this SLR. This correlation reveals that *DL models* are the most extensively proposed solution, with 432 articles (D2; D3; D4; D5; D6; D7; D8; D9; D10; D12; D13; D14; D15; D16; D17; D18; D19; D20; D21; D22; D23; D24; D25; D27; D28; D29; D30; D31; D32; D34; D36; D37; D39; D40; D41; D43; D44; D45; D46; D47; D48; D49; D50; D51; D52; D53; D54; D55; D56; D57; D58; D59; D60; D61; D62; D63; D64; D66; D67; D68; D69; D70; D71; D72; D73; D74; D76; D77; D78; D79; D80; D81; D82; D83; D84; D86; D87; D88; D89; D90; D91; D92; D93; D94; D95; D96; D97; D98; D99; D100; D101; D102; D103; D105; D106; D107; D108; D109; D111; D115; D116; D117; D118; D119; D120; D121; D122; D123; D124; D125; D126; D127; D128; D129; D130; D131; D132; D133; D134; D135; D136; D137; D138; D139; D140; D141; D142; D143; D144; D145; D146; D147; D148; D149; D151; D153; D154; D155; D156; D157; D158; D159; D160; D161; D162; D164; D165; D166; D168; D169; D171; D172; D173; D174; D175; D176; D177; D178; D179; D180; D181;D182; D183; D184; D185; D186; D187; D190; D191; D192; D193; D194; D195; D196; D197; D198; D199; D200; D201; D202; D203; D204; D205; D206; D207; D208; D209; D211; D212; D213; D214; D215; D216; D217; D218; D219; D220; D221; D222; D223; D224; D225; D226; D227; D228; D229; D231; D232; D233; D234; D236; D237; D238; D239; D240; D241; D242; D243; D244; D245; D247; D248; D249; D251; D252; D253; D254; D255; D256; D258; D259; D260; D261; D262; D263; D264; D265; D266; D267; D268; D269; D270; D271; D272; D273; D274; D276; D277; D278; D279; D280; D282; D283; D284; D285; D286; D287; D288; D289; D290; D291; D292; D293; D294; D295; D296; D297; D298; D299; D300; D301; D302; D303; D304; D305; D306; D307; D308; D309; D310; D311; D312; D313; D314; D315; D316; D317; D318; D319; D321; D322; D323; D324; D325; D328; D329; D330; D331; D332; D333; D334; D335; D336; D337; D338; D339; D340; D341; D342; D344; D346; D347; D348; D349; D350; D351; D353; D354; D355; D356; D357; D358; D359; D360; D361; D362; D363; D364; D365; D366; D367; D369; D371; D372; D373; D374; D375; D376; D377; D379; D380; D381; D382; D383; D385; D386; D389; D390; D391; D392; D393; D394; D395; D396; D397; D398; D399; D400; D401; D402; D403; D404; D405; D406; D408; D411; D412; D413; D414; D415; D416; D418; D419; D421; D422; D423) D424; D425; D426; D427; D428;

D429; D430; D431; D432; D433; D434; D435; D436; D437; D438; D439; D440; D441; D444; D445; D446; D448; D449; D450; D451; D452; D453; D454; D455; D456; D457; D458; D459; D460; D461; D462; D463; D464; D465; D467; D468; D469; D470; D472; D473; D474; D475; D476; D477; D478; D479; D480; D481; D482; D483; D484) dedicated to developing models for *disease* monitoring. Additionally, 29 articles (D1; D11; D26; D33; D38; D42; D85; D104; D110; D113; D152; D163; D230; D250; D257; D281; D327; D343; D368; D370; D378; D388; D407; D409; D410; D442; D443; D447; D467) focused on developing *practical tools and applications*, strongly emphasizing translating research into deployable solutions for real-world use. Further, 21 articles (D35; D65; D75; D114; D150; D170; D188; D189; D210; D235; D246; D275; D320; D326; D345; D352; D384; D387; D417; D420; D472) proposed new *methods*, highlighting the diverse approaches to tackling plant diseases. *Framework* (D112) and *algorithm* (D167) were proposed in 1 article each. Further, no articles for *data acquisition systems/datasets* and *metrics* are listed, suggesting potential gaps or less emphasis in these areas. The significant focus on models and practical applications underscores the importance of accurate prediction and management techniques in combating plant diseases, reflecting DL's critical role in enhancing agricultural productivity and health. This detailed categorization provides insights into the current state of research and highlights areas for future exploration to fully leverage DL in monitoring plant disease.

Pest monitoring also received considerable attention, with 80 articles (P1; P2; P3; P4; P6; P10; P11; P13; P14; P15; P16; P17; P18; P20; P21; P22; P23; P24; P26; P27; P30; P31; P32; P33; P34; P35; P36; P37; P39; P40; P42; P44; P46; P47; P49; P50; P51; P52; P53; P56; P58; P59; P60; P61; P63; P64; P65; P66; P67; P69; P70; P71; P72; P73; P74; P75; P76; P77; P78; P79; P80; P81; P82; P83; P84; P86; P87; P90; P91; P92; P94; P95; P96; P97; P98; P99; P100; P101; P102; P103) dedicated to creating *DL models* for pest monitoring. Additionally, 18 articles (P5; P7; P8; P9; P12; P25; P28; P29; P38; P41; P43; P45; P54; P68; P85; P88; P89; P93) on *practical tools and applications* highlight efforts to translate these models into actionable solutions. 5 articles (P19; P48; P55; P57; P62) focused on *methods*, reflecting the diverse explored approaches. However, no articles for *algorithms*, *data acquisition systems/datasets*, *frameworks*, and *metrics* indicate potential areas for future research and development.

Weeds monitoring has been addressed in 90 articles(W1; W2; W3; W4; W6; W7; W8; W9; W10; W12; W13; W14; W15; W16; W17; W18; W19; W21; W22; W23; W24; W25; W26; W27; W29; W30; W31; W32; W33; W34; W36; W37; W38; W39; W40; W41; W42; W43; W44; W45; W46; W47; W48; W50; W51; W52; W53; W54; W55; W56; W57; W58; W59; W60; W61; W62; W63; W64; W65; W66; W67; W69; W70; W71; W72; W73; W74; W76; W77; W78; W79; W80; W81; W82; W84; W85; W86;

W87; W88; W89; W90; W91; W93; W94; W95; W96; W98; W100; W101, W104) dedicated to creating *DL models* for weed monitoring. This highlights the significant effort to use advanced computational techniques to address weed-related issues in agriculture. Additionally, 11 articles (W5; W11; W20; W28; W35; W49; W68; W83; W99; W102; W103) proposed *practical tools/applications* that indicate efforts to implement models into actionable solutions. Additionally, 2 articles (W75; W97) focus on *methods*, while one addresses *metrics* (W92) reflecting the diverse approaches being explored. Notably, no articles on *algorithms*, *data acquisition systems/datasets*, and *frameworks* suggest areas for potential future research. This distribution underscores the critical role of model development and practical applications in enhancing weed management strategies through deep learning.

It has been investigated that combined stress is less frequently addressed; the primary focus for combined stress appears to be on *model* development, with the most significant attention given to the *disease & pest* category, which includes 25 articles (D&P1; D&P2; D&P3; D&P4; D&P8; D&P9; D&P10; D&P11; D&P12; D&P13; D&P14; D&P16; D&P17; D&P18; D&P19; D&P21; D&P22; D&P23; D&P24; D&P25; D&P26; D&P27; D&P28; D&P29; D&P30) on models and 3 articles (D&P5; D&P15; D&P20) on *practical tools and applications*. This highlights the effort to utilize DL to manage complex interactions between *diseases & pests*. Additionally, 2 articles (D&P6; D&P6) on *frameworks* indicate some groundwork in supporting models. For the combined stressor of *disease & nutritional deficiency*, 9 articles (D&ND1; D&ND3; D&ND5; D&ND6; D&ND8; D&ND9; D&ND11; D&ND12; D&ND14) focused on models and 3 on methods (D&ND4; D&ND7; D&ND10), reflecting the minor efforts to address the nutritional aspects alongside disease management. Further, 1 article for each *tool/application* (D&ND2) and *dataset/data acquisition system* (D&ND13) identified in this category. The combined stressor of *disease, pest & nutritional deficiency* was addressed in 6 articles (D,P&ND2; D,P&ND3; D,P&ND4; D,P&ND5; D,P&ND6; D,P&ND8) that proposed *models* and 1 on *data acquisition systems* (D,P&ND1) and *tools/applications* (D,PND7) each, suggesting initial steps in integrating multiple stress factors into a cohesive monitoring strategy. *Pests & weeds (P&W1)* and *disease, weed & nutritional deficiency (D,W&ND1)* stressors have minimal focus, with only 1 article for the *model* indicating limited research and development in these areas. The absence of articles in categories such as *algorithms*, *data acquisition systems* (except for one in *disease, pest & nutritional deficiency*), *metrics*, and *tools/applications* across most combined stressors points to significant gaps and potential areas for future research.

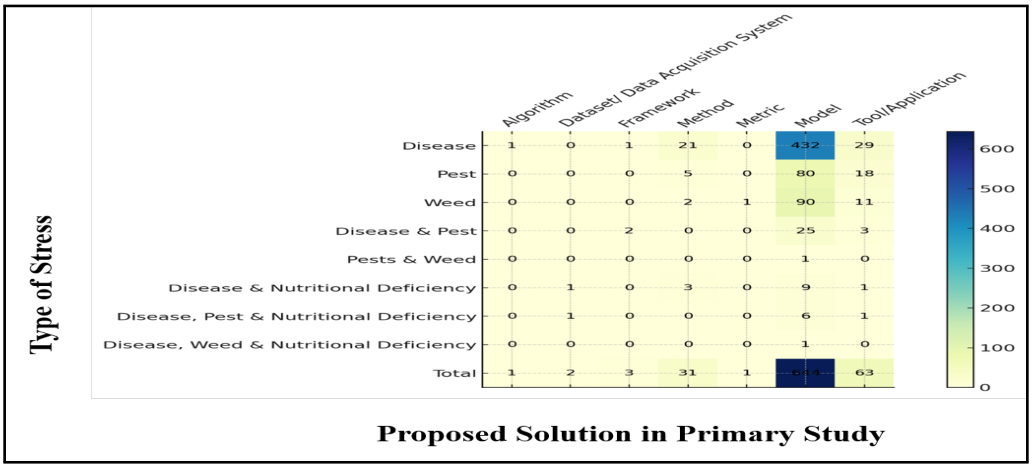


Figure 2.9: Heatmap Illustrating the Distribution of Solutions Proposed in Primary Studies Considered in the Systematic Literature Review

2.4.6 RQ6: What are the Key Characteristics of the Datasets Used for Training and Evaluating Deep Learning Models in Plant Stress Monitoring?

To address RQ6, the authors examined several critical facets, including the modality of the data, dataset accessibility, predominant datasets, crop diversity considered in the primary studies, dataset environment, dataset capturing device, and dataset geographical distribution.

A. Dataset Modality

Figure 2.10 highlights the distribution of research articles based on the data modalities used. The predominant modality is the *image* utilized in 720 articles, indicating a firm reliance on visual data. *Video* and *text* are significantly less common, with only 4 (W34; W43; W55; D265) and 2 (D&P3; D414) articles, respectively, further *image & video* (P11; P12; D81; D&P11; D226; P75) and *image & text* (D19; D89; D116; D&ND11; D430; DP30) are used in 6 articles each. A slightly higher number of articles, 7 (D129; D136; D&P13; P56; D339; D357; D390), use *image & meteorological/environmental data*, suggesting an integrated approach that combines visual data with environmental information. This distribution underscores the importance of image data in research while indicating potential areas for expanding the use of other data modalities and combinations to enrich research outcomes.

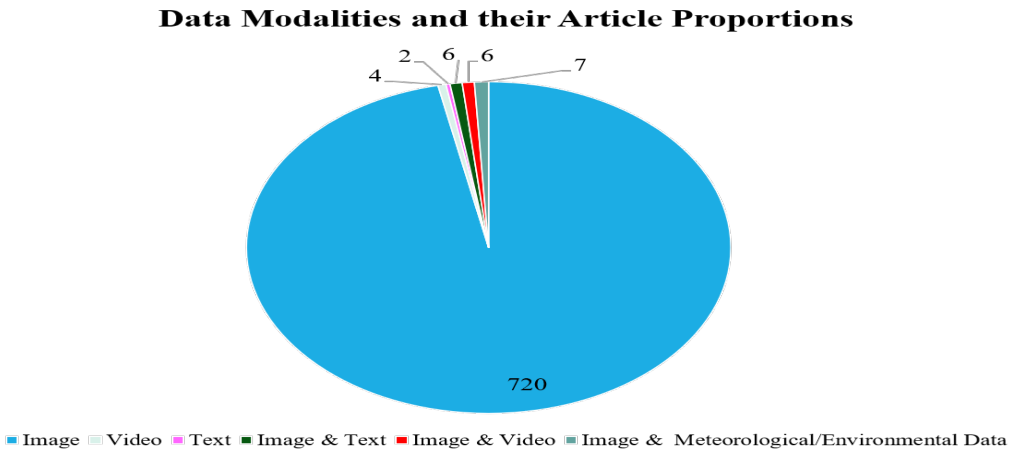


Figure 2.10: Pie Chart Illustrating the Distribution of Various Data Modalities Within the Primary Studies Assessed in the Systematic Literature Review

B. Dataset Accessibility

Figure 2.11 presents a distribution of primary studies according to the dataset availability. 335 articles consider self-gathered data to be kept confidential, indicating that many researchers prefer to collect their data to ensure its relevance and accuracy for their specific studies while maintaining confidentiality. Additionally, 258 primary studies refer to datasets from previous studies, suggesting a reliance on existing research to build upon and validate findings. There are 47 articles where datasets are adapted and enhanced from existing ones, showing efforts to improve and expand on available data. In another 85 articles, datasets were collected personally and released publicly, reflecting a commitment to sharing data with the wider research community. Further, 19 primary studies have no details about their source datasets, raising concerns about transparency and reproducibility. Only one primary study refers to the dataset that is self-gathered and partially released, indicating minimal partial data sharing among researchers.

This data reveals a diverse approach to dataset handling, while many researchers prefer to keep their data confidential, there is also a significant effort to share data publicly by releasing collected data or using and enhancing existing datasets. The reliance on previous studies indicates the importance of building on established research. However, the lack of detail about some datasets' sources suggests a need for greater transparency and data sharing to enhance reproducibility and collaborative efforts in the field.

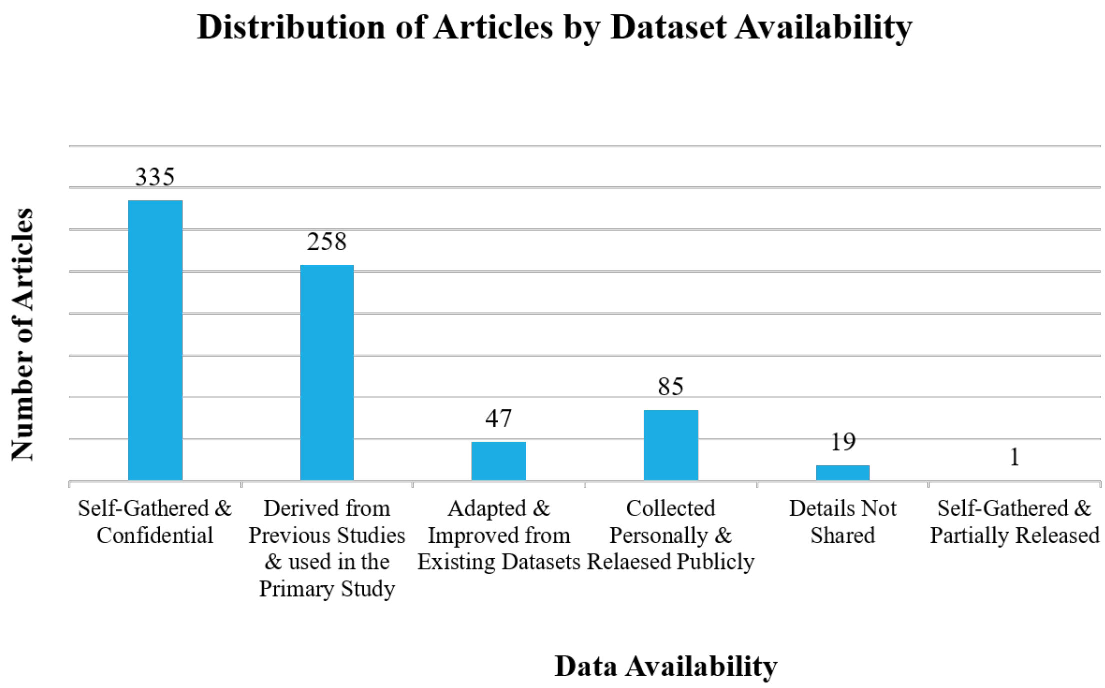


Figure 2.11: Distribution of Primary Studies Considered in the Systematic Literature Review According to the Dataset Availability

C. Predominant Datasets

A detailed breakdown of the named datasets used in biotic stress monitoring, alongside the number of articles utilizing each dataset, is presented in Figure 2.12. The “PlantVillage” dataset is the most extensively used, cited in 114 articles, indicating its prominence and reliability in the research community. The “AI Challenger” dataset follows, with 12 articles referencing it, highlighting its significant role. Other datasets, such as “IP102” and “Kaggle,” are used in 6 and 4 articles, respectively, showing moderate usage in this domain. The DeepWeeds, BoniRob, and Rice Leaf Disease Image Samples are each cited in 3 articles, suggesting a niche but vital role in specific research areas. Additionally, the adapted PlantVillage dataset is used in 7 articles, reflecting efforts to enhance and modify existing datasets for more specific research needs. The “Others” category includes 589 articles, with 194 datasets uniquely named and each used in one or two articles, as detailed in Table II.3. The remaining 395 articles use unnamed datasets, this indicates a diverse range of less commonly used datasets, highlighting the extensive breadth of data sources within the field.

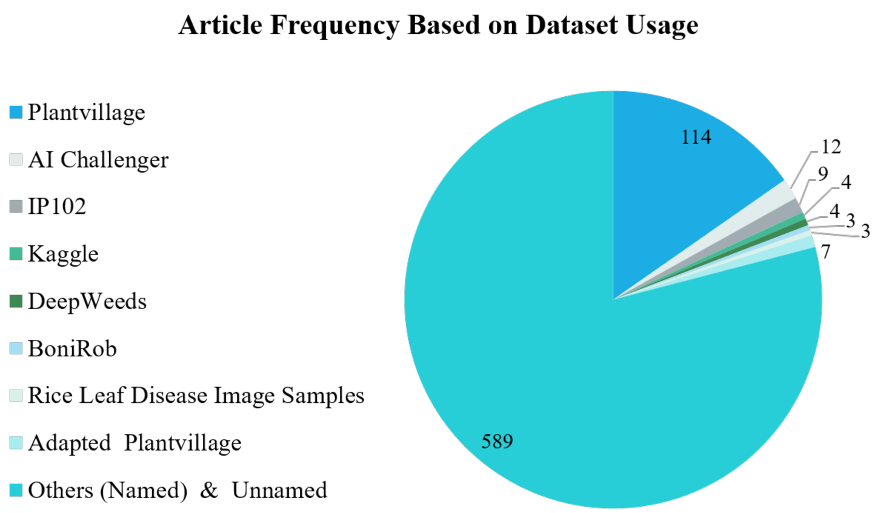


Figure 2.12: Distribution of Primary Studies Included in the Systematic Literature Review Based on the Dataset Utilized

D. Crop Diversity in the Dataset

Figure 2.13 illustrates the distribution of articles based on their crop specificity. The majority, comprising 533 articles, focus on single-crop datasets, indicating a strong preference for specific crops. Multi-crop datasets, used in 145 articles, reflect efforts to develop models applicable to multiple crops, enhancing the versatility of the research. Finally, 67 articles utilize datasets that are either not crop-specific or where the crop information is not mentioned, suggesting a smaller yet significant portion of research focusing on unspecified data sources.

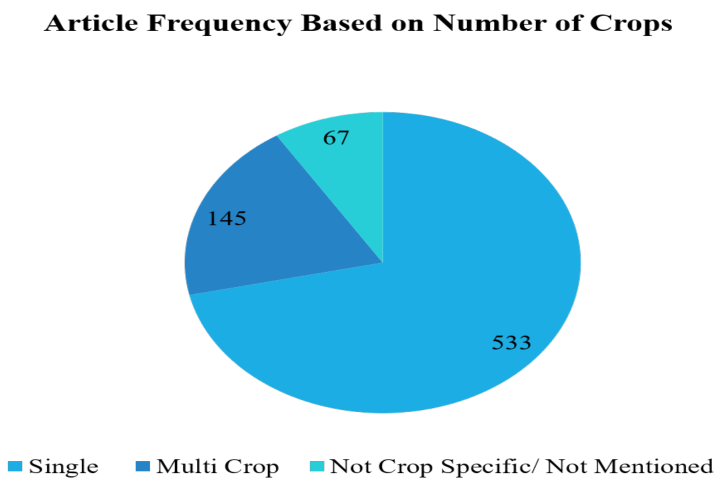


Figure 2.13: Distribution of Primary Studies Referred by the Systematic Literature Review by Crop Diversity

E. Dataset Environment

Figure 2.14 illustrates the various environmental settings of the datasets and the corresponding number of articles associated with each set. Hereafter, “Real/In-field” refers to data collected from farms, fields, and the internet. “Laboratory” indicates data collected in laboratory settings. “Controlled environment” denotes data collected in agricultural institutions or after applying controlled settings, such as data collected against a plain background.

It is evident from the figure that the *real/in-field* environment has the highest number of articles, totalling 410 (P1; W1; D1; W2; P2; D&P1; D5; P3; D6; P4; D&P2; W3; W4; D10; W5; W6; D&P3; P6; D13; D14; D15; P8; D19; D20; P10; D22; D25; W7; P13; W8; D26; D&P4; D27; P14; P15; P16; D30; W9; D32; P17; D34; D35; P19; W10; W11; D41; W12; D42; D46; W13; D&P5; P20; W14; D&ND2; P21; D53; P22; D54; D57; W16; D60; D61; W17; D62; W18; D64; W19; D66; W20; W21; P24; D72; D73; W23; D76; D78; D82; D&P6; P25; D83; W24; D85; P26; W25; D86; D87; D88; D89; D90; P27; P29; D92; W26; D93; D94; D&P7; P30; D97; D&P8; D98; D99; W27; D101; P32; W28; D104; D&P9; P33; W29; D109; P34; D111; P35; D113; D114; D116; P36; D&ND3; D117; P37; D118; W30; D&ND4; W31; W32; D125; D129; P39; P40; D134; D135; P41; D136; D138; D142; D145; D,P&ND4; D148; D151; W36; D152; W31; D156; D157; W37; D160; D161; D162; W38; P43; P44; D163; P45; D165; W39; W40; P46; P47; W41; P48; W42; W43; D&ND5; D&P14; D171; D172; D173; D175; P49; P50; D177; D178; W44; D180; W45; W46; D181; P51; D&P15; D183; D185; W47; D186; D187; W48; W49; P52; W50; W51; D195; W52; D196; D198; P54; P55; W53; W54; W55; W56; D&P16; D204; D205; D&ND6; D&P17; P56; D207; P57; D&ND7; D209; P59; D212; D215; W57; P60; D219; D,P&ND7; W58; D220; D222; D224; D225; P61; W59; W60; D227; W61; P62; P63; D230; D231; D&ND8; W62; W63; D237; D238; W64; D&P19; D240; P65; D244; D245; W65; P67; D247; P68; W66; D249; D250; W67; P69; D252; D253; D254; W68; D256; D257; W69; D259; D265; D269; P70; D273; D285; D286; D291; D293; D294; D295; D296; D298; D303; D304; P71; D307; D315; D316; D317; W70; D319; D320; D321; W71; D324; P73; D325; W72; P74; D&P21; D328; P75; D329; D330; W73; D334; D335; W75; D336; W76; D341; D342; D343; D346; D347; D348; P76; D349; D352; W77; P77; W78; D354; D&P22; P&W1; W79; W80; D355; D357; W81; P78; D361; W82; D364; W83; D365; W84; D&P23; W85; D371; D372; D375; W86; D377; P81; P82; D380; P83; W87; P84; D384; D385; D&P25; D390; D391; D394; D&ND9; D396; P85; W88; D399; P86; W89; D405; D406; D&P26; P88; D411; D413;D414; W90; W91; D&ND10; D&P28; D422; D423; D424; D426; D430; P89; W92; W93; D434; P102; W94; D438;

D440; P91; P92; D&ND12; D443; D444; D447; W95; W96; D450; D451; P95; W97; P96; W98; D456; P97; D457; D458; D460; W99; D463; P98; D464; P99; D467; P103; D468; D470; D476; D478; D&P30; W101; W102; D484; D485). This is followed by the *laboratory* environment with 164 articles (D7; D8; D9; P5; D11; D12; D21; D23; P11; D24; D28; D29; D31; D37; D40; D43; D44; D49; D50; D52; D55; D58; D59; D68; D70; D71; D74; D75; D77; D80; D84; D91; D103; D105; D112; D115; D119; D120; D123; D126; D130; D131; D132; D133; D137; D139; D143; D144; D146; D150; D159; D164; D167; D169; D176; D179; D184; D,W&ND1; D188; D189; D190; D191; D192; D193; D194; D199; D200; D201; D&P18; D206; D208; D210; D211; D213; D214; D217; D218; D228; D233; D234; D235; P64; D239; D241; D243; D246; D251; D258; D260; D261; D262; D263; D266; D268; D270; D272; D274; D275; D276; D277; D278; D282; D287; D289; D297; D300; D301; D302; D305; D306; D309; D310; D311; D313; D314; D331; D340; D344; D345; D350; D358; D359; D362; D363; D367; D368; P79; D373; D381; D382; D387; D389; D393; D395; D398; D403; D410; D412; D417; D419; D427; D429; D431; D432; D433; D435; D436;D437; D439; D441; P93; D448; D452; D455; D459; D460; D464; D465; D468; D470; D479; D480; D&ND14; D481; D482) and the *controlled* environment with 41 articles (D33; D81; D121; D128; D,P&ND3; D140; D141; W34; P42; D166; P53; D216; D226; P66; D283; D288; D290; D292; D318; D323; D326; D327; D333; W74; D337; D338; D366; D379; D386; D392; D402; D407; D418; D425; D&ND13; D453; D472; D473; D474; D475; D479). Other notable entries include *greenhouse*, with 28 articles (D18; D&ND1; D45; D47; D56; W22; D79; P31; D110; P38; W33; D&P11; D&P12; D153; D155; D168; D232; D, P&ND8; D264; D279; D332; P80; D400; D415; D421; P90; D454; W100) and *laboratory & real/in-field*, with 53 (D3; P9; P12; D48; W15; P23; D63; D69; P28; D95; D,P&ND2; D102; D106; D127; D147; D149; D154; D158; D182; D197; D202; D203; D,P&ND6; D221; D229; D236; D255; D271; D281; D&P20; D308; D322; D339; D369; D374; D&P24; D388; D397; D401; D404; P87; D&P27; D409; D416; D420; D428; D&P29; D442; D445; D446; D477) articles. There are also several entries with specific combinations of environments, such as *greenhouse & real/in-field* with 10 articles (D2; D17; D51; D96; D100; D,P&ND5; D174; D248; D267; D356), real/in-field & controlled with 6 articles (D65; D107; D170; D284; D383; W104), and *real/in-field, controlled, laboratory & greenhouse* with 2 articles (D462; W103). Some less common environments, like *aquaponics* (D370), *hydroponics* (D38), and *reference books & real/in-field* (D408), each have only 1 article. Additionally, there are 25 articles where the environment was not explicitly mentioned.

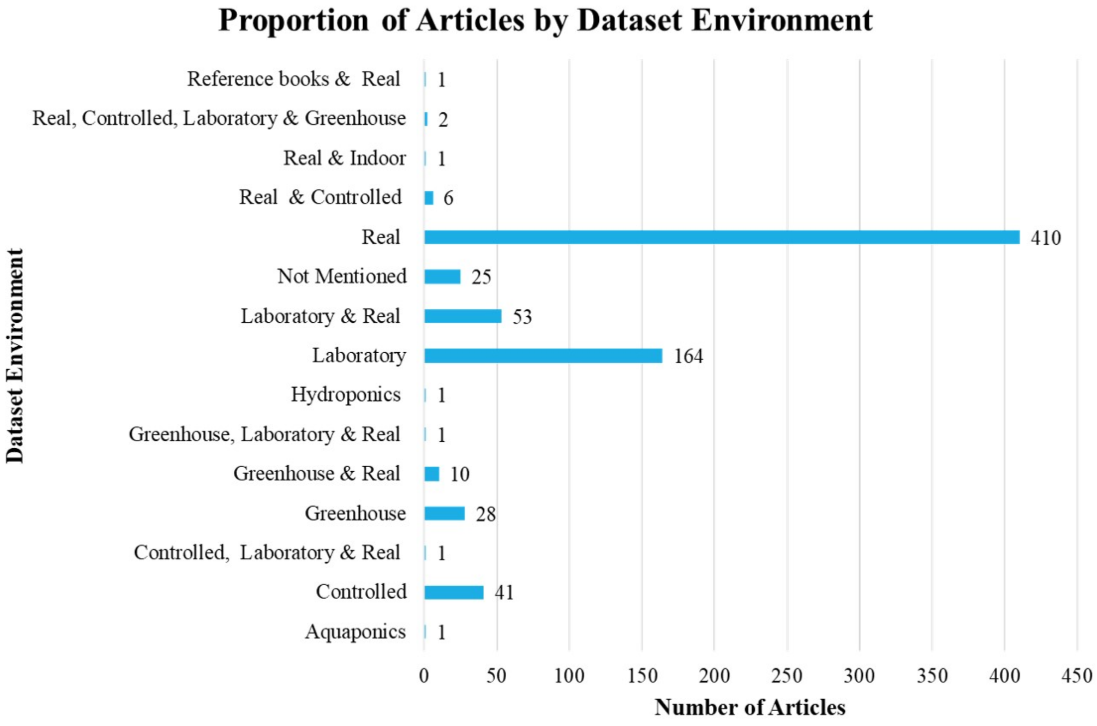


Figure 2.14: Distribution of Primary Studies Included in the Systematic Literature Review Based Dataset Capturing Environment

F. Dataset Capturing Device

Figure 2.15 presents the distribution of research articles based on the dataset-capturing devices used. The most frequently used device is the *camera*, with 274 articles (P1; W2; D3; D&P1; D5; D9; W4; D10; P5; D11; D12; D13; D15; P8; D18; D21; P10; D23; D24; W7; W8; D28; D29; D32; D35; D37; D40; D43; D44; W13; D47; D49; D50; D52; D55; D58; D59; D61; W17; W18; D64; W20; D68; D70; D71; D74; D75; D77; D79; D80; D81; D82; D&P6; D88; D91; D92; D93; D97; P31; D105; D108; D110; D112; D115; D117; D123; D126; D127; W33; D130; D132; D133; D137; D139; D143; D144; D146; D147; D,P&ND4; D148; D150; D151; D152; D157; W37; W38; P45; D166; D167; P47; W41; P48; D169; D175; D176; P49; P50; D177; D180; W45; W46; D181; D182; D184; D187; W48; W49; D188; W50; D191; D192; D193; P53; D194; D198; D199; D200; W53; D201; W55; D&P16; D204; D&ND6; D207; P57; D210; D211; D,P&ND6; D213; D214; D215; D217; W57; D218; P60; W58; D225; W35; D226; W60; D228; D229; D235; P64; D237; D,P&ND8; D&P19; D239; D241; D243; D247; D248; D250; W67; D251; D253; W68; D258; D260; D261; D262; D263; D264; D266; D267; D268; D269; D270; D272; D275; D276; D277; D278; D281; D282; D287; D288; D289; D296; D297; D300; D301; D302; D304; D305; D309; D310; D311; D313; D314; D317; W70; D318;

D322; D323; D324; D326; D327; P75; D329; D331; D332; W75; D336; D337; W76; D338; D340; D344; D345; P76; D349; D350; W77; W79; D358; D359; W82; D362; D363; D372; D373; D375; W86; P81; P82; D379; D382; D383; D384; D388; D393; D395; D396; D398; D403; D410; P88; D412; D413; D415; D417; D419; D427; D429; D431; D432; D435; D436; D439; D441; D442; D&ND12; P93; D444; D448; W95; D&ND13; D450; D452; D459; D460; D462; D463; D465; W104; D468; D470; D474; D476; D477; D480; D481; D482; D484) followed by *not mentioned*, which accounts for 150 articles, indicating a significant number of studies where the capturing device was not specified. *Smartphones* are also commonly used, with 61 articles (D1; D&ND1; D20; D26; D27; D30; D33; D34; D51; P21; P22; D56; W16; D60; D62; D65; D83; D&P8; D101; P34; P35; D118; P38; D,P&ND3; D141; W34; D145; P61; D159; D163; D174; D178; D185; D186; D196; P54; D232; D244; D245; D255; D265; P70; D303; P73; D346; D347; D361; W84; P84; D389; D394; D397; W89; D405; W90; D&ND10; D428; D453; D454; D467; D472), and *Unmanned Aerial Vehicles (UAV)* (W6; P16; W9; W10; W12; D54; W19; D76; W24; D&P7; W28; W29; D119; W30; D125; D138; W36; D160; W39; W40; W43; W44; P52; W51; W54; D209; D219; D224; P63; W62; W63; W64; W65; D249; D254; D274; W71; P72; D333; D341; D342; D&P22; W80; W85; D368; D377; D380; D381; W87; W88; W98) in 51 articles. Further, *camera & smartphones* (D17; D25; P19; D41; &ND2; W15; D66; D69; W22; D84; D85; D86; D87; D94; D96; D,P&ND2; D&P9; D106; W31; D120; D142; D,P&ND5; D153; D158; D183; D195; D&P17; D223; D227; W61; D291; P71; D315; D325; D330; D334; D343; D356; D369; D374; D&P24; D&ND9; D399; D404; D406; D&P27; D445; D449; W97; P96; D468; D476; D&ND14) appear in 53 articles . *Internet* was used in 33 articles (P2; P3; P6; P13; P14; P17; D46; P27; D104; D&ND3; P37; P39; P43; D222; D231; D240; P65; P69; D273; D286; D320; P74; D335; P77; P86; D423; P89; P91; P92; D451; D456; P103; D&P30), *an automated system* was used in 24 articles (P11; P12; D38; W11; D,P&ND1; P24; D72; P25; P26; P28; P33; P36; D155; P44; P46; P59; P62; D234; P67; W72; W74; P90; P98; W100), and *Robots* (W1; D45; W14; W25; W32; W47; W52; W59; W66; W69; W73; W91; D421; W93; W103) and *Camera & Internet* (D14; D19; D&P5; P20; D111; P40; D149; D236; P68; D271; D319; D401; D409; D455) in 15 and 14 articles, respectively. There are smaller counts for combinations of devices such as *Internet & not mentioned* (P18; D109; D165; D&P20; D&P26; D408; D&ND11; D430; D446), *Internet & smartphones* (P51; P85; D&P28; D443; P97; D484), and *IoT Sensors* (P9; P29; D98; D168; P66), each contributing a few articles. Less common combinations like *cameras, internet & smartphones* (D205; P80; D416; D462), and *smartphones & UAVs* (D&P2; W3; D&P4; D&P21; P102) each appear in 4 and 5 articles respectively, while various other combinations and specific devices like *microscopes* (D233; D367; P79) and *camera*

& meteorological sensors (D129) are mentioned sporadically, reflecting a diverse range of capturing technologies employed in research. This diversity highlights researchers' multifaceted approaches to collecting data, with a significant reliance on cameras and a mix of traditional and modern technologies. The other category includes the following each used in one article: *surveys & simulated sensor*; *automated system & not mentione*; *imaging sensors, IoT sensors & smartphones*; *smartphones & not mentioned*; *electronic devices*; *camera & automated system*; *hand-held devices & UAV*; *mobile application, environmental sensors & UAV*; *internet & surveys*; *light trapping device*; *mobile application*; *camera, IoT sensors & smartphones*; *books & internet, camera, internet & not mentioned*; *camera & automated system*; *meteorological sensors & smartphones*; *plant protection experts & smartphones*; *video capturing device*; *camera, monitoring equipment & smartphone*; *camera, IoT sensors & smartphone*. Overall, this SLR highlights cameras' dominance as the primary device for dataset capturing in research while also showcasing the diversity of other devices used, albeit to a lesser extent. This information underscores the need for diversification in capturing technologies to enhance the richness and variety of research data.

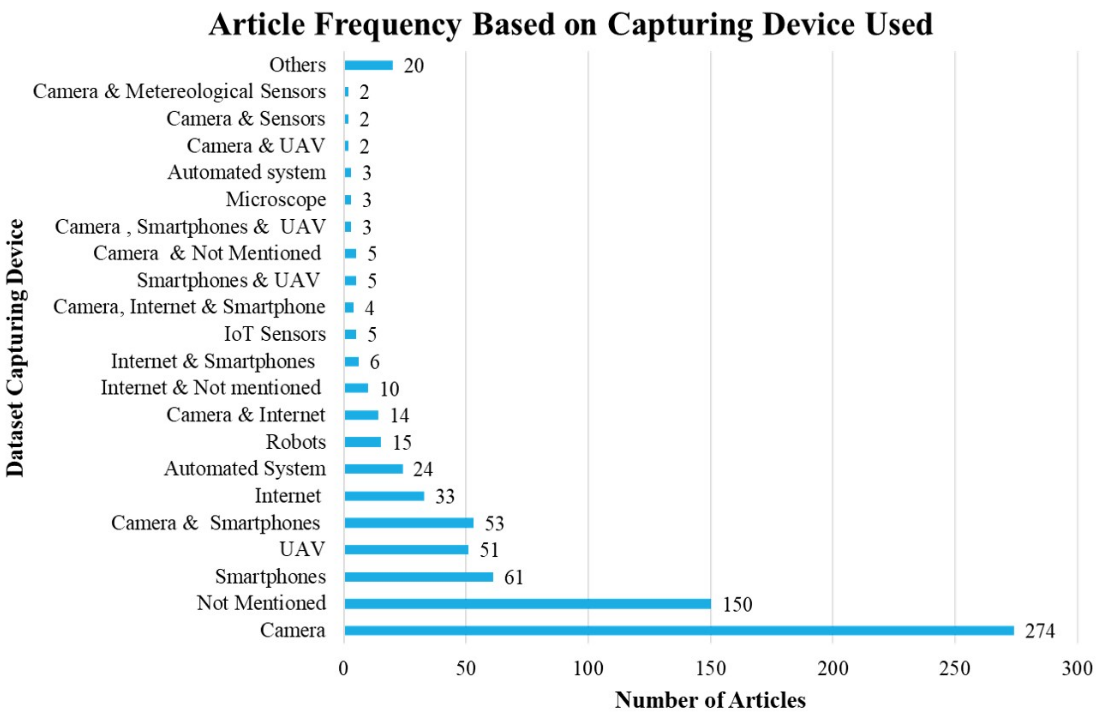


Figure 2.15: Distribution of Primary Studies Included in the Systematic Literature Review Based Dataset Capturing Environment

G. Dataset Geographical Distribution

Figure 2.16 illustrates the global distribution of article frequencies, with countries colour-coded according to the number of research articles that utilized data originating from each location. The United States leads with over 200 articles, highlighting its dominant role in global research. China follows with 151-199 articles, indicating its indicating its robust research output. Countries like Russia, India, and Australia contribute moderately, with 41-50 articles each. However, many regions, particularly in Africa, Central Asia, and parts of South America and Southeast Asia, show low research output, with fewer than ten articles. This disparity underscores the need for increased investment in research infrastructure and collaboration in underrepresented regions. Future implications include the potential for growth in these areas through international partnerships, funding initiatives, and capacity-building efforts to foster a more balanced global research landscape.

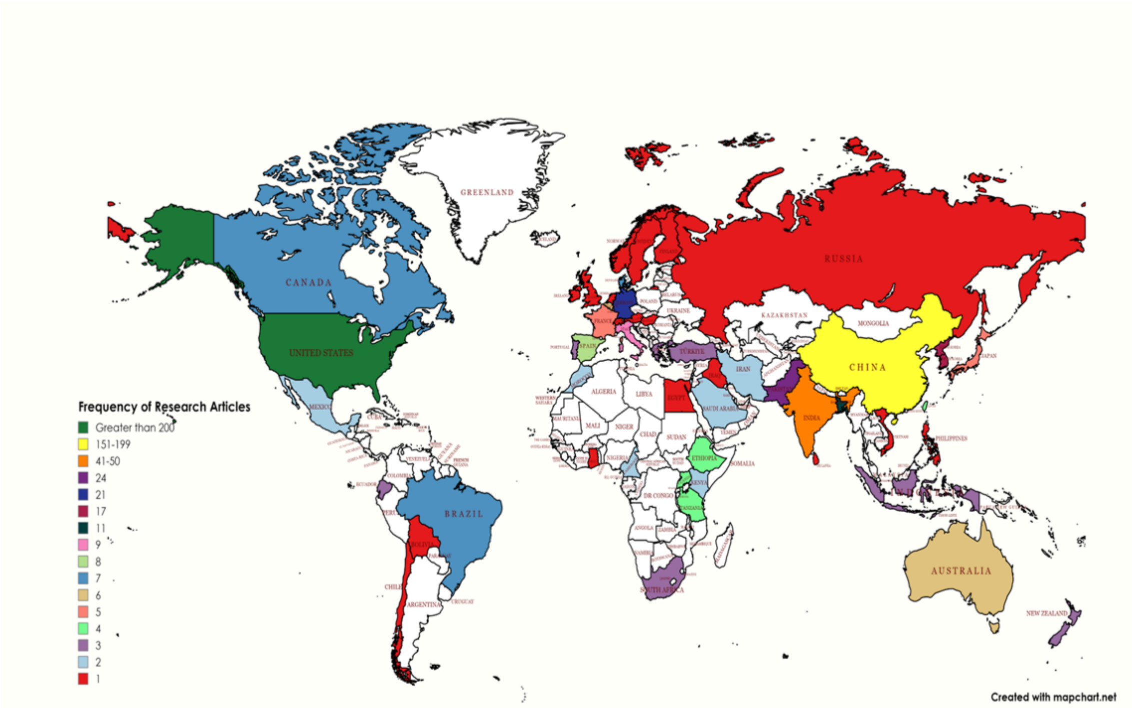


Figure 2.16: Global Distribution of Research Articles by Dataset Capturing Country, Indicating the Frequency of Publications Across Different Regions

2.4.7 RQ7: What Performance Metrics are Employed to Evaluate the Effectiveness of Deep Learning Models in Monitoring Biotic Stress?

Figure 2.17 reveals the performance metrics used to evaluate DL-based solutions for biotic stress monitoring and the number of primary studies considered in SLR employing each metric. The most frequently used metric is *accuracy*, appearing in 532 articles, followed by *precision* (458 articles) and *recall* (426 articles). *F1-score*, a balanced measure considering precision and recall, is used in 376 articles. *mean Average Precision (mAP)* appears in 165 articles, and *Receiver Operating Characteristic* is utilized in 78 articles. Metrics like *Number of Parameters* (137 articles), *Inference Speed* (168 articles), and *Size* (79 articles) are also considered, while *Memory Requirements* (12 articles) and *Floating-point operations (FLOPs)* (58 articles) are less commonly used. The heavy reliance on traditional metrics like accuracy, precision, recall, and F1-score may overlook other important aspects of model performance, such as computational efficiency and scalability.

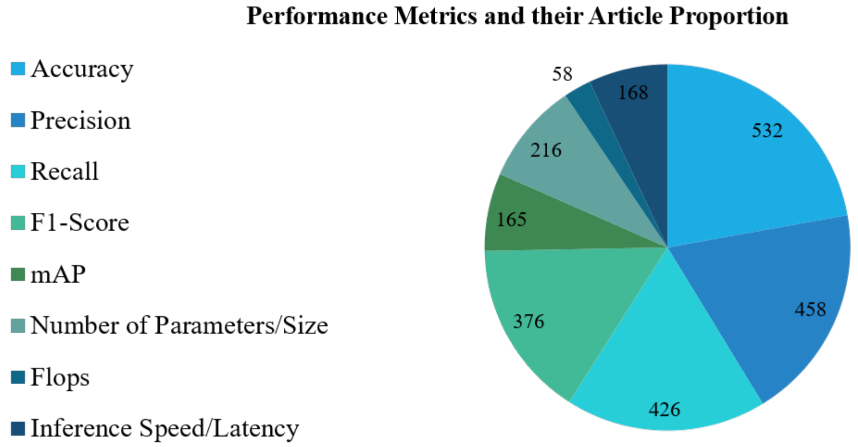


Figure 2.17: Distribution of Primary Studies Considered in the Systematic Literature Review by Performance Metrics Used to Evaluate Deep Learning-Based Solutions

2.4.8 RQ8: To What Extent Are the Explainability and Interpretability of Deep Learning Models Considered in Plant Biotic Stress Monitoring?

The explainability of the DL model is vital for multiple reasons. It fosters trust and transparency among users by clarifying model predictions, which is essential for widespread adoption. Explainable models enable better validation, debugging, and refinement, that leads to more robust and accurate outcomes. They provide actionable insights for targeted interventions, optimize resource use, and support ethical accountability by tracing decision pathways. Explainability also promotes scientific discovery and secures support from policymakers and funding agencies. Despite its importance, only 114 out of 745 primary studies in this article address explainability. Figure 2.18 illustrates the various explainability techniques used in DL models for biotic stress monitoring and the number of research articles employing each technique. Heat maps are the most frequently used, appearing in 34 articles, followed by Grad-CAM (34) and activation visualization (20). Techniques like Grad CAM++ (6 articles), CAM (13 articles), and LIME (3 articles) are also utilized. At the same time, more specialized methods such as Occlusion sensitivity, Score-CAM, AblationCAM, HiResCAM, Guided propagation and deconvolution, XGradCAM, SmoothGrad, Vanilla back-propagation, Reference-Based Visualization, DeepLIFT, ECLF-CS, and SHAP are less common, each appearing in 1 or 2 articles. Further, two articles did not explicitly mention the technique.

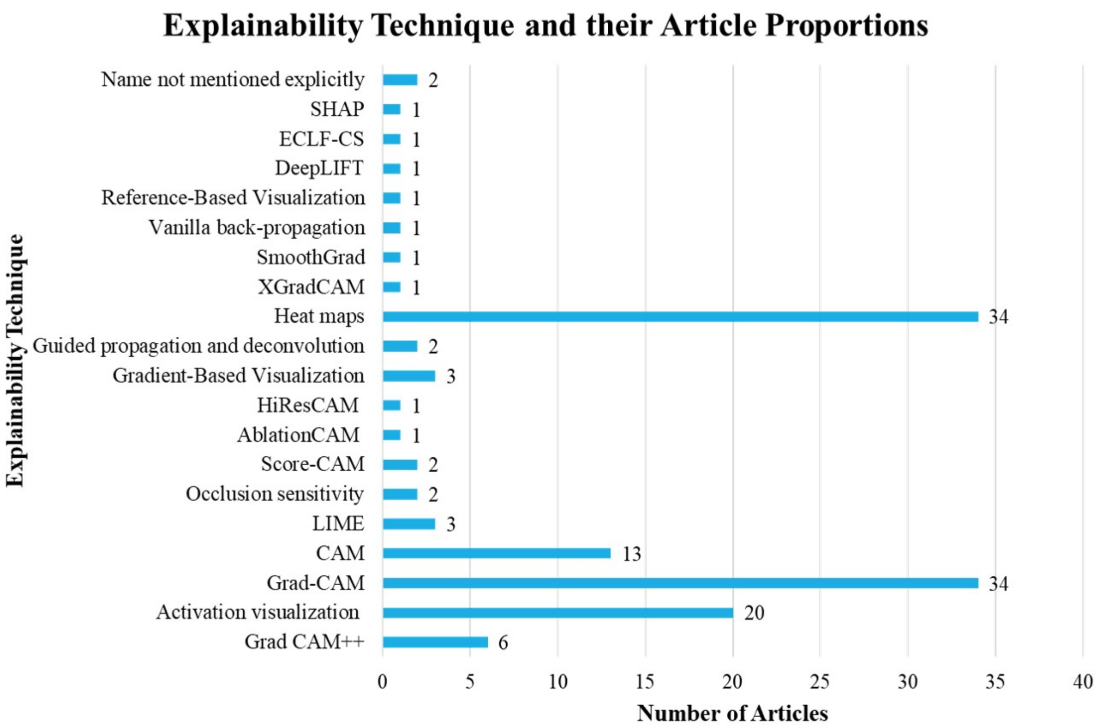


Figure 2.18: Distribution of Primary Studies Assesed in the Systematic Litearture Review by Various Explainability Techniques

2.5 Additional Discussions

The analysis of plant organ consideration for stress monitoring reveals a strong emphasis on leaves, with 451 studies focusing on them due to their early stress response, while broader assessments, covering the canopy, crown, or entire fields, were addressed in only 14 studies, emphasizing their utility in monitoring overall plant health. A holistic approach was adopted by six studies examining multiple plant parts to provide comprehensive insights into stress interactions, whereas seven studies targeted the entire plant, and 40 focused on fruits and vegetables, highlighting an interest in harvest quality. Stems and flowers were the subject of 14 studies, and a diverse array of other plant parts was explored in 22 articles. Notably, 260 studies did not specify the plant organ, impacting reproducibility and applicability.

In the context of stress severity and fine-grained identification, only 53 of the 745 studies evaluated stress severity, indicating a significant research gap in precision agriculture. Multiclass consideration is also underrepresented, with only 74 studies accounting for multiple stressors, pointing to a need for more comprehensive plant pathology research. Augmentation techniques were employed in 334 studies, predominantly using traditional methods, while only a few utilized GAN or proposed novel approaches, revealing a reliance on conventional methods. Generalizability was addressed in 169 studies, 89 of which validated their findings in real-world settings, but 576 studies lacked this crucial aspect, highlighting the necessity of broader applicability. Finally, supervised learning dominated the field, used in 98% of the studies, whereas semi-supervised, weakly supervised, and self-supervised methods were notably underutilized, suggesting an overreliance on labelled data and a missed opportunity to leverage unlabelled data in plant stress research.

2.6 Research Gaps and Open Issues

Deep learning has shown significant potential in plant stress monitoring and enhancing plant biosecurity. Despite the tremendous progress, the SLR highlights several research gaps limiting the effectiveness and applicability of current models. Thus, research gaps which have been identified are as follows:

- **Over-reliance on supervised learning techniques**: Current models demand large amounts of labelled data, which are often scarce, especially in diverse agricultural environments.

- **Focus on leaf data**: Most studies focus primarily on leaf datasets, neglecting other plant organs such as roots, stems, and fruits, which can also show early signs of biotic stress.

- **Underestimation of hybrid models**: Hybrid approaches combine various DL models and are often overlooked despite their potential to offer more robust solutions.

- **Model generalization issues**: Existing models struggle to generalize across different conditions, particularly under covariate shifts, resulting in reduced performance when applied to real-world, unseen data.

- **Limited understanding and explainability**: There is a lack of transparency in model behaviour, leading to challenges in trust and the wider adoption of DL solutions in agriculture.

- **Inadequate attention to computational efficiency**: Many models are computationally intensive, making them impractical for large-scale, real-time applications in agriculture.

- **Regional disparities in research output**: It has been identified that some regions receiving less attention despite being highly vulnerable to biotic stress.

- **Neglect of concurrent abiotic and biotic stress**: A significant portion of the research overlooks the coexistence of multiple stresses, such as nutritional deficiency combined with diseases.

2.7 Chapter Summary

This chapter offers a comprehensive overview of the application of DL in plant biotic stress monitoring. This article expounds on significant trends and advancements from 2016 to 2024, highlighting the dominance of CNN and the emergence of hybrid models. Despite the tremendous progress, this study highlights important gaps, such as the need for various data sources, data scarcity, and dependence on high-quality, annotated datasets. The analysis emphasizes integrating multiple tasks and enhancing model generalization to improve practical applications. Additionally, the study highlights the underutilization of efficiency metrics and the limited focus on explainability and interpretability, which are essential for trust and usability in real-world applications. Overall, the findings shed light on the landscape of DL breakthroughs in biotic stress monitoring, highlighting key challenges and suggesting practical solutions. The study emphasizes the importance of addressing limitations posed by the research gaps and exploring new modes to improve DL model's performance in biotic stress monitoring.

Chapter 3

Integration of Deep Learning and Plant Biosecurity : SWOT Analysis

This chapter comprehensively reviews significant research efforts integrating deep learning with plant biosecurity. In addition to summarizing critical advancements in the field, it offers a detailed SWOT analysis. This analytical framework thoroughly evaluates the inherent strengths, weaknesses, opportunities, and threats associated with DL-driven solutions, particularly in their role as facilitators or barriers to achieving robust plant biosecurity. By exploring these aspects, the analysis delves into the internal and external factors that shape the development and implementation of digital technology for crop protection. It highlights the advantages that can propel progress while addressing potential challenges that impede adoption. Ultimately, this evaluation provides a balanced perspective on how DL applications could impact the future of plant biosecurity, considering both the positive potentials and the risks involved.

3.1 SWOT Matrix- An Overview

SWOT stands for Strengths, Weaknesses, Opportunities, and Threats. A SWOT matrix is a structured planning tool presented in Figure 3.1, to assess an area's strengths, weaknesses, opportunities, and threats [61]. This analytical technique forms the basis for evaluating the internal capabilities and limitations, as well as the potential opportunities and threats stemming from the external environment. It considers all the positive and negative factors that impact the growth and scope of a particular field. The SWOT analysis encompasses the following scenarios: internal strengths & weaknesses and opportunities & threats in the external environment.

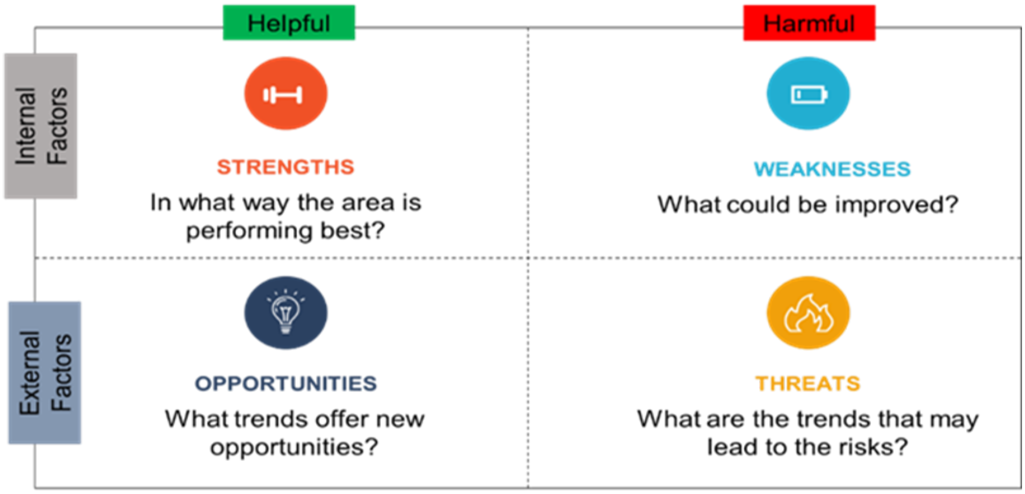


Figure 3.1: Generic SWOT Matrix

3.2 SWOT Analysis for the Integration of Deep Learning & Plant Biosecurity to Achieve Agriculture Sustainability

This section provides a structured SWOT analysis of DL-driven trends that can play an essential role in achieving plant biosecurity to strengthen agriculture sustainability. The SWOT matrix, as illustrated in Figure 3.2, highlights the potential contributions, opportunities, weaknesses, and threats toward the applicability of DL to ensure plant biosecurity. It recommends the researchers for an aligned use of DL for plant biosecurity. The following subsections expound on the details of four aspects of SWOT.

3.2.1 Strengths

A. Early Outbreak Warning

In recent years, the need for fast and accurate solutions for pest, disease, and weed control has increased for better, more reliable, and precise decision-making. Early warning systems play a crucial role in plant protection, offering valuable tools that provide farmers with timely forecasts. Due to advances in CV and DL, the identification of crop disorders has shifted from conventional techniques to optical identification (use of digital images). DL-driven solutions provide accurate and swift detection methods and hold outstanding potential that enables timely treatment. This can significantly mitigate total crop loss failure, reducing financial setbacks and ensuring food security [14].

B. Improves Crop Yield and Lowers Production Costs

Traditionally, monitoring crop abnormalities relied on human experts, which was expensive and time-consuming. DL resolves this issue and is employed to provide solutions for automated crop abnormalities detection without expert scouting. It improves productivity and lowers the cost incurred in traditional scouting techniques and blanket spraying of costly chemicals on plants [17].

C. Healthier Food Quality

Crop abnormalities affect crop yield and their nutritious value. The rise in plant diseases, pests, and weed outbreaks threatens food safety in various regions worldwide. Simultaneously, a global pandemic is endangering the health and well-being of millions of people on our planet. Further, this situation is worsened by farmers' blanket spraying of chemicals, pesticides, herbicides, and other chemicals without precise knowledge about these abnormalities. This has a significant impact on consumers', producer's health and ecology. The DL-based automated solutions contribute towards maintaining nutritious food values by timely identifying phenotypic changes in plants and suggesting the exact abnormality and its possible solution [62].

D. Economic Benefits to Farmers, Consumers, and Country

Monitoring plants' health and diagnosing disorders is crucial for promoting sustainable agriculture and enhancing trade. Automated DL-based early diagnosis solutions have emerged as valuable tools in disease, pest and weeds monitoring, aiding in selecting appropriate control techniques to improve productivity. Ultimately, this improvement benefits farmers, consumers, and the overall economy of nations[63].

E. Low Environmental Impacts

Agricultural practices and ecology are interconnected. Pests, diseases, and weeds are often controlled with artificial chemicals, which are harmful to producers, consumers, and ecology if not used in the correct amount. Hence to strengthen ecology, agricultural activities need to be redesigned. The introduction of DL in agricultural production is revolutionizing the farming sector. This advancement optimized inputs such as fertilizers, pesticides, herbicides, and other chemicals in a notable 21% reduction in Greenhouse Gas (GHG) through the more efficient use of chemicals [64].

3.2.2 Weaknesses

A. High Upfront Cost

DL has great potential for stress monitoring in plants. However, the adoption of this technology in plant biosecurity has been relatively slow due to various factors. These include the high initial investment, limited technical expertise, and growing data privacy concerns. As DL applications tend to be computationally intensive, the requirement for substantial processing power is one of the major weaknesses. Additionally, DL-grounded solutions heavily rely on large amounts of data leading to significant costs associated with data processing. Overcoming these challenges is crucial for the widespread adoption of DL in plant health monitoring. By addressing the above-mentioned issues, plant biosecurity can fully leverage the potential of DL to meet the growing food demand effectively [64].

B. Low Awareness Among Farmers

Researchers are proposing automated solutions for plant abnormalities monitoring. However, low awareness among producers (farmers) about these tools and solutions is another hurdle. Easy comprehension, understanding, low access, and operational costs of radio broadcasts make them affordable for farmers seeking valuable insights regarding crop health. The automated DL solutions are being accessed by educated farmers only; less educated farmers are not exploiting these solutions because they need to gain basic knowledge about the usage of these solutions. Additionally, low-income farmers with small land areas have low interest in using these automated solutions [65].

C. Slow Adoption Rate in Developing Countries

Numerous automated solutions based on DL have been proposed by researchers for monitoring pests, diseases, and weeds that hinder crop quality and quantity. However, only a few examples showcase positive impacts on rural livelihoods; these successes have yet to reach the expected scale. Inadequate infrastructure and resources, unreliable internet connections, and a need for more skilled professionals in the field are significant limitations. Overcoming these barriers is crucial for promoting the widespread adoption of DL in plant phenotyping. Efforts should focus on raising awareness, improving infrastructure, expanding resources, strengthening internet connectivity, and fostering the development of skilled professionals to maximize the potential benefits of DL for rural communities [65].

D. Non-Availability of in-Field Dataset

As identified in Chapter 2 majority of existing DL-based solutions to identify pests, diseases, and weeds are built using datasets captured in controlled conditions or considered only specific crops or diseases/pests/weeds. However, any technique used in practice must be prepared to deal with different environmental circumstances, diverse crops, pests, diseases, and weeds. Further, most self-collected datasets have yet to be released to be fully exploited for further research [13, 18, 66].

E. Heavy Models

DL-based solutions typically demand significant computational power and resources, making them less suitable to deploy on lightweight devices like mobiles and the Internet of Things (IoT). However, training these models can be exceedingly expensive due to the data models' complexity. Furthermore, the requirement for costly Graphics Processing Unit (GPU) adds to the overall cost for developers and users. Additionally, efficient tuning of hyperparameters is necessary for optimizing the performance of these models[13, 18, 66].

F. Low Generalizability of Automated Solutions

As discussed above, most existing solutions are trained on laboratory-based datasets. Hence, their accuracy drops when these models are utilized for inference in field conditions. Further, researchers considered some specific crops or specific abnormalities, but in actual field conditions, varieties of crops and abnormalities exist. Hence a model/ solution developed for a particular crop is not generalizable to other crops[13, 18, 66].

3.2.3 Opportunities

A. Awareness Among Farmers

To fully exploit the potential of DL for plant biosecurity, it would be beneficial if the government could circulate the various policies, websites, and apps for plant phenotyping through media. Digital literacy programs should be conducted for farmers. Further, farmers should also be encouraged to employ DL -based solutions to save their crops from pests, diseases, and weeds and make precise control decisions. Additionally, infrastructure (smartphones) should be made available to low-income farmers.

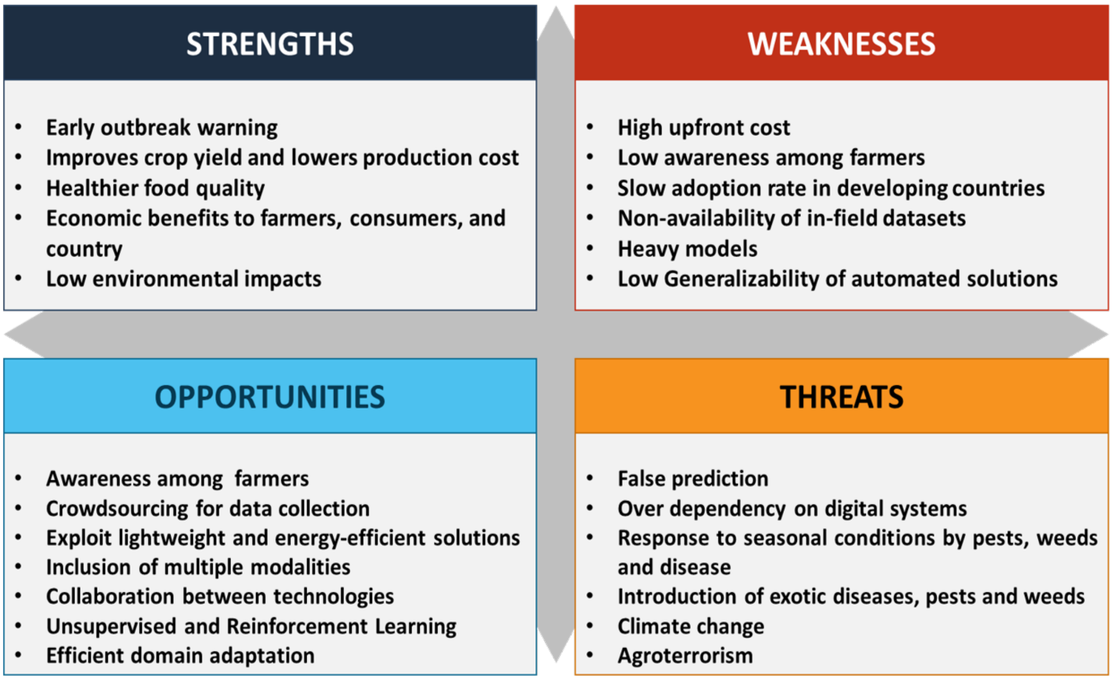


Figure 3.2: SWOT Matrix for Deep Learning in Plant Biosecurity

B. Crowdsourcing for Data Collection

A significant area for improvement in this field is the unavailability of standard datasets for DL . To make a model generalizable, it is required that researchers have datasets that are collected from diverse graphical conditions with varying weather conditions, illumination conditions, diversity of pests, diseases & weeds, and many more. Researchers alone cannot collect this data; hence crowdsourcing can generate many training data of good quality through social media or any other medium [67].

C. Exploit Lightweight and Energy-Efficient Solutions

As discussed above, heavy DL models cannot be deployed on embedded devices and mobile phones to be further utilized by farmers as a decision-making tool. Heavy models consume substantial energy resources that hinder the ecology facet. Considering these weaknesses, developing lightweight and energy-efficient models opens various opportunities for DL models to be fully utilized for plant biosecurity to improve agriculture sustainability [13, 18, 66].

D. Inclusion of Multiple Modalities

Multimodal learning is where models are trained to process and analyze multiple forms of input data, such as text, images, audio, video and many others. Most existing models primarily focus on visual information in embodiments for plant biosecurity, neglecting the potential insights from other modalities. However, incorporating multiple modalities holds immense potential for enhancing the monitoring of pests, diseases, and weeds [14, 17, 62, 63]

E. Collaboration Between Technologies:

To fully leverage the benefits of DL in plant biosecurity, collaboration among various technologies is essential. While DL has the potential to revolutionize this field, it is still evolving, and costs can be high. Therefore, ensuring widespread adoption will necessitate collaboration among different technologies. Integrating DL approaches with UAV can facilitate the development of advanced intelligent solutions. Further, cloud computing can be integrated with DL to handle resource-intensive models, while edge computing can be combined with DL to reduce latency during inference. These are just a few examples of potential collaborations that can be explored to enhance the effectiveness and efficiency of plant biosecurity efforts [14, 17, 62, 63].

F. Unsupervised and Reinforcement Learning

Existing DL solutions for plant biosecurity are based on supervised learning. However, the potential of unsupervised and reinforcement learning still needs to be addressed. To overcome the barriers of requiring large amounts of annotated data and building a heavy model for extensive labelled data exploring the solutions based on unsupervised and reinforcement learning is the need of the hour [14, 17, 62, 63].

G. Efficient Domain Adaptation

Domain adaptation is a CV field that aims to train a neural network on a source dataset and achieve high accuracy on a target dataset that significantly differs from the source dataset. The purpose of domain adaptation is to enable a pre-trained model to perform optimally on new data without retraining on a different dataset. Rather than starting from scratch with each new dataset, domain adaptation allows the adaptation of existing models to the target dataset, thereby saving time and resources. This approach facilitates the transfer of knowledge and learning from the source to the target dataset, enabling the model to perform well even in significantly different data domains. By leveraging domain adaptation, advancements can be made in strengthening plant biosecurity measures and addressing specific challenges related to detecting and preventing pests, diseases, and other weaknesses for plant health [14, 17, 62, 63].

3.2.4 Threats

A. False Prediction

A model trained on a poorly annotated dataset may lead to inaccurate predictions when tested in natural field conditions. However, farmers may adopt control measures as per these false predictions, which may lead to complete crop loss failure and challenges to food security. Further, the inputs (pesticides, herbicides, fertilizers, and other chemicals) utilized as control measures will have poor impacts on ecology and causes economic loss.

B. Over-Dependency to Digital Systems

DL -based solutions can be employed with the help of digital devices only, like computers & smartphones; this increases farmers' dependency on these digital devices to make decisions. However, these digital gadgets may lead to GHG emissions, and the model deployed may cause high energy requirements.

C. Response to Weather Conditions by Pests, Weeds, And Diseases

A pest, disease, or weed may respond differently in different weather and geographic conditions. Considering all weather and geographic locations in a single dataset is almost impossible. This may cause a prediction bias and lead to poor results [2].

D. Introduction of Exotic Pests, Diseases, and Weeds

Exotic organisms refer to organisms introduced into an area beyond their natural range and become pests in the new environment. They are also known as alien, non-native, or introduced organisms. The entry of such exotic organisms poses a significant threat to plant security, as existing models may fail to recognize them, leading to wrong forecasts. This can result in financial losses, environmental damage, food production disruptions, and adverse effects on agriculture industries [68].

E. Climate Change

Climate change has complex and global impacts on agricultural ecosystems. This creates favourable conditions for the proliferation of pests and diseases, particularly in temperate zones. The effects of climate change have led to economically essential crop pests becoming more destructive, posing an increasing threat to food security and the environment. With the anticipated drastic changes in climate in the future, this situation may worsen [2].

F. Agroterrorism

Agroterrorism involves deliberate attacks on the food supply chain, targeting livestock and crops during various stages, including production, harvesting, storage, or transport. Agroterrorism poses a significant threat to achieving plant biosecurity and ultimately challenges the sustainability of agriculture. Terrorist actions to disrupt the food supply can have far-reaching consequences on economic stability and public health. These factors highlight the critical importance of addressing measures to counter agroterrorism to safeguard plant biosecurity and ensure the sustainability of agriculture [69].

3.3 Chapter Summary

In this chapter, a SWOT analysis was conducted, revealing key strengths, weaknesses, opportunities, and threats in the application of DL for plant biosecurity. Based on the findings, the author emphasize the need for researchers to leverage the strengths and opportunities of DL while addressing its weaknesses and threats through targeted solutions. Additionally, governments are encouraged to implement digital literacy programs, provide infrastructure support for low-income farmers, and promote policies, websites, and apps focused on plant phenotyping. Lastly, fostering collaboration between DL and other digital technologies is critical to further enhancing plant biosecurity and achieving sustainable agriculture.

Chapter 4

A Novel Plant Disease Diagnosis Framework to Overcome Data Scarcity

Plant disease monitoring is a critical research area for plant biosecurity and agriculture sustainability. CNN are the pre-eminent DL -based algorithm used to automate plant disease diagnosis that has proven decisive on various datasets in the last decade. However, a substantial part of the research lacks adequate attention to specific issues like over-reliance on supervised learning, underestimation of hybrid models, unavailability of labelled datasets, high annotation costs and non-conformity of the models. In response to these limitations and to fill the research gaps, this chapter presents a novel framework for classifying plant diseases. The proposed framework, which integrates semi-supervised and ensemble learning, is crucial because its *semi-supervised* nature effectively utilizes both labelled and unlabelled data, enabling the DL solutions to learn from a broader dataset without the heavy reliance on costly labelled samples. Furthermore, by incorporating *ensemble learning*, the framework enhances accuracy by combining the strengths of multiple models, thereby reducing bias and improving overall performance. Ultimately, this method provides a scalable, cost-effective solution for plant disease classification, offering greater adaptability and effectiveness in real-world agricultural challenges. The proposed framework is further validated using an innovative classification model applied to benchmark datasets such as PlantDoc and PlantVillage.

Additionally, to improve the accuracy of identifying the precise locations of plant diseases and minimize the widespread use of indiscriminate chemical spraying, this chapter implements You Only Look Once (YOLO)v5 object detection algorithm. YOLOv5 offers real-time, high-performance detection by efficiently localizing and classifying diseases within images. This targeted approach not only enhances the precision of disease identification but also promotes sustainable agricultural practices by enabling site-specific interventions, thereby reducing the excessive application of pesticides and ensuring more environmentally conscious plant protection strategies.

4.1 Introduction

The literature review has highlighted that integrating semi-supervised learning with ensemble learning is an underexplored yet highly promising area. Despite its potential to significantly enhance model performance, limited research has delved into this combination for plant disease identification. Hence, to fully exploit the potential of this underestimated approach and to address the gaps (over-reliance on supervised learning, the underutilization of hybrid models, the limited availability of labelled datasets, the high costs associated with data annotation, and the lack of conformity in existing models) identified in Chapter 2, this work proposed a novel framework.

Further, this study has investigated two key RQs, as mentioned below, to evaluate the effectiveness and potential of the proposed framework for plant disease classification.

- **RQ1:** Does the integration of semi-supervised and ensemble learning improves the performance for plant disease classification?
- **RQ2:** How does the performance of the proposed framework is susceptible to the amount of unannotated/unlabelled data?

By investigating these questions, the research aims to assess whether the combined use of semi-supervised and ensemble learning can offer measurable improvements in accuracy and reliability for plant disease diagnosis compared to traditional methods that rely solely on labelled data. Furthermore, it seeks to understand the framework's adaptability to varying labelled and unlabelled data levels. It is critical for practical application in real-world agricultural settings where labelled data is often scarce. Ultimately, this study aspires to advance the field of plant disease diagnosis by demonstrating how leveraging labelled and unlabelled data can optimize classification outcomes.

4.2 Dataset and Methodology

This section provides a comprehensive explanation of the dataset utilized in this study, detailing its characteristics, and relevance to the task at hand. Additionally, it elaborates on the DL techniques employed to achieve optimal performance in the proposed framework.

4.2.1 Dataset Exploration

This study employed two publicly available repositories: PlantDoc [70] and PlantVillage [71]. The PlantDoc repository was collected in natural-field conditions consisting of 2569 images across 27 classes (17 diseased and 10 healthy) in 13 crop species, whereas PlantVillage, introduced by "Penn State University," consists of 54,305 images for 14 crop species, divided into 38 categories(26 diseases and 12 healthy). A significant limitation of the PlantVillage repository is that the images were not taken in a natural environment; instead, they were collected in a laboratory setup-only plant leaf images on a plain background. As depicted in Figure 4.1, PlantDoc consists of diseased plant images with different types of surroundings, multiple leaves, fruits and varying lighting and illumination conditions. However, in PlantVillage, images are captured with clear backgrounds, homogeneous capture, and lighting conditions. Another critical aspect of the datasets considered is that the distribution of images in each class is highly imbalanced. To get more insights, the PlantVillage and PlantDoc statistics are presented in Figure 4.2 and Figure 4.3, respectively.

Figure 4.1: Sample Images from PlantVillage and PlantDoc Repositories

4.2.2 Transfer Learning

The training of the DL model is a resource-demanding and time-consuming operation. Powerful computing resources and millions of training examples are required for the model training and optimization. Tranfer Learning (TL)[72] is a widely used technique that overcomes the isolated learning paradigm—where the models must be reconstructed from scratch whenever the feature-space distribution changes and limited annotated data are available. TL facilitates a model developed for a specific problem that is reutilized and

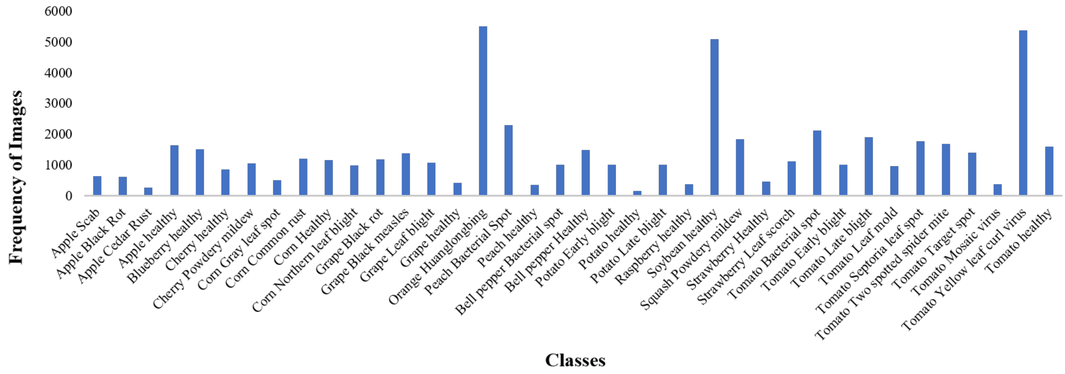


Figure 4.2: Statistics of PlantVillage Dataset

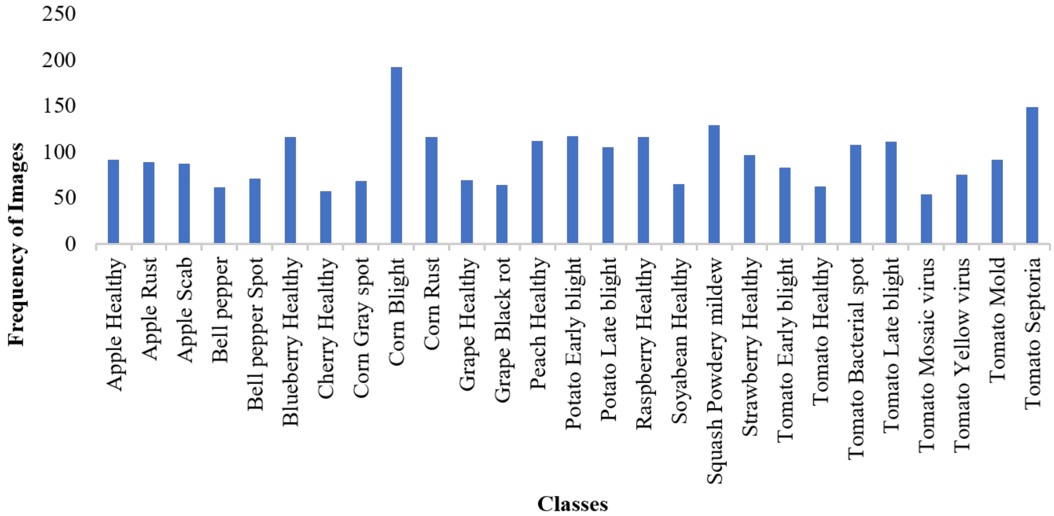


Figure 4.3: Statistics of PlantDoc Dataset

applied to a different but analogous problem; here, transfer means that training is not required to be restarted from scratch for every new task. This allows researchers to develop powerful models that can perform better with limited data, less computing power and less time[73]. With encouraging results, image classification problems are being addressed using TL. A model can be built upon existing knowledge and use the weights & biases learned from previously trained models to solve a new task.

4.2.3 Semi-Supervised Learning

Semi-supervised learning [74] is a hybrid technique between supervised learning (only labelled training data) and unsupervised learning (only unlabelled training data). This the technique is motivated by the problem domains where unlabelled data are abundant, and obtaining labelled data is costly and tedious. This technique enables training of an initial model on a limited labelled sample and then iteratively applies it to the pool of unlabelled data. This technique exploits the knowledge in the unlabelled data to train an improved model that could be trained with only supervised data.

Mathematically, semi-supervised learning assumes a dataset of labelled and unlabelled examples that can be presented as Eq. 4.1 and 4.2 , respectively. where S_L represents labelled dataset; S_U denotes unlabelled dataset; x_i represents a sample from dataset; y_i denotes the corresponding label for the sample from S_L ; N_L and N_U denotes the number of labelled and unlabelled samples in the whole dataset, usually $N_U >> N_L$.

$$S_L = \{x_i, y_i\}_{i=1}^{N_L} \tag{4.1}$$

$$S_U = \{x_i\}_{i=1}^{N_U} \tag{4.2}$$

Semi-supervised learning integrates the knowledge from unlabelled samples to surpass the classification performance that can be obtained either by discarding the pool of unlabelled data and performing supervised learning or neglecting the limited labels and performing unsupervised learning. Therefore, semi-supervised learning is an attractive and promising technique to subdue challenges like over-reliance on supervised learning, unavailability of labelled datasets, high annotation costs and non-conformity of the models to automate plant disease monitoring with limited labelled samples.

4.2.4 Ensemble Learning

Ensemble learning is an approach that integrates the insights from various base models (weak learners) to build a better and optimum predictive model (ensemble model). The inspiration is that an ensemble model conquers the issue of high variance when the base models are intuitive regarding input values, noise, and feature bias. This approach combines multiple weak models to create a more robust predictive model. Each weak model is trained on the dataset and provides its predictions. However, the final prediction is determined by aggregating the individual models' accuracy and resilience, leading to improved overall performance. While numerous ensemble methods can be applied to any predictive task, the most prominent techniques in ensemble learning are bagging, boosting, and stacking [75].

An ensemble model can be represented as Eq. 4.3 where E represents the ensemble learning process, which integrates multiple weak learners to improve predictive accuracy. The term S refers to the ensemble modelling strategy, which could include bagging, boosting, or stacking. These strategies are crucial as they determine how the weak learners are

combined to form a stronger, unified model.
D is the dataset that serves as the input for individual weak learners and the overall ensemble. The weak learners are denoted by M, where each M_n refers to an individual weak learner within the ensemble. These models, often, may perform moderately well but are combined to achieve better results. The total number of weak learners is represented by n, which accounts for each learner contributing to the ensemble.
The variable R stands for the results or outputs generated by the weak learners, and A represents the analysis process, where the results from the learners are evaluated or processed further. This analysis helps produce the ensemble model's final prediction or outcome. Finally, I represents the individual learning process, which combines the dataset D, the $n-th$ weak learner M_n, the results R, and the analysis A, to generate a model's predictions.
This equation succinctly captures the essence of ensemble learning, where multiple weak models are trained on the same dataset, and their outputs are aggregated using a defined strategy to produce superior results.

$$E(S, D, M, R, A) = S\left(\sum_{n=1}^{N} I(D, M_n, R, A)\right) \tag{4.3}$$

4.3 Proposed Framework and Model Selection

In this section, the author proposes a novel framework to classify plant leaf diseases using limited labelled samples and many unlabelled samples. A classifier based on this framework will try to understand the features of the diseased plant images and, in more detail, the relationship of the pixels and classify the disease into a particular class.
First, an ensemble classifier, referred as *M1*, is integrated into the proposed framework. This ensemble classifier leverages four CNN models, where each model generates a set of predictions based on bootstrapping techniques. These individual predictions, or likelihoods, are combined to produce the final classification result.

The deatiled functional flow of the proposed framework is illustrated in Figure 4.4, while the specific steps involved are outlined in the pseudo-code presented in Algorithm 1. In this approach, a portion of the test set is utilized as unlabelled data/images, and the following steps are performed to achieve the final result: In *step-1*, The original labelled data is split into two parts, namely training data and test data. The training data trains the ensemble classification model *M1* created using four pre-trained models. In *step-2*, the test data is splitted into two parts: labelled and unlabelled. Further, the unlabelled proportion of the data is tested on the *M1* model, which predicts labels for the unlabelled data. The labels received in this step are named "annotated pseudo-labels." It is important to mention here that the authors have generated annotated pseudo-labels only once since the single semi-supervised learning results in lower computational power requirement and almost equivalent performance to iterative semi-supervised learning, unlike literature [76]. Further, in *step-3) (3A)*, Combine "annotated pseudo-labels" obtained in Step 2 with the original training data in Step 1, eventually increasing the count of training samples in the training set. *(3B)* Train the model *M1'* (here M1' is the same ensembled model as *M1*, but for the sake of readers' understanding, it is represented as another model *M1'*) with a new training set (original training set plus annotated pseudo-samples). *(3C)* Finally, evaluate the model *M1'* for the endure portion of the test set.

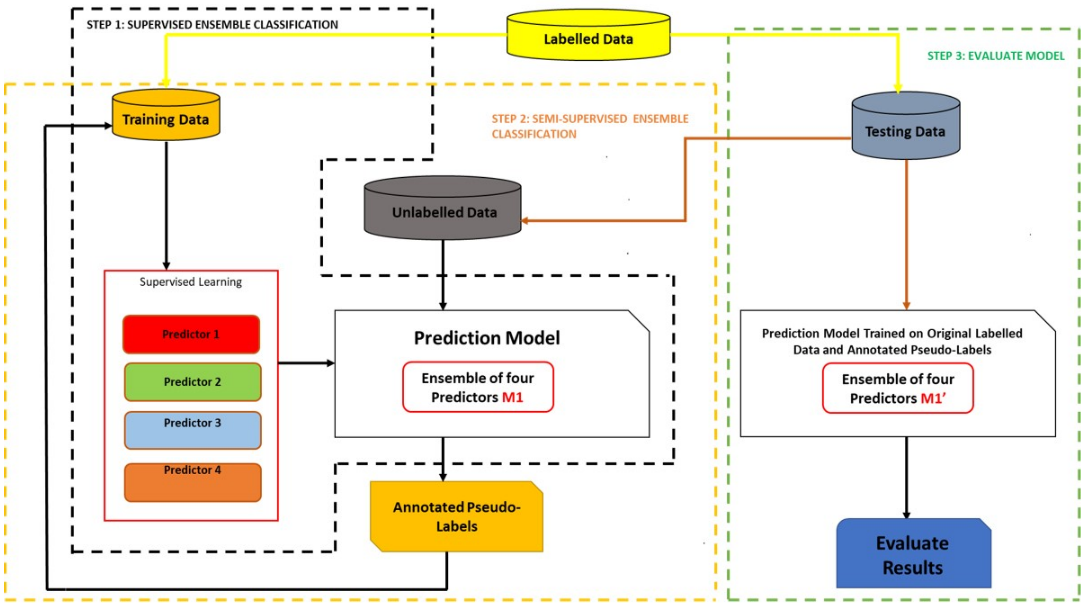


Figure 4.4: Proposed Framework Workflow for Classification of Plant Disease

4.3.1 Model Selection

Different algorithms have specific purposes and have been employed to classify plant diseases. Currently, however, no standard model/framework uses semi-supervised and ensemble learning, a preliminary study is executed to choose four representative CNN models to experiment with the proposed framework in the previous section. Considering the medium size of the disease dataset, Visual Geometry Group (VGG)-16 [77] is selected to represent the VGG series. Xception [78], inspired by the Inception model, is selected as a candidate for its profound depth. Inception-ResNet-v2 [79] is a candidate for the ResNet [80] series, derived by fusion of the Inception model and the residual connection.

Algorithm 1 Pseudo-code for the Proposed Framework

Input: Dataset $D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, Ensemble model $M1$

Process:

1. Splitting the dataset and train model $M1$
I. Split D into S_{train} and S_{test}
II. Train $M1$ using S_{train}

2. Split test set and obtain pseudo-labels for unlabelled test samples
I. Split S_{test} into $S_{L\text{-test}}$ and $S_{U\text{-test}}$, where
$S_{L\text{-test}} = \{(x_i, y_i)\}_{i=1}^{m}$ and $S_{U\text{-test}} = \{x_i\}_{i=1}^{k}$
II. Test $S_{U\text{-test}}$ on trained $M1$ and get corresponding y_i for each x_i in $S_{U\text{-test}}$ (only
when confidence score is greater than 95%) and name this set as
$S_{\text{annotated pseudo-labels}}$

3. Retrain model $M1$ with increased training data and evaluate
I. Combine S_{train} and $S_{\text{annotated pseudo-labels}}$
II. Train $M1$ on the combined dataset and name this model $M1'$
III. Test $M1'$ with $S_{L\text{-test}}$

Output: Accuracy, Precision, Recall, F1 score values

The motivation to use residual connections is to avoid degradation problems in deep networks and to reduce training time. Additionally, MobileNetv2 [81], representative of the lightweight model in application development for mobile devices, is also selected for its fantastic performance and a lesser number of parameters. The process of model selection for the ensemble model is visually illustrated in Figure 4.5.

4.4 Experiments

This section is dedicated to the performance metrics and experimental settings to assess the proposed framework.

4.4.1 Evaluation Metrics

Four standard classification performance metrics are used to validate the proposed framework's performance: Accuracy, Precision, Recall and F1 score. *Accuracy* can be measured as the proportion of correctly predicted samples to the total no. of samples in the dataset. The higher the value the model achieves, the better its performance. *Precision* refers to the proportion of the true positives out of total positive predictions. *Recall* refers

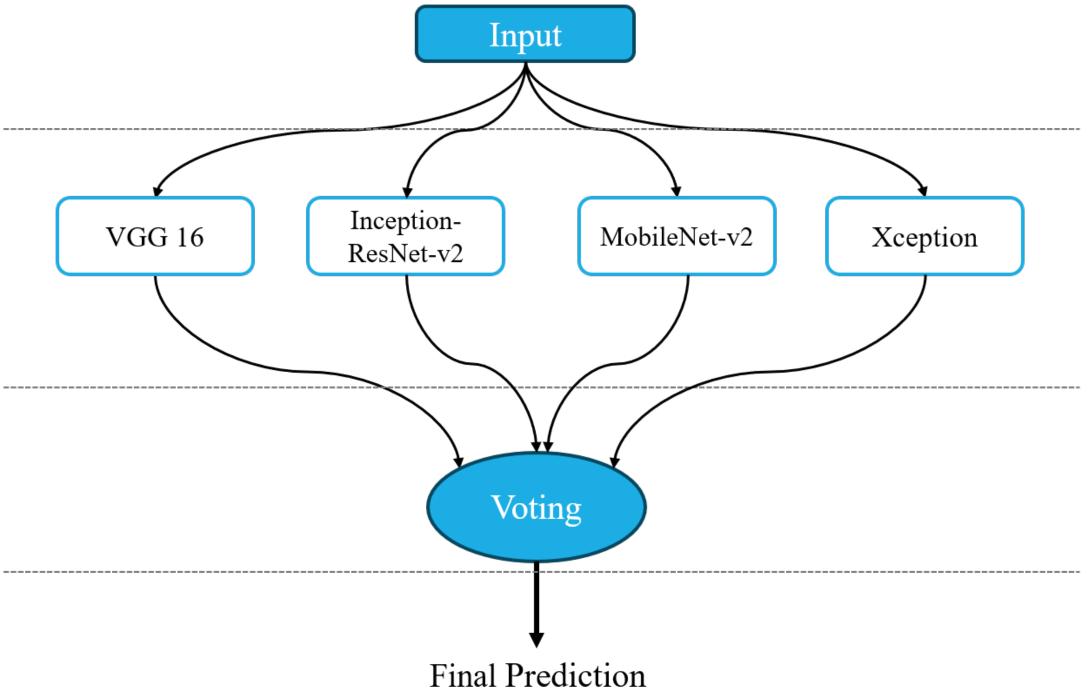


Figure 4.5: Ensemble Model using Four Weak Learners

to the count of the true positives found. *F1 score* is the harmonic mean between precision and recall.

4.4.2 Experimental Setup and Training Strategy

The proposed framework is trained and tested on a Windows workstation. Essential software and hardware configuration are listed in Table 4.1. The authors used TensorFlow with Keras to implement this work, and Python is utilized as the programming language. Images are resized into 224×224, followed by a normalization pre-process step converting the pixels to a range of [0, 1]. The dataset is split into 80% for training and 20% for testing. The test set is split in half; one is used to predict the annotated pseudo-labels, and the other is used to evaluate the final model. The author freezes each model on the last layer, using the initial weights provided by Keras from the Imagenet dataset. The fully connected layer is adjusted to predict the number of classes in the dataset. Moreover, the authors used a dropout of 0.1, an Adam optimizer with categorical cross-entropy, and a learning rate of 0.001 for the loss function with batch sizes 32 and 50 epochs. An early stop was made to prevent overfitting of the model, with patience equal to 10. Table 4.2 summarizes hyperparameters and their value used to implement the proposed framework.

Table 4.1: Summary of Software and Hardware Requirements to Implement the Proposed Framework

Configuration	**Values**
Graphics Processor Unit	Nvidia-smi, Tesla V100-PCIE
Operating System	Windows 10
DL Framework	TensorFlow 2.8.0
Compiler	Spyder 5.2.1
Programming Language	Python 3.8.0

Table 4.2: Summary of Hyperparameters and Their Values Used to Implement the Proposed Framework

Hyperparameter	**Values**
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Learning Rate	0.001
Batch Size	32
Dropout	0.1

4.5 Results

This section presents the results obtained through extensive experiments to evaluate the proposed framework potential using benchmark datasets, namely PlantDoc and PlantVillage, for plant disease classification.

4.5.1 Experiment 1: Performance Evaluation of the Proposed Framework on PlantDoc and PlantVillage Datasets

To address RQ1, the proposed framework was implemented with four weak learners as illustrated in section 4.3.1 for plant disease classification, utilizing the two aforementioned datasets. The resulting performance metrics are summarized in Table 4.3 and Table 4.4.

A detailed comparison of the proposed technique with the traditional supervised technique is also presented in Figure 4.6 on the PlantDoc dataset. For the presentation purpose, the author refer supervised learning as *S*, semi-supervised learning as *SS*, supervised learning integrated with ensemble learning as *H1* and semi-supervised integrated with ensemble learning as *H2* hereafter. It is worth to mention here that for S and SS, the authors consider MobileNetv2 because it is lightweight and performs better than the other three models considered in this work.

Further, the confusion matrix presented in Figure 4.7 summarizes the detailed results of the classification model on the PlantDoc dataset.

Table 4.3: Performance of the Proposed Framework on the PlantDoc Dataset

Class Index	**Plant Class**	**A**	**P**	**R**	**F1**
0	Apple Healthy	65	70	78	74
1	Apple Rust	58	57	50	53
2	Apple Scab	53	50	33	40
3	Bell pepper	20	0	0	0
4	Bell pepper Spot	38	33	43	38
5	Blueberry Healthy	60	60	55	57
6	Cherry Healthy	47	50	40	44
7	Corn Gray spot	41	50	29	36
8	Corn Blight	62	58	82	68
9	Corn Rust	77	75	82	78
10	Grape Healthy	46	44	67	53
11	Grape Black rot	31	29	33	31
12	Peach Healthy	84	80	73	76
13	Potato Early blight	52	60	27	37
14	Potato Late blight	22	23	50	31
15	Raspberry Healthy	49	47	67	55
16	Soybean Healthy	45	43	50	46
17	Squash Powdery mildew	95	90	69	78
18	Strawberry Healthy	70	71	56	63
19	Tomato Early blight	26	20	12	15
20	Tomato Healthy	52	50	33	40
21	Tomato Bacterial spot	29	25	09	13
22	Tomato Late blight	33	27	27	27
23	Tomato Mosaic virus	20	0	0	0
24	Tomato Yellow virus	44	43	43	43
25	Tomato Mold	20	22	22	22
26	Tomato Septoria	25	35	57	43
Macro Average		47.76	45	44	43
Weighted Average		49	48	48	46

*Note**: A: Accuracy; P: Precision; R: Recall; F1: F1 score*
*Note **: Numeric values for A, P, R, and F1 are percentage values*

Table 4.4: Proposed Framework Performance on Test Data using PlantVillage

Class Index	Plant Class	A	P	R	F1
0	Apple Scab	88	88	92	91
1	Apple Black Rot	86	86	92	92
2	Apple Cedar Rust	94	92	93	91
3	Apple Healthy	95	93	99	88
4	Blueberry Healthy	93	92	97	91
5	Cherry Healthy	94	90	98	91
6	Cherry Powdery mildew	93	90	96	92
7	Corn Gray leaf spot	94	94	99	94
8	Corn Common rust	93	91	92	91
9	Corn Healthy	94	93	92	91
10	Corn Northern leaf blight	95	90	92	91
11	Grape Black rot	88	87	92	91
12	Grape Black measles	87	88	92	90
13	Grape Leaf blight	85	90	92	91
14	Grape Healthy	95	96	84	93
15	Orange Huanglongbing	93	87	86	92
16	Peach Bacterial Spot	9	84	95	94
17	Peach Healthy	94	90	92	90
18	Bell pepper Bacterial spot	93	94	97	87
19	Bell pepper Healthy	95	92	96	86
20	Potato Early blight	96	91	92	84
21	Potato Healthy	92	89	90	86
22	Potato Late blight	89	88	97	92
23	Raspberry Healthy	96	92	92	91
24	Soybean Healthy	97	93	96	93
25	Squash Powdery mildew	87	94	97	96
26	Strawberry Healthy	92	95	92	95
27	Strawberry Leaf scorch	93	83	85	96
28	Tomato Bacterial spot	92	90	92	91
29	Tomato Early blight	98	88	97	86
30	Tomato Late blight	97	92	96	87
31	Tomato Leaf mold	95	94	92	98
32	Tomato Septoria leaf spot	88	92	90	88
33	Tomato Two spotted spider mite	92	89	97	91
34	Tomato Target spot	92	87	92	96
35	Tomato Mosaic virus	94	90	96	91
36	Tomato Yellow leaf curl virus	97	91	97	94
37	Tomato Healthy	84	90	92	92
Macro Average		92.48	90.24	93	91.22
Weighted Average		92	92	92	91

*Note**: A: Accuracy; P: Precision; R: Recall; F1: F1 score*
*Note **: Numeric values for A, P, R, and F1 are percentage values*

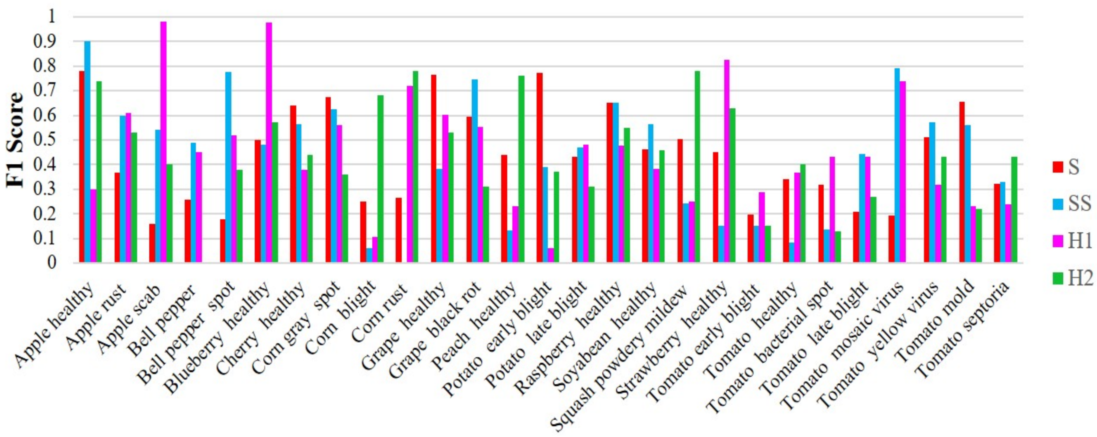


Figure 4.6: Distribution of F1-Score on 27 Crop Species of the PlantDoc Dataset

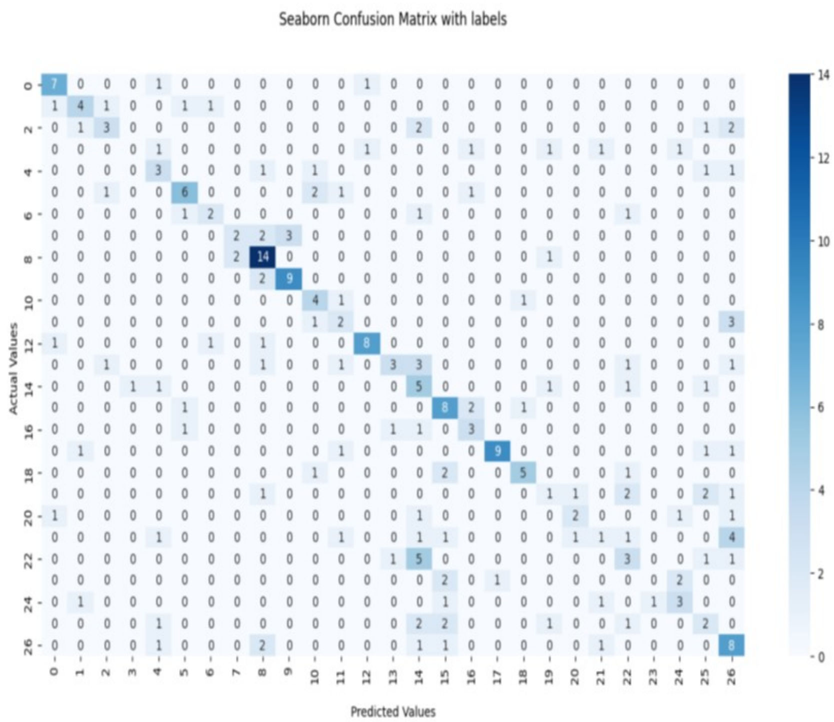


Figure 4.7: Confusion Matrix for the PlantDoc Dataset

4.5.2 Experiment 2: Comparative Analysis of Results with Different Proportions of Unlabelled Data

To answer the RQ2, and to ensure that achieved results are not just consequences of a choice of only 10% as unlabelled data, the author further performed experiments expanding the proportion of unlabelled data. As presented in Table 4.5 an increase in the proportion of unlabelled data does not degrade the performance of the proposed framework (till the specific value). As long as we increase the proportion of unlabelled data from 10% to 30%, the classifier performance keeps improving for both datasets. This indicates that the proposed framework can assign pseudo-labels to unannotated data correctly and is taking benefit from the unlabelled data in an expected manner. Further, increase in unlabelled data reduces the performance in the PlantDoc dataset; this might be because if we increase the unlabelled samples beyond 30%, the proposed model produces wrong pseudo-labels due to the diversity of images and morphology similarities, and consequently, performance drops. Surprisingly, in the case of PlantVillage, the results are improving as we increase the proportion of unlabelled data up to 50%. A valid conclusion is, the PlantVillage samples are collected in controlled conditions since the background is simple, light conditions are homogeneous, and there is comparatively low noise in PlantVillage, hence proposed model is producing comparatively less wrong pseudo-labels for unannotated data and does not lead to a drop in performance till 50% samples are labelled. This experiment concludes that the proposed framework's performance is susceptible to the amount of unannotated data and the diversity of images. Background, noise, lightning conditions, illumination conditions, and occlusion are the essential factors for the proposed approach and play an important role while selecting the unlabelled proportion.

Table 4.5: Classification Results of the Proposed Framework Demonstrating the Impact of Unlabelled Data Variations

Unlabelled Data (%)	**PlantDoc**				**PlantVillage**			
	A (%)	**P (%)**	**R (%)**	**F1(%)**	**A (%)**	**P(%)**	**R (%)**	**F1(%)**
10	47.76	45	44	43	92.48	90.24	93	91.22
20	49.86	48.75	50.02	49.38	93.36	92.25	93.88	93.06
30	50.36	51.22	50.88	51.05	95.52	94.86	95.61	95.23
40	49.32	50.36	49.96	50.16	96.42	95.86	96.36	96.10
50	46.28	47.51	48.32	47.91	96.31	96.11	96.89	96.50

*Note**: A: Accuracy; P: Precision; R: Recall; F1: F1 score*

4.5.3 Experiment 3: Evaluation of the Proposed Framework's Generalizability in Real-World Field Conditions

To further test the generalizability of the proposed framework in the real-world scenario, the framework is validated on an in-field dataset, namely DiaMOS Plant dataset [82] consisting of 3505 samples for pear leaf and fruit. The author has attained the performance results as tabulated in Table 4.6. A comparative analysis of the results from implementing the proposed framework on this dataset demonstrates its generalizability across leaf and fruit. This work performs well because the the author managed to take advantage of the unannotated samples using semi-supervised and ensemble learning.

Table 4.6: Performance Comparison Results Evaluating the Generalizability of the Proposed Framework on DiaMOS Dataset

	Precision (%)	**Recall (%)**	**F1-Score (%)**
[82]	75.25	77.75	74.5
Proposed Approach	**74.83**	**78.63**	**73.8**

4.5.4 Experiment 4: Evaluating the Proposed Framework Against Recent Research Findings

This section compares the proposed framework results with state-of-the-art work. As presented in Table 4.7, attained results outperform the results reported by work [70] on the PlantDoc repository. Literature [70] employed TL on VGG16 and reported accuracy and F1 score of 29.73% and 28%, respectively. This concludes that the proposed approach outperforms state-of-the-art with an improvement in accuracy and F1 score of 18.03% and 15%, respectively, for classification. It is important to mention here that the proposed work might not outperform some of the work on the PlantDoc dataset because, in those works, network training was done only for a few epochs, less than five, or they utilized very heavy CNN-DenseNet architecture without feature optimization techniques that require very high computational power and redundant features may cause overfitting.

Table 4.7: Comparison with Latest Work Reported in the Literature on the PlantDoc Dataset

Reference	**Accuracy (%)**	**F1 Score (%)**
[70]	29.73	28
Proposed approach	**47.76**	**43**

4.5.5 Experiment 5: Evaluation of Detection Outcomes

In addition to the classification, this work seeks to accurately detect the locations of infections within the PlantDoc dataset to make precise chemical spraying. Considering the high inference speed and better performance, the YOLOv5 algorithm trained on the Microsoft Common Objects in Context (MS COCO) repository [83] is employed to locate the disease. The YOLO, "You Only Look Once," splits images into a grid structure where each grid cell is accountable for localizing objects. A detailed YOLOv5 architecture is presented in Figure 4.8.

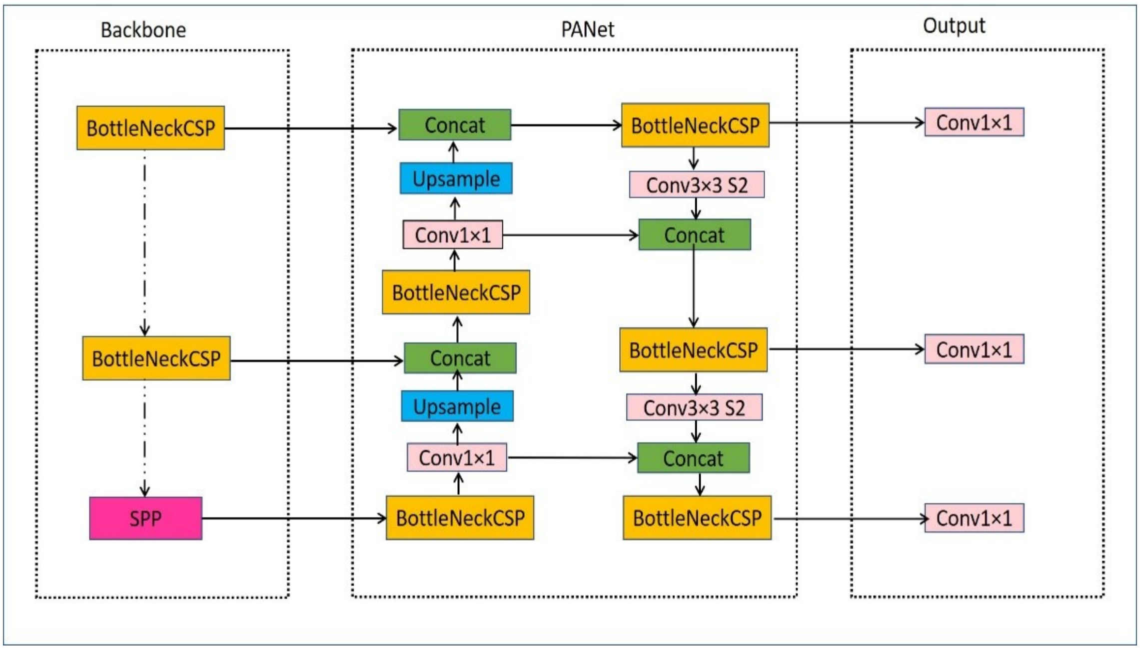


Figure 4.8: Yolov5 Architecture

Detection results using YOLOv5 and comparison with existing work on the PlantDoc are shown in Table 4.8 and Figures 4.9 & 4.10. This work outperformed previous works for precisely locating diseases in the PlantDoc dataset and achieved mAP of 52.25%, validation box loss of 0.027592 and validation object loss of 0.010462.

Table 4.8: Disease Detection Results in the Proposed Work

Model	**Pre-trained Dataset**	**mAP (at 50% IoU)**
SSD [84]	COCO	38.3
FSSD [84]	COCO	37.6
RefineDet [84]	COCO	35.9
EfficientDet [84]	COCO	39.7
YOLOv3 [84]	COCO	39.5
YOLOv4 [84]	COCO	38.1
YOLOv5 [84]	COCO	41.7
Transvolution Detection Network [84]	COCO	50.3
YOLOv5 (Proposed Work)	**COCO**	**52.25**

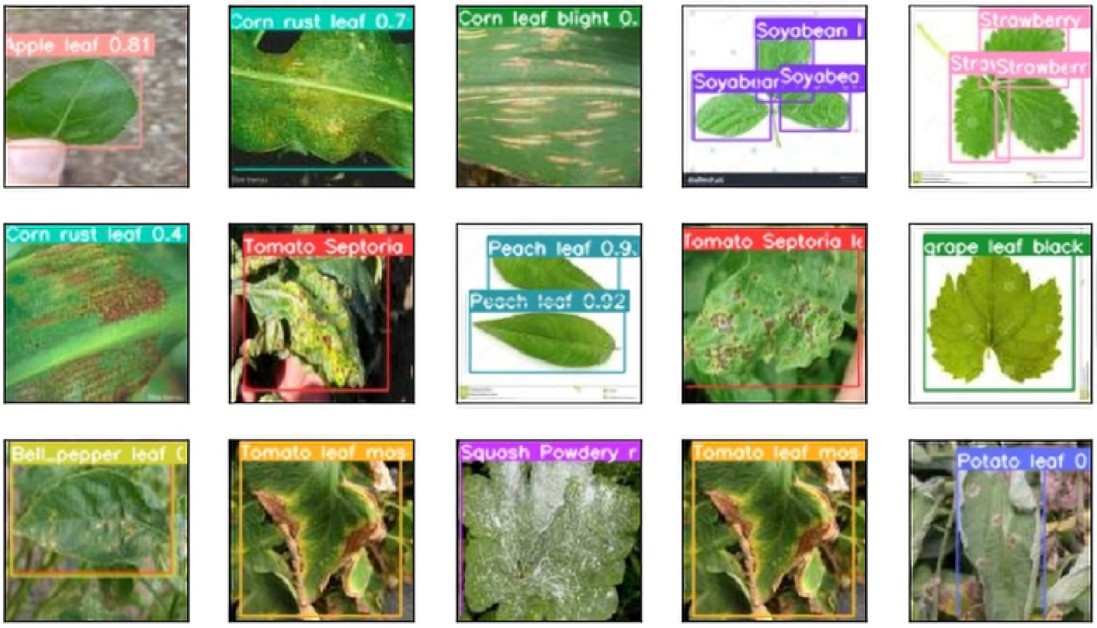


Figure 4.9: Disease Detection Results with Bounding Boxes Indicating Class Labels Using YOLOv5

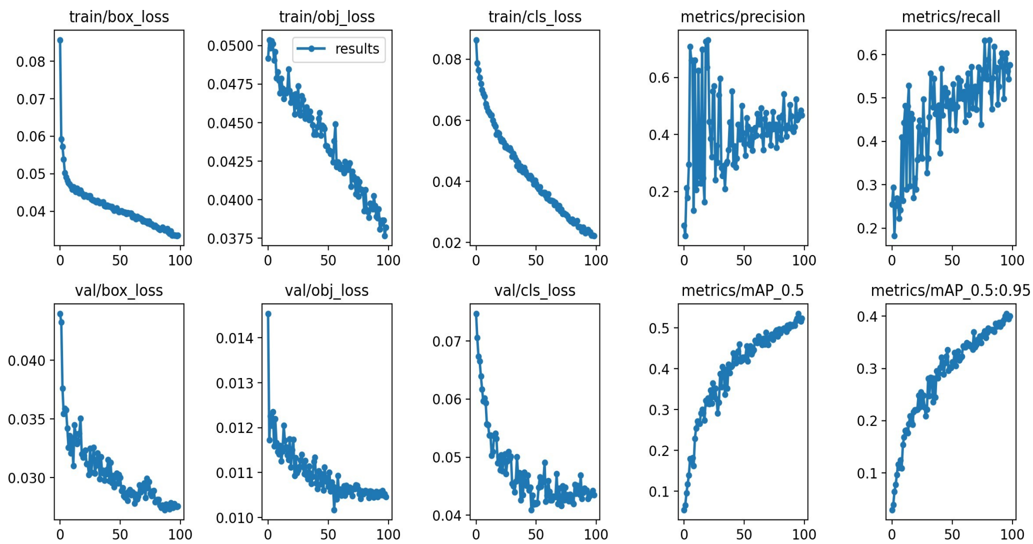


Figure 4.10: Epoch-wise Performance of YOLOv5 in the Proposed Work

4.6 Discussions

Supervised learning (S) only employs labelled data for training, whereas semi-supervised learning (SS) benefits from the plentiful unlabelled data and labelled data. In the case of SS, the additional data (unlabelled data) contributes to its performance improvement. Further, the improved results of H1 over S are explanatory; four weak learners in H1 built up a robust ensembled classifier responsible for its improvement over S. However, H1's performance is lower than SS because the former uses only labelled data, and information from unlabelled data is completely ignored. Additionally, one could easily argue that the overall performance of SS is better than H2 (proposed technique), so it is worth mentioning here that in the case of SS, only some classes get the benefit of unlabelled data and are dominating the overall results. However, classes with high diversity and noise cannot utilize the benefit of unlabelled samples. This motivates us to combine semi-supervised learning with ensemble learning to overcome the bias of a single model towards the dataset.

The confusion matrix presented in Figure 4.7 demonstrates that the framework classifies apple healthy leaf, corn leaf blight, corn rust leaf, peach healthy leaf, squash powdery mildew leaf and strawberry healthy leaf with an F1 score of more than 60%. Bell pepper healthy class is misclassified as bell pepper spot, peach healthy, soybean healthy and tomato diseases. It was also noted that tomato leaf mosaic virus is misclassified as raspberry healthy, squash powdery mildew and tomato yellow virus. To further explore the reason for misclassifications, misclassified images were analysed again, through analysis we conclude that in bell peppers, most misclassifications were due to the background similarity, some diseased lesions in healthy leaves, morphology similarities, and interference with another leaf. At the same time, tomato leaf mosaic virus is misclassified due to the morphology similarities of leaves and the least number of training samples. Hence, it can be concluded that data imbalance and diversity of images are the two influencing factors for the proposed framework.

In the PlantVillage dataset, 28 classes achieve an F1 score above 90%, and 10 classes report an F1 score 84% to 90%. Most of the classification in the PlantVillage dataset is due to the morphology similarity of different diseases or leaves and, in some cases, due to data imbalance, as discussed.

The difference in performance between PlantVillage and PlantDoc is justifiable; the PlantVillage repository has more than 1000 images for most of the classes. Moreover, the repository is collected in the laboratory with a plain background. In contrast, the PlantDoc repository exhibits natural field conditions with messy backgrounds, multiple leaves in images, illumination and lighting conditions. In addition, the authors can argue that the PlantDoc repository is relatively small, which is responsible for performance differences. Finally, to answer *RQ1*, we can state that, yes, integration of semi-supervised and ensemble learning improves the performance of the classifier for disease classification. However, small-sized datasets will benefit more from this approach. Motivated by the results presented in section 4.5.2, *RQ2* can be answered that the performance of the proposed framework is susceptible to the amount of unannotated data and the diversity of images.

4.7 Chapter Summary

This chapter addresses issues like over-reliance on supervised learning, underestimation of hybrid models, unavailability of labelled datasets, high annotation costs and non-conformity of the models in automated plant disease diagnosis using DL. The motivation behind this work is to use the pool of unlabelled data, reduce the costs and efforts involved in the annotation of that data and improve classification and detection models/frameworks. A new framework has been proposed and validated to address the aforementioned challenges. The results of this study indicate that the proposed framework outperforms state-of-the-art methods by 18.03% in accuracy and 15% in F1 score. Additionally, a 13.25% improvement in detection performance was achieved using YOLOv5. This research contributes to sustainable agriculture by developing DL models that enhance plant biosecurity, ensuring early and accurate disease detection. Safeguarding crops from biotic stressors promotes higher crop productivity and quality, supporting long-term food security. Ultimately, this work aids in meeting the demands of future generations for reliable, sustainable food production systems.

Chapter 5

S^2AM: A Model for Sustainable Crop Protection

Agriculture serves as the cornerstone that weaves together all the Sustainable Development Goals (SDGs), underpinning global efforts toward sustainability. However, the massive population explosion and ecosystem degradation have pressurized various components of agriculture, primarily food security, plant biosecurity and crop protection. Although the penetration of digital technologies brings new opportunities to modern agriculture, the environmental facet has been neglected. Given this, the potential of sustainable computing and DL is investigated to handle critical agricultural technology impediments, lower resource expenditure, and propel sustainable agrarian developments. This chapter analyzes the relationship between smart agriculture and sustainable computing to balance the three pillars of sustainable agriculture practices—socio-economic–and environmental. Motivated by the analysis, this chapter presents a DL-based lightweight, computation-efficient, performance-optimized, and explainable crop protection model to classify mango crop diseases. The proposed DL model offers a sustainable and innovative solution for improving plant biosecurity, enhancing agricultural yields, reducing pesticide usage, and promoting environmental preservation through energy-efficient resource utilization. To ensure its broader applicability, the model has been validated on multiple crop types, demonstrating its effectiveness in safeguarding diverse agricultural systems while supporting sustainable practices.

5.1 Introduction

With the emergence of digital technologies and the industrial revolution, the agriculture era has changed from conventional to sustainable agriculture [85]. The transformation

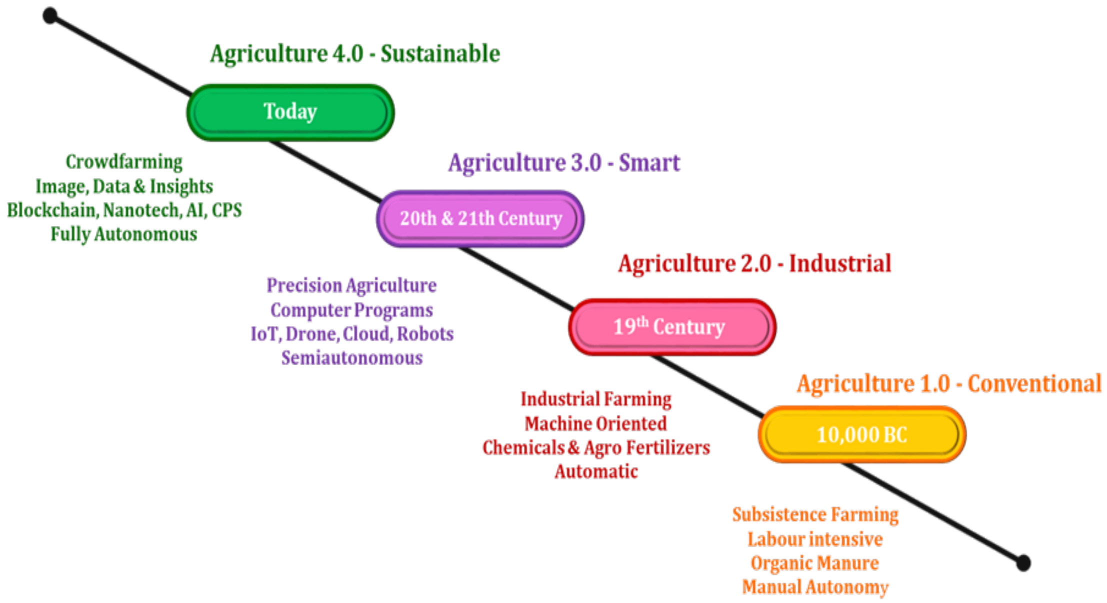


Figure 5.1: Agricultural Revolution Timeline

of agricultural trends and technologies is represented in Figure 5.1. The four agricultural revolutions bring remarkable changes in the development of agriculture history [86]. However, due to rapid population expansion and finite natural resources, ensuring global food security has become vital in agriculture, demanding meticulous focus to meet the universal requirement for effective food supply chain management [87]. Food production or availability is decreasing to keep up with the level of crop harvests in various regions of the world, negatively impacting crop yields and quality. Therefore, plant biosecurity, specifically monitoring biotic stress, is a significant area that requires the utmost attention to save crops from various threatening parameters like diseases, weeds, pests, and many others.

According to estimates from the "Food and Agriculture Organization of the United Nations," plant diseases cost about $220 [88]. Farmers spend significant effort and money trying to prevent plant diseases. However, symptoms of diseases are hard to perceive through human sight. To this extent, Agriculture 3.0 has come into existence to automate plant disease identification. Numerous innovative agricultural solutions have been deployed to classify and detect plant diseases using intelligent techniques such as CV, IoT, cloud computing, ML, DL, or hybrid versions [89].

From 2016 to the present, numerous DL based solutions have been proposed by researchers to automate plant disease diagnosis. These solutions provide a foundation for developing automatic screening tools for plant disease monitoring. However, their significant limitations identified in the literature [9, 14] cannot be neglected:

- High computational power is required to train a model that eventually increases the expenditure on hardware resources and amplifies the strain on ecology and sustainability.
- The unavailability/limited availability of natural field datasets.
- The real-time application of the model is troublesome and relatively slow due to the low inference speed or high latency.
- Heavy models cannot be deployed on end devices for in-situ usage by farmers.

Driven by the above-stated challenges, this work proposes a novel, fast, sustainable, explainable, and improved plant disease classification model- *Sustainable Smart Agriculture Model (S^{2}AM)* that considers the hypothesized impact of the proposed *Comprehensive Comprehensive Sustainable Smart Agriculture Framework (S^{2}A)* on enhancements in plant disease identification performance. S^{2}AM propounds a DL-based solution that adds two S elements in agriculture, giving it a Sustainable Smart dimension. The proposed model is based on a DL technique that assimilates the CNN and adapted encoders from the ViT to optimize the model performance, computation requirements, and latency.

The term *'Sustainable Smart'* manifests the two fundamental pillars of the framework. *Smart* refers to the diffusion of digital technology in agriculture, specifically DL. *Sustainable* concerns about the ecological aspect of the framework and, more specifically, *Sustainable Computing* refers to the introduction of resource-saving intelligent models from the perspectives of the environment and has emerged as a new research area to address the technological bottlenecks in smart agriculture [90]. Consequently, integrating the three key terminologies, namely, Smart Agriculture, Sustainable Agriculture, and Sustainable Computing, has come with the term *Sustainable Smart Agriculture* as represented in Figure 5.2.

The designated RQs under investigation within this study are outlined as follows:

- **RQ1:** Does the integration of CNN and ViT effectively mitigate the inherent limitations of individual architectures, yielding a lightweight and computationally efficient model suitable for deployment on embedded devices for in-situ plant disease classification?
- **RQ2:** Can the proposed model be effectively generalized to classify diseases in other crops, and what challenges may arise in achieving this cross-crop generalizability?
- **RQ3:** How successful is the use of StyleGAN3 in producing synthetic images to augment the diversity of the gathered dataset to classify plant diseases?

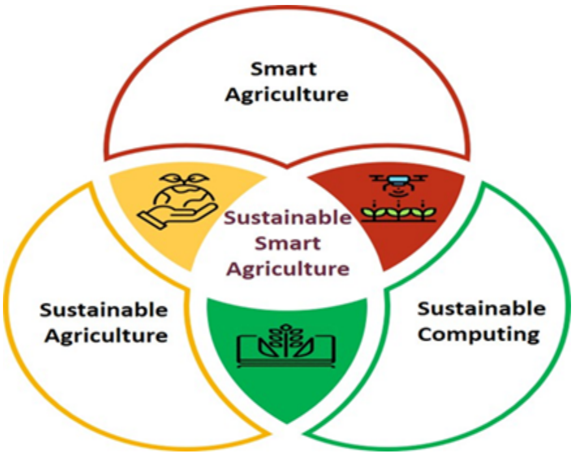


Figure 5.2: Sustainable Smart Agriculture—A Crossway

5.2 Proposed Framework

The world's population will reach nearly 10 billion by 2050 [88]. Thus, there is a substantial need to produce 60% more food to feed 10 billion mouths soon without exploiting natural resources. Hence, the transition towards an innovative and sustainable agriculture system is indispensable to increase crop yields in an environmentally safe manner. However, sustainability researchers, digital technologists, and agronomic experts have been researching it in separate tanks. Recently, some researchers have taken their current knowledge towards the unison of sustainable and intelligent agriculture with innovative computing practices. But, an allied conceptual framework has yet to be proposed. Hence, given this requirement, this research analyses the relationship between three major domains: Smart Agriculture [91, 92], Sustainable Agriculture [21], and Sustainable Computing [8, 93, 94]. As a result, a Collaborative Sustainable Smart Agriculture framework is introduced and presented in Figure 5.3, consolidating the three critical aspects of agriculture. To address the negative environmental impacts of agricultural digitalization, the proposed Sustainable Smart Agriculture framework offers a favourable solution and can be integrated into smart agriculture solutions.

With this goal in mind, a Comprehensive Sustainable Smart Agriculture Framework (S^2A), as depicted in Figure 5.4, has been developed. The proposed S^2A represents and emphasizes the respective subdomains of the three participating entities of the Collaborative Sustainable Smart Agriculture framework, Smart Agriculture, Sustainable Agriculture, and Sustainable Computing.

In agriculture, a variety of *abiotic* (water, drought, heat stress, cold stress, soil properties, and metals) and *biotic* (disease, pests, and weeds) factors cause crop yield loss. Thus, with the motive of *Crop Protection* (subdomain of Smart Agriculture) from biotic stress, specifically plant diseases, the author aspires to build a technically competent and environmentally sustainable agricultural solution that will classify plant diseases using DL. Simultaneously, to balance the most neglected aspect of sustainability, i.e., the environment, the two crucial sustainable computing facets, namely *Software & Deployment Optimization*; to improve the proposed model's efficiency, and *Power & Energy management*; to reduce energy usage and computations involved, have been incorporated into the S^2A.

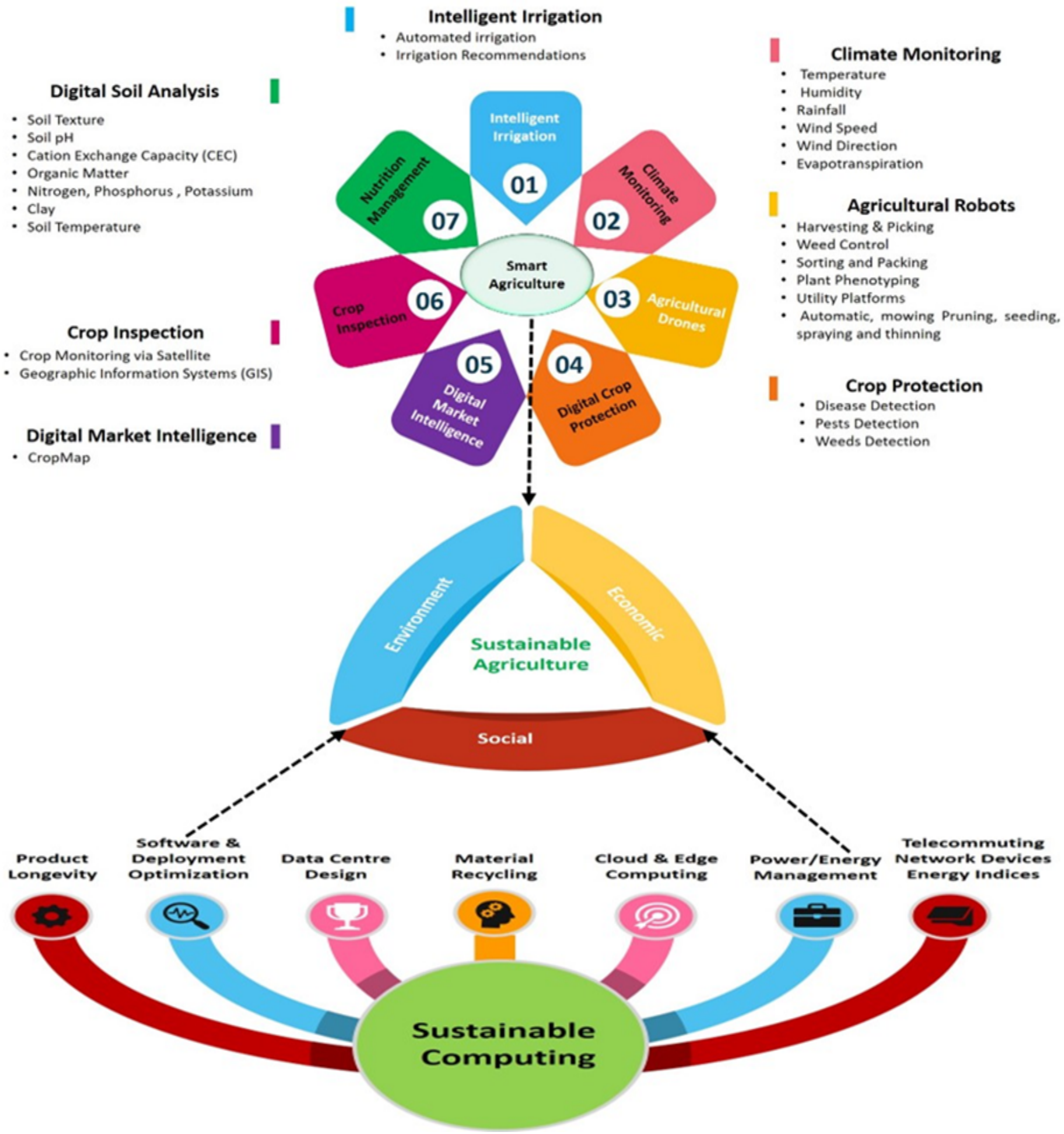


Figure 5.3: Collaborative Framework for Sustainable Smart Agriculture

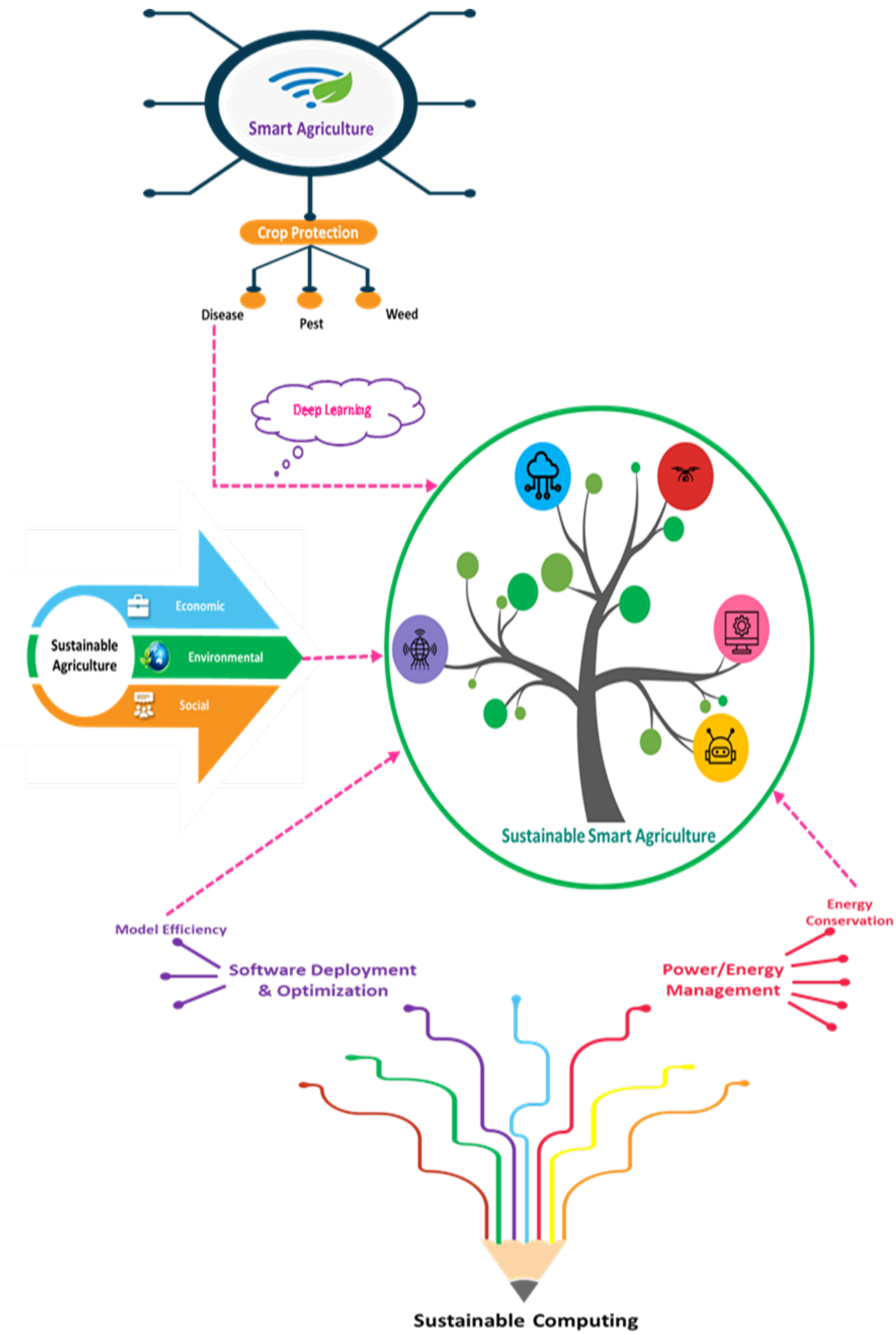


Figure 5.4: Sustainable Smart Agriculture – A Comprehensive Framework

5.3 Dataset and Methodology

This section offers an in-depth overview of the dataset used in this study. Furthermore, it discusses the DL techniques to ensure optimal performance within the proposed framework.

5.3.1 Dataset Exploration

Mango (Mangifera) is deep-rooted in Indian culture and tradition. Although India is the top mango producer and contributes 51% of the world's total production, little research has been conducted on this crop due to a lack of standardized datasets [95]. However, diseases are among the highly problematic constraints in mango cultivation. Mango diseases affect tree endurance, fruit quality, yield, consumer health, and trade [96]. Consequently, early detection is crucial to disease management, containment, and prevention. Hence, to address the critical need for reliable and timely disease diagnosis, a dataset has been collected to support the development of effective diagnostic models. A collective dataset of 555 images for multiple organs of mango (leaves, stems, fruits, panicles, and flowers) has been acquired for five categories, namely- anthracnose, powdery mildew, bacterial black spots, nutrient deficiencies, and healthy from the multiple geographical locations of India mainly from Uttar Pradesh, Andhra Pradesh, Maharashtra, Gujarat, and Karnataka, and internet sources. These images were captured using smartphones, avoiding multiple diseases in a single picture. Afterwards, diseases were annotated in each image by a human expert. Figure 5.5 demonstrates the representative images from the dataset. As the number of acquired images was inadequate for model training and data was highly imbalanced, more images were generated using StyleGAN3 [97]. The collective (raw & augmented data) mango disease dataset's statistics have been enumerated in Table 5.1.

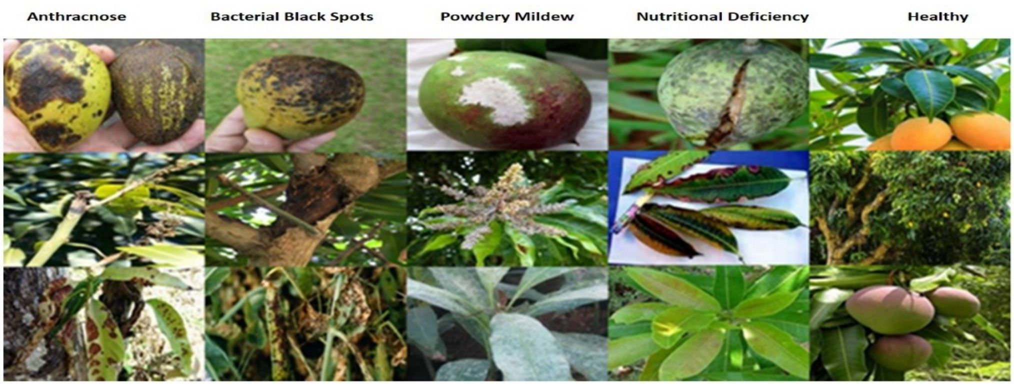


Figure 5.5: Sample Images from Mango Disease Dataset

Table 5.1: Description of the Dataset

Class	Scientific Name of Disease	Causing Agent	Symptoms	No. of Samples (RD)	No. of Samples (AD)
Anthracnose	Colletotrichum gleosporioides	Fungus	Small, dark, irregularly shaped lesions; fruit staining; leaf spotting; blossom blight and eventually rot.	224	10000
Bacterial Black Spot	Xanthomonas campestris	Bacterium	Angular, water-logged lesions on leaves; black cankerous lesions on stems that crack and release a gummy substance; irregular black spots on fruits and fruits that drop from the plant.	117	10000
Nutritional Deficiency	-	Calcium, Manganese, Nitrogen, Potassium, Iron, Phosphorus, Magnesium, Sulphur, Boron, Copper, Zinc	white, yellow, orange, or brown chlorotic spots; fruit cracking, cutting of leaves, flower drop.	49	10000
Powdery Mildew	Odium Mangifera	Fungus	Gray-white chalky fungal production on leaves, a panicle stem, flowers, and fruits; frizzle, disfigured shoots; fruit aborted and dropped from a tree.	110	10000
Healthy	-	-	Green, healthy leaves, flowers, stems, panicles, and fruits	55	10000

*Note**: RD: Raw Dataset; AD: Augmented Dataset*

5.3.2 Deep Learning Methodologies used in S^{2}AM

This section provides an overview of prominent DL algorithms used in this work, namely CNN and ViT.

A: Convolutional Neural Network

CNN is a popular DL algorithm inspired by the visual cortex of the living creatures [98]. It is a feed-forward neural network that processes data with a grid pattern, like images. It is designed to learn features of an input image automatically and adaptively, from low to high-level features. It comprises three basic building blocks: convolution layers, pooling layers, and fully connected layers. A series of convolution and pooling operations are performed for feature extraction, followed by fully connected layers that maps the extracted activation maps (features) into the final output class. A convolutional layer is the core building block of CNN; a digital image is given as input to a convolutional layer in which a small kernel performs the mathematical operation at each image position. While one layer feeds its output feature maps into the subsequent layer, extracted feature maps can hierarchically and progressively become more and more complex. The process of optimizing the hyperparameters such as kernels is called model training. A CNN model is recursively trained using backpropagation to minimize the difference between the actual and predicted output. The CNN architecture used for classification is presented in Figure 5.6

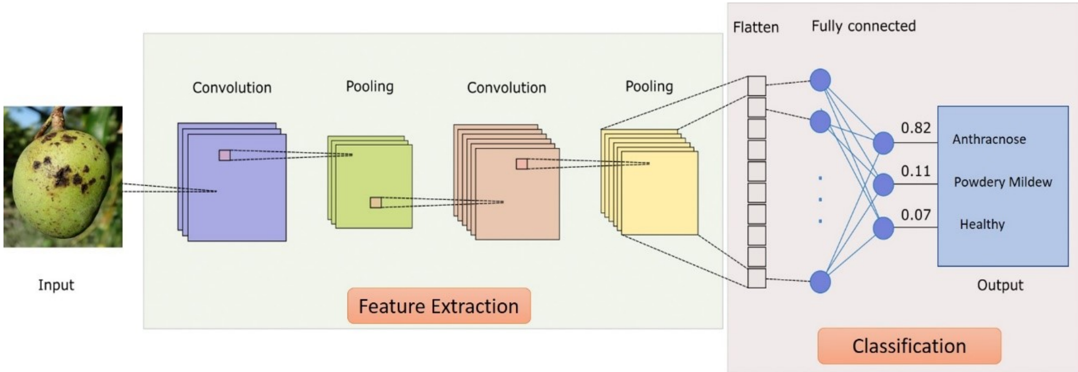


Figure 5.6: **Convolutional Neural Network Architecture:** CNN Comprises an Input Layer, a Stack of Alternating Convolutions and -Pooling Layers, a Fully-Connected Layer, and One Classification Layer

B: Vision Transformer

The Transformer model was introduced in the “Attention is all you need” study [99], incorporating an embedding layer, an encoder, and a decoder. Motivated by the achievements of transformers in NLP problems, ViT [100] was introduced. The essential components of ViT include linear projection, positional embeddings, and encoder. The network architecture of the original ViT is presented in Figure 5.7, where an input image is initially partitioned into small patches; these small patches are then fed into a trainable linear projection layer. The role of the embedding layer in a transformer is played by this linear projection layer that outputs fixed-sized vectors for the patches. Further, positional information for each patch is added to these vectors; the positional information is employed to keep the positional details of patches in context to the initial input image. Afterwards, the output obtained is fed to transformer encoder blocks. The fundamental building blocks of the transformer encoder comprise Multi-Head Self-Attention (MHSA) and Multi-Layer Perceptrons (MLP); both have a normalization layer in front of them and a residual connection at the end. The organization of MHSA and MLP is shown in the transformer encoder block. MHSA expands self-attention, wherein numerous attention operations called “heads” are performed parallelly. The MHSA layer concatenates the

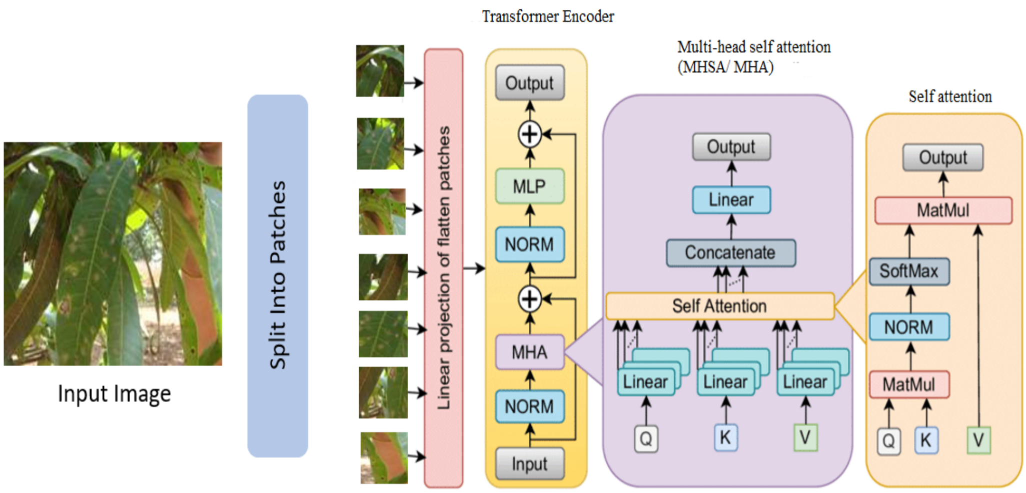


Figure 5.7: **Vision Transformer Architecture:** An image is split into fixed-size patches, and then patches are embedded to linear projection to output fixed-size vectors. Afterwards, positional embeddings are added to the output received from the previous layer and feed the resulting sequence of vectors to a standard transformer encoder to perform classification

output of these parallel operations linearly to produce the final attention score; Eqs. 5.1, 5.2, and 5.3 represents the mechanism for MHSA. Initially, a linear transformation is applied to the input matrices Q, K, and V, and then attention is performed as given in eq. 5.1 and eq. 5.2

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{2d_k}} + b\right)V \tag{5.1}$$

Wherein trainable weight matrices:

$$W_i^Q \in \mathbb{R}^{d \times d_k}, \quad W_i^K \in \mathbb{R}^{d \times d_k}, \quad W_i^V \in \mathbb{R}^{d \times d_k}$$

$$W_0 \in \mathbb{R}^{hd \times d_k}, \quad d_k = d_v = \frac{d}{h}$$

$$h_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \tag{5.2}$$

The multi-head attention derives h distinct depiction of Q, K, and V, calculates self-attention for each depiction, and concatenates them. This can be expressed in eq. 5.3

$$\text{MultiHead}(Q, K, V) = \text{Concat}[h_1, h_2, \ldots, h_n]W_0 \tag{5.3}$$

MHSA gives the transformer encoder great power to encode multiple relationships and nuances for each patch. The output of the MHSA block in ViT can be computed using eq. 5.4. In the encoder block, MLP is applied after the MHSA layer. MLP comprises artificial neural network layers along with a Gaussian error linear unit (GELU) activation function.

$$\text{MHSA}_{\text{Output}} = \text{MHSA}(\text{NORM}(x)) + x \tag{5.4}$$

x is the input fed into the transformer encoder block; $NORM$ is the normalization layer, and $MHSA$ is multi-head self-attention and $\text{MHSA}_{\text{Output}}$ is the output of MHSA.

The final output of the transformer encoder block can be computed using eq. 5.5

$$\text{TfEnc}_{\text{Output}} = \text{MLP}(\text{NORM}(\text{MHSA}_{\text{Output}})) + \text{MHSA}_{\text{Output}} \tag{5.5}$$

Wherein MLP is the multilayer perceptron block and $\text{TfEnc}_{\text{Output}}$ is the output of the transformer encoder block.

5.4 Proposed Model

In recent years, CNN emerged as a breakthrough in image processing. It surpasses human experts in various CV tasks. Since 2016, numerous applications have been proposed for automatic plant disease identification using CNN. Recently, ViT has attracted significant attention and emerged as a competitive alternative to CNN; however, it must be more maturely exploited for plant pathology applications. The complementary characteristics of CNN and ViT [101] encourage us to build a hybrid model for plant disease identification.

In this work, the author has combined the two architectures mentioned above CNN and ViT, consequently, an improved and explainable plant disease classification model S^2AM has been proposed. MobileNetv2 [81] and EfficientNetv2 [102] motivated us to address the shortcomings of ViT (high inference time, a large number of parameters, and a heavy model) by replacing traditional encoders in ViT with adapted Fused-MBConv.

The block-wise architecture of S^2AM is delineated in Figure 5.8, S^2AM expects a color input image of size 224×224×3. The convolutional stem unsheathes the local features in an image, and extracted feature maps are then fed to the stack of adapted Fused-MBConv to fetch global features. Embeddings enrich the representation of features before we reduce their spatial resolution. Finally, the classification task was performed by MLP. The output equation can be derived as eq. 5.6

$$Y = \prod_{i=1}^{m} \text{Adapted Fused-MBConv}(\text{PatchEmbedding}(x)) \tag{5.6}$$

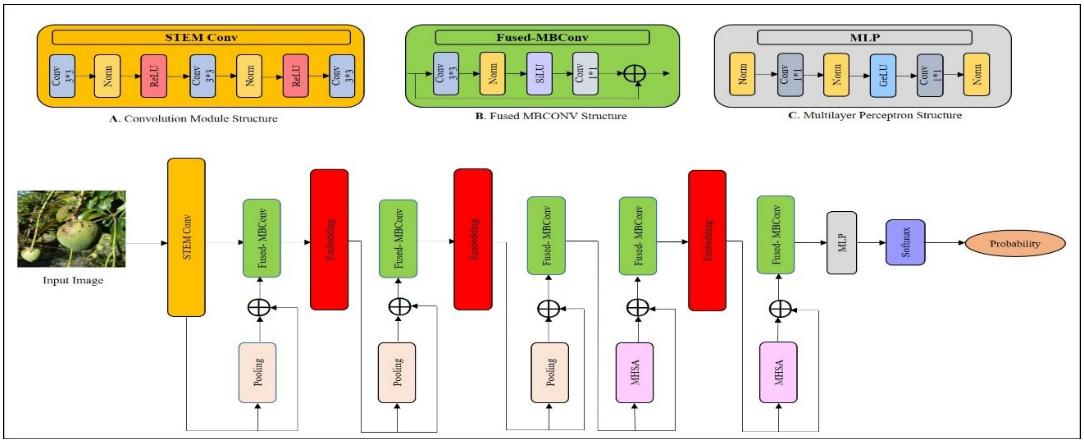


Figure 5.8: **Block-wise architecture of proposed S²AM:** An image is fed as an input to the convolutional stem, output from the convolution stem is fed to a stack of adapted Fused-MBConv for rich feature extraction. Finally, classification is performed by the MLP

where x is the input image batch, Y is the desired output, and m is the count of adapted Fused-MBConv.

The following sub-sections illustrate the critical components of the model.

5.4.1 Convolutional Block

Numerous studies have proven the complementarity between CNN and ViT [103]. CNN possess inherent inductive bias; therefore, a convolutional stem was prefixed to adapt ViT blocks for enhanced feature extraction. The convolutional stem comprised three standard convolution layers, each with a convolutional kernel size of 3×3, a stride of 2, and padding of 1. The number of kernels in each convolution layer was 24. The initial two convolutions were followed by batch normalization and Rectified linear unit (ReLU) activation operations to facilitate easy and fast training.

5.4.2 Adapted Fused-MBConv

For lightweight and easier deployment on end devices for real-time usage, the Fused-MBConv block was adopted from MobileNetv2. S^{2}AM entailed two adapted versions of the Fused-MBConv, code-named Pooling Fused-MBConv and MHSA Fused-MBConv, as illustrated in Figure 5.9. Furthermore, one MBConv was deficient in extracting dense features; hence, a stack of adapted Fused-MBConv was employed. Three Pooling Fused-MBConv were introduced after the convolution stems to extract dense features and a residual connection was provided to minimize the loss of information. MHSA in the

Fused-MBConv block was introduced to inherit the ViT property. The primary purpose of the MHSA was to embed attentive features globally across the overall image and help the model learn spatial features. Furthermore, the attention blocks were only beneficial after extracting dense features; thus, two MHSA Fused-MBConv were applied after CNN blocks only. Multiple patch embeddings were adopted to extract the deep spatial features from the input image and enhance performance.

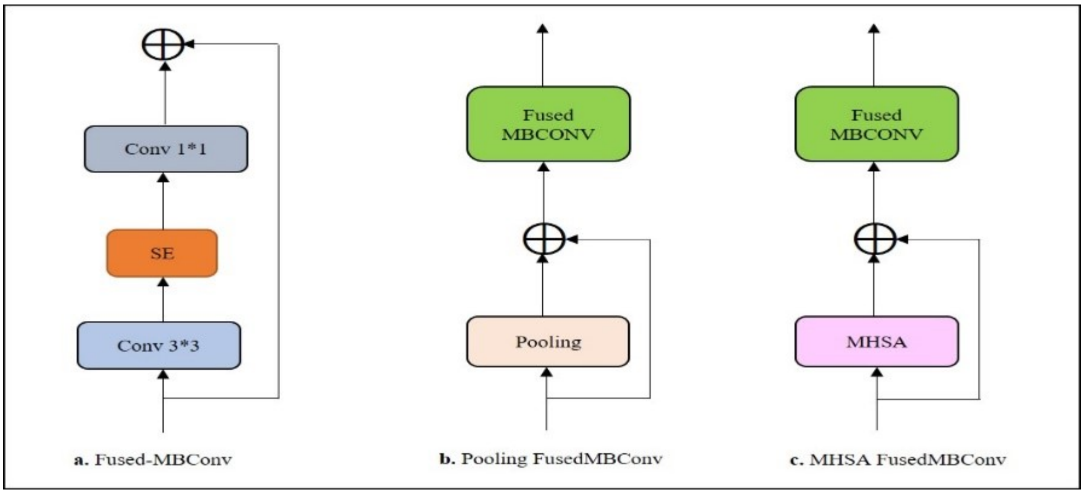


Figure 5.9: (a) Original Fused-MBConv; (b) Pooling Fused-MBConv; and (c) MHSA Fused-MBConv

5.4.3 MLP Head

MLP is a multi-layered linear block that contains non-linearity to fix the overfitting problem. To ensure the lightweight of S^2AM, fully connected layers were replaced with a 1×1 convolution layer. Ultimately, the network's output was normalized using the softmax activation function to a probability distribution across the anticipated output class.

5.5 Experiments

This section highlights the various performance measures used to evaluate the efficacy of the proposed model. Further, the experimental settings and the training strategy are also specified to ensure the reproducibility of the results.

5.5.1 Evaluation Metrics

Seven performance metrics have been used to validate the classifiers' performance, including accuracy, precision, recall, F1-score, FLOPs, number of trainable parameters, and inference latency. *Accuracy* is quantified as the ratio of correctly predicted samples to the total number of samples within the dataset. A higher value attained by the classifier indicates superior performance. *Precision* refers to the proportion of the true positives out of total positive predictions. *Recall* signifies the count of the true positives found. *F1-score* is the harmonic mean between precision and recall. The mathematical representation of these metrics is presented in eqs. 5.7, 5.8, 5.9 and 5.10

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{5.7}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{5.8}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5.9}$$

$$\text{F1 Score} = 2 \cdot \frac{(\text{Precision} \cdot \text{Recall})}{\text{Precision} + \text{Recall}} \tag{5.10}$$

Where TP, TN, FP and FN are the counts of true positive, true negative, false positive, and false negative, respectively. The *number of trainable parameters* expresses the model's size. The lesser the parameters count, the more lightweight the model is, and it will need less hardware to run. *FLOPs* imply the number of floating-point operations executed for a single forward pass. The fewer the FLOPs, the shorter the execution time and computation power the model requires. *Latency* is an essential metric concerned with real-time systems. It can be described as the time the model/system takes to process one image. Less latency is desirable.

5.5.2 Experimental Setup and Training Strategy

To pacify data insufficiency and improve S^{2}AM's performance, StyleGAN3T, a variation of StyleGAN3, was used to generate synthetic data. The original images were resized to 512×512 to generate high-resolution images. For StyleGAN3T training, authors used two Nvidia V100 GPUs with gamma ten and a total iteration of 5K. Ten thousand images for each class with 0 to 10000 seeds were generated. The output images had a resolution of 512×512. "the PyTorch deep learning framework" was utilized to train the model. Nvidia CUDA accelerated platform, PyTorch 1.11 with CUDA 11.3, and cuDNN version 8.2 were adopted to expedite the training process. The dataset underwent division, with 80% allocated for training and 20% for testing purposes. The optimizer employed was ADAM, configured with a weight decay of 1×10^{-4} and a maximum learning rate of 3×10^{-5}.

This weight decay was explicitly applied to all layers except the bias and Norm layers. The epsilon value for ADAM was set to 1×10^{-8}. A warm-up phase encompassing 10% of the total training steps was integrated, during which the learning rate progressively increased linearly. Subsequently, post-warm-up, the learning rate gradually decreased with a minimal slope. Each classifier was trained with a batch size of 64 and for a total of 100 epochs. The training was implemented using two Nvidia Tesla V100 GPUs, each equipped with 32GB memory and utilizing FP16.

5.6 Results

This section presents the results of the comprehensive experiments conducted to evaluate the proposed model. Key performance metrics have been used to assess the classifiers' effectiveness, including accuracy, precision, recall, F1-score, FLOPs, the number of trainable parameters, and inference latency. It is important to mention here that for the visualization of tensor board plots, a technical name- AttentionEfficientNet, is given to the proposed model and used in place of S^2AM

5.6.1 Experiment 1: Comparative Performance Analysis of S^2AM and State-of-the-Art Models

The comparative performance of six classifiers, namely, AlexNet [104], VGG16 [77], ResNet50 [80], Inceptionv3 [105], MobileNetv2 and S^2AM (AttentionEfficientNet) is showcased in Figures 5.10, 5.11, 5.12, 5.13, 5.14 and 5.15, respectively. Furthermore, Table 5.2 presents that the proposed model achieved impressive metrics with accuracy, precision, recall, and F1 score reaching 99.4%, 99.4%, 99.5%, and 99.6% respectively, surpassing other state-of-the-art models. Additionally, to assess the impact of data augmentation, an ablation study is conducted in which S^2AM is trained and tested solely on the raw dataset. The results of the ablation study are also presented in Table 5.2 (with entries for augmented and raw datasets highlighted in green and red, respectively). Furthermore, the impact of each class on the overall performance across all six classifiers is presented in Tables 5.3, 5.4, 5.5, 5.6, 5.7, and 5.8, while detailed insights can be gleaned by examining confusion matrices depicted in Figures 5.16, 5.17, 5.18, 5.19, 5.20, and 5.21.

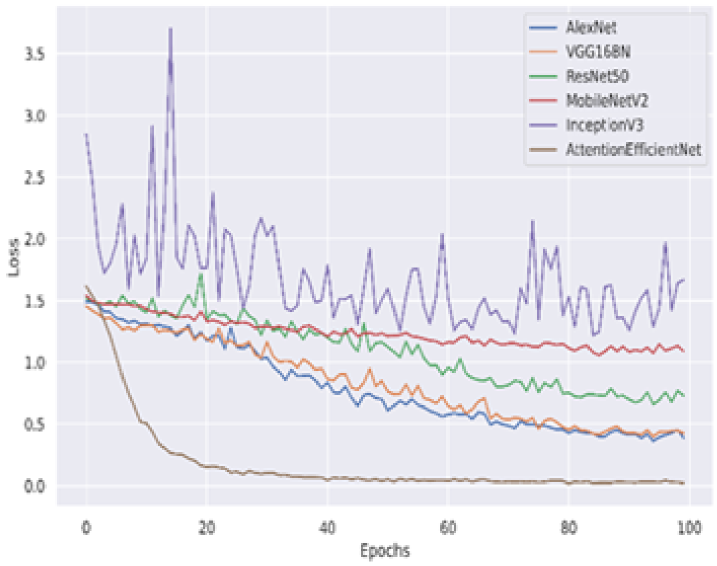


Figure 5.10: Analysis of Loss Metrics for Test Data Across Models

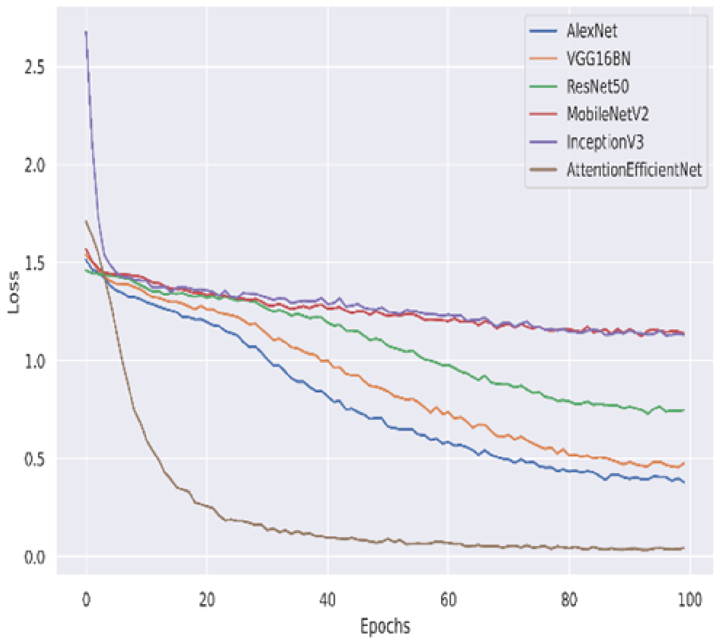


Figure 5.11: Analysis of Loss Metrics for Test Data Across Models

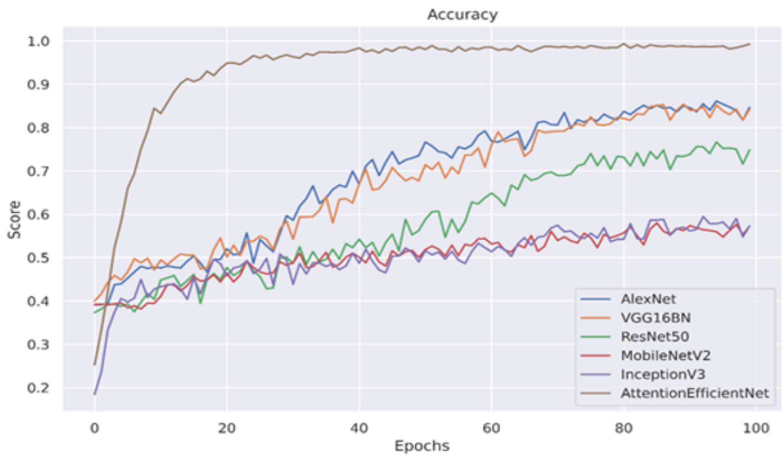


Figure 5.12: Accuracy Comparison of Various Classifiers Applied in This Study

Figure 5.13: Precision Comparison of Various Classifiers Applied in This Study

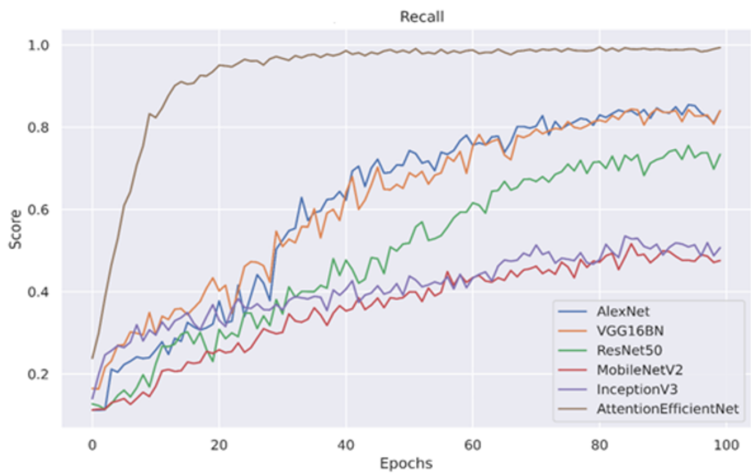


Figure 5.14: Recall Comparison of Various Classifiers Applied in This Study

Figure 5.15: F1-score Comparison of Various Classifiers Applied in This Study

Table 5.2: Comparison Indicators with State-of-the-art Models

Model Type (With AD* vs RD)**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
AlexNet	86.12	83.53	87.83	85.42
	66.34	64.81	63.07	63.30
ResNet50	76.65	74.57	76.97	75.54
	61.53	59.82	57.71	57.97
VGG16	85.38	83.79	85.24	84.42
	68.26	72.69	69.91	70.87
MobileNetV2	57.99	49.27	59.94	51.66
	61.53	56.58	61.90	57.09
InceptionV3	59.46	50.50	63.64	51.85
	67.30	68.05	71.96	68.66
S^{2}AM	99.35	99.35	99.46	99.58
	80.76	84.81	79.02	81.19

*AD - Augmented Data (Highlighted in Green Colour)
**RD - Raw Data (Highlighted in red Colour)

Table 5.3: Classwisw Performance for AlexNet Model

Metric	**Anth (%)**	**BBS (%)**	**Healthy (%)**	**ND (%)**	**PM (%)**
Accuracy	91.80	77.02	75.83	80.39	92.62
	73.80	58.62	66.66	58.33	66.66
Precision	91.80	77.02	75.83	80.39	92.62
	73.80	58.62	66.66	58.33	66.66
Recall	82.87	82.21	91.91	89.13	93.05
	70.45	68.00	44.44	70.00	62.50
F1-score	87.11	79.53	83.10	84.53	92.84
	72.09	62.96	53.33	63.63	64.51

*Note**:Anth: Anthracnose; BBS: Bacterial black spots; PM: Powdery Mildew; ND: Nutritional Deficiency*

Table 5.4: Classwise Performance for ResNet50 Model

Metric	Anth (%)	BBS (%)	Healthy (%)	ND (%)	PM (%)
Accuracy	78.68	71.17	71.66	64.70	86.63
	60.00	61.29	42.85	60.00	75.00
Precision	78.68	71.17	71.66	64.70	86.63
	60.00	61.29	42.85	60.00	75.00
Recall	77.24	69.91	73.50	82.50	81.73
	64.86	73.07	50.00	37.50	63.15
F1-score	77.95	70.53	72.57	72.52	84.11
	62.33	66.66	46.15	46.15	68.57

*Note**:Anth: Anthracnose; BBS: Bacterial black spots; PM: Powdery Mildew; ND: Nutritional Deficiency*

Table 5.5: Classwise Performance for VGG16 Model

Metric	Anth (%)	BBS (%)	Healthy (%)	ND (%)	PM (%)
Accuracy	87.35	83.40	87.39	72.27	88.53
	65.78	56.25	71.42	83.33	86.66
Precision	87.35	83.40	87.39	72.27	88.53
	65.78	56.25	71.42	83.33	86.66
Recall	84.19	84.16	83.87	82.95	91.03
	62.50	72.00	71.42	71.42	72.22
F1-score	85.74	83.78	85.59	77.24	89.76
	64.10	63.15	71.42	76.92	78.78

*Note**:Anth: Anthracnose; BBS: Bacterial black spots; PM: Powdery Mildew; ND: Nutritional Deficiency*

Table 5.6: Classwise Performance for InceptionV3 Model

Metric	Anth (%)	BBS (%)	Healthy (%)	ND (%)	PM (%)
Accuracy	74.23	51.58	37.50	15.53	71.42
	69.23	61.29	71.42	58.33	80.00
Precision	74.23	51.58	37.50	15.53	71.42
	69.23	61.29	71.42	58.33	80.00
Recall	58.81	49.35	66.17	76.19	67.68
	62.79	67.85	62.50	100.00	66.66
F1-score	65.63	50.44	47.87	25.80	69.50
	65.85	64.40	66.66	73.68	72.72

*Note**:Anth: Anthracnose; BBS: Bacterial black spots; PM: Powdery Mildew; ND: Nutritional Deficiency*

Table 5.7: Classwise Performance for S^2AM Model

Metric	Anth (%)	BBS (%)	Healthy (%)	ND (%)	PM (%)
Accuracy	99.53	98.20	100.00	99.01	100.00
	75.60	78.12	85.71	100.00	84.61
Precision	99.53	98.20	100.00	99.01	100.00
	75.60	78.12	85.71	100.00	84.61
Recall	98.83	99.09	100.00	100.00	100.00
	86.11	80.64	75.00	68.75	84.61
F1-score	99.18	98.64	100.00	99.50	100.00
	80.51	79.36	80.00	81.48	84.61

*Note**:Anth: Anthracnose; BBS: Bacterial black spots; PM: Powdery Mildew; ND: Nutritional Deficiency*

Table 5.8: Classwise Performance for MobileNetv2 Model

Metric	Anth (%)	BBS (%)	Healthy (%)	ND (%)	PM (%)
Accuracy	74.52	43.04	42.50	17.47	68.80
	67.50	63.33	50.00	33.33	68.75
Precision	74.52	43.04	42.50	17.47	68.80
	67.50	63.33	50.00	33.33	68.75
Recall	54.67	49.23	67.10	56.25	72.46
	65.85	61.29	50.00	80.00	52.38
F1-score	63.07	45.93	52.04	26.60	70.58
	66.66	62.29	50.00	47.05	59.45

*Note**:Anth: Anthracnose; BBS: Bacterial black spots; PM: Powdery Mildew; ND: Nutritional Deficiency*

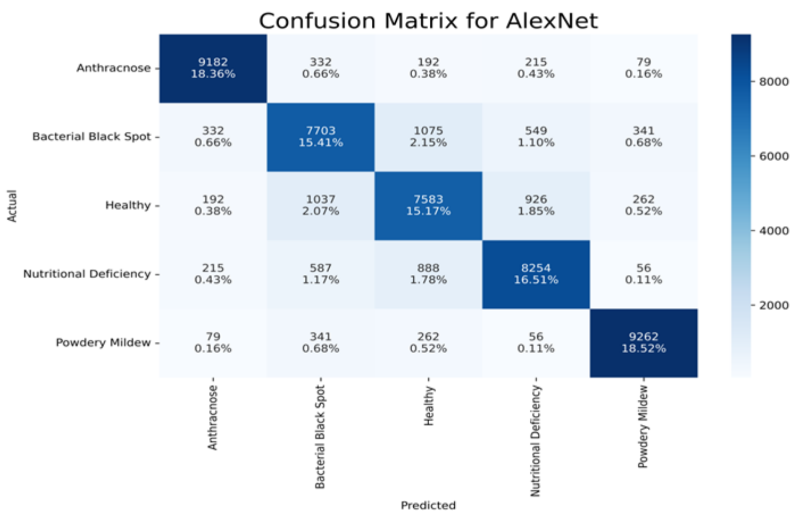


Figure 5.16: Confusion Matrix for AlexNet Model

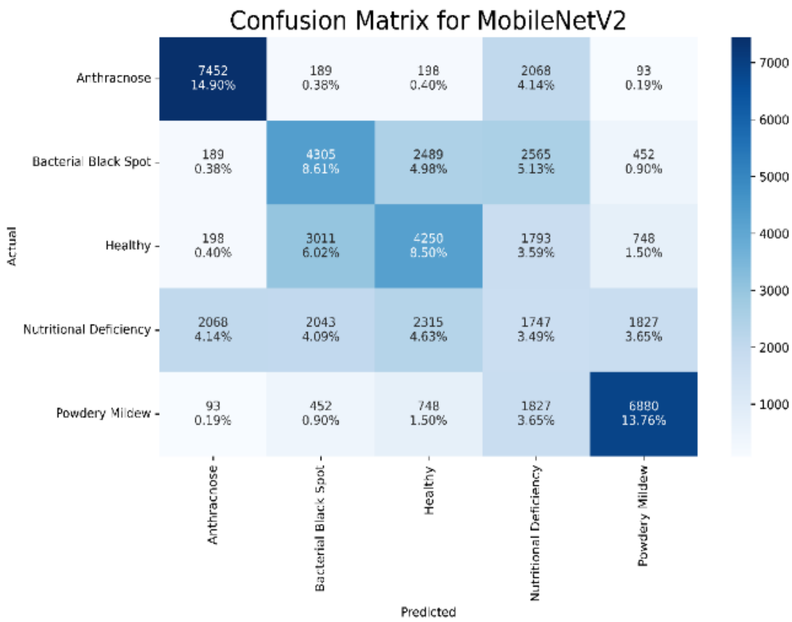


Figure 5.17: Confusion Matrix for MobileNetv2 Model

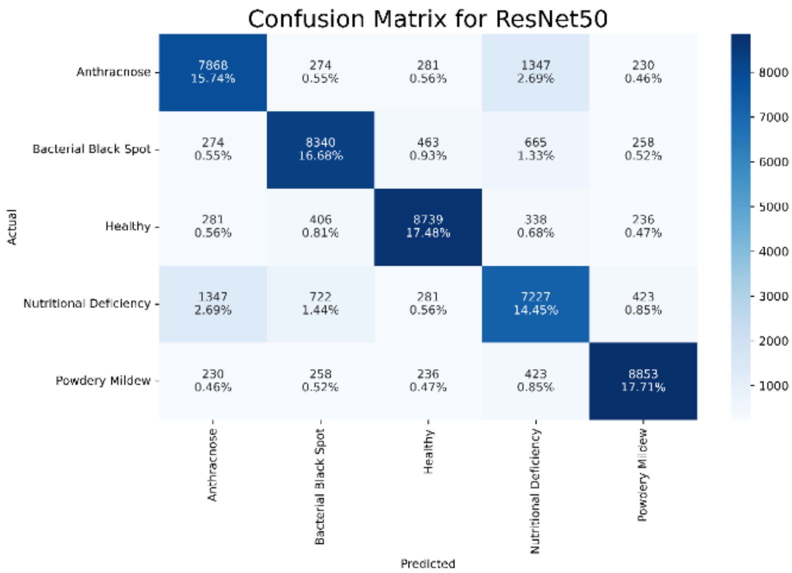


Figure 5.18: Confusion Matrix for ResNet50 Model

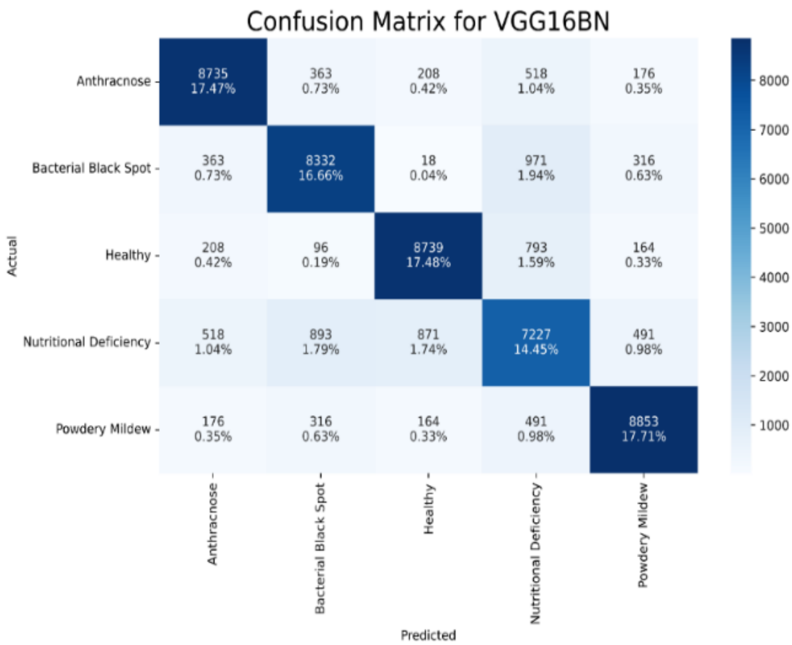


Figure 5.19: Confusion Matrix for VGG16 Model

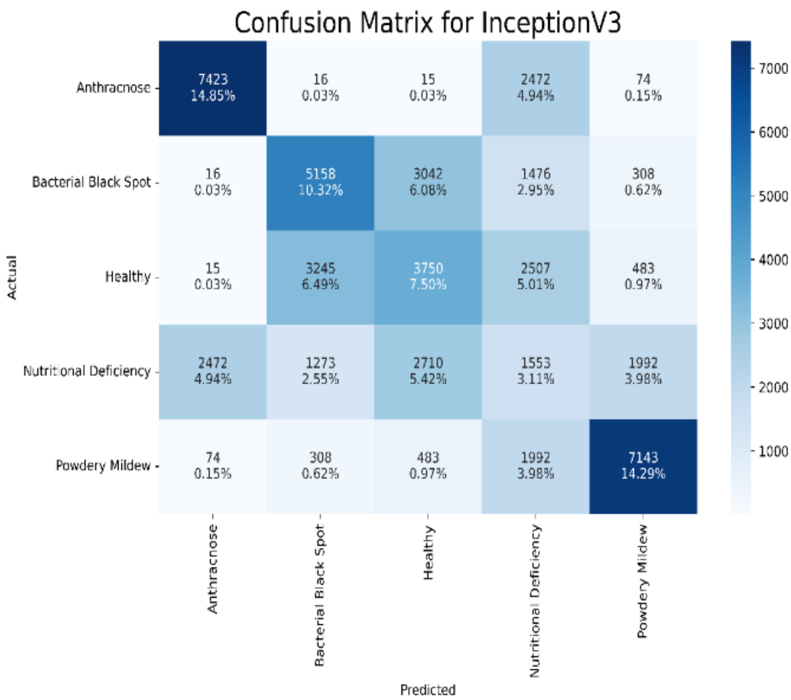


Figure 5.20: Confusion Matrix for Inceptionv3 Model

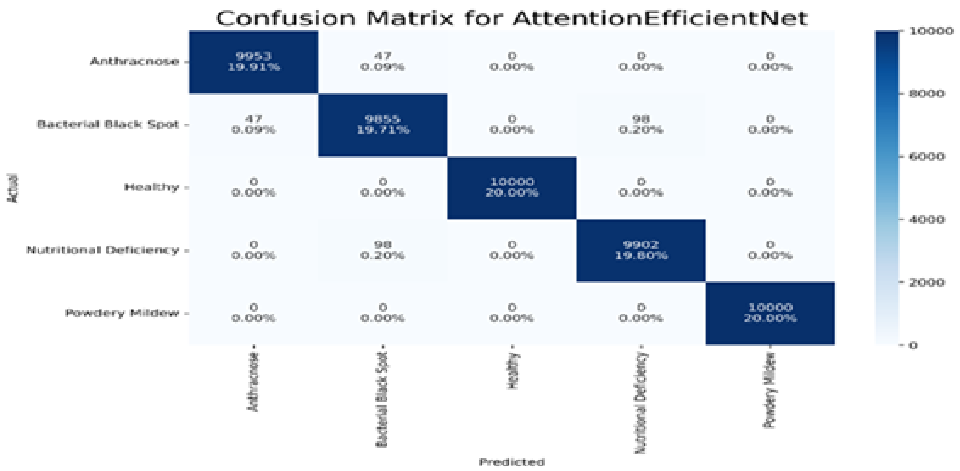


Figure 5.21: Confusion Matrix of S^{2}AM

5.6.2 Experiment 2: Performance Comparison for FLOPs and Number of Parameters

A detailed comparison between S^{2}AM and state-of-the-art models for FLOPs and no. of trainable parameters is listed in Table 5.9. It is evident from the table that the proposed S^{2}AM improved the F1-score by 15%, using $6.29\times$ fewer trainable parameters and $1.88\times$ fewer FLOPs.

Table 5.9: Comparison of Number of FLOPs and Trainable Parameters for Various Models

Model Type	F1-Score (%)	FLOPs	Parameters
AlexNet	85.42	0.727B	61.1M
ResNet50	75.54	4B	25.6M
VGG16	84.40	16B	138.4M
MobileNetV2	51.66	0.3B	3.5M
InceptionV3	51.85	6B	27.2M
S^{2}AM	99.58	8.8B	22M

5.6.3 Experiment 3: Performance Comparison for Latency

This section presents the latency comparison of the models on Central Processing Unit (CPU), Nvidia Tesla T4, and Nvidia Tesla A100. The latency was calculated in both the training and inference phases. The single-batch and four-batch latency is calculated and tabulated in Tables 5.10, 5.11, 5.12, and 5.13.

The above-stated tables show that the latency of S^{2}AM is close to MobileNetV2 with 48% better performance.

Table 5.10: Inference Latency of Models with One Batch

Model	CPU Latency (ms)	Nvidia Tesla T4 (ms)	Nvidia Tesla A100 (ms)
AlexNet	14.26	2.54	1.13
ResNet50	61.93	15.90	10.96
VGG16	176.97	9.42	5.31
MobileNetV2	18.64	11.43	7.32
InceptionV3	65.95	28.80	16.47
S^{2}AM	32.51	9.90	3.89

Table 5.11: Inference Latency for Models with Four Batches

Model	CPU Latency (ms)	Nvidia Tesla T4 (ms)	Nvidia Tesla A100 (ms)
AlexNet	45.96	2.48	1.84
ResNet50	212.95	16.17	15.52
VGG16	695.73	29.66	4.58
MobileNetV2	48.05	11.39	8.32
InceptionV3	186.62	29.33	20.43
S^{2}AM	92.39	14.62	10.44

Table 5.12: Training Latency for Models with One Batch

Model	CPU Latency (ms)	Nvidia Tesla T4 (ms)	Nvidia Tesla A100 (ms)
AlexNet	12.82	2.72	1.49
ResNet50	69.92	18.43	14.30
VGG16	145.16	9.98	5.67
MobileNetV2	26.82	15.67	11.28
InceptionV3	68.22	36.83	21.71
S^{2}AM	42.38	16.63	12.59

Table 5.13: Training Latency for Models with Four Batches

Model	CPU Latency (ms)	Nvidia Tesla T4 (ms)	Nvidia Tesla A100 (ms)
AlexNet	38.48	2.63	3.67
ResNet50	209.97	20.65	14.76
VGG16	560.51	29.48	5.91
MobileNetV2	67.83	17.39	11.93
InceptionV3	170.00	37.47	25.15
S^{2}AM	117.49	17.88	13.20

5.6.4 Experiment 4: Evaluation of S^2AM Performance in Comparison to Prior Mango Crop Research

This section analyses S^2AM's performance in mango crop disease classification against existing models and architectures. As previously discussed, this study represents the initial endeavor to discern diseases affecting all conceivable plant organs. Conversely, prior studies solely focused on leaf diseases. Moreover, this work addresses the potential for misclassification resulting from similarities in disease symptoms attributable to pathogens and nutritional deficiencies. The S^2AM model stands out with high precision, recall, and F1-score across multiple organs and classes, demonstrating its superior performance compared with previous research on mango crop to other models in terms of various performance metrics tabulated in Table 5.14.

5.6.5 Experiment 5: Assessing the Generalizability of S^2AM on Other Crops

To assess the applicability of the S^2AM across diverse crops, the proposed model was tested on two distinct datasets, namely the Tomato disease dataset (Dataset1) and the Almond disease dataset (Dataset2). Dataset1 was sourced from the publicly available PlantDoc repository [70], real fields, and agriculture websites, while Dataset2 was compiled from online sources. Each dataset comprises 50 images within every class. Sample images for the above-mentioned datasets are presented in Figure 5.22. It is imperative to emphasize that the selection of these two datasets was deliberate for the following reasons: (1) The PlantDoc dataset has emerged as a benchmark, explicitly addressing the disease of interest. Further, no other datasets have adequately tackled this ailment or have done so under uniform background conditions. (2) The inclusion of the Indian almond crop as Dataset 2 was motivated by its morphological similarity to the mango leaves. This choice allowed the author to explore whether disease symptoms alone are decisive in disease classification or if other factors contribute significantly. Table 5.15 presents the model's performance on Dataset1 and Dataset2.

Subsequently, Dataset 2 is combined with randomly selected samples from the mango disease dataset to create Dataset 3. Upon implementing S^2AM on this combined dataset, a discernible decline in accuracy by 5 to 6% is observed, as presented in Table 5.16. This decline in accuracy suggests that combining crops with similar morphology may introduce variability in non-disease-related features, affecting the model's performance. It highlights the need for careful consideration of dataset composition when addressing cross-crop disease classification.

Table 5.14: Comparison of the Proposed Model with State-of-the-art Models for Mango Disease Classification

	Model	Dataset	NoI	Organ	Classes	A (%)	P (%)	R (%)	F1 (%)	NoP	FLOPs	Latency
[106]	ANN with Feature Selection	Self-built	450	Leaf	Anthracnose, Gall Midge, Powdery mildew, Healthy	85.45	82.5	81.5	82	-	-	-
[107]	Customized AlexNet	Self-built	2200	Leaf	Anthracnose	97.13	-	-	-	-	-	-
[108]	CROLFD-optimized Mo-bileNetV2	Self-built	380	Leaf	Anthracnose, Bacterial black spots, Sooty mold, Healthy	94.5	99.56	98.03	95.67	-	-	-
[109]	AlexNet Transfer Learning	Self-built	1216	Leaf	Bacterial black spots, Healthy, Powdery mildew, Scab	89	89.5	90.5	90	-	-	-
[110]	CNN Model	Self-built	1200	Leaf	Anthracnose, leaf gall, Alternaria leaf spot, leaf webber, healthy leaf burn	96.67	-	-	-	-	-	-
[111]	Customized VGG16	Self-built	46500	Leaf	16 Pests classes	76	-	-	-	-	-	2s to 2.99s
[112]	FrCNnet-Segmentation	Self-built	8880	Leaf	Anthracnose and apical-necrosis	98.9	-	0.01	-	-	-	-
[113]	Leaf vein-seg approach	Self-built	135	Leaf	Healthy, Powdery mildew, Sooty mold	95.5	-	-	-	-	-	-
[114]	CSUBW optimized CNN	Kaggle	435	Leaf	Diseased or healthy	91.2	0.94	-	0.92	-	-	-
[115]	CNN Model	Others Dataset	-	Leaf	Powdery mildew, Anthracnose, Dieback, Phoma Blight, Bacterial Canker, Red Rust, Healthy, Golmachi	98.12	-	-	-	-	-	-
[116]	ESDNN	Self-built (Plain BG)	2000	Leaf	Powdery mildew, Anthracnose, Dieback, Phoma Blight, Bacterial Canker, Red Rust, Sooty Mold, Mango Malformation, Healthy	98.57	98.57	98.57	98.57	-	-	-
S^{2}AM	Attention EfficientNet	Self-built	50000	Leaf, Stem, Fruit, Pani-cles, Flow-ers	Anthracnose, Powdery mildew, Bacterial black spots, ND, Healthy	99.35	99.35	99.46	99.58	22M	8.8B	3.89ms

Table 5.15: Performance of S^{2}AM on Tomato and Almond Disease Dataset

Dataset	Accuracy (%)	F1-Score (%)
Tomato Disease Dataset (Dataset 1)	95.03	96
Almond Disease Dataset (Dataset 2)	98.7	99

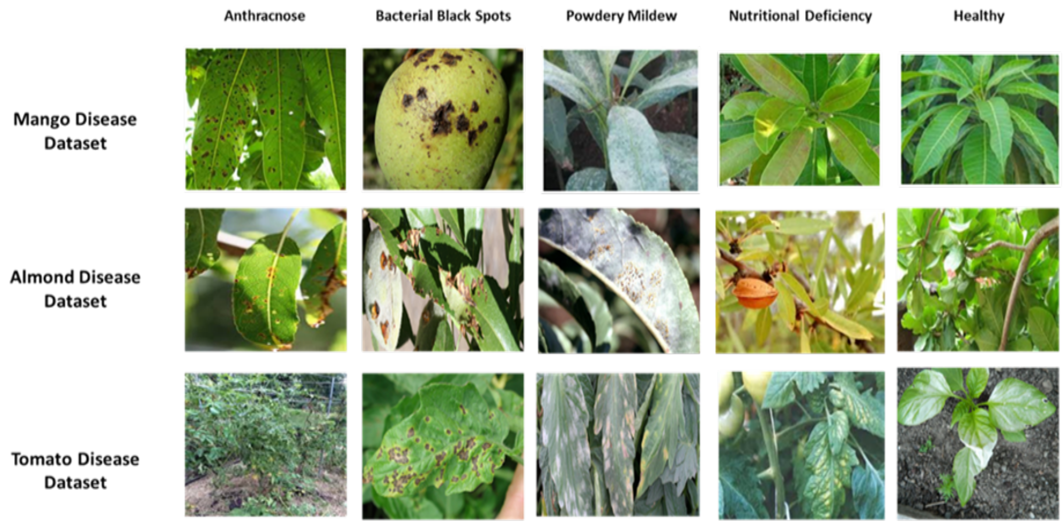


Figure 5.22: Sample Images of the Three Datasets Tested for Generalizability of the S^2AM

Table 5.16: Performance of S^2AM on Combined Dataset

Dataset	Accuracy (%)	F1-Score (%)
Combined Mango disease dataset & Almond disease dataset (Dataset 3)	90.3	91

5.6.6 Experiment 6: Explainability of S^2AM

Despite the contribution of DL classifiers in numerous CV tasks such as image detection and image classification, the prevalent weakness of DL models is that the end-to-end model remains a “black box” for users. Therefore, unpacking the intrinsic logic of DL models is significant. It helps to understand the models’ behaviour better. Hence, an understandable explanation of the model makes its predictions convincing. In this work, the authors used the Class Activation Map (CAM), which makes the proposed model transparent by visualizing the image regions supreme for the predictions. Figure 5.23 presents the weighted activation maps generated by S^2AM; these weighted activations were responsible for classifying diseases into a particular category. Note that the samples in the upper row in Figure 5.23 are the raw images, and the bottom row samples are the positioning images exhibited by the visual technology of CAM. These plots conclude that the proposed model only focuses on the critical diseased part.

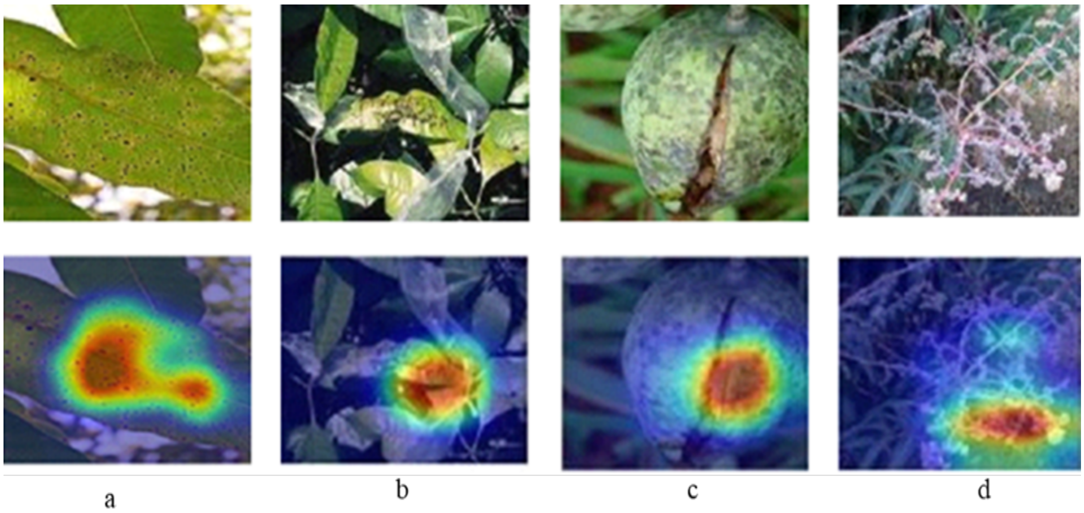


Figure 5.23: **Class Activation Mapping:** (a) Anthracnose (b) Bacterial Black Spot (c) Nutritional Deficiency (d) Powdery Mildew. The Upper Row Represents the Input Image While the Bottom Row Highlights the Class-Specific Discriminative Regions

5.7 Discussions

The results obtained through extensive experimentation with the S^{2}AM model shed light on several critical aspects of the effectiveness and applicability of the proposed approach. In this section, the author discusses how these findings address the RQ posed in this chapter.

- **RQ1:** Does the integration of Convolutional Neural Networks and Vision Transformer effectively mitigate the inherent limitations of individual architectures, yielding a lightweight and computationally efficient model suitable for deployment on embedded devices for in-situ plant disease classification?

  The integration of CNN and ViT within the S^{2}AM model proved highly effective in mitigating the limitations inherent in individual architectures. By combining the strengths of both architectures, S^{2}AM achieved superior performance in terms of accuracy, precision, recall, and F1-score while also demonstrating faster convergence during training and testing. As presented in Figure 5.10 and Figure 5.11, the S^{2}AM testing and training loss converged faster than other classifiers, implying that S^{2}AM required significantly fewer epochs to achieve maximum performance. Further, Figures 5.12, 5.13, 5.14 and 5.15 demonstrated that accuracy, precision, recall, and F1-score converged to 97% in less than 20 epochs for S^{2}AM, while other classifiers took more than 80 epochs to converge. Eventually, after 100 epochs,

S^2AM achieved outstanding performance (close to 100%). At the same time, other state-of-the-art classifiers were not even closer to 85%, which proclaimed S^2AM as the best classifier among all in standard performance metrics. Further, Table 5.9, demonstrated that the S^2AM model exhibited a lightweight and computationally efficient architecture as it improved the F1-score by 15%, using $6.29\times$ fewer trainable parameters and $1.88\times$ fewer FLOPs, making it well-suited for deployment on embedded devices.

- **RQ2:** Can the proposed model be effectively generalized to classify diseases in other crops, and what challenges may arise in achieving this cross-crop generalizability?

  The findings suggested that the proposed S^2AM model held promise for effective generalization to classify diseases in other crops beyond mangoes. The robust performance of S^2AM across multiple disease classes indicated its potential applicability to diverse agricultural contexts. As delineated in Table 5.15, the proposed model demonstrated robust generalizability across two crops, namely tomato and almond. However, a marginal decrease in accuracy was noted in the case of the Tomato Disease Dataset (Dataset 1). This diminution could be attributed to the dataset's inherently cluttered environment, exacerbated by the distinct morphology of tomato leaves, which significantly differed from the mango disease dataset. Noteworthy was the observation that in the Almond Disease Dataset (Dataset 2), the morphology and vein patterns of leaves closely resembled those in the training dataset. Consequently, this dataset exhibited higher accuracy than Dataset 1, approaching results comparable to the mango disease dataset. Further results presented in Table 5.16 represented a discernible decline in accuracy by 5% to 6% on the Combined Mango disease dataset & Almond disease dataset (Dataset 3).
  To delve deeper into the causes of misclassifications and the ensuing accuracy drop, a meticulous analysis of misclassified images was undertaken. It was deduced that most misclassifications arose from background similarity, morphological similarities of leaves, and interference with adjacent leaves. Hence, to answer RQ2, it could be deduced that the proposed S^2AM held promise for effective generalization to classify diseases in other crops beyond mangoes. However, challenges might have arisen in achieving cross-crop generalizability due to variations in disease manifestations, the morphology of leaves, vein patterns, image quality, and environmental conditions among different crops. Further research and validation across a broader range of crop types were warranted to assess the model's generalizability

comprehensively and to address any potential challenges that might have arisen.

- **RQ3:** How successful is the use of StyleGAN3 in producing synthetic images to augment the diversity of the gathered dataset for the classification of plant diseases?

  Using StyleGAN3 for generating the synthetic images proved successful in augmenting the diversity and variety of the dataset for plant disease classification. The augmented dataset facilitated improved model training by providing a more comprehensive representation of disease manifestations and variations. As demonstrated in Table 5.2, S^2AM trained on the augmented dataset achieved superior performance compared to models trained solely on the raw dataset. Whereas, training the S^2AM on the raw dataset resulted in a drop in accuracy, precision, recall, and F1-score by 18.59%, 14.54%, 20.44%, and 18.39%, respectively. This highlighted the importance of data augmentation techniques, such as StyleGAN3, in enhancing the robustness and effectiveness of DL models for plant disease classification.

  In summary, the results obtained with the S^2AM provided valuable insights into the efficacy and applicability of the proposed approach. By addressing the research questions posed in this study, the authors' findings contributed to advancing the field of agricultural digitalization and plant disease monitoring through innovative DL techniques. The proposed work encompassed all pertinent metrics deemed appropriate for a lightweight, resource-efficient, and performance-optimized model. This study underscored that the proposed approach stood as the pioneering effort in developing a transformer-based model for mango disease classification across multiple organs while achieving an inference speed akin to MobileNetv2.

5.8 Chapter Summary

Smart agriculture rests on improving farm productivity using digital technologies. The enduring impacts of smart agricultural innovations have been gauzed concerning productivity, farm wages, employment, and trade. Nevertheless, the potential of digital technologies to realize integrated agriculture sustainability goals will only be fruitful if the power of digitalization is exploited considering all three aspects of sustainability- economic, environmental, and social. Considering the negative impacts of digitalization on the environment, incorporating sustainability in smart agriculture is the need of the hour. In this view, this chapter proposed a S^2A to shape a sustainable and smart agriculture model for crop protection using intelligent learning. The efficacy of the proposed framework was demonstrated through a lightweight and resource-optimized proposed S^2AM for plant disease classification. The proposed model was validated with real-time images collected from the farms and analysed to predict the disease in multiple organs of the mango plant. A comparative analysis of the classifiers was presented, and the proposed model outperformed state-of-the-art models. Additionally, the model demonstrated strong generalizability across different crops. This capability underscores its potential for broader applications in cross-crop disease detection. The ability to adapt to diverse plant species enhances its practical value in agricultural diagnostics. This work will benefit sustainable crop cultivation by improving crop yields, productivity, and quality for future generations.

Chapter 6

Effective Weed Detection to Enhance Cotton Yield in India

Weed infestation presents a formidable obstacle to cotton farming, resulting in diminished yields and escalated operational expenditures. Recent advancements in DL algorithms have facilitated the automation of weed identification, providing farmers with valuable insights for judicious herbicide utilization. Despite these substantial strides, developing a robust weed detection solution tailored to Indian cotton farms remains an unaddressed challenge. In light of this, this chapter explored various DL algorithms to develop a robust weed detection model tailored for effective weed monitoring in Indian cotton fields. The most optimal model was identified and presented as the preferred solution for enhancing weed control strategies through comprehensive experimentation and analysis.

6.1 Introduction

Agriculture is central to human civilization and is the foundation of modern society. It is vital for food production, employment, economic growth, and sustainability [1]. As the most prominent industry on a global scale, it is the source of employment for over 1.3 billion people worldwide. In India, agriculture accounts for about 15% of Gross domestic product (GDP). It is a significant source of employment, with over 400 million people working in the agricultural sector. Agriculture also contributes billions of dollars to the Indian economy through exports. However, weeds are a major problem in Indian agriculture, causing significant yield losses, poor product quality, and loss of economy [117]. According to an estimate by the National Research Council of India (NRCWS), weeds cause annual losses of up to rupees 1050 billion ($14 billion) in India. Cotton crops take up about 2.5% of all arable land on earth, and the world's second-largest producer country is India, following China. India constitutes approximately 26% of the total fibre in the fashion and textiles industry [118]. Cotton cultivation in India has helped lift 100 million people out of poverty since 1990. From 2020 to 21, India exported 6.3 billion worth of cotton. However, India's cotton productivity per hectare is comparatively lower than that of other significant cotton-producing nations. Many factors, such as climate change, pests, diseases, and weeds, affect cotton production and its growth [119]. Among the various challenges in cotton production, weed management remains one of the most significant yet overlooked issues. Weed infestation persists in Indian cotton fields, especially in rainfed and resource-limited regions, where it can cause yield losses of 30–60% if not effectively controlled. Traditional weeding practices are labor-intensive and time-consuming, and with rising labor costs and shortages during peak farming seasons, there is a growing need for automated weed management solutions.

Additionally, weeds can harbor pests and diseases, making effective control crucial for protecting cotton yield. Genetically modified herbicide-resistant crops have made herbicide use the dominant weed management strategy. However, widespread and indiscriminate use has led to herbicide-resistant weeds, environmental harm, and rising costs, emphasizing the need for sustainable monitoring techniques to reduce herbicide reliance. With innovative agricultural technologies such as AI, wireless sensors, robots, location systems, and IoT, traditional agriculture has shifted towards sustainable practices [86]. DL solutions have emerged in the past decade to automate agricultural processes. DL algorithms have enabled automatic weed diagnosis and assisted farmers in making informed decisions regarding herbicide applications. However, despite significant advancements in this field, a robust weed detection system is a pressing need because of unstructured field conditions and the substantial biological variance in weeds. Furthermore, no studies have addressed weed detection in Indian cotton farms [18]. This motivates us to analyze the performance of DL-based object detectors in Indian cotton farms, aiming to enhance the quantity and quality of cotton while maintaining ecological balance to strengthen agriculture sustainability. In this view, the main objectives of the research are as follows:

- To assess various DL-based object detectors for weed detection in Indian cotton fields
- To find the optimal model for effective weed control monitoring.

6.2 Dataset and Methodology

The present section presents a preface about the dataset and various deep learning based object detectors employed in this work.

6.2.1 Dataset Exploration

An open-source cotton-weed dataset [120] is employed in the study that consists of 570 images with 766 annotated bounding boxes, with an average of 1.4 bounding box per image. The dataset consists of two classes, namely weeds and cotton, where 518 and 248 bounding boxes represent weeds and cotton, respectively. The images in this dataset vary in size, with a Median Image Ratio of 617x617; all images are in Joint Photographic Experts Group (JPEG) format collected through smartphones in varying lighting conditions and captured from different angles. Sample Images from this dataset are represented in Figure 6.1.

Figure 6.1: Sample Images From the Cotton-Weed Dataset

6.2.2 Overview of Object Detectors Utilized in This Study

Object detection is a fundamental task in the field of CV, where the goal is to automatically identify and locate objects within digital images or video streams. This process involves two key components: predicting bounding boxes around objects of interest and assigning classification labels describing each object. Bounding boxes are rectangular coordinates that define the spatial extent of an object within an image. At the same time, classification labels indicate the type or category of the object, such as “mango,” “apple,” or “orange”.

The significance of object detection lies in its ability to mimic human visual perception, allowing machines to understand and interact with visual data meaningfully. This capability is essential for various real-world applications, including autonomous driving, surveillance systems, robotics, and medical imaging, where accurate identification and localization of objects are critical.

In DL-based object detection, there are two primary categories of detectors: single-stage and two-stage. Single-stage detectors, such as Single Shot Detector (SSD) and YOLO, are designed to predict object bounding boxes and classification labels in one pass through the network. These models directly predict object locations and their respective categories by dividing the input image into a grid or using anchor points to estimate object boundaries. Each grid cell or anchor point is responsible for predicting the presence of objects within a specific region. Because of this streamlined approach, single-stage detectors are generally faster and more efficient, making them ideal for real-time applications such as autonomous driving and video surveillance [84].

However, the simplicity of single-stage detectors comes with trade-offs. While they are computationally efficient, the precision of their bounding boxes is often lower than that of more complex models. Single-stage models tend to struggle with small object detection and can be sensitive to overlapping objects in dense scenes. Despite these limitations, they remain popular for tasks where speed is more critical than achieving the highest possible accuracy.

Two-stage detectors, such as Faster R-CNN[121], employ a more intricate approach to object detection. The first stage of the model generates region proposals, which are potential areas where objects might be located within the image. Once these proposals are generated, the second stage of the detector refines the bounding box predictions and classifies each proposed region to identify the object type. This two-step process allows for more accurate predictions, especially in complex scenarios with multiple or overlapping objects.

While two-stage detectors often outperform single-stage models in terms of accuracy, they are typically slower due to the additional computational steps involved. Moreover, their performance relies heavily on carefully engineered components, such as the anchor box generation process, which determines the initial object regions, and non-maximum suppression, which reduces overlapping bounding boxes. The dependence on these components makes two-stage detectors more challenging to optimize for different applications [122].

A new alternative to address the limitations of traditional object detectors, transformer-based models [123] have emerged as a promising alternative. Unlike SSD and Faster R-CNN, transformer-based detectors do not rely on handcrafted components like anchor boxes or non-maximum suppression. Instead, they utilize attention mechanisms, which allow the model to focus on different parts of the image and capture complex relationships between objects and their surroundings.

Transformers offer a more flexible and scalable solution for object detection, as they can adapt to various input conditions without the need for manual tuning. These models have shown great potential in achieving robust performance trade-offs, providing competitive accuracy while maintaining reasonable inference speeds. As a result, transformers are increasingly viewed as a new generic framework for object detection, capable of overcoming the traditional bottlenecks associated with both single- and two-stage detectors.

Drawing upon recent advancements in the literature [62, 63], this study adopts a comprehensive approach by utilizing state-of-the-art object detectors across three key categories: one-stage, two-stage, and transformer-based models. Specifically, the one-stage detectors used in this study include Yolov5 [124] and RetinaNet [125], both of which are well-established for their balance between speed and accuracy in real-time object detection tasks.

In the two-stage detector category, Fast R-CNN [126] and Faster R-CNN were selected as representative models. These detectors are widely recognized for their high detection accuracy, leveraging region proposal methods to enhance object localization and classification.

Additionally, the study incorporates DEtection TRansformer (DETR) as a promising model from the transformer-based family of detectors. DETR stands out for its innovative use of attention mechanisms, offering an alternative to traditional detection frameworks by eliminating the need for components like region proposals and non-maximum suppression. This diverse selection of detectors ensures a comprehensive evaluation of the latest techniques across different object detection paradigms.

6.3 Experimental Setup

This section presents the performance metrics to assess the object detectors employed in this study. Further, the experimental settings to train and validate the detectors will be discussed.

6.3.1 Evaluation Metrics

Three standard object detection performance metrics are exploited to validate the selected model's performance: mAP, the number of trainable parameters/model size, and inference speed. *mAP* is calculated by averaging the precision scores at different recall levels. A higher mAP score indicates better detector performance. A standard threshold for good performance is Intersection over Union (IoU)= 0.5. The *number of trainable parameters* in a neural network is the number of weights and biases the network learns during training.

The number of parameters can be a good indicator of the complexity of the network and the amount of data it will need to be trained on. *Inference speed* is the time for a DL model to predict a new piece of data.

6.3.2 Experimental Setup and Training Strategy

The dataset was split into a 70:15:15 ratio for training, validation, and testing, respectively. The model was trained on the training set, validated using the validation set, and its final performance was evaluated on the testing set. The training used transfer learning, where detectors were pre-trained on the MS COCO dataset. Trained is performed for 300 epochs with a batch size 16, and early stopping was used to prevent overfitting. The other hyperparameters were set to the default values in the official implementations. The ImageDataGenerator tool under the Keras framework is realized for real-time data amplification. This study employs traditional augmentation techniques like a blur, brightness contrast, crop, gauss noise, horizontal flip, hue saturation, random rotation, random scale, random translate, random shear, colour jitter, random erasing, and cutout to increase the size of the training set to 543 images.

6.4 Results and Discussions

The performance of five DL-based detectors were investigated for weed detection in Indian cotton farms. YOLOv5 outperformed other detectors significantly, showcasing its potential to revolutionize weed management practices in Indian cotton farming. The mAP of the YOLOv5 model surpassed the RetinaNet, Fast Region-based Convolutional Neural Network (R-CNN), Faster R-CNN, and DETR by a margin of 8% to 20%, highlighting the superiority of YOLOv5 for weed detection in complex agricultural scenarios. Table 6.1 and Table 6.2 present the results exhibited by YOLOv5 on the original and augmented datasets, respectively. Additionally, Figure 6.2 presents the performance of YOLO5 on training and validation sets.

As tabulated in Table 6.1, YOLOv5 initially achieved a mAP of 40.3% on the original cotton weed dataset. To enhance the model's performance and mitigate the risk of overfitting, the dataset underwent augmentation. The results, detailed in Table 6.2, reveal a significant improvement, with the mAP increasing by 8% on the augmented dataset. Additionally, the visualization results generated by YOLOv5 on this enhanced cotton weed dataset are illustrated in Figure 6.3.

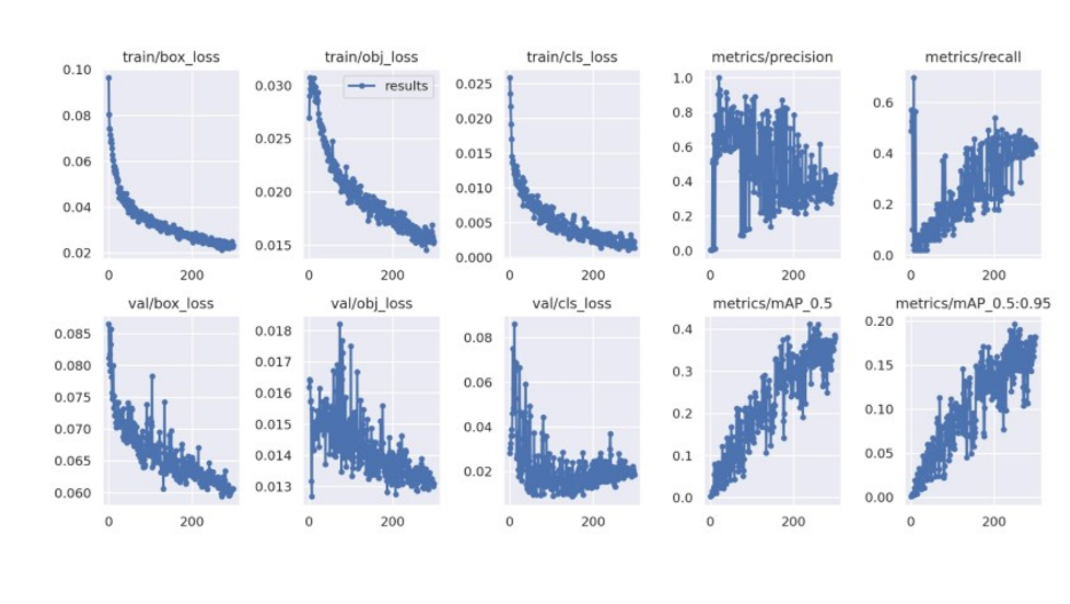


Figure 6.2: Performance of YOLOv5 on Training and Validation Sets

Table 6.1: YOLOv5 Results on the Raw Dataset

	Precision(%)	Recall	mAP@0.5	mAP@0.5:0.95
All	0.474	0.441	0.403	0.198
Cotton	0.292	0.560	0.469	0.283
Weeds	0.655	0.321	0.337	0.113

Table 6.2: YOLOv5 Results on the Augmented Dataset

	Precision	Recall	mAP@0.5	mAP@0.5:0.95
All	0.609	0.479	0.483	0.271
Cotton	0.535	0.600	0.547	0.340
Weeds	0.684	0.357	0.419	0.203

****No. of Parameters:** 7,249,215
****GFLOPs:** 16.7
****Inference Time:** 2.77 seconds/image

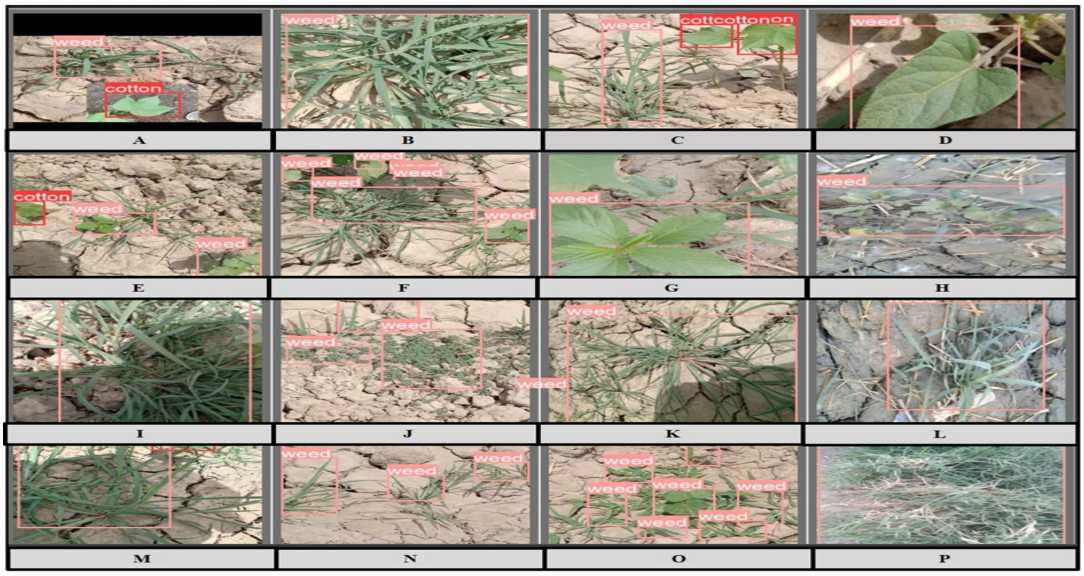


Figure 6.3: YOLOv5 Visualization Outcomes on the Augmented Cotton Weed Dataset

6.5 Chapter Summary

Automatic weed detection using DL represents a significant advancement in smart agriculture. This research has investigated the feasibility of five popular object detectors, RetinaNet, YOLOv5, Fast RCNN, Faster RCNN, and DETR, to accurately locate weeds in cotton farms, addressing a critical challenge that cotton farmers face in India. The empirical results of this study underscore the potential of YOLOv5 to revolutionize traditional weed identification practices. The empirical findings underscore the model's effectiveness, as it attains precision, recall, and mAP scores of 60.9%, 47.9%, and 48.3%, respectively. These results are reasonable considering the complexity of the problem, as weeds can often resemble cotton plants, making accurate identification challenging. The model's ability to effectively identify and classify weeds among cotton crops not only aids in optimizing crop yield but also significantly reduces reliance on harmful herbicides, contributing to more sustainable and environmentally friendly agricultural practices. Furthermore, the YOLOv5 architecture offers considerable potential for future experimentation and fine-tuning, which could lead to even better detection results and enhanced accuracy in weed management.

Chapter 7

Conclusion, Future Scope and Social Impact

Plant biosecurity holds immense significance for every nation as it plays a crucial role in protecting crops, ensuring food security, and safeguarding ecology and the livelihoods of individuals. In this regard, plant biosecurity constitutes a vital component of sustainable agriculture progress. Digitalization is the new go-to strategy to address agriculture's productivity, sustainability, and resilience challenges. In recent years, DL has been applied in every agricultural practice. Researchers from multidisciplinary areas strive to use these technologies and propose novel solutions to expedite the in-field workflow. However, they struggle to put their solutions into production, deliver tangible results, and obtain favourable outcomes with limited in-field datasets. In this view, this thesis presents groundbreaking research by integrating DL with plant biosecurity, aligning with the goals of the *Digital Agriculture Mission*.

By leveraging the advanced capabilities of DL, the research addresses critical challenges in monitoring and safeguarding plant health. This integration enhances the classification and detection of plant diseases, pests and weeds, contributing to more effective biosecurity measures. The findings push the boundaries of plant protection strategies and set the foundation for future innovations in sustainable agriculture, supporting the Digital Agriculture Mission's vision of modernizing agriculture through technology-driven solutions.

The key contributions of this thesis, which delve into the innovative intersections between DL and plant biosecurity, are presented in the following section. These contributions reflect a significant leap forward in harnessing DL within the agricultural domain by addressing complex challenges related to plant biotic stress identification.

7.1 Research Contributions and Social Impact

7.1.1 *Research Contribution 1:* Biotic Stress Monitoring in Plants Using Deep Learning: A Systematic Literature Review

The thesis began with an introductory overview highlighting the importance of biotic stress monitoring and the growing interest in utilizing DL techniques to improve classification accuracy. Further, it conducts a SLR to identify the advancements in the domain while critically evaluating the trends and challenges in biotic stress monitoring. The review identifies critical research gaps that have hindered progress in applying DL to plant biosecurity. The crucial issues include the limited availability of high-quality datasets, an over-reliance on supervised learning techniques, the high costs associated with data labelling, and the general lack of focus on computational efficiency metrics. Additionally, the review points to the poor generalizability of existing models and significant regional disparities in research output. By identifying these gaps, this research paves the way for targeted solutions that can enhance DL applications in agriculture, ultimately contributing to more effective and sustainable plant biosecurity practices.

7.1.2 *Research Contribution 2:* Integration of Deep Learning and Plant Biosecurity Toward Sustainable Agriculture: A SWOT Analysis

This work thoroughly explores the integration of DL within the domain of plant biosecurity. Beyond summarizing significant research advancements, it conducts a detailed SWOT analysis to assess the feasibility and impact of DL-driven solutions on sustainable agriculture. The SWOT analysis offers a balanced evaluation of this technology's internal strengths and weaknesses, such as its ability to enhance early disease detection and improve classification accuracy, alongside external opportunities and threats, including scalability challenges and potential barriers to widespread adoption.

By examining both the facilitators and obstacles to the successful implementation of DL in plant biosecurity, this contribution sheds light on how these innovations can shape the future of agricultural practices. It highlights key areas where DL holds transformative potential while also addressing the critical risks and challenges that must be managed to achieve sustainable, resilient agricultural systems.

7.1.3 *Research Contribution 3:* A Novel Plant Disease Diagnosis Framework by Integrating Semi-supervised and Ensemble Learning

In this research, the author addresses the specific challenges identified in research contribution-1 while leveraging the opportunities outlined in research contribution-2. The work tackles critical issues such as the over-reliance on supervised learning, the underutilization of hybrid models, the scarcity of labelled datasets, the high costs associated with data annotation, and the lack of model standardization in automated plant disease. Building upon the identified opportunities—such as developing hybrid models, utilizing unlabelled data, reducing annotation costs and efforts, and improving classification and detection solutions —this research proposes a novel framework for classifying plant diseases.

The proposed framework integrates *semi-supervised learning and ensemble learning* to overcome these challenges. The semi-supervised approach effectively harnesses labelled and unlabelled data, enabling DL solutions to learn from a broader dataset without heavily relying on costly labelled samples. By incorporating ensemble learning, the framework further enhances classification accuracy by combining the strengths of multiple models, thereby reducing bias and improving overall performance. This scalable and cost-effective solution offers greater adaptability and effectiveness in addressing real-world agricultural challenges. The framework is rigorously validated using benchmark datasets such as PlantDoc and PlantVillage, demonstrating its practical applicability and robustness. Additionally, this research utilizes the YOLOv5 object detection algorithm for real-time, accurate localization of plant diseases, enabling targeted interventions and reducing excessive harmful chemical usage.

From a *social impact perspective*, this research holds significant potential to revolutionize agricultural practices. Providing more accessible and affordable disease diagnosis tools can empower small-scale and resource-limited farmers to protect their crops more effectively. This, in turn, contributes to food security, reduces economic losses from crop failures, and supports sustainable farming practices, ultimately benefiting communities and the agricultural industry at large.

7.1.4 *Research Contribution 4:* S^{2}AM: A Sustainable Smart Agriculture Model for Crop Protection Based on Deep Learning

In this work, the author addresses the specific challenges identified in research contribution-1, while capitalizing on the opportunities outlined in research contribution-2. As digital technologies penetrates the modern agriculture, they present several new opportunities, but the environmental aspect has often been overlooked. To address this gap, the potential of *sustainable computing* and *deep learning* is explored to overcome critical technological barriers in agriculture, reduce resource consumption, and drive sustainable agricultural development. This research examines the relationship between *smart agriculture* and *sustainable computing*, focusing on balancing the three pillars of sustainable agriculture—social, economic, and environmental.

Building on this analysis, this research proposed a DL-based, lightweight, computation-efficient, performance-optimized, and explainable crop protection model, S^2AM, designed to classify diseases in mango crops. The proposed model provides an innovative and sustainable solution by improving plant biosecurity, increasing agricultural yields, reducing reliance on poisonous chemicals, and promoting environmental conservation through energy-efficient resource use. To ensure its widespread applicability, the model has been validated on multiple crop types, proving its effectiveness in protecting diverse agricultural systems and advancing sustainable farming practices.

From a *social impact perspective*, this research empowers farmers by providing accessible and efficient tools for disease monitoring, leading to improved crop health and yields. Furthermore, it contributes to environmental preservation by minimizing chemical use and promoting energy-efficient agricultural technologies. Moreover, it supports socio-economic growth by reducing resource wastage, ensuring long-term sustainability for both farming communities and ecosystems.

7.1.5 *Research Contribution 5:* Weed Detection in Indian Cotton Farms Using Deep Learning

This research addresses the critical challenge of weed infestation in cotton farms, particularly in India. This work explored the feasibility of five popular object detection models—RetinaNet, YOLOv5, Fast RCNN, Faster RCNN, and DETR—to accurately detect and classify weeds in cotton fields. Among these, YOLOv5 emerged as the most effective to revolutionize traditional weed identification practices by overcoming the complexities of distinguishing weeds from cotton plants, which often exhibit similar features. By accurately identifying and localizing weeds, the model improves crop management and yields and minimizes the need for harmful herbicides, fostering more sustainable and environmentally responsible agricultural practices.

From the *social impact perspective*, the introduction of automated weed detection has far-reaching economic benefits for India, a major cotton producer and exporter. By increasing cotton yields and reducing the reliance on chemical herbicides, this research supports more efficient farming practices, lowering operational costs for farmers and boosting productivity. This increases cotton output, enhancing India's agricultural trade potential and contributing to GDP growth. As the model promotes sustainable farming, it improves the global competitiveness of Indian cotton in international markets, where there is a growing demand for eco-friendly and sustainable agricultural products. By modernizing cotton farming practices, this research not only benefits individual farmers but also strengthens India's position in global agricultural trade, driving economic growth and contributing to rural development.

7.2 Future Work

The framework and models developed in this thesis mark a noteworthy advancement in DL and sustainable agriculture, especially concerning biotic stress monitoring in real environments. Nonetheless, as with any research initiative, numerous opportunities remain for further exploration and improvement. Below are several key avenues for future work.

- Future research should prioritize collecting and curating diverse datasets encompassing various crop types, geographical regions, and environmental conditions to enhance the generalizability and robustness of DL models in agricultural applications. By including a wide range of crop types, researchers can ensure that models accurately learn the specific stress responses associated with each crop while incorporating data from different geographical areas exposes models to varying climate and soil factors, thereby improving their adaptability.

- Incorporating multi-modal data sources, such as remote sensing, soil health indicators, and climatic data, can provide a more holistic view of plant health. Future work should explore the fusion of these data types with DL models to improve accuracy in biotic stress monitoring.

- The development of a mobile-based application is recommended to provide farmers with real-time, rapid, and accurate identification of plant stress. Such an application would empower farmers to make timely decisions regarding the application of chemicals, enhancing their ability to manage plant health effectively.

- Further exploration into optimizing model architectures and employing techniques such as model pruning or quantization can enhance computational efficiency and accuracy. This is particularly important for deployment in resource-limited environments, ensuring accessibility and usability of the technologies developed.

- Future work on the weed detection model should focus on extending its capabilities to enable species-level classification, allowing the differentiation between harmful and beneficial weeds. This enhancement would promote more targeted and ecologically sound weed management strategies. Furthermore, integrating Large Language Models (LLMs) can transform the weed detection framework into an interactive, multilingual advisory system that interprets detection results, answers farmer queries, and provides region- and crop-specific recommendations. Such advancements would significantly broaden the model's utility, making it a comprehensive and intelligent decision-support tool for sustainable weed management in diverse agricultural settings.

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Appendices

Appendix I: Primary Studies Considered in the Systematic Literature Review

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Appendix II: Supplementary Tables for Thesis Insights

Table II.1: Search Fields Utilized in Various Academic Databases

Database	**Database Search Fields**
Scopus	Title, Abstract, Keyword
ACM	Abstract
IEEE Xplore	Metadata
Wiley	Abstract
Engineering Village	Subject, Title, Abstract
Springer Link	Full text

Table II.2: Distribution of Articles Across Various Sources

Venue/Source	**NoA**	**Venue/Source**	**NoA**
Frontiers in Plant Science	157	IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing	2
IEEE Access	119	Horticulturae	2
Multimedia Tools and Applications	82	Precision Agriculture	2
Agronomy	59	Applied Sciences	2
Remote Sensing	33	IEEE Robotics and Automation Letters	2
Plants	27	Knowledge-Based Systems	2
Computers and Electronics in Agriculture	27	Biosystems Engineering	2
Scientific Reports	27	NeoBiota	1
PLoS ONE	16	Biology	2
Artificial Intelligence in Agriculture	15	Weed Science	2
Computational Intelligence and Neuroscience	14	Internet of Things (Netherlands)	2
Information Processing in Agriculture	14	Geocarto International	1

Venue/Source	NoA	Venue/Source	NoA
Journal of Agriculture and Food Research	11	Foods	2
Sustainability (Switzerland)	11	ACM Computing Surveys	1
Insects	7	Plant Pathology	2
Plant Methods	8	Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications	1
Alexandria Engineering Journal	7	International Journal of Molecular Sciences	1
Plant Phenomics	6	Environmental Research Communications	1
Forests	5	Technologies	1
Expert Systems with Applications	4	Egyptian Journal of Remote Sensing and Space Science	1
Ecological Informatics	5	Biosensors and Bioelectronics: X	1
Journal of King Saud University - Computer and Information Sciences	4	Array	1
Intelligent Systems with Applications	3	Journal of Pest Science	1
Journal of Integrative Agriculture	3	Computers and Electrical Engineering	1
Multimedia Systems	2	The Visual Computer	1
Phytopathology	2	Engineering Science and Technology, an International Journal	1
Artificial Intelligence Review	2	Emerging Science Journal	1
Plant Phenome Journal	2	Journal of Environmental Informatics	1
Neural Computing and Applications	2	Frontiers in Earth Science	1
Heliyon	2	Journal of Computing Sciences in Colleges/not found	1
Scientific Data	1	BMC Plant Biology	1
MDPI	1	Computers in Industry	1
ICT Express	1	ACM Transactions on Intelligent Systems and Technology	1
Engineering Applications of Artificial Intelligence	1	Proceedings of the National Academy of Sciences of the United States of America	1
Ecosphere	1	ACM Transactions on Sensor Networks	1
Eurasip Journal on Wireless Communications and Networking	1	Journal of Field Robotics	1
Agronomy Journal	1	Remote Sensing in Ecology and Conservation	1
IEEE Transactions on Industrial Informatics	1	Plant and Soil	1

Venue/Source	NoA	Venue/Source	NoA
IEEE Journal on Emerging and Selected Topics in Circuits and Systems	1	PLoS Biology	1
Pervasive and Mobile Computing	1	Journal of Cloud Computing	1
Frontiers in Ecology and Evolution	1	The Journal of Supercomputing	1
International Journal of Applied Earth Observation and Geoinformation	1	Journal of Big Data	1
Methods in Ecology and Evolution	1	Applications in Plant Sciences	1
Scientific African	1	IEEE Transactions on Automation Science and Engineering	1

*Note**: NoA represents the number of articles corresponding to each journal.*

Table II.3: Datasets Used in Primary Studies Assessed in the Systematic Literature Review for Plant Stress Monitoring

Dataset Name	Count	Dataset Name	Count
Rice Leaf	2	Vine Leaf Disease	1
DiaMOS	2	Wang	1
HQIP102	2	Weed25	1
D0	2	WeedAI “2022—WA Sandplain and Narrow-leafed lupin	1
Cottonweed	2	Weeds Growing Point (WGP)	1
Apple Leaf	2	Wheat	1
CottonDisease	2	Wheat 2014-2016	1
Leaf	2	Wheat Disease Database 2017 (WDD2017)	1
RoCoLe	2	Wheat Rust Classification	1
Pest	2	Wheat Fungi Diseases (WFD2020)	1
Rice Leaf Diseases	2	SLD10k	1
Plant Pathology 2020-FGVC7	2	FieldPlant	1
Rice Pest and Disease Image	1	Wheat-stripe-rust	1
RPW	1	YangLing	1
R pedestris	1	Yellow-Rust-19	1
Rice-weed	1	Yellow-sticky-traps	1
Rice	1	Cassava Leaf Disease and Wheat Leaf Disease	1
Corn or Maize Leaf Disease	1	CASTIPest	1
Rice Leaf Diseases Data Set	1	Cauliflower Field Images (CWF-788)	1
PlantDoc	1	Crop Diseases and Pests Corpus	1
Plantix Smartphone Application	1	Early Crop Weed	1
Pest ID	1	Merged Tomato and Cottons	1

Dataset Name	Count	Dataset Name	Count
NZDLPlantDisease-v2	1	V2 Plant Seedlings	1
New Plantvillage	1	UCI Machine Learning Repository	1
OD	1	TomatoWeeds	1
SugarBeets	1	Tomato Plant Disease	1
PLD	1	SLSD	1
PLDD	1	Multi-class Pests 2018 (MPD2018)	1
PNS-Cyst	1	Paddy Line Segmentation: Paddy–Millet Detection	1
Pepper	1	Small Cotton Wilt Disease	1
Pepper Leaf	1	Soybean Field Weed	1
Pest24	1	Soybean Stress	1
PlantifyDr	1	Strawberry Common Diseases Image (SCDID)	1
PestImgData	1	Strawberry Disease Detection	1
PestNet-AS	1	Strawberry Disease	1
Plant Pathology 2021	1	Strawberry Segmentation	1
Plant Seedlings	1	Sugar Beet 2020	1
Plant Disease Diagnosis	1	Sugar Beet	1
PlantCLEF	1	Sunflower	1
PlantDiseaseCL	1	TAMU Nutsedge	1
PlantDoc PlantVillage	1	TDSD	1
SPVD	1	TLm & GBIFm	1
RumexWeeds	1	TTALDD-4	1
Wheat Disease Images (Small)	1	Tea Disease	1
VQA	1	Tea Sickness	1
Crop Weed Field Image (CWFID)	1	Date Palm Data — Kaggle	1
DSIS	1	iNaturalist	1
The Tiger Beetle	1	ADCG-18	1
Tobacco Aerial	1	CWFID	1
Tomato Leaf Diseases	1	Cardamom 2021	1
NZDLPlantDisease-v1	1	Cassava Disease	1
MSALDD	1	Cassava Disease Classification	1
Moving Fields Weed (MFWD)	1	Forest Pest	1
ALDID	1	GLDP12k	1
APHID-4K	1	Gpest14	1
ASDID	1	Grape Leaf Disease	1
ATLDS	1	IF	1
AgriPest	1	INSECT10K7C640_SAT	1
Apple Leaf Disease Object Detection (ALDOD)	1	Image Database for Agricultural Diseases and Pests (IDADP)	1
Apple Diseases	1	In-Field Pest in Food Crop (IPFC)	1
BPLD	1	Instance Segmentation: TJ-Tomato	1

Dataset Name	Count	Dataset Name	Count
BRACOL	1	Jasmine Leaf	1
Bean Leaf	1	Kaggle	1
Black Pepper Leaf Disease	1	Kaggle Plant Pathology 2020- FGVC7	1
Bonn	1	LLPD-26	1
CASTIPest	1	MCCN	1
CD&S Corn Disease with Removed Backgrounds	1	MDSD	1
CDTS	1	MPD2021	1
CIAT Banana Image Library	1	Strawberry_wilt	1
CLDD	1	Maize	1
CNN_Olive	1	Maize Leaf Disease	1
CWF-788	1	Maize Plant Leaf Image	1
APD-229	1	MangoleafBD	1
ALDD	1	Field-based Wheat Diseases Images (FWDI)	1
Mini Plant Disease	1	FSIP52	1
AI Studio	1	FGVC-Plant-Pathology-2020-challenge	1
MWFI (Maize/Weed Field Image)	1	Deng's crop dataset	1
Tomato Plant Anomalies Description	1	Rice blast disease dataset	1
Tomato Microscopic Images	1	Cassava Leaf Disease Classification	1
UAVWeedSegmentation	1	Rice Leaf Disease with Segmentation Labels	1
Wheat-Crop-Weeds	1	Chatzivariti's Vineyard	1
AppleLeaf 9	1	Chicory Plant	1
Citrus Leaves Images	1	Cotton-weed, Soybean-weed, Corn-weed	1
CottonDisease (SCDD)	1	Citrus Diseases and Pests	1
FGVC7	1	Citrus Fruits and Leaves	1
Baidu AI Studio	1	Citrus Image	1
Large Wheat Disease Classification (LWDCD2020)	1	RealPestImage	1
Lincoln Beet (LB)	1	PDDD	1
OLID	1	Corn Disease & Severity (CD&S)	1
PFD	1	Enhanced Rice Leaf Disease	1
Pest24	1	Cotton	1
Tomato Disease and Pest	1	DIV2K	1
Crop Pest and Disease Detection	1	Xie1	1

List of Publications with Proofs

- **Journal 1: Sharma, P.**, & Sharma, A. (2024). "A novel plant disease diagnosis framework by integrating semi-supervised and ensemble learning". *Journal of Plant Diseases and Protection*, 131(1), 177-198. https://doi.org/10.1007/s41348-023-00803-y (**SCIE Journal, Impact Factor: 2.2, Publisher: Springer**)

Journal of Plant Diseases and Protection
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ORIGINAL ARTICLE

A novel plant disease diagnosis framework by integrating semi-supervised and ensemble learning

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Abstract
Plant disease diagnosis is one of the latest critical research areas of sustainable agriculture. The evolution of computer vision-based systems in order to identify, classify and localize diseases has automated the process of plant disease identification. CNNs are the pre-eminent deep learning-based algorithms used to automate plant disease recognition that has proven decisive on various benchmarks. However, a substantial part of the research lacks adequate attention to specific issues like the unavailability of datasets, high annotation costs and non-conformity of the models. Therefore, there is a pressing need to exploit the latest trends and technologies in this area to solve the above-mentioned problems. As a step ahead in this direction, a new framework has been proposed using semi-supervised & ensemble learning. The proposed framework is validated through a series of experiments on benchmark datasets. The results reported a significant performance improvement in classifying plant diseases, outperforming existing works with an improvement of 18.03% and 15% regarding the accuracy and F1 score, respectively. The mean average precision for detection is improved by 13.35%. Findings from this research will be beneficial for farmers, plant pathologists and researchers, which in turn will strengthen the sustainable facet of agriculture.

Keywords Plant disease diagnosis · Convolutional neural networks (CNNs) · Semi-supervised learning · Ensemble learning · Transfer learning

Introduction

Over the last decades, various factors have compromised food security, including pollinator degeneration, environmental changes and plant illnesses. Plant illness threatens food security and quality, which eventually affects a country's economy and consumers' health. In developing countries, farmers are not much aware due to which they unknowingly have been applying considerable amounts of herbicides, pesticides, fertilizers and other chemical substances to control plant diseases and intensify crop production, negatively impacting the ecology. Diseases on plants cost approximately US $220, as it is suggested by the "Food and Agriculture Organization of the United Nations (FAO)" (FAO 2019) and further stated (Arunnehru et al. 2020), more than 50% of agriculture production is destroyed by plant infections. At the same time, more than 90% of individuals depend on agriculture directly or indirectly (Mukti and Biswas 2019), while the Indian population's dependency on agriculture reaches 75% (Himani 2014). Diseases can easily lead to crop failures, seriously influence agricultural products' nature and cause food safety problems. Therefore, on-time identification of plant diseases is critical.

Farmers are investing plenty of money and time in preventing crop diseases. However, for most diseases, the symptoms are visible only in the late stages after the manifestation, which often leads to the failure of entire crops. For this reason, many investigations have turned their attention to traditional machine learning (ML) applications to automate plant disease diagnosis (Sarker 2021a, b). However, the great efforts in feature engineering have been the primary barrier to applying conventional ML algorithms for plant disease diagnosis.

Deep learning (DL) (Sarker 2021a, b), especially convolutional neural networks (CNNs) (Indolia et al. 2018), because of inherent automatic feature extraction abilities, has recently stimulated an explosion of image recognition research. Numerous CNN-grounded plant disease classification

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Journal of Plant Diseases and Protection
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ORIGINAL ARTICLE

S^{2}AM: a sustainable smart agriculture model for crop protection based on deep learning

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Abstract

Agriculture is the golden thread that fastens all the sustainable development goals globally. However, the massive population explosion and ecosystem degradation have pressurized various auxiliaries of agriculture, primarily food security, crop protection, and disease identification. Although the penetration of digital technologies brings new opportunities to modern agriculture, the environmental facet has been neglected. Given this, the potential of sustainable computing and deep learning is investigated to handle critical agricultural technology impediments, lower resource expenditure, and propel sustainable agrarian developments. This research analyzes the relationship between Smart Agriculture and Sustainable Computing to balance the three pillars of Sustainable Agriculture practices—socio-economic–environment. Motivated by the analysis, the proposed work presents a deep learning-based lightweight, computation-efficient, performance-optimized, and explainable crop protection model to classify plant diseases. The proposed model reports accuracy, precision, recall, and F1-score of 99.4%, 99.4%, 99.5%, and 99.6%, respectively, outperforming state-of-the-art models. Further, the F1-score is improved by 15%, using 6.29 × fewer trainable parameters and 1.88 × fewer FLOPs that facilitate seamless deployment of the model on embedded devices, particularly for automated in situ plant disease classification. Moreover, to confirm the applicability of the proposed model across various crops, validation is conducted on additional crops, showcasing the model's efficacy. The proposed model serves as a sustainable and innovative technological solution, aiding in the preservation of agricultural yields, enhancement of quality, and reduction of pesticide usage to safeguard the environment, achieved through energy-efficient resource utilization.

Keywords Sustainable agriculture · Sustainable computing · Crop protection · Plant disease · Deep learning · Computation-efficient

Introduction

Food is a fundamental need for survival and is an integral part of life. The evolution of human beings gradually pushed off the mode of food management from hunter-gatherers to conventional agriculture. The consistent growth and continuous development of the agriculture sector are crucial and essential for social welfare as a step toward achieving a more equitable society. It plays a vital role in supporting livelihoods, producing raw materials, improving the national economy, enhancing agri-business, conserving the environment, providing food security, and many more (Eastwood et al. 2017). With the advent of digital technologies and the industrial revolution, the agriculture era has changed from conventional to sustainable agriculture (Rolandi et al. 2021). The four agricultural revolutions bring remarkable changes in the development of agriculture history (Liu et al. 2021). The transformation of agricultural trends and technologies is presented in Fig. 1.

Due to rapid population expansion and finite natural resources, ensuring global food security has become a vital aspect of agriculture, demanding meticulous focus to meet the universal requirement for effective food supply chain management (Kakaei et al. 2022). Food production or availability is decreasing to keep up with the level of crop harvests in various regions of the world, negatively impacting crop yields and quality. Therefore, crop protection is a significant area that requires the utmost attention to save crops from various threatening parameters such as diseases, weeds,

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CABI Reviews

REVIEW

Deep learning to improve plant biosecurity and agriculture sustainability: A systematic literature review

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Abstract

Plant stress significantly threatens agricultural productivity and quality, necessitating advanced solutions for effective plant biosecurity. Manual inspection is time-consuming and requires expert knowledge, making automated monitoring crucial for crop protection and food security. While deep learning has shown significant potential in plant stress monitoring and improving plant biosecurity, the existing literature remains unsystematic and highlights numerous challenges that hinder its real-time application. Therefore, a systematic literature review is essential to consolidate current knowledge, offer a comprehensive overview of deep learning-based plant biotic stress monitoring, and identify research gaps, trends, and challenges. In this view, this article employs the PRISMA framework to analyze 745 articles from six recognized electronic databases published between 2016 and April 2024, addressing eight research questions. Findings from this study indicate that convolutional neural networks dominate the field, appearing in 85.23% of articles, with limited consideration for hybrid models. Further, the reliance on supervised learning and high-quality annotated datasets highlights significant challenges related to data availability, diversity, and model generalization. Besides, the limited focus on efficiency metrics for model evaluation further compounds these issues, hindering accurate assessment of model performance in real-world applications. Additionally, only 8.19% of the articles offered directly applicable solutions to farmers, highlighting the necessity for practical and scalable applications. Moreover, while 63.42% of studies originated from the USA and China, research output from Africa, Central Asia, South America, and Southeast Asia remains low. These findings highlight the need for equitable research and localized solutions to address challenges in underrepresented regions. Future research should explore unsupervised and semi-supervised learning to reduce reliance on annotated datasets, integrate IoT, edge computing, and cloud-computing for real-time deployment, and incorporate efficiency metrics to ensure robust real-world performance. This review offers a comprehensive overview of the latest advancements and outlines potential future directions for computer science, agriculture, and ecology.

Keywords: agriculture, biotic stress, deep learning, plant biosecurity, sustainable agriculture

Introduction

Agriculture is central to the global economy, food security, and sustainable development. However, challenges like population growth, escalating food demand, climate change, and plant stress are pressuring its ability to meet future needs (Eastwood *et al*., 2019; Kakaei *et al*., 2022; Lin *et al*., 2023). Among the most significant stressors, biotic stress—caused by pests, diseases, and weeds—threatens global food production, leading to an estimated loss of 20 to 40% of crop yields, valued at billions of dollars annually (FAO, 2019; Lal *et al*., 2023; Manghwar and Zaman, 2024). Traditional methods for monitoring plant biotic stress, such as manual field inspections, are limited by issues of accuracy, scalability, and timeliness (Kashyap and Kumar, 2021), while excessive chemical use to combat these stresses harms the environment and public health (Vasileiou *et al*., 2024). With the rise of digital agriculture and artificial intelligence (AI), deep learning (DL) offers a promising solution for automating the monitoring of biotic stress, reducing chemical dependence, and enhancing long-term agroecosystem health (Erisman *et al*., 2016; Singh *et al*., 2018; Klerkx and Rose, 2020; Noon *et al*., 2020; Singh *et al*., 2021; Devi *et al*., 2022; Houetohossou *et al*., 2023). This systematic literature review (SLR), based on 6479 articles from multiple databases, explores the potential of DL in biotic stress monitoring. It aims to provide valuable insights and identify gaps in current research, guiding future developments in sustainable agriculture.

ORGANIZATION OF THIS REVIEW

The rest of the paper is organized as follows. Section "Background" provides a brief background required for the present study. Section "Related surveys and rationale of this systematic literature review" summarizes the need for the present systematic review. Section "Review methodology" details the review process, research

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