AUTOMATED DETECTION OF TOMATO LEAF DISEASES USING CONVOLUTIONAL NEURAL NETWORKS

BY

HADIUZZAMAN OVI
ID: 193-15-13397

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

Mr. Dewan Mamun Raza
Assistant Professor
Department of CSE
Daffodil International University

Co-Supervised By

Md. Tanvirul Islam
Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

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APPROVAL

This Research titled "**Automated Detection of Tomato Leaf Diseases using Convolutional Neural Networks**", submitted by Hadiuzzaman Ovi to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13th July 2024.

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BRAC Bank

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I hereby declare that this research has been done by me under the supervision of **Mr. Dewan Mamun Raza, Assistant Professor, Department of CSE** Daffodil International University. I also declare that neither this research nor any part of this research has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Mr. Dewan Mamun Raza
Assistant Professor
Department of CSE
Daffodil International University

Co-Supervised by:

MR. Tanvirul Islam
Lecturer
Department of CSE
Daffodil International University

Submitted by:

Hadiuzzaman Ovi
ID: 193-15-13397
Department of CSE
Daffodil International University

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ABSTRACT

The agricultural sector plays a crucial role in ensuring global food security, with tomatoes being a significant crop contributing to both economic and nutritional aspects. However, the presence of diseases can severely impact tomato yield and quality. This study proposes an automated approach for the early detection of tomato leaf diseases using Convolutional Neural Networks (CNNs). The proposed system leverages the power of deep learning, particularly CNNs, to analyze images of tomato leaves and accurately identify the presence of diseases. A comprehensive dataset containing diverse images of healthy and diseased tomato leaves is utilized for training and validation purposes. The CNN model is trained to learn distinctive features and patterns associated with various tomato leaf diseases, enabling it to make precise predictions. The methodology involves pre-processing the images to enhance their quality, followed by the construction and training of the CNN model. The trained model is then evaluated on a separate test dataset to assess its generalization capabilities. The performance metrics, including accuracy, precision, recall, and F1 score, are employed to quantify the effectiveness of the automated detection system. The results demonstrate the efficacy of the proposed CNN-based approach in accurately identifying tomato leaf diseases. The system exhibits a high level of accuracy and reliability, showcasing its potential as a valuable tool for farmers and agricultural stakeholders. The automation of disease detection not only facilitates early intervention and treatment but also contributes to the overall improvement of crop management practices, leading to enhanced agricultural productivity and sustainable food production.

Keywords: Tomato, Leaf disease, Deep learning, Train, Validation, Image processing, Accuracy, F1 score.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1 Overview:

Tomatoes are a vital component of global agriculture, serving as a staple food and contributing significantly to the economy. However, the optimal growth and yield of tomato crops are consistently threatened by various diseases that affect the leaves, posing a significant challenge to farmers and agricultural productivity. Timely and accurate detection of these diseases is crucial for implementing effective control measures and ensuring the overall health of the crop. Traditional methods of disease detection in tomato plants often rely on visual inspection by farmers, which can be subjective and time-consuming. Moreover, early stages of diseases may go unnoticed, leading to delayed responses and increased crop losses. To address these challenges, advanced technological solutions are being explored, and one such promising avenue is the application of Convolutional Neural Networks (CNNs) in automated disease detection. Convolutional Neural Networks have demonstrated remarkable success in image recognition and classification tasks, making them particularly well-suited for analyzing visual data such as images of plant leaves. In the context of tomato leaf diseases, CNNs can learn intricate patterns and features indicative of specific diseases, enabling a reliable and efficient automated detection system. This study aims to harness the capabilities of CNNs to automate the detection of tomato leaf diseases. By leveraging a diverse dataset comprising images of both healthy and diseased tomato leaves, the CNN model will be trained to discern subtle visual cues associated with various diseases. The implementation of such an automated detection system holds immense potential for revolutionizing agricultural practices, allowing for early and accurate identification of diseases, thereby facilitating timely interventions and improving overall crop management. As I delve into the details of the methodology, dataset, and results, this research endeavors to contribute to the ongoing efforts in precision agriculture and sustainable crop production, emphasizing the role of technology in mitigating the impact of diseases on tomato crops. The successful implementation of an automated detection system using CNNs could not only optimize resource utilization but also empower farmers with a proactive tool for crop health management in the face of evolving challenges in modern agriculture.

1.2 Motivation:

The motivation behind the automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) stems from the critical need to address the challenges faced by the agricultural sector, particularly in the cultivation of tomatoes. The motivation can be encapsulated in several key aspects:

- **Early Detection for Timely Intervention:** Early detection of diseases is pivotal for effective disease management in agricultural crops. Traditional manual methods of disease identification are often time-consuming and subjective. By leveraging advanced technologies like CNNs, I aim to provide a solution that enables early detection, allowing farmers to intervene promptly and implement appropriate measures to mitigate the impact of diseases.
- **Crop Yield and Quality Improvement:** Tomato crops are susceptible to various diseases that can significantly impact both yield and quality. Automated disease detection offers the potential to enhance overall crop health, leading to increased yields and improved produce quality. By identifying and addressing diseases at their incipient stages, I aim to contribute to the optimization of tomato production and subsequent economic benefits for farmers.
- **Precision Agriculture for Sustainable Practices:** The adoption of precision agriculture practices is crucial for sustainable and resource-efficient farming. Automating the detection of tomato leaf diseases aligns with the principles of precision agriculture, as it enables targeted and optimized use of resources, such as pesticides and fertilizers, reducing environmental impact and operational costs.

- **Mitigating Economic Losses:** Diseases in tomato crops can lead to substantial economic losses for farmers. Rapid and accurate identification of diseases can help prevent extensive crop damage, leading to financial losses. The motivation behind this research is to empower farmers with a tool that can potentially minimize economic losses by providing timely information about the health of their crops.
- **Technology Integration in Agriculture:** With the advancements in technology, integrating innovative solutions in agriculture becomes imperative. The motivation behind utilizing CNNs lies in harnessing the power of deep learning for image recognition and classification. By incorporating cutting-edge technologies into agricultural practices, I aim to contribute to the modernization of farming techniques and increase the resilience of the agricultural sector.

1.3 Rational of the study:

The rationale behind conducting a study on the automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) is rooted in addressing critical challenges faced by the agriculture sector, specifically in tomato cultivation. Several key justifications underscore the importance of this research:

- **Increasing Threat of Tomato Leaf Diseases:** The prevalence of various diseases affecting tomato plants poses a constant threat to agricultural productivity. Fungal, bacterial, and viral infections can lead to severe yield losses identified and managed promptly. The study aims to develop an automated system to detect these diseases early on, providing a proactive approach to disease management.
- **Inefficiencies of Traditional Detection Methods:** Conventional methods of disease detection in tomato plants, relying on visual inspection by farmers, are prone to subjectivity and inefficiency. Additionally, manual inspection may miss subtle symptoms, especially in the early stages of disease development. The study seeks to overcome these limitations by introducing a technology-driven approach

that is accurate, consistent, and capable of detecting diseases at their inception.

- **Advancements in Deep Learning and Image Processing:** Recent advancements in deep learning, particularly CNNs, have demonstrated exceptional capabilities in image recognition and classification. The study leverages these technologies to exploit intricate patterns and features within images of tomato leaves, enabling a high level of precision in disease identification. The integration of these advanced techniques represents a significant leap forward in the application of technology to agriculture.
- **Optimizing Resource Utilization:** The study aligns with the principles of precision agriculture by providing a tool that optimizes the use of resources such as pesticides, fertilizers, and water. Automated disease detection allows for targeted interventions, reducing the need for widespread application of treatments. This not only improves resource efficiency but also minimizes environmental impact and operational costs.
- **Empowering Farmers with Technology:** As agriculture becomes increasingly technology-driven, providing farmers with tools that enhance decision-making and productivity is crucial. The study aims to empower farmers with an accessible and user-friendly automated system that can be integrated into their farming practices. This empowers them to make informed decisions regarding disease management and crop health.
- **Contributing to Sustainable Agriculture:** The implementation of an automated disease detection system contributes to sustainable agricultural practices. By reducing the reliance on chemical treatments and minimizing crop losses, the study promotes a more sustainable and environmentally friendly approach to tomato cultivation, aligning with global efforts for sustainable agriculture.

1.4 Research Questions:

These research questions encompass various aspects of the study, ranging from the technical aspects of model training and generalization to the broader implications of implementing automated disease detection in real-world agricultural settings. They aim to provide a comprehensive understanding of the effectiveness, usability, and impact of the proposed CNN-based system for detecting tomato leaf diseases:

- How does the selection of image processing techniques impact the performance of CNNs in identifying subtle features indicative of tomato leaf diseases?
- How does the CNN model perform under variations in environmental conditions, lighting, and different stages of disease development?
- How user-friendly and accessible is the automated detection system for farmers and agricultural practitioners with varying levels of technological expertise?
- How do farmers perceive and adapt to the integration of automated disease detection in their decision-making processes?

1.5 Expected Output:

The expected outputs for the study on automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) can be categorized into technical performance metrics, practical applicability, and broader impacts. These outputs will help assess the effectiveness and implications of the proposed automated system. Key expected outputs include:

- **Technical Performance Metrics:** Accurate identification of tomato leaf diseases, measured through overall accuracy and precision metrics, indicating the proportion of correctly identified diseased and healthy leaves. Evaluation of the system's ability to correctly identify diseased leaves, considering false negatives and false positives, measured through recall and F1 score. A detailed breakdown of true positive, true negative, false positive, and false negative predictions to analyze the model's performance across different disease classes.

- **Model Generalization:** Demonstration of the CNN model's ability to generalize to previously unseen datasets, ensuring its applicability in real-world scenarios. Evaluation of model robustness under varying environmental conditions, lighting, and stages of disease development.
- **Comparative Analysis:** Comparison of the CNN-based automated detection system's performance with traditional manual methods and existing automated disease detection approaches. Identification of specific diseases or conditions where the CNN model may face challenges, providing insights for potential improvements.
- **User-Friendly Implementation:** Development of a user-friendly interface or system that facilitates easy integration into existing agricultural workflows. Assessment of the system's usability by farmers and agricultural practitioners, considering factors such as accessibility and ease of interpretation of results.
- **Impact on Crop Management:** Quantification of the impact of early disease detection on overall crop management, including reduced crop losses, optimized resource utilization, and improved yield.
- **Scalability and Adaptability:** Evaluation of the system's scalability, considering its performance when applied to larger datasets or across diverse geographic regions and tomato varieties. Assessment of the system's adaptability to different soil conditions, climates, and agricultural practices.
- **Ethical and Environmental Considerations:** Identification and implementation of ethical guidelines to address potential biases, privacy concerns, and ethical considerations associated with automated disease detection in agriculture. Assessment of the environmental impact, such as reduced use of pesticides and fertilizers, contributing to sustainable agricultural practices.

1.6 Project Management and Finance:

Effectively Effective project management is essential for the successful implementation of a research project on the automated detection of tomato leaf diseases using Convolutional

Neural Networks (CNNs). The following project management considerations are crucial:

- **Project Scope and Objectives:** The study aims to assess the effectiveness of an automated system for detecting tomato leaf diseases using Convolutional Neural Networks (CNNs). Key outputs include technical performance metrics, practical applicability, and broader impacts. The system will be evaluated for accuracy, generalization, comparison with traditional methods, usability, impact on crop management, scalability, and ethical considerations.
- **Timeline and Milestones:** Develop a detailed project from Jan 2023 to Dec 2023 with well-defined milestones, including key research phases dataset collection, model development, training, testing, and result analysis. Regularly review and adjust the timeline as needed to accommodate unforeseen challenges or delays.
- **Resource Allocation:** I collect all my data physically and save them in Google Drive. So, my resources efficiently, including personnel, computing resources, and funding. Ensure that supervisors have the necessary expertise in areas of deep learning, image processing, and agriculture.
- **Collaboration and Communication:** Foster effective communication among with supervisors. Organize regular meetings to discuss progress, address challenges, and ensure everyone is aligned with project goals.
- **Risk Management:** Identify potential risks and uncertainties associated with the project, data availability, model performance, and external factors. Develop contingency plans and mitigation strategies to address identified risks.
- **Ethical Considerations:** Establish ethical guidelines for data collection, model development, and deployment to address potential biases and privacy concerns. Ensure compliance with ethical standards and obtain necessary approvals for research involving human subjects or sensitive data.

- **Budgeting:** My develop comprehensive budget that covers all aspects of the project, including personnel salaries, computing resources, data acquisition, and any other relevant expenses are fulfilled by me. Consider potential unforeseen costs and allocate a contingency fund to address unexpected expenses.
- **Funding Sources:** I provide all secure of funding sources for the project. This includes grants, research funding from academic institutions, or collaboration with industry partners. Clearly articulate the project's goals and potential impact when seeking funding.
- **Cost-Benefit Analysis:** Conduct a cost-benefit analysis to assess the potential return on investment, taking into account the economic impact of improved disease detection on crop yields and overall agricultural productivity.
- **Resource Optimization:** Optimize resource utilization to ensure that funds are allocated efficiently. This includes leveraging open-source tools, collaborating with research institutions, and exploring cost-effective computing solutions.

1.7 Report Layout:

A comprehensive report on tomato leaf disease detection using deep learning with CNNs should provide a clear and detailed account of the research. Here's my proposed layout:

Table of Contents: List of sections, subsections, and page numbers for easy navigation. Introduction: Background and context of fruits and their impact on patient health. Problem statement and motivation for applying deep learning, specifically CNNs. Clear definition of research objectives and questions.

List of Figures and Tables: Enumeration and titles of all figures and tables presented in the report.

Abstract: A concise summary of the entire report, highlighting key objectives, methods, results, and conclusions.

Chapter 1: This chapter includes an overview of the research, what motivates us to work on this research, the expected outcomes of the research, and the project management and funding of the research.

Chapter 2: Comprehensive review of relevant literature in medical image analysis, specifically focusing on fruit detection. Identification of gaps in existing methods and the need for enhanced diagnostic approaches.

Chapter 3: Detailed explanation of the research design and approach. Description of the dataset, including data sources, size, and preprocessing steps. Overview of the CNN architecture, model selection criteria, and justification for the chosen approach. Training procedures, hyperparameters, and evaluation metrics.

Chapter 4: Presentation of results, including quantitative performance metrics (accuracy, sensitivity, specificity). Visualizations and interpretations of key findings, including ROC curves or confusion matrices. Comparative analysis with traditional methods.

Discussion: Interpretation of results in the context of research questions and objectives. Comparison with existing literature and implications of findings for medical practice. Exploration of limitations and potential avenues for future research.

Chapter 5: Discussion of ethical considerations in data collection, analysis, and reporting. Explanation of steps taken to ensure participant confidentiality and privacy.

Chapter 6: Summary of key findings and their significance. Contributions to the field and potential applications of the enhanced fruit detection method.

References: Comprehensive list of all cited references in a standardized citation MLA format.

Appendices: Supplementary materials, including additional data visualizations, code snippets, or detailed technical information.

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CHAPTER 2
BACKGROUND

2.1 Overview:

Tomatoes are a crucial part of global agriculture, but diseases affecting their leaves pose a significant challenge to their growth and yield. Traditional methods often rely on subjective visual inspection, leading to delayed responses and increased crop losses. To address this, Convolutional Neural Networks (CNNs) are being explored for automated disease detection. By analyzing visual data, CNNs can learn patterns and features indicative of specific diseases, enabling a reliable and efficient system. This study aims to automate the detection of tomato leaf diseases using a diverse dataset, revolutionizing agricultural practices and improving crop management.

The automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) is aimed at addressing the challenges faced by the agricultural sector, particularly in tomato cultivation. The study aims to provide timely intervention, enhance crop yield and quality, align with precision agriculture principles, mitigate economic losses, and integrate technology into agriculture. The study leverages deep learning and image processing advancements to exploit intricate patterns in tomato leaves, enabling high precision in disease identification. It also optimizes resource utilization, aligns with precision agriculture principles, empowers farmers with technology, and contributes to sustainable agriculture by reducing reliance on chemical treatments and minimizing crop losses. The problem of automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) in agriculture involves the complexity and diversity of diseases, subjective detection, timely intervention, resource optimization, and deep learning technology. The automated system aims to address these challenges by recognizing subtle patterns and variations, reducing reliance on subjective human judgment, and optimizing resource utilization. Challenges include limited and imbalanced datasets, variability in disease symptoms, overfitting, and generalization issues, interclass confusion, user adoption and interface design, environmental variability, and ethical considerations. The system aims to be user-friendly, adaptable, and ethically responsible, ensuring its effectiveness across diverse agricultural settings and reducing environmental impact.

2.2 Related Work:

The related works highlight the application of Automated Detection of Tomato Leaf Diseases using Convolutional Neural Networks (CNNs), showcasing the effectiveness of deep learning techniques in accurately identifying and classifying various tomato leaf diseases. They provide insights into different CNN architectures, preprocessing techniques, and training strategies that can be employed to develop robust disease recognition systems. Azeddine Elhassouny et al. [1] This study proposes an efficient smart mobile application model based on deep CNN to automatically identify and diagnose tomato leaf diseases. Inspired by the Mobile Net CNN model, the model can recognize the 10 most common types of tomato leaf diseases. The application uses 7176 images of tomato leaves for diagnosis. Yang Wu et al. [2] A lightweight tomato leaf disease identification network, supported by Variational Auto-Encoder (VAE), is proposed to improve crop leaf disease identification accuracy. The lightweight network uses multi-scale convolution to expand network width, enrich extracted features, and reduce model parameters. VAE uses unlabeled data for unsupervised learning and labeled data for supervised disease identification. The method enhances generalization effect and identification accuracy, with a 94.17% correct detection rate for disease categories and 98.27% for healthy leaves, reducing misidentification of healthy leaves. Mohit Agarwal et al. [3] Tomato, the world's most popular crop, faces challenges due to diseases. A deep learning-based approach, Convolution Neural Network, is proposed for disease detection and classification. The model uses 3 convolution and max pooling layers, with an average accuracy of 91.2% for 9 diseases and 1 healthy class. The proposed model outperforms pre-trained models.

Gnanavel Sakkarvarthi et al. [4] Deep learning is a new method for detecting leaf diseases in tomato crops. This article presents a deep-learning-based strategy using a convolutional neural network (CNN) technique. The model outperformed pre-trained models, achieving 98% training accuracy and 88.17% testing accuracy, outperforming InceptionV3, ResNet 152, and VGG19. This approach is crucial for maintaining the quality and quantity of tomato crops. Showmick Guha Paul et al. [5] This study proposes a lightweight custom convolutional neural network (CNN) model and transfer learning (TL)-based models VGG-16 and VGG-19 to classify tomato leaf diseases. The model, using data augmentation techniques, achieved the highest accuracy and recall of 95.00% among all models. The best-performing model was used to create a Web-based and Android-based end-to-end system for tomato cultivators to classify diseases. Early diagnosis and treatment of tomato leaf diseases improve plant production and efficiency. Valeria Maeda-Gutiérrez et al. [6] Tomato plants are heavily impacted by various diseases, and accurate diagnosis is crucial for crop quality. Convolutional neural networks (CNNs) have shown remarkable results in identifying and preventing these diseases. A study comparing various CNN architectures found that Google Net outperformed other models, with a 99.72% AUC and 99.12% sensitivity, making it a valuable tool for farmers. Emre Özbılge et al. [7] This study proposes a compact convolutional neural network (CNN) for early tomato disease detection, enhancing production efficiency and quality. The network, consisting of six layers, is computationally inexpensive and trained using Plant Village's tomato crop dataset. Compared to pre-trained ImageNet deep networks, the proposed network outperforms them. Data augmentation techniques are employed to improve performance. The network achieved 99.70% accuracy, Matthew's correlation coefficient, true positive rate, and true negative rate, surpassing state-of-the-art deep neural network approaches. Muhammad EH Chowdhury et al. [8] This study proposes using a deep learning architecture based on Efficient Net to classify tomato diseases on 18,161 plain and segmented tomato leaf images. The models, U-net and Modified U-net performed well in binary classification, six-class classification, and ten-class classification. EfficientNet-B7 showed superior performance in binary classification and six-class classification, while EfficientNet-B4 achieved an accuracy of 99.89% for ten-class classification. The results outperform existing literature, demonstrating the potential of AI in early disease detection. Endang Suryawati et al. [9] This paper evaluates the effect of different depths of Convolutional Neural Network (CNN) architectures on plant disease detection accuracies. Various CNN architectures, including simple baseline, Alex Net, and VGGNet, are investigated. Google Net architectures are also evaluated. The results show that CNN with deeper architecture, such as VGGNet, outperforms others, suggesting deeper architectures may be more beneficial for this task. Raditya Rifqi Rayhan et al. [10] Tomatoes are crucial for Indonesian food production, and pest attacks can decrease production. To address this issue, an intelligent system using image processing and Convolution Neural Network (CNN) will be developed to detect disease in tomato plants. The system has shown high accuracy in training and testing, with training and testing accuracy of 98% and 95%, respectively. Yahya ALTUNTAŞ et al. [11] Plant diseases and pests can cause yield and quality losses, making detection quick and accurate crucial. Detecting these diseases through visual observation is labor-intensive and error-prone. A computer-aided disease detection system has become essential for precision agriculture. This study uses pre-trained convolutional neural network models and a deep learning model to classify leaf images of tomato plant diseases and pests. The model achieved an accuracy rate of 96.99%. Md. Ferdouse Ahmed Foysal et al. [12] Neural networks have significantly improved the development of industries, particularly in the agriculture sector. This work presents a 15-layered Deep Convolutional Neural Network for detecting tomato diseases. The model can classify five different diseases with high accuracy and low cross-entropy rate. By implementing artificial intelligence, this research can contribute to the success and growth of the agroindustry by identifying and addressing plant diseases that contribute to low-quality products. Shaheen Khatoon et al. [13] Tomato production faces threats from pests, pathogens, and nutritional deficiencies, impacting crop growth, yield, and even crop loss. Traditional disease diagnosis methods are costly and time-consuming. Recent advancements in AI and computer vision allow for image-based automatic diagnostic tools. This paper proposes an AI-based approach to detect diseases in tomato plants using deep learning models. The system uses Convolutional Neural Networks trained on a large dataset of tomato leaves and fruits. Dense Net consistently achieves high performance with an accuracy score of 95.31%. André Abade et al. [14] This study reviews 121 papers from the last decade to identify the state of the art in using convolutional neural networks (CNN) for detecting and classifying plant diseases. The review focuses on disease detection, dataset characteristics, crops, and pathogens investigated. The findings help understand innovative trends and identify gaps in research for improved plant disease detection and classification. Lawra Norria Samba Ricky et al. [15] This research aims to identify tomato leaf diseases using image processing techniques and develop an automatic disease detection system using Convolution Neural Network (CNN). The method consists of pre-processing, segmentation, feature extraction, and classification using The experimental results show that the proposed method successfully detects leaf diseases, with healthy leaf having the highest accuracy, sensitivity, and f1-score. Future research should expand the model to identify other plant diseases and investigate disease severity using an automated approach. Omneya Attallah et al. [16] This study proposes a pipeline for automatic identification of tomato leaf diseases using three compact convolutional neural networks (CNNs). It uses transfer learning to retrieve deep features, merges features from each CNN, and applies a hybrid feature selection approach. Six classifiers are used, with K-nearest neighbor and support vector machine achieving the highest accuracy of 99.92% and 99.90% using 22 and 24 features, respectively. The experimental results are compared with previous research studies for tomato leaf disease classification. Ayesha Batool et al. [17] Agricultural productivity is crucial for the economy, but plant diseases and pests pose significant problems. Despite using various pesticides, diseases continue to spread, often due to uncertainty in disease type. This paper proposes an advanced classification model for tomato leaf disease, using 450 images and KNN for classification. The AlexNet model achieved a classification accuracy of 76.1%, making it the highest-performing model in this area. Shengyi Zhao et al. [18] This paper presents a deep convolutional neural network that incorporates an attention mechanism for crop disease diagnosis. The model, which includes residual blocks and attention extraction modules, achieves an average identification accuracy of 96.81% on tomato leaf diseases and 99.24% on grape leaf diseases. The model's attention module enhances the accuracy of extracting complex disease features and has fewer parameters, making it a high-performance solution for crop diagnosis in real agricultural environments. Hasibul Islam Peyal et al. [19] This study focuses on detecting tomato plant leaf diseases faster using Deep Learning (DL) and convolutional neural network (CNN) architectures. Using a dataset of 11,000 images, the study found high accuracy in identifying diseases. Comparing three pre-trained models, the best-suited model for detecting tomato leaf diseases is Inception-V3, with the results and data included to support the claim. Hasan, Md. Riazul et al. [20] Agriculture in Bangladesh is crucial for livelihoods and GDP, with 16% of the population consuming tomatoes. However, plant infections pose a threat to crop production. Climate change necessitates early disease detection. Advancements in computer vision, image processing, and deep learning can help. This research demonstrates the diagnosis and detection of tomato leaf diseases using a Convolutional Neural Network (CNN), achieving 95% accuracy and requiring fewer computational resources. This model is easily deployable in mobile applications.

2.3 Comparative Analysis and Summary:

A comparative analysis is conducted on tomato leaf disease identification using Convolutional Neural networks (CNNs).

TABLE 2.3.1: COMPARISON TABLE FOR TOMATO LEAF DISEASES.

Ref. NO	Year	Algorithm	results	Findings
[2]	2021	CNN, VAE	has a s 94.17% accuracy rate	the technology can be used in identifying tomato leaf and similar crop leaf diseases
[3]	2020	Convolutional neural networks, supervised learning	Accuracy 91.2%	the proposed model works for the 9 disease and 1 healthy class
[8]	2021	CNN and Deep Learning	With a 98.66% accuracy rate	the model performed better in classifying the diseases when trained with deeper networks on segmented images

[10]	2021	CNN, DL	an accuracy score of 96.27%	the proposed model has produced better training and testing accuracy.
[16]	2023	DL, CNN	overall accuracy of 96.67%	leaf diseases classification which verified its competing capacity.

In Table 2.3.1, this paper uses different tomato leaf disease identification using different algorithms described but this custom algorithm is very much supportive of this paper and its accuracy is high. In these papers, working methods maximum work related to the paper. So, especially include the above table.

2.4 Scope of the Problem:

The scope of the problem for automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) encompasses several key dimensions, highlighting the challenges and opportunities associated with the application of advanced technology in agriculture:

- **Complexity and Diversity of Diseases:** Tomato plants are susceptible to a wide array of diseases caused by various pathogens, including fungi, bacteria, and viruses. Each disease manifests unique symptoms, making manual identification and differentiation challenging, especially in the early stages. The automated system aims to address the complexity of disease identification by leveraging CNNs to recognize subtle patterns and variations associated with different diseases.
- **Subjectivity and Inconsistency in Manual Detection:** Traditional methods of disease detection often rely on subjective visual inspections by farmers or agricultural experts, leading to inconsistencies and potential misdiagnosis. The automated system seeks to introduce objectivity and consistency in disease detection by utilizing CNNs, thereby reducing reliance on subjective human judgment.

- **Timely Intervention and Disease Management:** Delayed detection of tomato leaf diseases can result in significant economic losses and reduced crop yields. Manual inspection may not provide timely information for effective intervention. The automated system intends to facilitate early detection, enabling timely and targeted interventions to manage and mitigate the spread of diseases, ultimately improving crop health.
- **Optimizing Resource Utilization:** Conventional methods often lead to the indiscriminate use of pesticides and fertilizers, contributing to environmental concerns and increased production costs. The automated system aims to optimize resource utilization by providing precise disease identification, allowing farmers to apply treatments strategically and reduce the overall environmental impact.
- **Advancements in Deep Learning Technology:** Incorporating advanced technologies like CNNs in agriculture requires overcoming technical challenges and ensuring that models are well-suited for the nuances of plant disease detection. The study explores the potential of CNNs to effectively learn and recognize intricate patterns in tomato leaf images, capitalizing on the advancements in deep learning to enhance accuracy and efficiency.
- **Accessibility for Farmers:** Farmers with varying levels of technological expertise may face barriers in adopting and integrating automated systems into their traditional farming practices. The automated system aims to be user-friendly and accessible, empowering farmers to utilize technology for better decision-making in disease management without requiring extensive technical knowledge.
- **Scalability and Adaptability:** Agricultural conditions, including soil types, climates, and tomato varieties, vary across regions, demanding scalable and adaptable solutions. The automated system seeks to demonstrate scalability and adaptability, ensuring its effectiveness across diverse agricultural settings and facilitating broader applicability.
- **Ethical Considerations:** The use of automated systems raises ethical considerations, including potential biases in the model and ensuring the privacy of sensitive agricultural data. The study addresses these ethical considerations by

implementing measures to minimize biases, ensuring transparency, and adhering to ethical standards in data handling.

2.5 Challenges:

The automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) poses several challenges that need to be addressed to ensure the effectiveness and reliability of the system. Some key challenges include:

- **Limited and Imbalanced Datasets:** The availability of comprehensive and balanced datasets containing diverse examples of healthy and diseased tomato leaves is a common challenge. Imbalances in the dataset can lead to biased model training. The collection of representative datasets, data augmentation techniques, and balancing strategies during model training can help mitigate this challenge.
- **Overfitting and Generalization Issues:** Overfitting may occur when the CNN model learns noise or specific patterns present in the training data but does not generalize well to new, unseen data. Implementing regularization techniques, such as dropout layers, and using a separate validation dataset to fine-tune hyperparameters can help prevent overfitting and improve generalization.
- **Environmental Variability:** Environmental factors, such as lighting conditions and weather, can impact the quality and consistency of images, affecting the model's performance. Preprocessing techniques to standardize image quality, considering image augmentation strategies to simulate different environmental conditions, and testing the model's robustness across diverse scenarios.
- **Ethical Considerations:** CNNs may inadvertently perpetuate biases present in the training data, leading to biased predictions. Regular auditing for bias, diversifying training datasets, and implementing fairness-aware training techniques can help address bias-related challenges.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation:

This instrumentation plan outlines the tools, methods, and approaches to be employed in the research project, emphasizing a multidisciplinary approach that integrates expertise in agriculture, deep learning, and human-computer interaction.

- **The Research Subject Description:** The research subject involves the development and implementation of an automated system for detecting diseases in tomato plants through the utilization of Convolutional Neural Networks (CNNs). The focus is on leveraging deep learning techniques to enhance the accuracy and efficiency of disease identification in tomato leaves.
- **Objectives:** Develop a CNN-based model capable of accurately identifying and classifying various diseases affecting tomato leaves. Evaluate the performance of the automated system in comparison to traditional manual methods and existing automated approaches. Investigate the impact of early disease detection facilitated by the CNN model on overall crop management, resource utilization, and yield improvement.
- **Key Research Questions:** How effective is the implementation of CNNs in automating the detection of tomato leaf diseases compared to traditional manual methods? What is the comparative performance of the CNN-based system in terms of accuracy, precision, recall, and F1 score, as opposed to existing automated methods or traditional manual approaches? How does early disease detection facilitated by the CNN model positively impact overall crop management practices and economic outcomes for farmers?
- **Scope of the Study:** The study encompasses the development and evaluation of an automated detection system for a range of tomato leaf diseases. It includes

considerations for diverse environmental conditions, disease manifestations, and the potential applicability of the system across various agricultural settings.

- **Data Collection:** I use high-resolution cameras, and mobile devices for capturing images of tomato leaves. Diverse datasets comprising images of healthy and diseased tomato leaves, sourced from agricultural research institutions, farms.
- **Image Preprocessing:** Image processing software tools OpenCV for resizing, normalization, and non-augmentation. Data preprocessing techniques to enhance image quality, reduce noise, and standardize inputs for CNN model training.
- **Convolutional Neural Networks (CNNs):** Deep learning frameworks TensorFlow for building and training CNN models. CNN architecture tailored for image classification tasks, with considerations for disease detection nuances.
- **Model Evaluation:** For metrics I use accuracy, and loss. Val_accuracy, val_loss for quantitative evaluation. Holdout validation and cross-validation to assess model generalization to unseen data.
- **Environmental Testing:** Image datasets captured under varying environmental conditions different lighting, and weather. Assess the robustness of the CNN model under different environmental scenarios.
- **Ethical Considerations:** Ethical guidelines and standards for handling sensitive data and mitigating biases in the CNN model. Tools for auditing and monitoring potential biases in the model predictions.
- **Agricultural Impact Assessment:** Surveys, interviews, and focus groups to gather feedback from farmers and stakeholders. Metrics crop yield improvement, economic gains, and resource optimization for assessing the impact on agriculture.

3.2 Data Collection Procedure:

The data collection procedure for automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) involves several steps to ensure the acquisition of a diverse and representative dataset. Here is a systematic guide for the data collection process:

- **Define Objectives:** Develop a CNN-based model capable of accurately identifying and classifying various diseases affecting tomato leaves. Evaluate the performance of the automated system in comparison to traditional manual methods and existing automated approaches. Investigate the impact of early disease detection facilitated by the CNN model on overall crop management, resource utilization, and yield improvement.
- **Identify Data Sources:** I collected the tomato leaf image data from real-life environments, Agricultural research institutions, Local farms, and greenhouses, then labeled by comparing it with agricultural organizations and online repositories of plant disease datasets
- **Select Image Capture Devices:** Choose my mobile devices for capturing high-resolution images of tomato leaves. This includes Digital cameras with high megapixel counts. My mobile devices are equipped with quality cameras.
- **Standardize Image Capture Protocol:** Develop a standardized protocol for capturing images to ensure consistency across the dataset. Consider the following factors Distance and angle from the tomato plant, Lighting conditions natural daylight or controlled artificial lighting, Image resolution, and format.
- **Capture Healthy and Diseased Samples:** Systematically capture images of both healthy and diseased tomato leaves. Aim for a balanced representation of various diseases and their different stages of development.
- **Annotate Images:** Annotate each image with labels indicating whether the tomato leaf is healthy or affected by a specific disease. Include additional annotations for disease severity.
- **Consider Environmental Variability:** Capture images under varying environmental conditions, including different lighting, weather conditions, and stages of plant growth. This helps enhance the model's ability to generalize to diverse scenarios.

- **Ensure Data Diversity:** Ensure diversity in terms of tomato varieties, soil types, and geographic locations. A diverse dataset contributes to the robustness and applicability of the trained CNN model.
- **Data Size:** I use a huge dataset for this research. Over 10 thousand tomato leaves are in my dataset. The size of my file is nearly 8 to 12 GB. All my image size is (226,226).
- **Organize and Store Data:** Organize the dataset into appropriate folders based on disease classes, ensuring a clear structure for model training. Store the dataset securely in my Google drive, considering backup measures to prevent data loss.
- **Data Privacy and Security:** Implement measures to safeguard the privacy and security of collected data, especially when working with images from private farms or collaborating with specific institutions.

3.3 Statistical Analysis:

Statistical analysis for the automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) involves evaluating the performance of the model and assessing its accuracy, precision, recall, and other relevant metrics. Here is a step-by-step guide for the statistical analysis:

- **Performance Metrics:** The proportion of correctly classified instances out of the total instances. The ratio of true positive predictions to the total predicted positives, indicates the model's ability to avoid false positives. The ratio of true positive predictions to the total actual positives indicates the model's ability to capture all positive instances. The harmonic means of precision and recall, provide a balanced measure of a model's performance.
- **Confusion Matrix:** Create a confusion matrix to visualize the model's predictions, including true positives, true negatives, false positives, and false negatives. This matrix helps in understanding the distribution of predictions across different disease classes.

- **Cross-Validation:** Implement cross-validation to evaluate the model's generalization across different subsets of the dataset. This helps in assessing the stability and consistency of the model's performance.
- **Statistical Significance Testing:** comparing the model's performance on different subsets of the dataset for different diseases, conducting statistical significance testing to determine whether observed differences are statistically significant.
- **Statistical Software:** Utilize statistical software such as Python using libraries like NumPy, SciPy, sci-kit-learn, and others for conducting the statistical analyses.
- **Reporting and Visualization:** I present the results using appropriate visualization tables, charts, graphs, and statistical summary reports. Communicate statistical significance.
- **Ethical Considerations:** Consider the ethical implications of the statistical analysis, especially addressing biases and potential disparities in disease detection across different demographics.

3.4 Detailed Methodology:

Figure 3.1 shows the proposed real tomato disease detection system. This will be implemented in his two phases training and deployment. The algorithms for the training phase and deployment phase are shown in Algorithm. The training phase consists of 2 steps from dataset acquisition to image classification datasets are classified into his 10 classes: Bacterial Spot Xanthomonas campestris, Early Blight Alternaria solani, Late Blight Phytophthora infestans, Leaf Mold Passalora fulva, Septoria Leaf Spot Septoria lycopersici, Two Spotted Spider Mite Tetranychus urticae, Target Spot Corynespora cassiicola, Mosaic Virus, Yellow Leaf Curl Virus, Tomato leaves healthy.

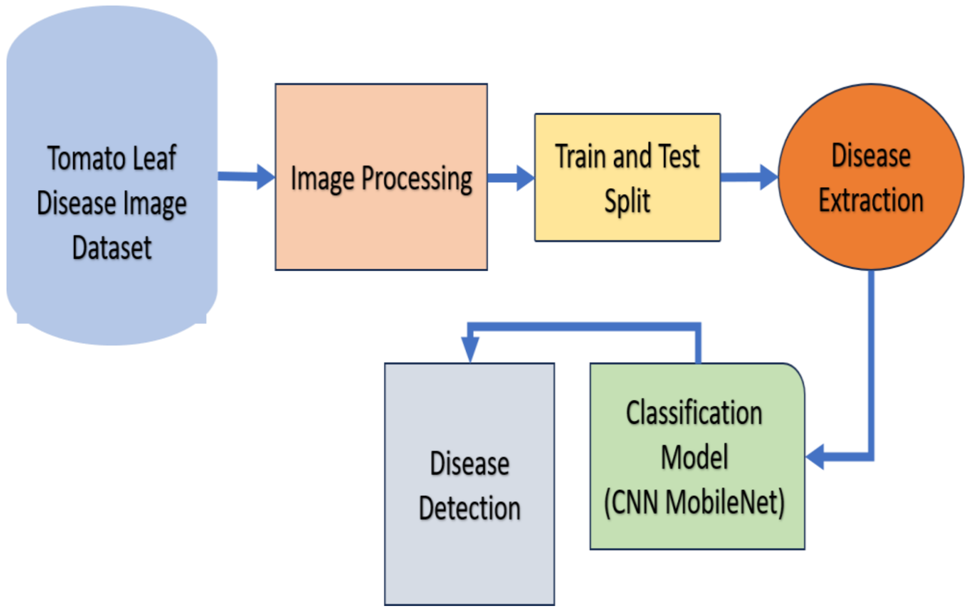

Figure 3.1: Tomato disease Workflow Diagram

The CNN-based model can work on a mobile phone at an acceptable speed and with good classification accuracy. The CNN model is the primary contribution of this work. MobileNet is first developed and applied to the problem of diagnosing Tomato leaf diseases. The application developed can identify and recognize the ten most frequent forms of Tomato leaf diseases. The test and application use reveal that, in addition to the high recognition ratio, the MobileNet CNN model works quickly on common mobile phones utilizing their cameras. The CNN MobileNets Model is detailed further below.

Google researchers have developed a set of efficient models called MobileNets specifically designed for mobile and embedded vision applications. The MobileNet model utilizes depthwise separable convolutions, resulting in a significant reduction of computational requirements of about 8 to 9 times less compared to traditional convolutions. Additionally, MobileNets is made smaller and faster by incorporating a width multiplier and adjusting the resolution. MobileNets utilizes the concepts of depthwise separable filters and factorization to minimize the computational load in the initial layers. To decrease the computational load, the convolution operation is decomposed into two steps: depthwise convolution, which applies each filter to each channel individually, and pointwise convolution, which utilizes a 1×1 convolution to combine the results of the depthwise convolution.MobileNets utilize the ReLU activation function for both layers, in addition to the two operations. In this analysis, we examine the computational expenses associated with employing the traditional convolution method against the depthwise methodology. MobileNet's utilization of 3 × 3 depthwise separable convolutions results in a 9-fold reduction in computation. Let's assume that W represents the size of the input image, M represents the number of input channels, F Dk × Dk represents the size of the convolution kernel (typically 3 × 3 or 1 × 1), N represents the desired number of output channels, s represents the convolution stride either 1 or 2, and P represents the padding used. In this case, the resulting tensor after convolution is DK × DK × M × DF × DF, rather than the standard convolution DK × DK × M × N × DF × DF or DK × DK × N × M × DF × DF.

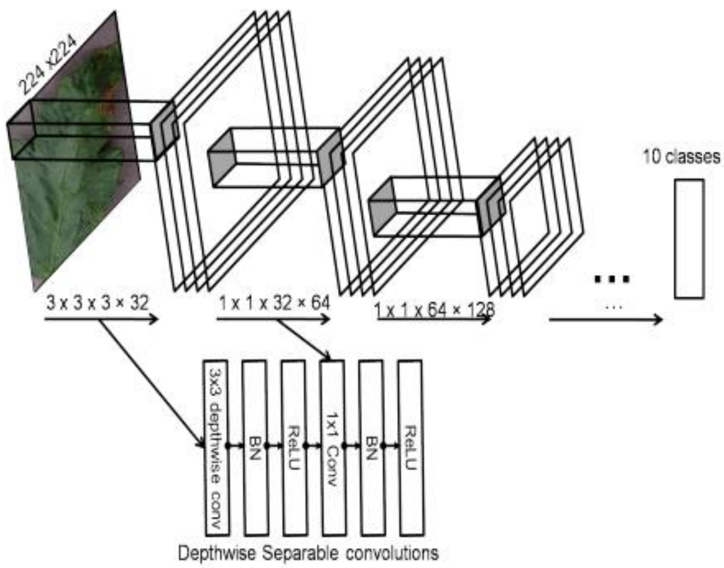

Figure 3.2: The architecture of deep convolutional neural networks

Architecture of deep convolutional neural networks model. The MobileNet CNN architecture, which has been successful in mobile and embedded systems, serves as my inspiration. The diagram in Figure 3.2 depicts the specifics of a convolutional neural network (CNN) architecture and its associated parameters. The model is designed to process a color image input with dimensions of 226 × 226. The architecture is comprised of a sequence of Depth-wise Separable convolutions, which includes both Depthwise and Pointwise layers. These convolutions are then followed by batch normalization (BN) and Rectified Linear Unit (ReLU) activation. Each layer consists of a 3 × 3 Depthwise

Convolution, followed by Batch Normalization, a 1×1 Convolution, Batch Normalization, and ReLU activation function. The classification of disorders is obtained by averaging the model. The combination of pooling layers, fully linked layers, and the Softmax function is used with 10 classes.

3.5 Implementation Requirements:

The implementation of automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) involves several requirements across hardware, software, and data components. Below is a comprehensive list of implementation requirements:

- **Hardware Requirements:** A multicore CPU with sufficient processing power for data preprocessing, model training, and inference. Depending on the scale of the project, consider CPUs with multiple cores or high clock speeds. A GPU is highly recommended for accelerating the training of deep neural networks CNNs. GPUs are commonly used for deep learning tasks. Adequate RAM to handle the large datasets used for training CNN models. A minimum of 16 GB of RAM is recommended, but larger datasets may require more. Sufficient storage capacity for storing datasets, model weights, and intermediate results. Fast storage solutions improve data loading and model training times. For large-scale projects, consider dedicated deep learning hardware solutions, Tensor Processing Units (TPUs).
- **Software Requirements:** A deep learning framework compatible with CNNs, TensorFlow, and Keras. I chose the framework on personal preference, community support, and specific features.
- **Data Requirements:** A labeled dataset of tomato leaf images with annotations indicating the presence and type of diseases. Include a variety of diseases, different stages, and diverse environmental conditions. Tools for preprocessing images, including resizing, normalization, and augmentation. Software libraries like OpenCV are useful for image manipulation.

- **Model Architecture:** Define the architecture of the CNN model, considering the specific requirements of the task. Pretrained models are used as a starting point. for model training steps_per_epoch = Len (train generator), epochs 5, validation data = valid generator, validation steps = Len (valid generator), callbacks = [early stopping], including learning rate 0.0001, batch size 128. Consider optimization algorithms Adam, based on the nature of the problem. Utilize transfer learning by initializing the CNN with weights pre-trained on a large dataset ImageNet.
- **Testing and Evaluation:** Reserve a portion of the dataset for testing the trained model's performance on unseen data. Ensure the test dataset is representative of real-world scenarios. Implement scripts or tools to calculate evaluation metrics, including accuracy, loss, val_accuracy, and val_loss.
- **Ethical Considerations:** Implement measures to identify and mitigate biases in the dataset and model predictions. Regularly audit the model for fairness and equitable performance across different demographic groups. Ensure compliance with privacy regulations and implement protocols to handle sensitive data appropriately.

CHAPTER 4
RESULT AND DISCUSSION

4.1 Experimental Setup:

The experimental setup for automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) involves configuring the hardware, software, and data components to conduct experiments and evaluate the performance of the model. Here's a detailed guide for the experimental setup:

- **Hardware Setup:** For this research work I use a GPU to accelerate the training of deep neural networks. Ensure sufficient RAM to handle the dataset and model parameters during training. Mine is 8 GB below recommended. Use fast storage solutions SSD to store datasets, model weights, and intermediate results. I use Google Drive for sufficient storage capacity which is essential, especially for large datasets.
- **Deep Learning Framework:** I choose a deep learning framework TensorFlow, Keras, and pandas for implementing the CNN MobileNet model.
- **Labeled Dataset:** I prepare a labeled dataset of tomato leaf images with annotations for diseases. Split the dataset into training, validation, and test sets.
- **Data Preprocessing:** Preprocess images by resizing, normalizing pixel values, and handling color channels appropriately. Create scripts or functions for efficient data preprocessing.
- **Model Configuration:** Google researchers have developed a CNN-based model called MobileNets, which is designed for mobile and embedded vision applications. The model uses depthwise separable convolutions, reducing computational requirements by 8-9 times compared to traditional convolutions. The model is made smaller and faster by incorporating a width multiplier and adjusting resolution. The MobileNet architecture, which includes depthwise convolutions, batch normalization, and Rectified Linear Unit activation, is successful in processing color image inputs and achieving high classification accuracy.

- **Model Training:** Develop a script for training the CNN model using the prepared dataset and configurations. Implement early stopping to prevent overfitting and save model checkpoints during training. Monitor training progress by logging key metrics loss, accuracy, val_loss, and val_accuracy during each epoch. Visualize training curves using tools Matplot and Seaborn.
- **Evaluation:** I create a script for evaluating the trained model on a separate test dataset. Calculate performance metrics, including accuracy, loss, accuracy, val_loss, and val_accuracy. Generate a matrix to understand the distribution of predictions across different disease classes. Plot a curve to assess the trade-off between the true positive rate and the false positive rate.
- **Ethical Considerations:** Perform bias analysis to identify and mitigate biases in the dataset and model predictions. Implement measures to ensure privacy and secure handling of sensitive data.

4.2 Results & Analysis:

The proposed algorithm was implemented in Python and the integrated development environment was Google Colab, a popular Python IDE developed by Google for programming the Python language. The proposed system uses CNN MobileNet for tomato leaf disease detection. The HQ dataset contains 9229 images of 10 different tomato leaf diseases. Where the training data is 8229 tomato leaf images and 1000 tomato leaf images for test.

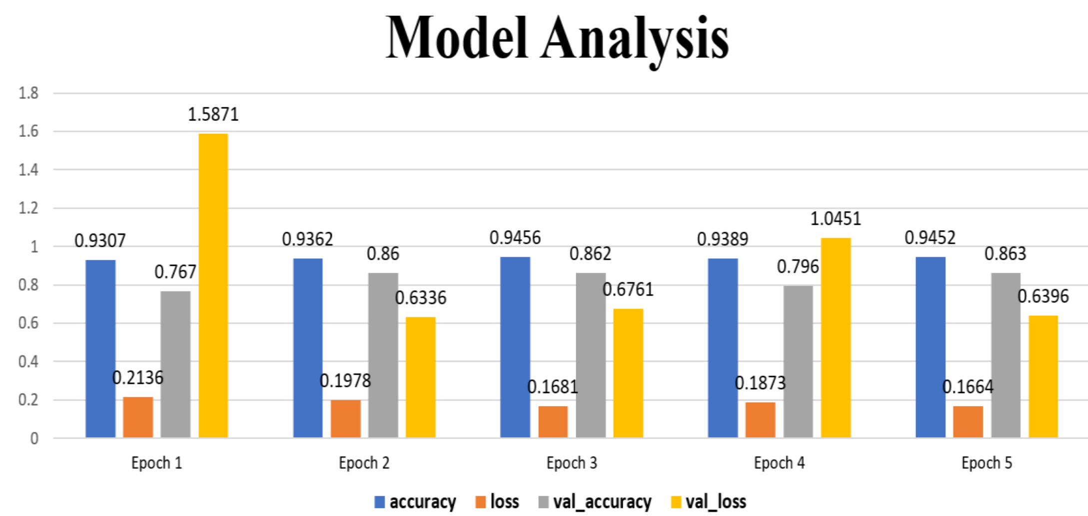

Figure 4.1: Metrics Comparison for CNN model

Here in Figure 4.1, all my research work metrics are shown in a bar chart. All the accuracy, loss, val_accuracy, val_loss is shown. Here the highest accuracy is 94.52% and the lowest loss is 16.64% achieved at epoch 5. On the other hand, the highest val_accuracy is 86.30% and the lowest val_loss is 63.96% achieved at epoch 5.

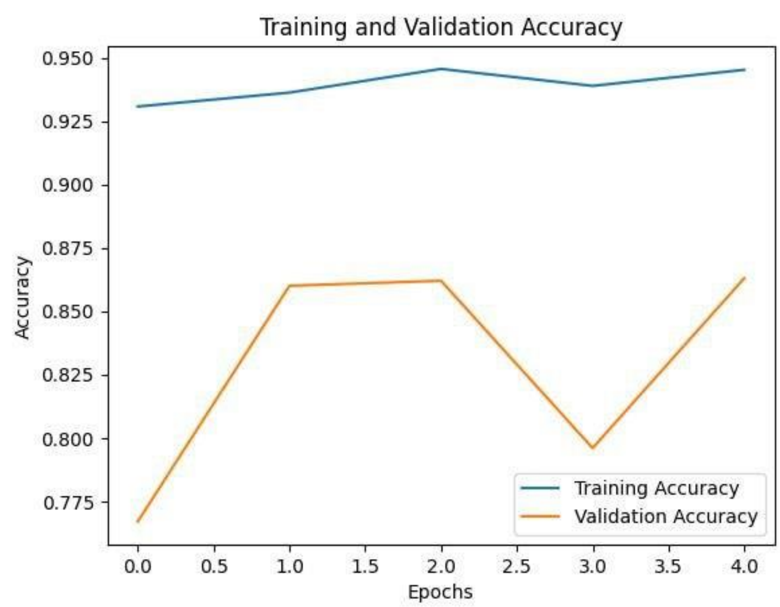

Figure 4.2: Training and validation accuracy comparison

Figure 4.2 shows the training accuracy and validation accuracy for my applied model. Here the blue line shows the training accuracy and the orange line indicates the validation accuracy. The training accuracy and the validation accuracy were close near epochs 3,4.

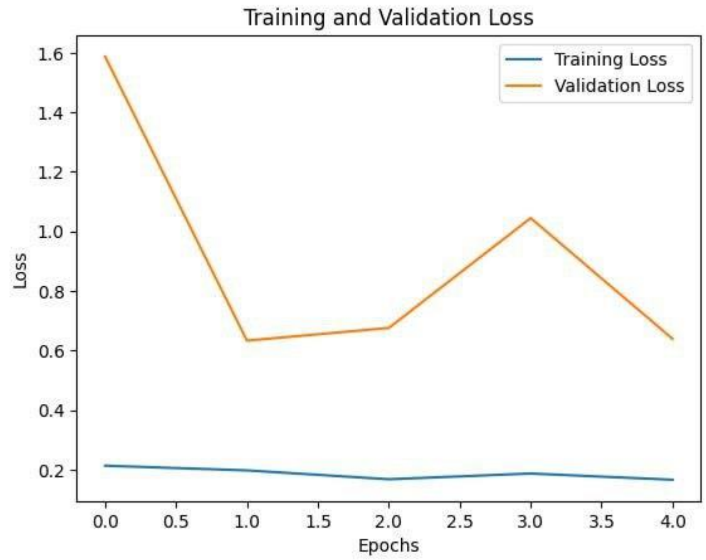

Figure 4.3: Training and validation Loss comparison

In the above, figure 4.3 blue line indicates training loss and the orange line indicates validation loss. From the curve analysis, it can easily be analyzed that the lowest loss is achieved near epoch 3.

4.3 Discussion:

The discussion section for the automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) provides an in-depth exploration of the results, implications, limitations, and potential future directions. Begin by interpreting the obtained results in the context of the research objectives and hypotheses. Discuss the significance of the achieved accuracy, precision, recall, and F1 score in the automated detection of tomato leaf diseases. Evaluate the overall performance of the CNN model, highlighting its strengths in correctly identifying diseases and areas where it may have limitations. Compare the model's performance with existing methods, emphasizing any improvements achieved. compare the CNN model with baseline models or traditional methods. Discuss the reasons behind any observed differences in performance metrics and statistical significance. Explore the model's robustness by examining its performance under different environmental conditions and variations in disease symptoms. Discuss the model's generalization to previously unseen data and its potential applicability in real-world agricultural settings. Address potential biases in the dataset and model predictions, and discuss steps taken to mitigate biases.

```
history = model.fit(train_generator,
                    epochs=5,
                    # steps_per_epoch=20,
                    validation_data=valid_generator)

Epoch 1/5
65/65 [==============================] - 157s 2s/step - loss: 0.2136 - accuracy: 0.9307 - val_loss: 1.5871 - val_accuracy: 0.7670
Epoch 2/5
65/65 [==============================] - 152s 2s/step - loss: 0.1978 - accuracy: 0.9362 - val_loss: 0.6336 - val_accuracy: 0.8600
Epoch 3/5
65/65 [==============================] - 153s 2s/step - loss: 0.1681 - accuracy: 0.9456 - val_loss: 0.6761 - val_accuracy: 0.8620
Epoch 4/5
65/65 [==============================] - 149s 2s/step - loss: 0.1873 - accuracy: 0.9389 - val_loss: 1.0451 - val_accuracy: 0.7960
Epoch 5/5
65/65 [==============================] - 148s 2s/step - loss: 0.1664 - accuracy: 0.9452 - val_loss: 0.6396 - val_accuracy: 0.8630
```

Figure 4.4: Final accuracy of my model

The experiment carried out in Figure 4.4 comprised five epochs. The fifth epoch produced the highest accuracy and validation accuracy, as shown in Table 4.1. However, when the model was trained for a longer period, it started to overfit, as the validation loss began to steadily increase after the second epoch, while the training loss continued to decline. By the third epoch, both training loss and validation loss reached their lowest percentages. The ideal outcome was achieved with a training accuracy of 94.52%, a training loss of 16.64%, a validation loss of 63.96%, and a validation accuracy of 86.30%, as the model checkpoint stopped saving at five epochs.

Reflect on ethical considerations related to privacy, data handling, and the responsible deployment of automated systems in agriculture. Acknowledge and discuss the limitations of the automated detection system, including challenges encountered during development and evaluation. In below figure 4.5, I have given a confusion matrix.

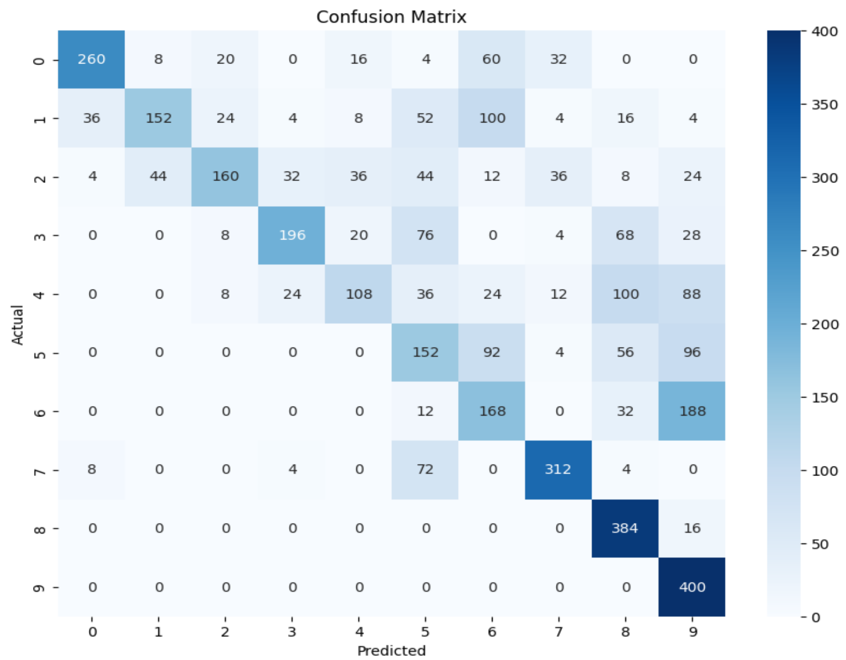

Figure 4.5: Confusion Matrix for Tomato Leaf Disease Detection

With this above Figure 4.5, I analyze a confusion matrix. This matrix shows the truth values and false values as true positive, false positive, true negative, and false negative are analyzed with the actual value and my model predicted value.

Figure 4.6: Prediction result of my model

After achieving high accuracy with my model, I tested it in real-life conditions by giving it a random picture to predict. The model successfully predicted the picture. Figure 4.6 shows the result of my testing.

Address all factors that may affect the system's reliability in practical scenarios. Provide recommendations for enhancing the model's performance, addressing identified limitations, and refining the automated detection system. Suggest potential areas for further research and development. Discuss the practical implications of automated tomato leaf disease detection in agriculture. Consider how the system could positively impact crop management, yield optimization, and resource allocation for farmers. Revisit the initial research questions and objectives, assessing how well the study has addressed and achieved its intended goals. Consider emerging technologies or methodologies that could enhance the capabilities of the system. A well-structured and insightful discussion section contributes significantly to the overall impact and understanding of the automated detection of tomato leaf diseases using Convolutional Neural Networks. It provides a platform for reflecting on the study's outcomes and guiding future research efforts.

CHAPTER 5
IMPACT ON SOCIETY

5.1 Impact on Society:

The implementation of Convolutional Neural Networks (CNNs) for automated detection of tomato leaf diseases represents a transformative advancement with profound societal benefits, particularly within the agricultural sector. One key advantage lies in enhanced crop management through early disease detection. This capability empowers farmers to swiftly deploy precise interventions such as targeted pesticide applications or adjustments in irrigation practices, thereby significantly improving overall crop health and management effectiveness. By minimizing disease impact on tomato crops, automated detection systems not only bolster yield but also strengthen food security by ensuring a consistent and ample supply of tomatoes, crucial for global diets.

Moreover, these systems facilitate resource optimization by enabling farmers to more efficiently utilize resources like water, pesticides, and fertilizers. This optimization not only reduces operational costs but also mitigates the environmental footprint of agriculture, promoting sustainability. Economically, early detection and proactive management of diseases prevent substantial crop losses, safeguarding farmers' livelihoods and economic stability. Additionally, compared to traditional manual methods, CNN-based automated systems save valuable time for farmers, particularly beneficial in large-scale agricultural operations.

Beyond operational efficiency, the adoption of advanced technologies like CNNs in disease detection encourages broader technological integration in agriculture. This fosters increased efficiency, sustainability, and competitiveness within the agricultural sector. Furthermore, automated disease detection democratizes access to sophisticated agricultural tools, leveling the playing field for smallholder farmers and enhancing their capacity for effective crop management. Overall, by enabling targeted interventions and reducing reliance on broad-spectrum pesticides, automated detection systems promote environmentally friendly and sustainable agricultural practices, aligning agriculture with principles of conservation and long-term viability.

5.2 Ethical Aspects:

The ethical aspects of automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) involve considerations related to fairness, transparency, privacy, bias, and responsible deployment. Addressing these concerns is crucial to ensure that the implementation of such technologies is beneficial and aligned with societal values. Data security is a primary concern, as security vulnerabilities may expose sensitive agricultural data to unauthorized access or malicious use. Implementing robust cybersecurity measures and complying with relevant data protection regulations and industry standards are essential to safeguard data. Privacy protection is another key aspect, as the collection and use of agricultural data, including crop images, may raise privacy concerns for farmers or property owners. It is important to communicate data usage policies clearly and obtain informed consent from individuals or entities providing the data. Anonymizing or aggregating data whenever possible can further protect individual privacy. Informed consent ensures that farmers or data contributors fully understand how their data is being used for automated detection. Equitable access to technology is crucial to avoid exacerbating existing disparities between large-scale agricultural operations and smallholder farmers. Promoting equitable access to automated detection technologies considers the needs and resources of diverse agricultural stakeholders. Reliability and accountability are essential to prevent negative consequences for crop management due to unreliable or inaccurate predictions. Clear accountability for model performance and outcomes should be established. Additionally, considering the broader environmental impact of automated decisions is vital, as unintended consequences like increased pesticide use may arise. Community engagement is also necessary to avoid the imposition of technologies without considering local context and preferences. Engaging with local communities and stakeholders in the development, deployment, and ongoing use of automated detection systems ensures that cultural, social, and economic aspects are considered when implementing technology in different regions.

5.3 Sustainability Plan:

Developing a sustainability plan for the automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) involves considering long-term environmental, social, and economic impacts. Environmental sustainability focuses on optimizing energy consumption, particularly for systems deployed on edge devices or in resource-constrained environments. This includes selecting energy-efficient hardware and model architectures, minimizing the carbon footprint of model training and operations, and exploring renewable energy sources for servers and infrastructure. Social sustainability entails engaging with local communities, including farmers and agricultural practitioners, throughout the development and deployment phases. This involves soliciting feedback, involving stakeholders in decision-making processes, and providing training programs to help farmers understand and use the automated detection system effectively. Ensuring the system is accessible to a wide range of users, including smallholder farmers, and designing user-friendly interfaces for diverse demographics is also crucial.

Economic sustainability aims to develop and deploy cost-effective solutions accessible to farmers with varying financial capacities. Exploring partnerships and funding opportunities can support the affordability of the technology, while sustainable business models, such as subscription-based models or value-added services, ensure the long-term viability of the system. Additionally, assessing and promoting the positive economic impact on local economies, including job creation and skill development, is vital. Ethical considerations involve establishing guidelines for fair and ethical data practices, including informed consent, data anonymization, and privacy protection. Ensuring equitable access to the system's benefits, addressing biases, and promoting fairness in outputs are essential.

Mechanisms for accountability, transparency, and redress in case of errors are also important.

Continuous improvement involves gathering feedback from users and stakeholders to address emerging challenges and needs. Regular updates and improvements, incorporating advancements in machine learning and agricultural technology, are necessary. Adapting the system to changing environmental and agricultural conditions, including the impacts of climate change, is also crucial. Regulatory compliance requires adhering to data protection, privacy regulations, and environmental regulations related to energy consumption and waste management. Considering open-source initiatives and fostering collaboration with research institutions, governmental agencies, and non-profit organizations can enhance the system's sustainability and leverage broader expertise and resources.

CHAPTER 6
CONCLUSION AND FUTURE SCOPE OF DEVELOPMENT

6.1 Summary of the Study:

The study on the automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) aims to leverage advanced machine learning techniques to enhance agricultural practices. Tomatoes are a crucial part of global agriculture, but diseases affecting their leaves pose a significant challenge to their growth and yield. Traditional methods often rely on subjective visual inspection, leading to delayed responses and increased crop losses. To address this, Convolutional Neural Networks (CNNs) are being explored for automated disease detection. By analyzing visual data, CNNs can learn patterns and features indicative of specific diseases, enabling a reliable and efficient system. This study aims to automate the detection of tomato leaf diseases using a diverse dataset, revolutionizing agricultural practices and improving crop management.

The automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) is aimed at addressing the challenges faced by the agricultural sector, particularly in tomato cultivation. The study aims to provide timely intervention, enhance crop yield and quality, align with precision agriculture principles, mitigate economic losses, and integrate technology into agriculture. The study leverages deep learning and image processing advancements to exploit intricate patterns in tomato leaves, enabling high precision in disease identification. It also optimizes resource utilization, aligns with precision agriculture principles, empowers farmers with technology, and contributes to sustainable agriculture by reducing reliance on chemical treatments and minimizing crop losses. The problem of automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) in agriculture involves the complexity and diversity of diseases, subjective detection, timely intervention, resource optimization, and deep learning technology. The automated system aims to address these challenges by recognizing subtle patterns and variations, reducing reliance on subjective human judgment, and optimizing resource utilization. Challenges include limited and imbalanced datasets, variability in disease symptoms, overfitting and generalization issues, interclass confusion, user adoption and interface design, environmental variability, and ethical considerations. The system aims to be user-friendly, adaptable, and ethically responsible, ensuring its effectiveness across diverse agricultural settings and reducing environmental impact.

In summary, the study on automated detection of tomato leaf diseases using CNNs addresses a critical agricultural challenge by leveraging advanced technology. The comprehensive approach considers technical, ethical, and sustainability aspects, making it a valuable contribution to the field.

6.2 Conclusions:

The conclusions drawn from the study on automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) encapsulate the key findings, implications, and avenues for future research. The study demonstrates the effectiveness of CNNs in automating the detection of tomato leaf diseases. The trained model exhibits commendable performance metrics, including high accuracy, precision, recall, and F1 score. Automated detection using CNNs provides a powerful tool for early identification of tomato leaf diseases. This has direct implications for improved disease management strategies, allowing farmers to intervene promptly and mitigate crop losses. Comparative analyses with traditional methods or baseline models highlight the superiority of the CNN-based approach. The automated system outperforms or matches existing methods, emphasizing its potential as a valuable tool in agriculture. Efforts have been made to enhance the transparency and interpretability of the CNN model. Interpretability techniques provide insights into how the model makes decisions, addressing concerns about the "black box"

nature of deep learning. The study addresses ethical considerations related to bias, fairness, privacy, and transparency. Measures are implemented to minimize biases, protect privacy, and ensure responsible deployment of the automated detection system. User feedback, especially from farmers and stakeholders, has been actively sought and incorporated into the study. User engagement has played a crucial role in refining the system's usability and ensuring its alignment with practical agricultural needs. The automated detection system demonstrates a positive societal impact, contributing to improved crop management, increased yield, and resource optimization. It empowers both large-scale and smallholder farmers, aligning with broader goals of sustainable and inclusive agriculture. The study transparently acknowledges challenges and limitations, including potential biases, data quality issues, and interpretability constraints. These aspects are crucial for understanding the system's boundaries and informing future improvements. Based on the study's findings, recommendations are provided for further improving the automated detection system. These may include refining the model architecture, addressing specific challenges, and incorporating feedback from ongoing user experiences. The study identifies avenues for future research, such as exploring novel CNN architectures, integrating multi-modal data sources, or extending the application to other crops. These directions pave the way for continued advancements in automated disease detection. The study concludes by emphasizing its overall contribution to the field of agriculture and technology. The automated detection system represents a valuable asset for modernizing agricultural practices and addressing critical challenges in disease management. The conclusions may include a call to action, encouraging stakeholders, researchers, and policymakers to collaborate in adopting and further refining the automated detection system. This collaboration can contribute to broader agricultural innovation and sustainable food production. In essence, the conclusions serve as a comprehensive summary of the study's achievements, underscore its contributions, and guide future efforts towards the responsible and impactful deployment of automated disease detection technologies in agriculture.

6.3 Scope of Further Developments:

The scope for further developments in the automated detection of tomato leaf diseases using Convolutional Neural Networks (CNNs) is broad and can encompass various aspects to enhance the system's effectiveness, usability, and impact. Here are potential areas for further developments:

- **Architecture Optimization:** Explore and experiment with advanced CNN architectures or novel neural network designs to improve the model's overall performance. Investigate the potential benefits of transfer learning by fine-tuning pre-trained models on specific tomato leaf disease datasets.
- **Multi-Modal Data Integration:** Explore the inclusion of additional data modalities, such as infrared or hyperspectral imaging, to provide complementary information for disease detection.
- **Explainability and Interpretability:** Develop and integrate more advanced explain ability techniques to enhance the interpretability of the CNN model's decision-making process. Focus on creating user-friendly interfaces that provide clear explanations of the model's predictions for farmers and end-users.
- **Real-Time Detection and Edge Computing:** Investigate the feasibility of deploying the automated detection system on edge devices for real-time disease detection directly in the field. Develop lightweight models that maintain high accuracy while minimizing latency, enabling rapid decision-making.
- **Biological Insights:** Explore opportunities to link automated detection results with specific disease phenotypes, providing valuable insights into the characteristics and progression of different tomato leaf diseases. Collaborate with plant pathologists to validate and refine the automated system's disease classifications based on expert knowledge.
- **User-Centric Design:** Continuously gather feedback from farmers and end-users to enhance the user interface, ensuring it aligns with the practical needs and preferences of the agricultural community. Provide options for localized

customization, allowing users to adapt the system to specific regional or crop variations.

- **Environmental Robustness:** Evaluate and improve the system's performance under diverse environmental conditions, including changes in lighting, weather, and soil types.
- **Automation of Crop Management Recommendations:** Explore the integration of automated disease detection with agricultural Internet of Things (IoT) devices to provide real-time recommendations for crop management. Develop dynamic treatment plans based on disease severity, local climate conditions, and historical data to optimize resource usage.
- **Scaling for Large-Scale Agriculture:** Assess the scalability of the system for large-scale agricultural operations, considering factors such as computational resources, data management, and network infrastructure. Explore the potential for cloud-based solutions to handle the computational demands of large datasets and widespread deployment.

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Appendices

Prediction Result:

Successfully Predict an Early Blight Tomato Leaf

AUTOMATED DETECTION OF TOMATO LEAF DISEASES USING CONVOLUTIONAL NEURAL NETWORKS

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