A

Project Report

on

Tomato Leaf Disease Classification Using Convolutional Neural Networks

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Submitted By

Harsh Kumar Singh (2100290100069)

Prateek Kumar (2100290100118)

Prince Rauniyar (2100290100119)

Under the supervision of

Prof. Pushpendra Kumar

KIET Group of Institutions, Ghaziabad

Affiliated to

Dr. A.P.J. Abdul Kalam Technical University, Lucknow

(Formerly UPTU)

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DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

Signature :-

Harsh Kumar Singh (2100290100069)

Signature :-

Prateek Kumar (2100290100118)

Signature :-

Prince Rauniyar (2100290100119)

Date:

CERTIFICATE

This is to certify that Project Report entitled "Tomato Leaf Disease Classification Using Convolutional Neural Networks" which is submitted by Student name in partial fulfillment of the requirement for the award of degree B. Tech. in Department of Computer Science & Engineering of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

Prof. Pushpendra Kumar

Assistant Professor (CSE)

Prof(Dr.) Vineet Sharma

Dean (CSE)

Date:

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Date:

Signature:-

Harsh Kumar Singh (2100290100069)

Signature:-

Prateek Kumar (2100290100118)

Signature:-

Prince Rauniyar (2100290100119)

ABSTRACT

Tomatoes are one of the most commonly grown and consumed crops worldwide, valued for both their nutritional content and economic impact. Yet, tomato plants are highly vulnerable to a range of leaf diseases like Early Blight, Late Blight, and Leaf Mold, all of which can seriously affect the quality and quantity of the harvest. Traditionally, identifying these diseases has relied on manual visual inspection—a process that is often slow, imprecise, and not always accessible to farmers in rural or under-resourced areas.

To overcome these challenges, our study presents a deep learning-based solution for the automatic detection of tomato leaf diseases. We leveraged Convolutional Neural Networks (CNNs), a powerful class of AI models known for image recognition, to classify disease types from leaf images. Using the publicly available Plant Village dataset, we tested five different models: DenseNet121, MobileNetV2, a simple custom CNN, InceptionV3, and a Multilayer Perceptron (MLP). The models were trained with careful preprocessing and data augmentation to improve their performance and adaptability.

Among the models, DenseNet121 and InceptionV3 achieved the highest validation accuracy of 95.5%, indicating strong potential for real-world use. MobileNetV2 and Simple CNN offered decent results with fewer computational demands, while the MLP model, although more basic, proved to be a strong baseline performer.

These findings show that deep learning—especially CNN-based methods—can provide a practical, fast, and accurate way to identify tomato leaf diseases. Importantly, lightweight models like MobileNetV2 open the door to mobile-based applications, empowering farmers to diagnose diseases in real time and make quicker, more informed decisions in the field.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

NAM	Network Animator
CNN	Convolutional Neural Network
MPL	Max Pooling layer
YLCV	Yellow Leaf Curl Virus
BS	Bacterial Spot
EB	Early Blight
LM	Leaf Mold
SLS	Spectorial Leaf Spot
TS	Target Spot
TSSMS	Two spotted Spider Mite Spot
MV	MosaicVirus

CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

Agriculture is still a backbone of the world economy, especially in the developing world where the majority of people rely on agriculture to earn a living. From all the different crops grown across the world, the tomato is prominent because of its high nutritional content, versatile use in the kitchen, and commercial significance. As a common food item in most diets and a standard commodity in the food industry, tomatoes are both nutritionally and commercially essential. Nonetheless, tomato production is lately being threatened by a number of leaf diseases like Early Blight, Late Blight, and Leaf Mold. These can significantly lower yields and compromise the quality of produce, translating into financial losses for farmers. In areas where agriculture is the mainstay of local economies, such losses are not merely economic but can destabilize the livelihood of communities. Moreover, widespread disease outbreaks have implications for food availability and food security, particularly in low-resource settings.

Traditionally, farmers have relied on manual inspection to detect plant diseases—visually examining the leaves for signs of infection. While this method is straightforward and has been used for generations, it has several limitations. It heavily depends on the individual farmer's experience and knowledge, making it subjective and sometimes inaccurate. What a disease appears to one farmer can be confused with something else to another. Such subjectivity may lead to incorrect diagnosis or even delay in responding. Second, physical examination is labor-intensive, particularly on big farms, and in most rural or far-flung locations, it is difficult to access agricultural extension officers or plant pathologists. If identification of disease is delayed, then infections can spread more quickly, further damaging crops and diminishing farmers' revenues. Early and proper detection is thus essential to avert widespread crop loss, and early intervention during a plant's growth cycle can salvage both the crop as well as the resources of the farmer.

With latest advances in computer vision and artificial intelligence, now it is possible to design automated systems for detecting plant diseases with high accuracy and effectiveness. These computer systems rely on images of leaves of plants and advanced algorithms to identify and classify disease symptoms. Among the strongest image-based analysis tools is the Convolutional Neural Network (CNN), an instance of deep learning architecture specially developed for visible pattern recognition. CNNs have already transformed medical diagnosis and facial recognition and are now taking big leaps in agriculture. In tomato disease detection, CNNs can inspect leaf images for slight differences in color, shape, and texture patterns related to particular diseases. The public availability of datasets, e.g., the PlantVillage dataset with thousands of labeled images of healthy and infected leaves, enables models to be trained efficiently. The labeled images enable CNNs to learn visual patterns of each disease for accurate classification.

In this work, we investigated how effectively CNN-based models could be used to recognize diseases in tomato leaves. From the PlantVillage dataset, we trained and compared five models: DenseNet121, InceptionV3, MobileNetV2, a Simple CNN that we built ourselves, and a Multilayer Perceptron (MLP). All five models were trained for 100 epochs with uniform preprocessing techniques and data augmentation methods applied to improve their generalization to new images. The aim was not only to obtain high accuracy but also to assess the appropriateness of each model to be deployed in actual agricultural environments. Of these, DenseNet121 and InceptionV3 performed the best, obtaining about 95.5% validation accuracy.

They had an excellent capability to learn disease-specific features from the images and exhibited steady training as well as validation curves. MobileNetV2 and Simple CNN also did not do badly and are also noteworthy for their lower computational requirements. MobileNetV2, in fact, is specially optimized for mobile and embedded platforms, making it a good choice for use in scenarios where high-end hardware is not available. The MLP model, although not as advanced as the CNNs, proved to be a good baseline and did well given its simplicity.

The use of AI in agriculture introduces a set of advantages, particularly for activities such as disease detection. AI algorithms are capable of producing quick, precise, and uniform analyses, which eliminate the weaknesses present in manual examination. After training, these algorithms may be utilized in mobile apps or web platforms, where farmers are able to upload or take pictures of tomato leaves and get instant diagnostic results. This direct access to disease recognition gives farmers the power to move swiftly—treatments are applied, infected plants are quarantined, or changing practices avoid their spread. For those rural communities where agricultural expertise is hard to reach, such AI-based systems could be a turning point. Models like MobileNetV2 that are light in weight enable this technology to be deployed on low-cost phones, possible even in poor environments. This pairing of affordability, accessibility, and precision places AI as a strong partner in green agriculture.

Overall, this research shows how CNN-based models can significantly enhance the detection and control of tomato leaf diseases. Through evaluation and comparison of several deep learning architectures under controlled settings, we learned about their strengths, weaknesses, and field applicability. The highest-accuracy models, DenseNet121 and InceptionV3, are both high-accuracy, high-generalization-capacity models appropriate for use in serious disease diagnosis applications. MobileNetV2 is the compromise between efficiency and performance necessary for field use. The general importance of this work is in advancing the application of AI to smart farming—increasing productivity, minimizing loss of crops, and enhancing food security. As technology keeps improving, such models can be refined with ongoing learning, user feedback incorporation, and extension to different crops and diseases. Eventually, this method represents a step in developing a wiser, more efficient, and more resilient agriculture system that uses data and automation to help farmers and maintain the integrity of worldwide food supplies.

1.2 PROJECT DESCRIPTION

The purpose of this project is to create a smart and easy-to-use system for the diagnosis of tomato leaf diseases based on deep learning, an advanced subfield of artificial intelligence. Tomato is one of the most globally grown and consumed vegetables, especially in nations such as India where it is a key component of both diet and agricultural revenue. As a result of their nutritional and economic worth, tomato cultivation sustains the income of large numbers of small and marginal farmers. The cultivation of tomatoes is, however, extremely sensitive to a number of diseases including Early Blight, Late Blight, and Leaf Mold. Such diseases tend to start small, as a patch, spots, or a mold on the leaves but can spread rapidly throughout the plant and to the adjacent crops. Unless detected and treated early, such infections may cause remarkable losses in terms of the quantity and quality of the harvest.

Conventional identification of plant diseases is dependent on the farmer's experience or advice from local agronomists. Although this approach has been effective for many years, it has a number of drawbacks. It may be slow, subjective, and erroneous, particularly when symptoms in their initial stages are faint. Additionally, a majority of rural and remote farmers might lack timely access to trained experts or the web to look for assistance. Under such circumstances, by the time the disease is correctly diagnosed, it may have already permeated far and wide, thus being harder and costlier to contain. To solve this problem, we embarked on developing a smart, image-based disease detection system that would assist farmers in detecting tomato leaf diseases automatically—just by viewing images of the leaves.

To achieve this, we employed Convolutional Neural Networks (CNNs), which are specifically geared towards performing image classification and object recognition tasks. CNNs function by learning image features—such as shapes, textures, and colors—and employing these to make determinations. CNNs have been applied successfully across a range of domains, from medical imaging and autonomous vehicles to agriculture and are now being adopted in agriculture with remarkable outcomes. We utilized the PlantVillage dataset in our project, a widely used and public repository of labeled images of both healthy and infected tomato leaves. This dataset contains thousands of images, each belonging to various classes depending on the nature of the disease or health condition. Through training our models using these images, we wanted to instruct the computer to identify and classify leaf diseases correctly.

We used and compared five unique models in our research: DenseNet121, InceptionV3, MobileNetV2, a Simple CNN built by us, and a Multilayer Perceptron (MLP). Each of these models has its own strengths and weaknesses in terms of accuracy, speed, and complexity. DenseNet121 and InceptionV3 are deeper, more complex models known for their high performance in image recognition tasks. MobileNetV2 is a lightweight model designed for mobile and embedded devices, making it ideal for real-world applications where computing power is limited. Simple CNN is a smaller network that we implemented from scratch to improve understanding of the operation of CNNs. The MLP, although not a convolutional model, was added to be used as a reference baseline, as it employs fully connected layers without regard for spatial information.

Prior to feeding the images into the models, we have performed various preprocessing on them like resizing the images to a standard size and normalizing the pixel values. We have also applied data augmentation methods like horizontal flipping, rotation, and zooming to make the training data more diverse. This makes the models robust and more generalizable and minimizes the likelihood of overfitting—where the model is strong on training data but weak on fresh, unseen data.

Upon training and experimenting with the models for 100 epochs, we discovered that DenseNet121 and InceptionV3 were the most accurate models, with both achieving approximately 95.5% validation accuracy. This indicates that the models accurately diagnosed the disease in approximately 95 out of every 100 test images. They also demonstrated consistent performance with minimal overfitting, thus being good options for precise disease detection. MobileNetV2, although less accurate, was much faster and used fewer computational resources, making it a huge plus point to deploy on mobile phones or rural locations with less hardware. Although the Simple CNN and MLP models were not as accurate, they gave us useful results and taught us the impact of varying architectures on performance.

The end result of our project is to design a useful tool that can be utilized by farmers easily. Think of a smartphone application in which a farmer just snaps a picture of a tomato leaf using their smartphone, and the application immediately informs them if the plant is healthy or infected, and if it's infected, what type of disease it has.". This kind of instant, automated feedback would enable early treatment, reduce crop damage, and save valuable time and money. It also reduces the farmer’s reliance on external experts, which is especially useful in areas where expert help is scarce or delayed.

In conclusion, this project highlights the powerful role that artificial intelligence—and specifically deep learning—can play in modern agriculture. Through the use of CNNs and image classification, we have demonstrated that it is feasible to develop a robust, accurate, and efficient tomato leaf disease detection system. These types of systems have the potential to revolutionize the means through which farmers keep track of their crops, and make agriculture more sustainable, resilient, and productive. Our work is a step towards more intelligent agriculture technologies that are accessible, scalable, and effective, particularly for small-scale farmers that are most impacted by crop disease. Through the integration of AI and agriculture, we seek to empower farmers, enhance food security, and enhance technological innovation within the agricultural sector.

1.3 Objective

The main goal of this project is to develop and deploy an intelligent, computerized system that can identify and classify frequent diseases in tomato leaves by processing digital images. The system is constructed with the aid of state-of-the-art deep learning methods, specifically **Convolutional Neural Networks (CNNs)**, that have yielded tremendous success in numerous image processing and pattern recognition applications. The objective is to support farmers—particularly those in rural, low-resource, or isolated regions—by offering a sure and user-friendly tool that is capable of enabling them to detect tomato leaf diseases like **Early Blight**, **Late Blight**, and **Leaf Mold** in a timely and precise way.

In most of the world, especially in developing nations, agriculture is the foundation of the economy. Tomatoes are an anchor crop because of their nutritional, economic, and versatility attributes. Tomato cultivation is, however, increasingly threatened by the development and dissemination of leaf diseases that can greatly lower the quality and yield of crops. Detection of the diseases at an early stage is very vital to the management of their effects, but existing detection is largely dependent on manual visual examination. This manual method takes a long time, is subjective, and susceptible to errors, particularly in cases with subtle or unknown symptoms to the practitioner.

In this endeavor, these challenges are addressed through designing a **deep learning–based solution** that involves minimal human intervention or expertise. By learning from a big, labeled dataset of healthy and diseased images of tomato leaves (e.g., the popular **PlantVillage** dataset), the model learns to classify various disease categories by visible features and patterns. The most important objective here is to make the model generalize well—i.e., it should be able to perform correctly not just on training data but also on novel, unseen images that could potentially arise in real-world field environments.

Apart from having high classification accuracy, yet another crucial objective is to design the system to be **lightweight, scalable, and deployable** on low-cost platforms such as smartphones and edge computing modules. In most agricultural areas, there may not be readily available high-end computing hardware or continuous internet access. Thus, models such as **MobileNetV2**, which are best suited for resource-limited settings, are given extra attention. The emphasis is on achieving a balance between computational cost and detection accuracy in order to provide an economically viable solution for real-world agricultural implementation.

The project also attempts to **reduce the time and effort** required for human disease detection. Through provision of **instant feedback** using an intelligent image classification system, farmers are able to make rapid, well-informed decisions regarding treatment. This minimizes the transmission of infection throughout the crop, minimizes the use of chemical pesticides (which have negative impacts on the environment), and saves resources. In the long term, early disease detection enables **sustainable farming methods**, minimizes crop losses, and enhances general productivity and revenues for farmers.

In addition, this project is part of a larger mission of **closing the digital divide** between cutting-edge technological research and conventional agricultural methods. Most farmers, particularly smallholder farmers, lack exposure to specialist agronomists or diagnostic labs. Through the provision of an easy-to-use and affordable solution, this system enables them to implement data-based methods in their agricultural endeavors. The long-term vision is to enable **smart agriculture** where farmers can easily integrate current AI technologies with their day-to-day tools and methodologies.

Through the fulfillment of these goals, this project hopes to contribute significantly to agricultural innovation and assist in guaranteeing food security, especially in regions where agriculture represents a major livelihood.

CHAPTER 2

LITERATURE REVIEW

This chapter is a literature review of classical plant disease detection methods. These classical methods involve mostly computer vision technology-based techniques like extracting texture, shape, color, and other visual features from images of infected plant leaves. Based on analyzing these features, the systems try to detect and classify different plant diseases. But these approaches typically need large amounts of agricultural disease expertise to construct functional feature extractors, which restricts their applicability and scalability. In addition, these conventional methods tend to have decreased identification efficiency because handcrafted features do not always capture sophisticated variations in actual disease symptoms.

With the swift development of artificial intelligence and deep learning technologies, numerous scientists have turned their attention to creating more robust and accurate plant disease detection models. Deep learning, most notably convolutional neural networks (CNNs), has proven extremely promising in automatically discovering suitable features from raw image data without the necessity for manual feature extraction. This data-based methodology enables models to more effectively learn fine and intricate patterns in plant diseases, thus achieving increased detection accuracy and dependability. Therefore, deep learning-based systems are progressively becoming the go-to option for automatic plant disease diagnosis.

Recent research has proven the efficacy of deep learning in detecting plant diseases in a range of crops, such as tomatoes, apples, grapes, and others. These models are usually learned from big labeled datasets of images of healthy and infected leaves, allowing them to predict the disease on the basis of visual symptoms. Disease classification is what most existing work tries to do, so that one can determine which disease is infecting a given plant. Several works also investigate methods like data augmentation, transfer learning, and fine-tuning pre-trained networks for enhanced performance, particularly in cases with limited or unbalanced datasets.

Regardless of these advances, hurdles still exist in creating universally deployable disease detection systems. Changes in lighting conditions, orientation of leaves, background noise, and disease progression can impact model performance. In addition, most deep learning models need massive computational power, which can restrict their use in real-time or constrained environments like farms. However, the existing literature shows that the combination of deep learning approaches with conventional computer vision methodologies along with domain expertise has the potential to develop practical, scalable, and user-friendly plant disease detection systems in the very near future.

1. Mane and Kulkarni (2017) – "A survey on supervised convolutional neural network and its major applications"

Mane and Kulkarni provided an extensive survey on supervised convolutional neural networks (CNNs), discussing their structure, training methods, and applications across various fields. Though not focused solely on tomato disease, their work laid a foundational understanding of CNN capabilities in image recognition tasks. Their research highlighted CNN's strengths and challenges, setting the stage for later applications in agriculture, particularly for plant disease detection, where accurate image classification is essential. They also explored optimization techniques and common pitfalls, offering valuable insights for future improvements in CNNbased systems. Their survey emphasized the importance of large datasets and computational power, which are critical factors for improving CNN performance in real-world scenarios.

2. Hong, Lin, and Huang (2020) – "Tomato disease detection and classification by deep learning"

Hong et al. used convolutional neural networks (CNNs) to identify and classify tomato leaf diseases and reported a large improvement over conventional manual diagnosis techniques. Their research proved that deep learning models could automate the process of disease detection with high accuracy and in less time. The automation provides useful advantages to farmers by being able to diagnose diseases faster and more accurately, which is critical to provide in time for treatment and crop management.

This groundbreaking effort served as important work in affirming the promise of artificial intelligence for precision agriculture. Through the demonstration of efficient use of CNNs for the detection of tomato diseases, Hong et al. opened the door to subsequent studies focused on creating more sophisticated, effective, and scalable models. The work of Hong et al. contributed to the establishment of a basis for future innovation in using AI technologies to enhance plant health monitoring and farm productivity.

3. Nawaz et al. (2022) – "A robust deep learning approach for tomato plant leaf disease localization and classification"

Nawaz and team built a convolutional neural network (CNN) model capable not just of classifying disease on the leaves of tomatoes but of localizing areas affected by disease too. Their system was able to pinpoint the exact area of the leaf with symptoms in addition to disease type. This double ability offers a more accurate diagnostic instrument with the capacity for targeted treatment planning and improved disease management.

By integrating localization with classification, their solution provides more comprehensive information compared to models developed for exclusive disease detection. The process exhibited robustness over a variety of disease types and environmental conditions and thus represents a viable method for practical agricultural implementation. This innovation extends the applicability of AI in precision agriculture by enabling both accurate diagnosis and useful advice.

4. Nag et al. (2023) – "Mobile app-based tomato disease identification with fine-tuned convolutional neural networks"

Nag et al. created a mobile app that leverages optimized CNNs to accurately diagnose tomato leaf disease in real time. The app places AI-driven diagnostic capabilities in farmers' hands, enabling them to make rapid and smart decisions without requiring specialized laboratory gear. With an emphasis on ease of use, high accuracy, and low latency, the app offers a viable solution to on-field disease management.

Their research proved the real-world applicability of using deep learning models on mobile platforms, overstepping problems associated with computational needs and connectivity. Their work shows the capability of mobile AI technologies to enable precision agriculture through facilitating cost-effective, efficient, and trustworthy disease detection, ultimately leading to enhanced crop health and productivity.

5. Debnath et al. (2023) – "A smartphone-based detection system for tomato leaf disease using EfficientNetV2B2 and its explainability with AI"

Debnath et al. presented a smartphone-compatible tomato leaf disease diagnosis system using the EfficientNetV2B2 model with a focus on AI explainability. Their system not only provides accurate disease predictions but also interpretable explanations to the users regarding the rationale of each diagnosis. Such transparency increases trust and promotes more active participation by farmers and farm workers.

The light weight of EfficientNetV2B2 facilitates quick processing on phones, making the system feasible to apply in remote settings where specialist assistance is wanting or lacking. With its fusion of high performance and interpretability, this work constitutes an important advancement in creating explainable and user-centered AI applications in agriculture towards greater uptake among non-specialist users.

6. Sharma et al. (2025) – "Deep learning based ensemble model for accurate tomato leaf disease classification by leveraging ResNet50 and MobileNetV2 architectures"

Sharma et al. created an ensemble model based on the strengths of ResNet50 and MobileNetV2 architectures to improve the classification of tomato leaf disease. Through the utilization of the high accuracy of ResNet50 and the computational efficiency of MobileNetV2, their method attains strong and trustworthy performance while the resource demands remain controllable.

This ensemble technique shows how combining various convolutional neural network (CNN) architectures can enhance generalization and robustness to make the model more applicable to various real-world agricultural settings. Its equilibrium between precision and parsimony makes it suitable for use on hardware-constrained devices, enabling precision farming even in such environments.

7. Pandiyaraju et al. (2024) – "Improved tomato leaf disease classification through adaptive ensemble models with exponential moving average fusion and enhanced weighted gradient optimization"

Pandiyaraju and others suggested adaptive ensemble models that employ exponential moving average fusion for enhancing the accuracy and stability of tomato leaf disease classification. This method assists the model in handling predictions more proficiently over time, leading to more stable and accurate outputs. Further, they also introduced an improved weighted gradient optimization algorithm for enhancing the learning process, enhancing model performance even further.

Their method is particularly successful in identifying fine disease characteristics and handling noisy or low-quality image data, typical issues in real agricultural settings. In overcoming these challenges, the approach provides a pragmatic and robust solution to disease detection so that it can provide precise diagnosis even in inconsistent image conditions usually experienced in the field.

8. Chen et al. (2024) – "Using a hybrid convolutional neural network with a transformer model for tomato leaf disease detection"

Chen et al. combined CNNs with transformer models to exploit both local feature extraction and global context understanding in tomato leaf disease detection. This hybrid model outperformed conventional CNNs by capturing more complex spatial relationships and providing better disease differentiation, especially for visually similar symptoms. Their work bridges traditional convolutional techniques and newer transformer architectures, marking a significant step toward more intelligent and accurate plant disease diagnosis systems.

9. Sun et al. (2025) – "Efficient deep learning-based tomato leaf disease detection through global and local feature fusion"

Sun et al. suggested a model that combines global and local image features to improve detection of tomato leaf diseases. By incorporating multiscale features, their approach can detect small or minor symptoms of disease that may be missed by conventional methods. This detailed feature extraction enhances the sensitivity of the model to various manifestations of disease.

The design is meant to meet both speed and accuracy in an effective balance, hence a good fit for real-time use in the field. It is efficient enough to perform fast and consistent disease identification, something that is essential in timely interventions and crop management effectiveness, leading to improved agricultural results.

10. Thuseethan et al. (2025) – "Siamese network-based lightweight framework for tomato leaf disease recognition"

Thuseethan et al. proposed a Siamese network architecture for light and efficient tomato leaf disease identification explicitly targeting low-resource platforms. Contrary to the conventional classification models, their method learns to identify similarities among images, which allows it to recognize diseases accurately with minimal labeled training data.

This similarity-based learning makes the model especially useful for farmers in far-flung or resource-limited regions, where high-performance hardware and large datasets are not readily accessible. By giving farmers a robust and effective means for disease detection, their framework facilitates enhanced crop management and disease control in adverse agricultural environments.

11. Chelladurai et al. (2025) – "Classification of tomato leaf disease using Transductive LSTM with an attention mechanism"

Chelladurai and colleagues applied transductive Long Short-Term Memory (LSTM) networks enhanced with attention mechanisms for tomato leaf disease classification. This approach captures temporal relationships in image sequences, which can model disease progression, while attention helps focus on critical features. Their innovative methodology leads to more accurate and interpretable disease detection, offering benefits for monitoring diseases over time rather than just static classification.

12. Oni and Prama (2025) – "Optimized custom CNN for real-time tomato leaf disease detection"

Oni and Prama proposed a dedicated convolutional neural network (CNN) architecture optimized for rapid and effective real-time detection of leaf diseases in tomatoes. Their lightweight model reduces computational requirements while retaining robust classification capability, making it suitable for implementation on mobile devices and embedded systems often employed in the field.

This method responds to the key challenge of having effective models to run on hardware with minimal processing power without compromising diagnostic accuracy. Through facilitating effective disease detection in resource-poor settings, their research aids realistic and scalable agricultural use, enabling farmers to make timely and informed decisions for crop management.

13. Wang and Liu (2024) – "An efficient deep learning model for tomato disease detection"

Wang and Liu designed a deep learning model focusing on efficiency, minimizing parameters and inference time while preserving accuracy. Their model is suitable for use in automated farming systems that require quick, reliable disease detection but have limited computing resources. The study balances model complexity with practical needs, providing a scalable solution for real-world tomato disease management.

14. Sun, Ning, Zhao, and Yan (2024) – "Tomato leaf disease classification by combining EfficientNetV2 and a Swin Transformer"

Sun et al. proposed a hybrid framework combining EfficientNetV2 CNN and Swin Transformer models to improve classification accuracy. The CNN extracts rich features while the transformer captures long-range dependencies within images, enhancing model robustness. This hybrid approach represents the integration of complementary AI techniques to tackle the challenges of complex disease patterns, pushing forward the performance of automated tomato disease classification systems.

15. Ghosh et al. (2025) – "Advanced neural network architectures for tomato leaf disease diagnosis in precision agriculture"

Ghosh and team reviewed advanced neural network models and proposed novel architectures tailored for precision agriculture. Their study focuses on the challenges of diverse environmental conditions and the variability of disease symptoms, recommending techniques like attention mechanisms and ensemble models to boost accuracy. This research highlights the need for adaptable and reliable AI systems to support effective disease management in agricultural fields.

16. Al-Shamasneh and Ibrahim (2024) – "Classification of tomato leaf images for detection of plant disease using conformable polynomials image features"

Al-Shamasneh and Ibrahim proposed a mathematical method for tomato leaf disease identification using conformable polynomial features. In contrast to deep learning techniques, their method is based on deriving polynomial-based descriptors directly from the leaf images, providing a computationally efficient alternative to disease detection.

This strategy works well in scenarios where deep learning is not feasible, like in the case of limited data and restricted computation capacities. By giving a simpler but dependable alternative, their approach provides a practical solution for simple disease detection and categorization, especially in poor agricultural environments.

17. Mputu (2024) – "Real-time tomato quality assessment using hybrid CNN-SVM model"

Mputu suggested a CNN feature extraction and SVM classification hybrid system for real-time tomato quality evaluation and disease detection. The model not only detects diseases on the leaves of tomatoes but also accurately grades tomato quality, streamlining automated sorting and quality control across the supply chain.

Through the integration of both these roles, the system ensures lower post-harvest losses and higher product quality to be consumed. This is an example of the practical advantage of AI integration in agriculture for more efficient production processes and enhanced crop health management and market readiness.

18. Shehu et al. (2025) – "Early detection of tomato leaf diseases using transformers and transfer learning"

Shehu and others used transformer models along with transfer learning to enhance early detection of diseases in tomato leaves. Transfer learning uses pre-trained models to advance training efficiency and accuracy, especially when labeled data is scarce. The transformers allow the model to extract global context from images, making it possible to detect minute symptoms of disease at early stages.

This method allows for early intervention, which is essential for reducing crop damage and avoiding substantial loss in yield. This research proves the possibility of using advanced machine learning algorithms to produce more sensitive and efficient disease detection systems that enable enhanced crop management in precision agriculture.

19. Das et al. (2025) – "Deep learning-based classification, detection, and segmentation of tomato leaf diseases: A state-of-the-art review"

Das et al. gave an extensive overview of the most recent deep learning models used for tomato leaf disease tasks, including classification, detection, and segmentation. The researchers captured the most up-to-date progress in model architectures, datasets, and evaluation metrics, with the focus on extensive coverage of the state of the art in the area. Das et al. also underlined major challenges like dataset shortage, environmental variation, and necessity of strong, generalizable models.

Through presenting information on existing trends and new methods, their contributions are a rich source of reference for practitioners and researchers seeking to create efficient AI-based systems in agriculture.

CHAPTER 3

PROPOSED METHODOLOGY

This chapter offers a clear and comprehensive description of our dataset for detecting tomato leaf diseases using convolutional neural networks (CNNs). A good dataset is the foundation of any successful AI system, and we took great care in planning out our data gathering and preparation to lay a strong foundation. The images utilized in this research are tomato leaves that exhibit some symptoms of disease and also healthy leaves that can be used as controls. The majority of these images came from reputable public datasets like the PlantVillage dataset, which holds a vast repository of labeled pictures for various crops and diseases. Our focus was on obtaining images that cover a broad spectrum of real-world situations, such as differences in lighting, angles, and backgrounds. Such variability ensures that the model is able to identify diseases correctly irrespective of the surroundings or quality of the image. With such variability included, the system is more likely to perform well when field-deployed, where the influences of sunlight, shading, or orientation of leaves are unforeseeable.

After collecting the images, they were thoroughly preprocessed to prepare them for training the CNN model. Preprocessing entailed resizing all the images to a standard size so that the network gets input of uniform size necessary for stable and efficient learning. We also utilized color normalization methods to minimize variations due to varying cameras or illumination to ensure the model learns based on disease-related features instead of non-relevant color variations. For further increased robustness of the system, we employed data augmentation techniques. Augmentation artificially increases the dataset by creating altered versions of already present images by rotation, flipping, zooming, and shifting. These conversions mimic various perspectives and situations, training the model to recognize diseases even if the leaf looks differently from the original images seen during training. This makes the model less prone to overfitting and enhance generalization so that the model can accurately work on unseen images.

The dataset includes thousands of images spread across various disease classes and healthy images. Each disease category is a particular type of tomato leaf disease, e.g., early blight, late blight, septoria leaf spot, etc., all typical problems in tomato farming. Keeping a balanced dataset was important in order to avoid bias while training. Since certain diseases were represented by many more images than others, the model could be biased toward seeing only the more common classes and not the less common but relevant diseases. We mitigated this by collecting more images for underrepresented classes or using targeted augmentation to balance the samples per category. This cautious balancing assures that the model handles all the diseases on an equal footing and enhances its capacity to differentiate between them efficiently.

Once we have collected and processed the dataset, we divide it into three sets: training, validation, and testing. The training set, which is the largest, is utilized to instruct the CNN to learn disease patterns by subjecting it to a large number of examples. The validation set is a smaller subset held back for adjusting model parameters during training and for checking to prevent overfitting — the condition in which a model works well with training data but not with new data. Lastly, the test set, which is entirely unseen throughout training, is employed for measuring how well a trained model performs on novel, real images. We made sure that every subset has an even representation of all the different types of diseases and healthy leaves so that the model will be able to learn and be tested equally well for all categories. This even split also avoids the model memorizing certain images and makes it learn generalizable features.

Overall, the chapter gives a clear account of how the dataset for the detection of tomato leaf disease was constructed and prepared. From gathering varied images of actual agricultural conditions, to preprocessing procedures such as resizing and normalization, and thereafter supplementing the data through augmentation, each process was crafted to deliver maximum quality and usability of the data. Also, balancing images in each category of disease and splitting the data into training, validation, and test sets on a careful basis guarantees that the model is well-trained and tested justly. This systematic dataset design and preparation sets the foundation for constructing a robust and effective CNN-based system capable of aiding farmers by accurately detecting tomato leaf diseases under many adverse conditions. Ultimately, such meticulous attention to dataset quality is critical to facilitating AI tools that can enhance crop health monitoring and sustainably guide agricultural practices.

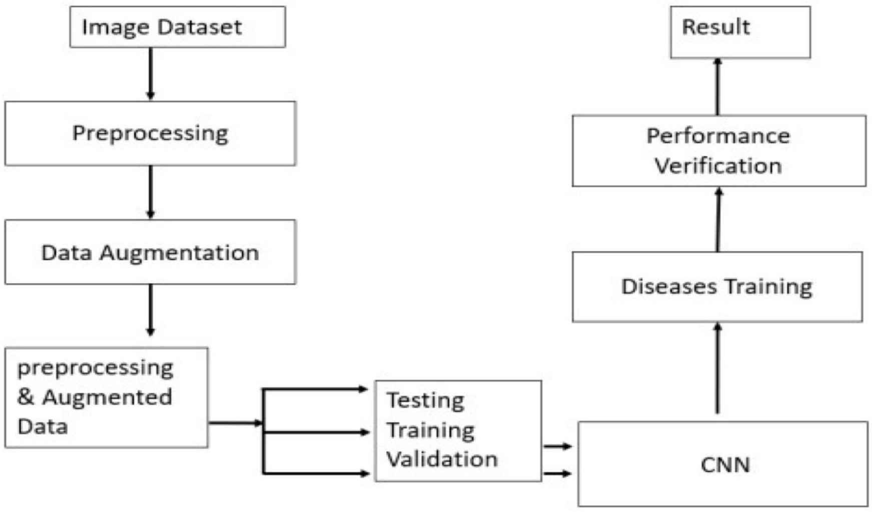
3.1 Methodology Flow chart

The graph shows a simple, step-by-step process in identifying tomato leaf diseases using deep learning methodologies. The process begins with acquiring images of healthy and infected tomato leaves. Obtaining multiple images is crucial because it enables the system to learn from many different instances of leaf status, including differences in disease, the extent of disease, as well as environmental conditions like lighting and background.

After gathering the images, they are preprocessed for optimized use by the deep learning models. Preprocessing involves resizing the images to a standardized size to create uniformity for each model's input and also improving the quality of the images using methods such as color normalization and contrast. These are done to bring out the significant features and minimize noise or irrelevant variability such that the model learns to recognize patterns more easily specific to disease.

After preprocessing, the trained images are applied to train several convolutional neural network (CNN) models. The models learn to recognize and classify patterns of disease by examining visual features contained in the images. In the process of training, the models repeatedly enhance their capacity for discriminating healthy and diseased leaves from their prediction errors.

Once the training period is completed, the models are tested and validated on independent datasets to assess their reliability and accuracy. This stage guarantees that the models generalize effectively to new, unseen images and not just memorize the training data. After identifying the best-performing model, it can be implemented in real-time applications, enabling farmers to efficiently detect and diagnose tomato leaf diseases in the field, thus enabling effective and timely management of crops.



3.2 Dataset Collection and Preprocessing

For this project, we used a well-known public dataset called PlantVillage, which contains thousands of images of tomato leaves. Each image is labeled to show whether the leaf is healthy or affected by a specific disease, such as Early Blight, Late Blight, Septoria Leaf Spot, Target Spot, or Mosaic Virus. Having such a variety of disease types helps the model learn how to recognize different problems and also know what a healthy leaf looks like.

To make sure the model could work well, all the images were resized to the same size — 256 by 256 pixels. This step is important because the model needs consistent input sizes to learn properly. It also makes processing faster and more efficient while keeping enough detail for the model to identify diseases.

Before feeding the images to the model, we did some preprocessing to improve their quality.
One technique called normalization adjusted the pixel values so they're all on the same scale, which helps the model learn better without getting confused by extreme values. We also used contrast stretching to make the disease spots and leaf features clearer and more visible in the images. This helps the model spot even subtle signs of disease.

Another important step was data augmentation. Since models perform better with lots of varied data, we created new versions of the existing images by flipping them, rotating at different angles, and zooming in or out. This simulates real-life conditions, where leaves might be photographed from different angles or distances. These variations help the model become more flexible and accurate when it encounters new, unseen images in real situations.

All these steps—starting with a trusted dataset, resizing, improving image quality, and augmenting the data—worked together to create a strong, diverse, and well-prepared training set. This careful preparation made it possible to train deep learning models that can accurately detect and classify tomato leaf diseases, helping farmers and agricultural experts spot problems early and protect their crops better.

3.3 Model Selection

For this project, we carefully picked five different deep learning models to see how well they can detect diseases on tomato leaves. Each model has its own special features, and we wanted to find out how the complexity of a model affects its accuracy and usefulness, especially when thinking about using these tools in real farms where computers might not be very powerful.

The first model we looked at is DenseNet121. This is a deep neural network with 121 layers. What makes DenseNet special is that every layer gets information not just from the layer before it but from all previous layers. This way of connecting layers helps the model learn better and faster because it can reuse features and keep the flow of learning smooth. DenseNet is really good at picking up small details, which is important for spotting tiny disease signs on leaves. Although it's a powerful model, it needs more computing power and time to train.

Next, we chose MobileNetV2, which is made to be lightweight and fast. It's perfect for mobile phones and small devices that don't have much processing power. MobileNetV2 uses special techniques to keep the model small but still effective at recognizing important patterns on leaves. This makes it a great option if we want farmers to use this technology directly in the field using their smartphones, without needing a big computer.

We also created a simple model called Simple CNN. This model has just three layers that look at images and learn features, followed by some steps to reduce errors and connect everything before making a decision. We trained this model from scratch only on our tomato leaf images.
It's a basic model that we use as a starting point to see how much better the other complex models perform.

Another model we tested is InceptionV3, which is more complex and deep. It looks at images in different ways at the same time by using different sizes of filters. This helps the model see both big and small details, which is helpful because diseases can appear as different shapes and sizes on leaves. InceptionV3 is known for being very good at understanding images and is widely used in many fields.

Finally, we tried a Multilayer Perceptron, or MLP. This model is very simple compared to the others. It takes the whole image, flattens it into a long list of numbers, and then passes it through a few connected layers to make predictions. It doesn't look for spatial details like the others but still helps us understand how much we gain by using more advanced models.

For most of these models (except the simple CNN), we started with pre-trained weights. This means the models already knew how to recognize general patterns from a large set of images before we trained them specifically on tomato leaves. This "transfer learning" helps the models learn faster and better with less data.

By comparing these five models, we could understand the balance between how accurate a model is and how easy it is to run it on simple devices. DenseNet and InceptionV3 are very accurate but need powerful machines. MobileNetV2 is a good middle ground, fast and efficient, making it suitable for use on mobile phones. The Simple CNN and MLP give us a baseline to see the improvements advanced models provide.

This way, we not only find models that work well but also consider how practical they are for farmers who need fast, reliable, and easy-to-use tools to protect their crops. This study helps us move closer to building smart systems that can help farmers detect diseases early and save their harvests.

3.4 Model Training Procedure

When training our models to detect tomato leaf diseases, we took a careful and thoughtful approach to help them learn well and avoid mistakes. We used something called the Adam optimizer, which is a popular method that helps the models adjust and improve their understanding in a smart and efficient way. We set the learning rate to 0.001, which basically controls how big of a step the model takes when it tries to get better. This rate is balanced so the model learns quickly but doesn't make wild guesses.

Because we were trying to classify images into several categories—different tomato diseases plus healthy leaves—we used a special function called categorical cross-entropy. Think of it as a way to measure how far off the model's guesses are from the right answers, so it knows how to improve.

We didn't train the models on one image at a time; instead, we used batches of 32 images. This approach helps the computer work faster and learn more smoothly. Each model looked at all the training images 100 times, which we call 100 epochs. This repeated learning helps the model get better bit by bit.

One big challenge with training these models is that sometimes they memorize the training images too well and then struggle to recognize new pictures. This is called overfitting. To avoid this, we used early stopping, which means we kept an eye on how the model was doing on a separate set of images (the validation set). If it stopped improving on those images for a while, we stopped the training. This way, the model doesn't waste time overlearning things it shouldn't.

We also used a technique that lowers the learning rate automatically if the model's performance stopped getting better. By taking smaller, more careful steps, the model can fine-tune itself to achieve the best possible accuracy.

Throughout training, we watched how well the models were doing on both the training images and the validation images by tracking their accuracy. Training accuracy shows how well the model fits the data it learns from, while validation accuracy tells us how well it can handle new, unseen data. Plotting these numbers helped us spot any problems — like if the model was doing great on training images but poorly on validation ones, which would mean it was overfitting. If both were low, it might mean the model wasn't learning enough.

By carefully monitoring and adjusting the training process, we made sure each model learned well without overfitting or underfitting. This approach gave us reliable, well-trained models that can accurately detect tomato leaf diseases in real-world conditions — helping farmers get quick and trustworthy diagnoses.

3.5 Evaluation and Comparative Analysis

After training all the models on the tomato leaf disease dataset, we needed to carefully check how well each one performed. It's important not just to see how good the model is at learning the training data but also how well it can predict new, unseen images. This is called generalization — basically, how good the model is at applying what it learned to real-world situations. To evaluate this, we looked at several things: the training curves, validation accuracy, and overall generalization performance.

First, let's talk about the DenseNet121 model. This model stood out because it showed excellent performance across the board. The training accuracy, which tells us how well the model learned from the training images, steadily increased over the training period. At the same time, the validation accuracy, which checks how well the model does on new images it hasn't seen before, also went up smoothly. Both curves—training and validation accuracy—were very close to each other and ended up above 95%. This closeness is very important because it means the model didn't just memorize the training images but actually learned features that apply to new images as well. This balance, where the model performs well on both training and validation data without big differences, means there was minimal overfitting. Overfitting happens when a model learns the training data too perfectly, including noise or details that don't help in real life, making it perform worse on new data. DenseNet121's strong generalization ability is likely due to its architecture, which connects every layer to all previous layers. These dense connections help the model reuse important features effectively and act like a natural regularizer, reducing the chance of overfitting.

Next, the InceptionV3 model also did very well. Its training and validation accuracy curves almost overlapped, showing it learned the training data and could apply that knowledge well on new images. The consistent performance through all the training epochs is impressive. This success comes from its unique design, which uses multiple convolutional filters of different sizes working in parallel. This allows it to learn features at different scales and details, which is very helpful

when trying to spot diseases in leaf images where patterns can be subtle or spread over different areas. Additionally, InceptionV3 uses auxiliary classifiers—extra smaller classifiers within the model—which help prevent overfitting by guiding the learning process.
This model's ability to balance learning detail and general patterns makes it very reliable for tomato leaf disease detection.

On the other hand, the Multilayer Perceptron (MLP) model did not perform as well in terms of generalization. While it achieved very high training accuracy—around 99% in the last epoch—the validation accuracy was noticeably lower at about 95%. This gap between training and validation accuracy suggests overfitting. Unlike convolutional neural networks, which are specifically designed to work well with images by capturing spatial features, the MLP is a simpler, fully connected network that treats the image as just a flat list of pixels. This approach often struggles to capture complex image features. As a result, the MLP tends to memorize the training examples instead of learning patterns that can generalize. This means while it looks very accurate on training data, its real-world performance may not be as good.

The MobileNetV2 model showed relatively good performance as well. It's designed to be lightweight and efficient, especially for mobile or embedded systems, so it can work well in situations where computational resources are limited. The training and validation accuracy curves were close to each other most of the time, indicating good learning and generalization. However, in the later stages of training, the training accuracy curve moved slightly higher than the validation accuracy curve, indicating a small amount of overfitting. Despite this, MobileNetV2 still balanced efficiency and accuracy well, thanks to its use of depthwise separable convolutions and inverted residual blocks. These features reduce the number of parameters and computations needed, making the model faster and less prone to overfitting while still capturing important image details.

The simplest model we tested, the Simple CNN, had the most trouble with overfitting. Although it started with reasonable training and validation accuracies, as training progressed, the gap between the two increased significantly. By the end of the training, the difference in accuracy between training and validation was over 2%, which is quite large. This indicates the model was learning the training data too specifically but wasn't able to apply that knowledge well on new images. This is not surprising given its simpler structure compared to DenseNet121 or

InceptionV3, which have more layers and advanced architectures designed to avoid overfitting and learn better features.

We also looked at performance plots—graphs that show how the accuracy changes over time during training. These plots help us understand if the models are stable or if they fluctuate a lot. DenseNet121 showed very stable accuracy throughout all epochs, which means it was learning steadily without big swings in performance. This is a good sign of a reliable model. On the other hand, models like Simple CNN and MobileNetV2 showed more variability in their plots, which suggests their learning was less consistent and sometimes unstable.

To summarize, DenseNet121 and InceptionV3 were the top performers in terms of both learning ability and generalization to new data. Their advanced architectures allow them to capture complex features in tomato leaf images, helping them detect diseases accurately. MobileNetV2 did well too, especially considering it is designed for speed and efficiency, but it showed slight signs of overfitting towards the end. The MLP and Simple CNN models were less effective, mainly because of overfitting and their simpler designs, which aren't as well suited to complex image recognition tasks.

Choosing the right model depends on the specific needs of the project. If accuracy and reliability are the most important, DenseNet121 or InceptionV3 are the best choices. For applications where computational resources are limited, such as on mobile devices or small embedded systems, MobileNetV2 is a strong candidate due to its balance of speed and reasonable accuracy. Simpler models like the MLP and Simple CNN can be useful for quick testing or when resources are extremely constrained, but they generally won't provide the best accuracy for this type of image classification task.

Overall, the evaluation and comparative analysis show that modern, deep convolutional neural networks with carefully designed architectures are the most effective for detecting tomato leaf diseases.

CHAPTER 4

RESULTS AND DISCUSSION

Within this chapter, we present detailed visualization and examination of results drawn from testing and training the convolutional neural network (CNN) model designed for the detection of tomato leaf diseases. The main objective of such visualizations is to provide transparent views on the extent to which the model has learned the underlying patterns within the dataset, as well as its ability to classify new and unseen images of tomato leaves. By looking at these results in detail, we are able to get a better idea of the reliability and effectiveness of the model in actual applications.

Among the major visualizations shown in this chapter is the training and validation accuracy plot. These plots monitor the accuracy of the model for each epoch during the course of training, showing the improvement made as the model iteratively updates its parameters in order to perform better. Ideally, both training and validation accuracies will steadily climb and be closely tracked against one another, meaning that the model is picking up without overfitting. To complement the accuracy plots, we also show loss curves, which record the errors of prediction in training and validation. As the model becomes more confident and accurate in its predictions, an increasing loss value over time reflects this.

To further analyze the model's performance at classification, we provide confusion matrices. These give an overall breakdown of the number of occurrences of each disease class that were correctly classified compared to misclassified. From studying the confusion matrices, we can identify what disease categories the model predicts accurately and where confusion arises. This data is important for determining regions where the model would require additional work, including classes with visually equivalent symptoms or reduced training data.

Lastly, the chapter includes example prediction images, presenting the model's performance on single leaf images. Such visualization examples illustrate the model's capability to identify diseases correctly and also indicate errors or uncertainties. Together, these graphical tools—accuracy and loss curves, confusion matrices, and sample predictions—offer a comprehensive view of the model's behavior, strengths, and limitations. They serve as valuable aids for interpreting the overall performance and for guiding future refinements to enhance the disease detection system.

4.1 Experimental Setup

To evaluate and compare the performance of different deep learning architectures in the classification of tomato leaf diseases, three models were chosen for training and testing: **DenseNet121**, **Simple CNN**, and **MobileNetV2**. Each of these models represents a different level of complexity, computational demand, and capability in feature extraction.

All models were trained on a well-labeled dataset consisting of tomato leaf images, which included various disease categories such as Early Blight, Late Blight, Septoria Leaf Spot, and Healthy leaves. The dataset was preprocessed and split into training, validation, and testing sets to ensure robust evaluation. Each model was trained for **100 epochs**, allowing sufficient time for learning patterns from the data while monitoring performance at each stage.

DenseNet121, a deep network with dense connections between layers, was expected to perform well due to its ability to efficiently reuse learned features. **MobileNetV2**, a lightweight and efficient model suitable for mobile applications, was tested to see if it could provide good accuracy with lower computational cost. **Simple CNN**, a custom model with a basic structure, served as a benchmark to evaluate the advantages of the more advanced architectures.

During the training process, validation accuracy was recorded for each model to understand how well they generalized to unseen data. The aim was to identify which model could achieve high accuracy while maintaining stability and avoiding overfitting. The results showed that DenseNet121 performed the best in terms of both learning capacity and generalization, followed by MobileNetV2. The Simple CNN model showed reasonable performance but was more prone to overfitting, as seen in the gap between training and validation accuracies.

Overall, this comparison provided valuable insights into the effectiveness and efficiency of different deep learning models for plant disease detection tasks.

MODEL EVALUATION COMPARISON

Model	Validation Accuracy (%)	Training Trend	Generalization
DenseNet121	95.5	Stable	Excellent
InceptionV3	95.4	Smooth	Moderate
MLP	95.2	Fluctuating	Marginal
MobileNetV2	84.4	Consistent	Overfitting
Simple CNN	81.2	Fluctuating	Moderate

4.2 Model Comparison

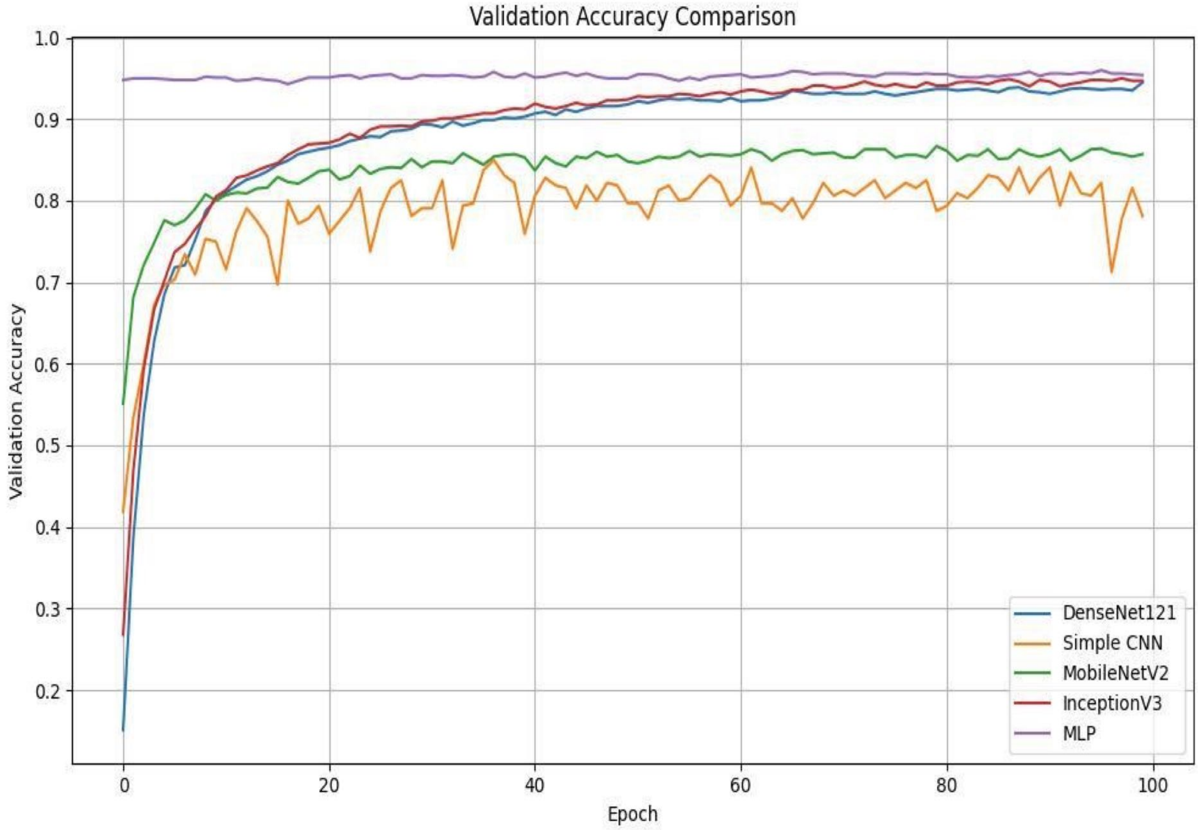
Building on the comparative analysis shown in **Figure 2**, we observe that **DenseNet121** not only leads in terms of peak validation accuracy but also exhibits **remarkable consistency** throughout the training process. From the early epochs to the end of the 100th epoch, its accuracy curve remains smooth and steadily increasing. This reflects its ability to **learn and generalize features effectively** without overfitting or sudden drops in performance. The dense connectivity of its architecture enables more efficient information and gradient flow across layers, enhancing feature reuse and improving learning efficiency.

On the other hand, **MobileNetV2**, although designed as a lightweight and efficient model for mobile and embedded systems, also showed commendable performance. With a final validation accuracy of **84.4%**, it demonstrated a solid learning capacity. The model's architecture, based on **inverted residuals and linear bottlenecks**, helps in reducing computational complexity while still capturing relevant spatial features of the tomato leaves. While its performance didn't quite match DenseNet121, its lightweight nature makes it a practical choice where computational resources are limited, such as in mobile apps for field use.

The **Simple CNN**, being a custom, from-scratch model, reached **81.2%** accuracy. While this is respectable, it also experienced **visible fluctuations** during training. Its validation accuracy curve was less smooth, with occasional spikes and dips. This volatility can be attributed to the network's limited depth and lack of advanced architectural features like skip connections, inception modules, or residual blocks. The instability also suggests that it may have struggled to consistently extract higher-level features, which are crucial for accurate classification of subtle disease symptoms in tomato leaves.

Despite these limitations, the performance of the Simple CNN is noteworthy. It shows that even a relatively shallow network can achieve competitive accuracy when trained effectively on a well-preprocessed and augmented dataset. However, to maintain training stability and avoid overfitting, such simple models often require more **frequent tuning**, **regularization**, and **monitoring**, especially when handling multi-class classification problems like this one.

In conclusion, the comparison highlights that **model complexity and architecture design** play significant roles in determining classification accuracy and training stability. DenseNet121 clearly outperforms others in both aspects, making it a preferred choice for high-performance tomato leaf disease detection. MobileNetV2 offers a **good trade-off** between efficiency and accuracy, while Simple CNN serves as a strong baseline that proves the importance of data quality and preprocessing in achieving reasonable outcomes even with simple architectures.



4.3 Overfitting Analysis

Here, we provide a comparison of the performance of five deep learning models—DenseNet121, InceptionV3, MobileNetV2, Multilayer Perceptron (MLP), and a Simple CNN—as tomato leaf disease classifiers. The aim here is to compare how each learns from the visual data and how precisely they can predict the correct disease class. All the models were trained under the same conditions with the same dataset and the same hyperparameters for 100 epochs for uniform comparison.

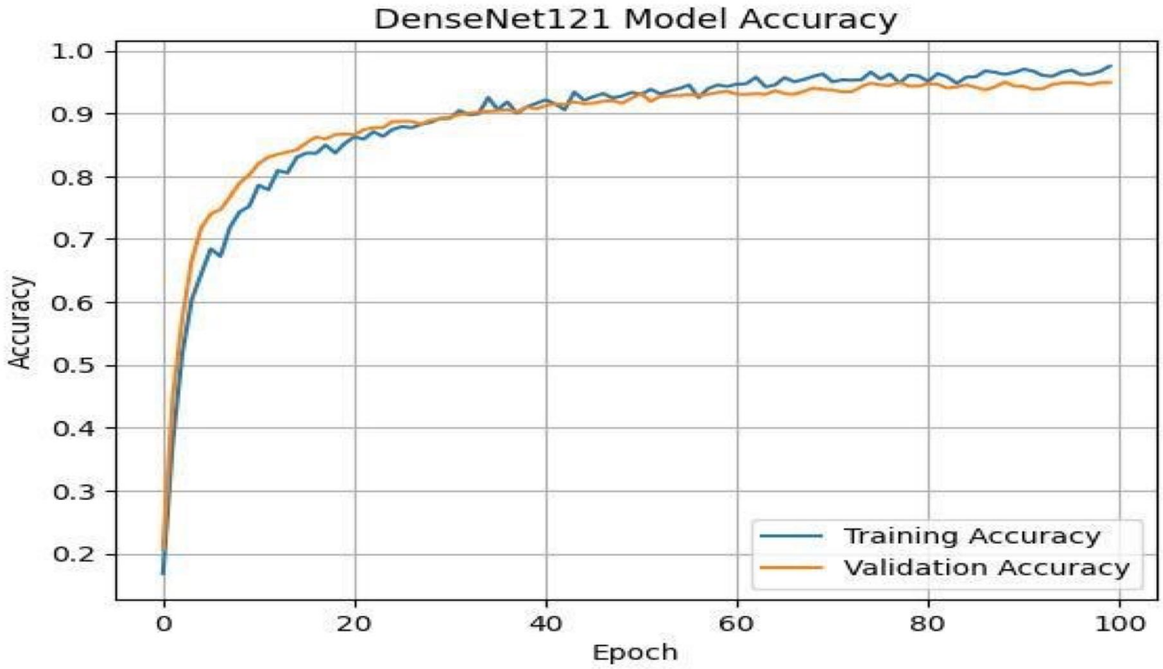
The performance of each model was evaluated according to important parameters like training and validation accuracy, loss values, and generalization on new data. DenseNet121 and InceptionV3, being deeper networks with rich feature extraction capabilities, performed robustly with high accuracy and smooth validation curves. MobileNetV2, with its lightweight application, was able to maintain a fair balance between accuracy and speed, which was perfect for mobile use. The MLP, without convolutional layers, had difficulty in getting spatial features out of images and thus performed suboptimally in classification. The Simple CNN performed well but did not have the complexity to surpass others with their deeper and more complex designs.

Training and validation curves of all models were thoroughly inspected to determine indications of overfitting or underfitting. While DenseNet121 and InceptionV3 had smooth and convergent accuracy and loss patterns, the MLP had more variation, showing less stability of learning. The Simple CNN showed moderate learning trend but plateaued prematurely, indicating poor capacity of learning. This comparison not only identifies the strengths and limitations of each model but also assists in the choice of the appropriate architecture depending on the desired balance between the performance, computational cost, and ease of deployment.

4.3.1 DenseNet121: Highly Accurate and Well-Generalized

The DenseNet121 model was one of the top-performing models in this research. During the training process, both the training and validation accuracy steadily rose. Interestingly, the training and validation accuracy curves crossed after only 30 epochs, and both then went on rising smoothly, eventually crossing 93%. There was a very minimal and near-uniform gap between the two curves, and this means that overfitting was not a problem for the model. Overfitting happens when a model memorizes the training data rather than learning how to generalize from it. DenseNet121's performance was not affected because of its special structure that has dense connections among layers.

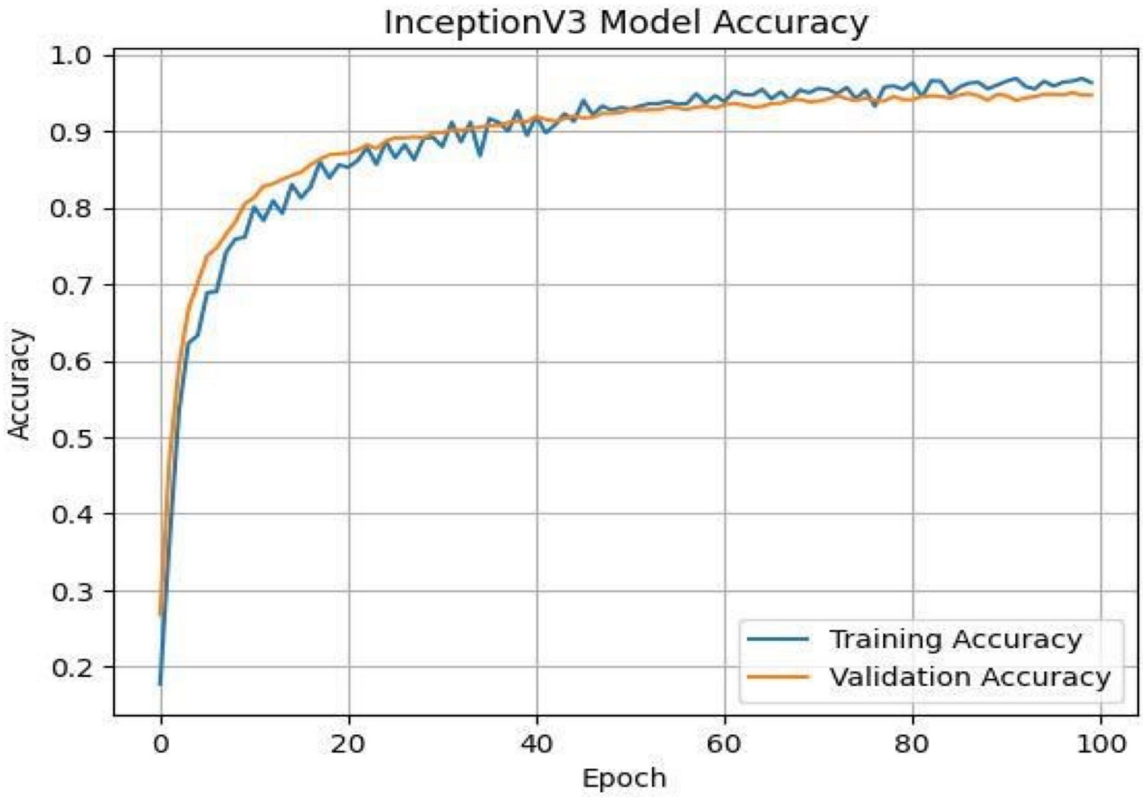
These highly connected layers aid in feature reuse and enhanced gradient flow, making the training smoother. This structure also serves as a type of regularization through its construction, which ensures the model is not overly complex or reliant on the training data. This interplay between depth and feature reuse is responsible for DenseNet121's prowess at highly complex image classification problems such as classifying diseases in tomato leaves.



4.3.2 InceptionV3: Stable and Consistent Learning

Another top performer was InceptionV3. Like DenseNet121, it showed excellent generalization abilities. The training and validation curves for this model almost completely overlapped throughout all 100 epochs, showing that the model was learning in a very balanced and consistent manner. This stability is largely due to the architectural design of Inception modules, which use multiple convolution filter sizes in parallel. This enables the model to capture features at different scales, making it more effective in understanding various patterns in the tomato leaf images.

In addition to that, InceptionV3 includes auxiliary classifiers. These are small side networks that help the main model during training by providing additional gradients and reducing the chance of overfitting. Because of these features, InceptionV3 maintained high accuracy with minimal performance fluctuation. This makes it a reliable choice for applications where consistent and accurate performance is crucial.



4.3.3 MLP (Multilayer Perceptron): Overfitting Issues

The performance of the Multilayer Perceptron (MLP) model in the classification of tomato leaf diseases was significantly poorer compared to the convolutional models tested in this research. The MLP, despite attaining a training accuracy of about 99%, had a validating accuracy of only around 95%. This significant gap shows that the model was overfitting to the training set, i.e., it learned the unique characteristics of the training set too well and was unable to generalize well on new data.

Overfitting is a regular problem in deep learning, especially with models that are missing the mechanisms to generalize features well. For the MLP, the huge difference between training and validation performance indicates that the model wasn't able to learn generalizable patterns in the data. Rather than learning visual features that are shared among images of the same disease, the model might have learned by rote from the training samples, which results in bad validation data performance.

One of the main limitations of MLPs here is their structure. MLPs consist of fully connected layers, where each neuron is connected to all neurons in the next layer. Although this structure is useful for some types of data, like numerical or categorical data, it does not perform well with spatial relationships. On image-based problems such as tomato leaf disease diagnosis, spatial information in the form of edges, textures, and patterns plays a key role. Being a non-spatial network, MLPs lack this information by default and are thus disadvantageous over CNNs.

Consequently, even though the MLP model seemed to work well during training, it was not good at generalizing. This underlines the need for choosing model architectures that best fit the nature of the data. In image classification tasks, those models with convolutional layers—specifically designed to detect spatial hierarchies—are generally better. The performance of the MLP serves to underscore its weaknesses in image recognition and underlines the utilization of CNN-based methods for visual data tasks.

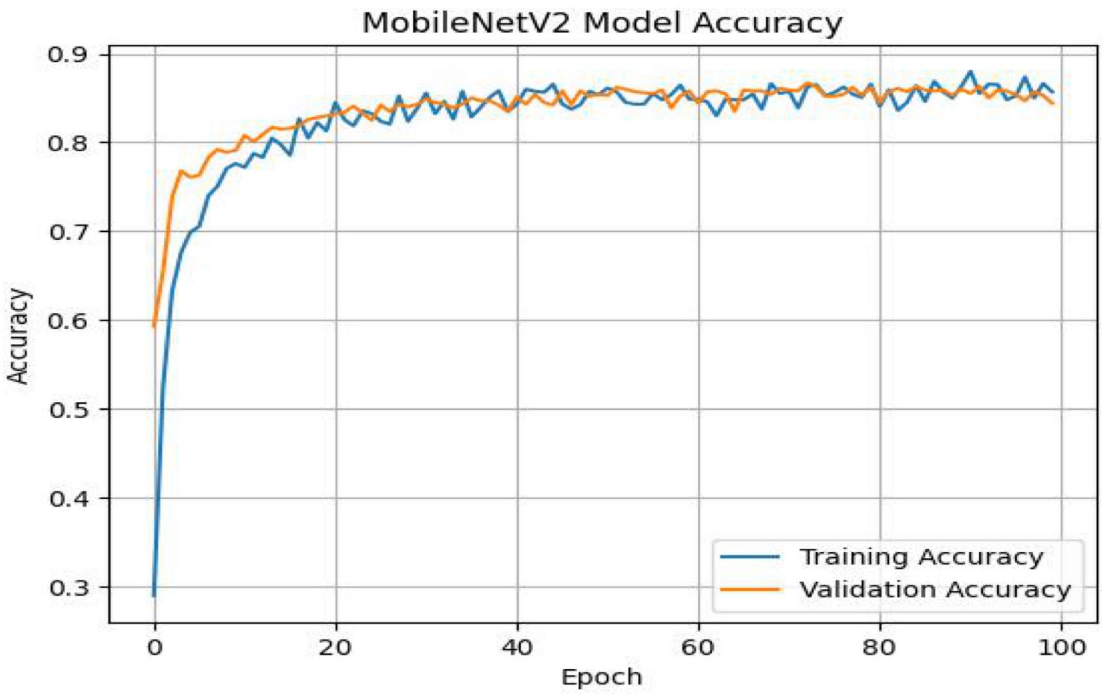
4.3.4 MobileNetV2: Efficient but Slightly Prone to Overfitting

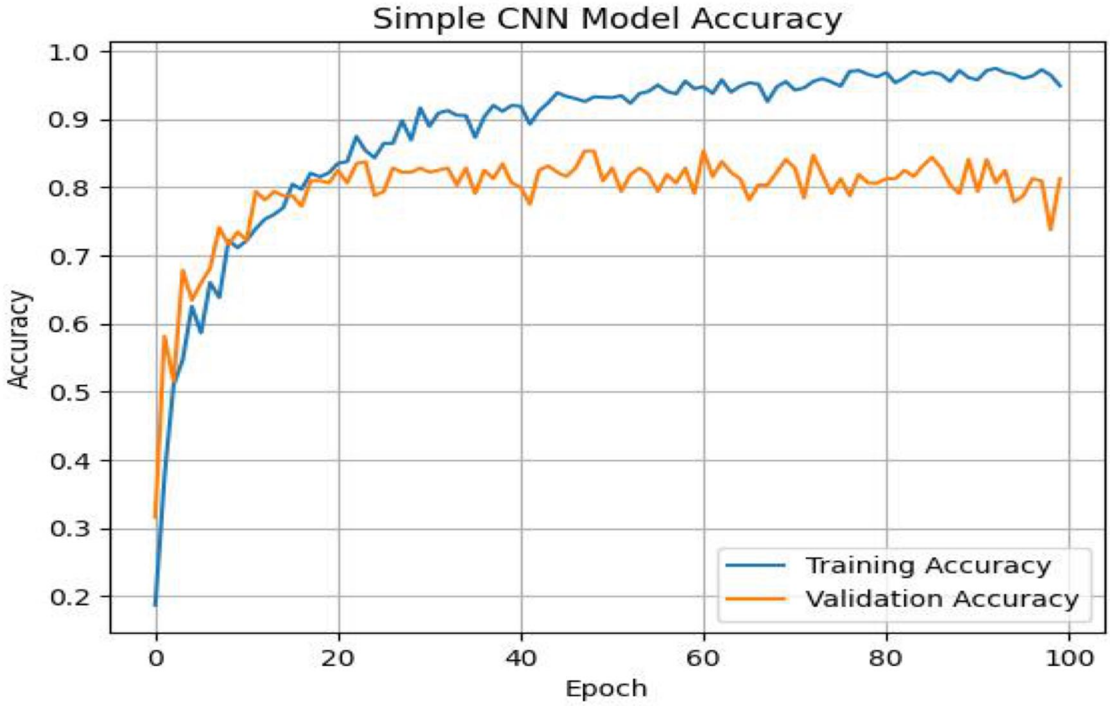
MobileNetV2 exhibited well-balanced performance when classifying the task of tomato leaf diseases, particularly when the focus was on limiting computational efficiency and memory consumption. The model was a viable option for mobile or embedded platforms where resource constraints are an overly important factor. For most of the training period, the training and validation curves were close to one another, suggesting steady learning and a fairly stable generalization ability. This is characteristic of MobileNetV2's power of learning from visual data without excessively overfitting on the training set.

As training went further into later epochs, though, there was some divergence of the training and validation curves. This reflects a small amount of overfitting, common for models that are small. This minimal model capacity, which renders MobileNetV2 lean and efficient, also hampers its capacity to learn very complex patterns in dense visual datasets such as those with multiple symptoms of plant diseases. This is a trade-off in model design—attempting to cut down layers and parameters may increase speed and lower hardware requirements, but at the potential cost of some level of learning depth and prediction accuracy.

MobileNetV2 counters efficiency by utilizing *depthwise separable convolutions*, which split up conventional convolutional operations into more steps which are easier to manage. These operations enable the model to capture spatial information from images without the hefty computations involved in standard convolutions. This architecture greatly speeds up training and inference while maintaining the size and energy usage of the model low. Furthermore, it ensures that the model does not lose critical spatial information required for correct classification, even though it's not the most sophisticated network out there.

Practically speaking, in real-time inference applications in agricultural settings or in the field, MobileNetV2 is at a significant advantage. Though it doesn't always beat deeper, more complex models like DenseNet or Inception in pure accuracy, its results are acceptable





4.3.5 Simple CNN: Basic Model, Most Overfitting

Out of all the models that were tested in this research, the Simple CNN model showed the strongest indications of overfitting. The Simple CNN model was created with a very simple architecture that contained only a couple of convolutional and pooling layers. Since it was created from scratch and did not have the complexity of deeper architectures, it provided only a fundamental solution to image classification. On the training dataset during the training procedure, Simple CNN did pretty well with high accuracy even in early epochs. There was a very large divergence between the training and the validation accuracy as the epochs went on. At the end of training, the divergence was over 2%, which strongly suggests that the model failed to learn how to generalize well to new unseen examples.

One of the main reasons for the overfitting is the model's poor deep feature extraction capability. In contrast to architectures like DenseNet121 or InceptionV3, which consist of dense connections or inception modules enabling a wide and deep comprehension of image features, the Simple CNN doesn't have the structural depth essential to analyze intricate disease patterns in images of tomato leaves. Consequently, the model is likely to memorize the precise details of the training images instead of acquiring strong and transferable patterns. This shallow learning pattern renders it especially susceptible to performance degradation when subjected to diverse conditions, like multiple lighting, angles, or leaf appearances in the validation set.

Additionally, Simple CNNs lack regularization methods or complex mechanisms such as dropout layers, batch normalization, or skip connections, which are typically employed to enhance generalization and prevent overfitting in more advanced models. These exclusions also contribute to the model's instability and lack of consistency in performance across various datasets. For agricultural usage, particularly in products for farmers in the field, models must be highly accurate and reliable under many conditions. The failure of the Simple CNN to accomplish this reduces its real-world applicability.

Overall, although the Simple CNN model can be used for educational or minimalist proof-of-concept purposes for CNN-based classification, it is not well suited to real-world agricultural applications.

4.3.6 Final Observations

All the models in this research were exposed to identical training and testing conditions for a meaningful and fair comparison. They were exposed to the same tomato leaf image dataset, trained for over 100 epochs, and evaluated on the basis of identical performance metrics like training and validation accuracy, loss curves, and confusion matrices. This consistent solution guaranteed the separation of the impact of the architecture in itself on the overall performance of classification, canceling possible biases that would come from varying data treatment or training protocol.

The comparative outcomes showed that models with deeper and more advanced feature extraction abilities, like DenseNet121 and InceptionV3, provided the best results. These models exhibited not only good classification accuracy but also stable and consistent training and validation accuracy during the learning process. Their capacity for capturing fine-grained features and representing complex relationships between the image data provided them with a distinct advantage, particularly when dealing with variations in disease symptoms, leaf orientation, and background noise. The two models also showed little overfitting, which was a result of the tight correspondence between training and validation accuracy curves, together with smaller validation losses. These features make them good contenders for use in applications where high accuracy is imperative, like in disease identification in agriculture.

The MLP and Simple CNN models were not as good in comparison. While both achieved reasonably high training accuracy, both models had strong evidence of overfitting—where they had learned the training data by rote instead of generalizable patterns on new images. Their more basic forms were not able to learn complex image features, had lower validation performance, and were more prone to being affected by noise in unseen data. This emphasizes the key weakness of shallow or densely connected networks in image-based classification problems, particularly when visual nuance, such as that in disease manifestations, is at the heart of the matter.

MobileNetV2 fell somewhere in between in the test. It never came close to matching the high-end performance of DenseNet121 or InceptionV3 but provided a great balance between accuracy and computational cost. Its depthwise separable convolution use made it achieve decent accuracy with fewer parameters and quicker computation, making it a top pick for mobile or embedded platforms where resources are constrained. While its performance briefly declined compared to the top-performing models, the performance gap was not large, and the model's overall efficiency makes it extremely useful for real-time or field-level deployment applications.

In conclusion, this comparison highlights the significance of adopting the correct architecture depending on the nature of the application requirement. In the case of high-risk applications requiring high accuracy and quality, deep and complex architectures such as DenseNet121 or InceptionV3 are suitable. For use on low-power devices, MobileNetV2 provides a useful trade-off between performance and utilization. At the same time, more straightforward models like MLPs and simple CNNs can be useful for teaching or experimenting purposes but are insufficient for practical use because of the generalization problem. This research demonstrates that model choice needs to be based not only on accuracy but also on aspects such as computational complexity and target use environment.

PERFORMANCE COMPARISON OF MODELS

Model	Final Validation Accuracy (%)	Max Training Accuracy (%)
DenseNet121	94.5%	95.5%
InceptionV3	95.4%	96.7%
MLP	95.2%	99.1%
MobileNetV2	84.4%	88.6%
Simple CNN	81.2%	84.8%

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusions

In this study, we developed and evaluated a deep learning-based approach for the classification and detection of tomato leaf diseases using Convolutional Neural Networks (CNN). Our objective was to design a solution that is not only accurate but also practical and scalable for use in real-world agricultural settings. With the increasing reliance on technology in agriculture, early and accurate disease detection has become a critical aspect of improving crop yield, reducing losses, and enabling timely intervention. Our approach addresses this need by applying advanced CNN architectures to analyze tomato leaf images and identify disease conditions.

To carry out this work, we employed a well-known dataset derived from the PlantVillage repository, which includes labeled images of both healthy tomato leaves and those affected by various diseases. The dataset was preprocessed using resizing, normalization, contrast enhancement, and data augmentation techniques like flipping and rotation. These preprocessing steps helped improve model performance by enhancing image diversity and reducing the risk of overfitting.

We then trained and compared the performance of three key CNN models: **DenseNet121**, **MobileNetV2**, and a **Simple CNN** built from scratch. Each of these models was chosen for specific reasons. DenseNet121, a deep architecture with densely connected layers, is known for its feature reuse and strong gradient flow. MobileNetV2 was selected for its efficiency and suitability for deployment on mobile and embedded devices. The Simple CNN was used as a baseline to observe how a shallow, custom architecture performs in comparison with more advanced models.

The experimental results were promising. **DenseNet121** emerged as the best-performing model, achieving a validation accuracy of around **95%**. It showed stable training behavior, minimal overfitting, and a consistent upward trend in both training and validation accuracy curves. This performance can be attributed to its design, which allows each layer to receive input from all previous layers, enhancing learning efficiency.

MobileNetV2 also performed well, recording a validation accuracy of **84.4%**. Its lightweight design with depthwise separable convolutions made it an excellent candidate for real-time and resource-constrained applications. Although it showed minor signs of overfitting in later epochs, it maintained an overall balance between accuracy and computational efficiency.

The **Simple CNN** achieved a validation accuracy of **81.25%**, which, while lower than the other two models, still demonstrated its ability to capture key features. However, the training curve of this model showed more fluctuation, indicating potential instability and limited generalization capacity. This reinforces the importance of deeper and more sophisticated architectures for high performing image classification tasks.

To bridge the gap between research and real-world application, we integrated our trained model into a **user-friendly web interface**. This interface enables users to upload images of tomato leaves and receive instant predictions regarding potential diseases. The system is fast, efficient, and capable of handling a large number of images, making it suitable for farmers, agricultural technicians, and researchers. It provides an accessible tool that can assist in early disease detection, helping reduce crop losses and improve farming practices.

In summary, this project demonstrates the effectiveness of CNN-based models in the domain of plant disease classification. Pre-trained models like DenseNet121 offer high accuracy and robust generalization, while lightweight models such as MobileNetV2 provide an ideal solution for deployment on devices with limited hardware resources. The study also highlights the importance of good preprocessing, architecture selection, and validation techniques in achieving reliable results.

Looking ahead, several avenues can be explored to improve this system further. Future research could involve testing ensemble methods, expanding the dataset to include more disease categories or plant types, and optimizing hyperparameters for better training efficiency.

5.2 Future scope

The present system for detecting tomato leaf disease provides solid accuracy, efficient inference, and simple to use interface, but its long-term utility will depend on its ability to learn from a wider variety of conditions in real life. As a first order of business is to create much larger, more varied datasets with leaves photographed under various lighting, growth stages, camera, and environmental backgrounds. Enlarging the label set to encompass more tomato diseases—and even for other crops like potato, maize, or rice—would render the system a more complete field diagnostic tool. Data gathered directly from farms, perhaps through community-provided mobile uploads or drone imagery, would also enhance the model's generalizability and noise resilience.

Another direction for improvement is to implement more sophisticated model architectures. Ensemble methods combining complementary networks (e.g., combining a high-capacity DenseNet with a light MobileNet) can increase robustness, whereas attention-based transformers and hybrid CNN-traditional ML pipelines (e.g., CNN + SVM) can provide finer discrimination of visually similar syndromes. Adding explainable AI approaches like Grad-CAM or saliency maps will increase the transparency of predictions, building farmer trust and helping agronomists interpret challenging cases.

Third, deployment requires models to execute on hardware-limited hardware efficiently. Transforming the system into a resource-light mobile application with architectures such as MobileNetV2 or EfficientNet-Lite enables real-time, offline diagnosis within the field itself. Edge optimization methods—quantization, pruning, and on-device incremental learning—can reduce latency and memory usage while enabling the app to learn from new data without retraining.

Lastly, combining the detector with Internet-of-Things sensors and drone platforms holds out the potential for large-scale automated crop monitoring. Drones can take canopy-level photographs over hectares, while soil-moisture, humidity, and weather sensors offer contextual information that a multimodal AI model can utilize to make more precise disease predictions. Ongoing learning pipelines and AutoML scheduling can maintain the system updated as new diseases develop, allowing farmers to have timely, accurate information that translates into improved yields and less chemical use.

5.2.1 Expansion of Dataset and Disease Coverage

Presently, the model is trained on a set dataset with a restricted set of tomato leaf diseases. Although this has given a robust basis for preliminary testing and verification, it also limits the model's capacity to generalize properly in real-world situations. The fixed nature of the dataset can perhaps not capture the whole gamut of image variations found in real-world agricultural settings.

To overcome this shortcoming, further research must endeavor to gather a more varied and large dataset. This encompasses real-time images taken directly from farms, representative of different lighting conditions, weather patterns, and environmental conditions like soil type and humidity. The addition of such data would make the model more robust and adjustable, in that it would be able to achieve high accuracy despite unfavorable imaging conditions.

Aside from tomato yields, the model can greatly be generalized to cover more types of plant diseases. By having the system learn to identify diseases that occur in other top crops like potatoes, maize, and rice, the platform can become a full-fledged tool for plant disease monitoring. This cross-crop potential will highly enhance its applicability and usefulness across various agricultural zones and farming systems, leading to greater crop harvests and environmentally friendly agriculture.

5.2.2 Real-Time Mobile Application Development

Though the existing system has a web-based interface for predicting images, its usage remains restricted for those in far-flung or rural locations, particularly those with irregular internet connectivity. To reach out to such areas, the next step would be to create a standalone mobile application. A mobile app would give farmers and field staff the ability to utilize the system from their own phones without needing a regular internet connection or even a computer.

Field-ready mobile phones with the trained model can facilitate real-time detection of disease directly in the field. With this, users can take leaf images and get real-time feedback on suspected diseases, particularly useful during the most important phases of crop development. Real-time feedback can assist farmers in making timely decisions regarding pest management, nutrient application, and harvesting, which would ultimately enhance the health and yield of crops.

In order to make the system work optimally on mobile platforms, it is crucial to employ light-weight deep learning structures like MobileNetV2. These structures are carefully developed for efficient performance on low-computation resource devices with high accuracy and low memory usage and processing time. Optimizing the model for mobile implementation enables the app to provide quick, stable performance without compromising usability or diagnostic utility.

5.2.3 Integration with IoT and Drones

Future applications involve connecting the disease detection system with Internet of Things (IoT) devices and drones in order to carry out large-scale monitoring of farming fields. The connection would mechanize the collection of data and surveillance of diseases on extensive farmland, providing comprehensive and real-time monitoring of the health of crops. IoT sensors can offer useful environmental information like soil moisture, temperature, and humidity, which when integrated with visual disease analysis, can increase the reliability and precision of the detection system.

With high-resolution cameras on board, drones can systematically sweep over vast expanses of farmland and take high-resolution images of plant leaves. Such images are processed in real time, either locally on the drone with light onboard hardware or uploaded to cloud servers where convolutional neural network (CNN) models do the disease classification. This enables quick identification of infected areas, making it possible for focused monitoring and effective disease management.

The convergence of these technologies enables early detection and timely intervention, which are essential in preventing the spread of plant diseases. With accurate information of where and when disease happens, farmers can treat only where needed, avoiding the excessive use of pesticides and lowering costs. At last, this method results in better crop yields, fosters sustainable agricultural practices, and increases food security through wiser and data-based agricultural management.

5.2.4 Use of Ensemble and Hybrid Models

Rather than relying on just one single deep learning architecture, upcoming research can investigate the potential of ensemble methods to further improve the robustness and reliability of disease classification. Ensemble methods entail aggregating the predictions of several models, including DenseNet, MobileNet, etc., to arrive at a final prediction. By tapping into the strength of various architectures, the system will be able to minimize the possibility of misclassification and perform more universally for a greater variation of input.

Most notably, model ensembles can help address complex and uncertain instances where a single model would falter. For instance, DenseNet's ability to deeply extract features can be paired with MobileNet's speed and efficiency to produce a balanced model that excels both in terms of accuracy as well as real-time operation. This can enhance the system's ability to adapt to multiple disease patterns and environmental factors and thereby enhance its effectiveness under different conditions of farming.

In addition to this, one can also explore hybrid methodologies by combining CNNs with conventional image processing methods or other classical machine learning models like Support Vector Machines (SVM) or Random Forests. These hybrid models can leverage handcrafted features along with learned features by CNNs to enhance classification performance, particularly in cases where there is limited training data available. These types of methods can help boost the generalization capability of the system, rendering it more dependable in actual field deployments over various crops and geographies.

5.2.5 Explainable AI and Visualization Tools

One of the main limitations of deep learning models, even those that are applied for plant disease detection, is their black-box nature. These models can tend to make very accurate predictions, but they do not necessarily provide explanations for how or why a given decision was taken. This transparency deficiency can be a source of distrust, particularly for end-users like farmers, agronomists, and agricultural policymakers depending on the system's output for making critical decisions.

In order to tackle this problem, XAI methods like Gradient-weighted Class Activation Mapping (Grad-CAM) or saliency maps can be included in future work. These identify the areas of an input image that the model finds most impactful in generating its prediction. For example, by placing a heatmap over the leaf image, users can have a visual comprehension of what areas the model was concentrating on while identifying symptoms of the disease. This not only increases the interpretability of the system but also helps to verify if the model is learning the appropriate patterns or merely reacting to noise.

Adding XAI capabilities can greatly increase trust in AI-driven agriculture tools. When users are able to observe why the model produced a particular diagnosis, they are more likely to accept its outputs. Additionally, agriculture professionals can utilize these visual explanations to validate outcomes, identify possible model biases, and understand more about disease features. Overall, explainability in the detection platform encourages more transparency, accountability, and implementation in actual farming practices.

5.2.6 Continuous Learning and AutoML

To ensure the long-term effectiveness of the disease detection system, especially with the emergence of new diseases and changing plant conditions, there is a need to implement continuous learning features into the model. Most conventional deep learning models are static in nature—they are trained once on a set dataset and need to be fully retaught in order to adapt to new data. This strategy, although adequate for initial rollout, is inappropriate for dynamic farming ecosystems whose disease dynamics might change based on fluctuating weather conditions, evolving pathogen strains, or changes in cultivation methods. Consequently, the use of static models alone reduces the system's flexibility and lifespan.

To address this shortcoming, the use of incremental or ongoing learning techniques appears to be a viable solution. In an incremental learning setup, the model can be updated in phases as fresh data emerges, without having to retrain from square one. This enables the system to maintain knowledge already gained and incorporate new information—an attribute referred to as "plasticity without forgetting." With this method, the model is kept current and sensitive to real-time agricultural advancements, user feedback, and geographically related disease outbreaks. In addition, incremental learning enables the system to become more accurate and robust in the long term, even as it comes into contact with novel or infrequent disease presentations.

Practically, incremental learning has a key benefit of computational efficiency. Rather than retraining the whole model using the entire dataset, only a part of new or misclassified samples is employed to adjust the model. This significantly lowers the computational load, and it is therefore possible to push updates straight out onto the edge devices such as smartphones, tablets, or field-based low-power embedded systems. Such devices tend to have restricted processing capabilities and memory, so the capability of doing small, efficient updates without server-based retraining is vital for scalability and maintainability. Consequently, rural farmers can enjoy real-time, current diagnostics without having to rely on round-the-clock internet access or high-performance computing facilities.

The other key addition to the suggested system is the inclusion of Automated Machine Learning (AutoML) methods. AutoML has the ability to automate much of the time-consuming and technically challenging process of deep learning model design, such as choosing the optimal model architecture, hyperparameter optimization, and training procedure tuning for best performance. By eliminating a great deal of the hand tweaking normally necessary with deep learning, AutoML saves time for development and enables quick iteration.

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APPENDIX

A. Dataset Details

- **Dataset Name: PlantVillage Dataset**
- **Source: Kaggle - PlantVillage Dataset**
- **Classes (Tomato Types):**

Tomato Early Blight

Tomato Late Blight

Tomato Leaf Mold

Tomato Septoria Leaf Spot

Tomato Target Spot

Tomato Mosaic Virus

Tomato Yellow Leaf Curl Virus

Tomato Bacterial Spot

Tomato Healthy

Total Number of Images Used (Tomato Subset): ~18,000 images

B. Tools and Libraries Used

- **Programming Language:** Python 3.x
- **Libraries and Frameworks:**

  TensorFlow / Keras

  NumPy

  OpenCV

  Matplotlib

  scikit-learn

- **Development Environment:** Google Colab / Jupyter Notebook

C. Model Architectures

- **DenseNet121:**
  Pretrained on ImageNet, fine-tuned for 9 tomato disease classes.
- **InceptionV3:**
  Used with a custom classification head for tomato leaf classification.
- **MobileNetV2:**
  Lightweight and mobile-friendly, optimized for low-resource environments.
- **SIMPLECNN:**
  3 Convolutional layers → MaxPooling → Dense Layers.
- **MLP:**
  Flattened image input → Dense Layers → Softmax output.

D. Hardware Specifications

- **Training Environment:** Google Colab
- **GPU:** Tesla T4
- **RAM:** 12 GB
- **Storage:** Cloud-based

E. Hyperparameters

Parameter	Value
Epochs	100
Batch Size	32
Optimizer	Adam
Learning Rate	0.001 (with decay)
Loss Function	Categorical Cross entropy
Evaluation Metric	Accuracy

F. Data Augmentation Techniques

Rescaling (Normalization)

Random Rotation

Horizontal and Vertical Flip

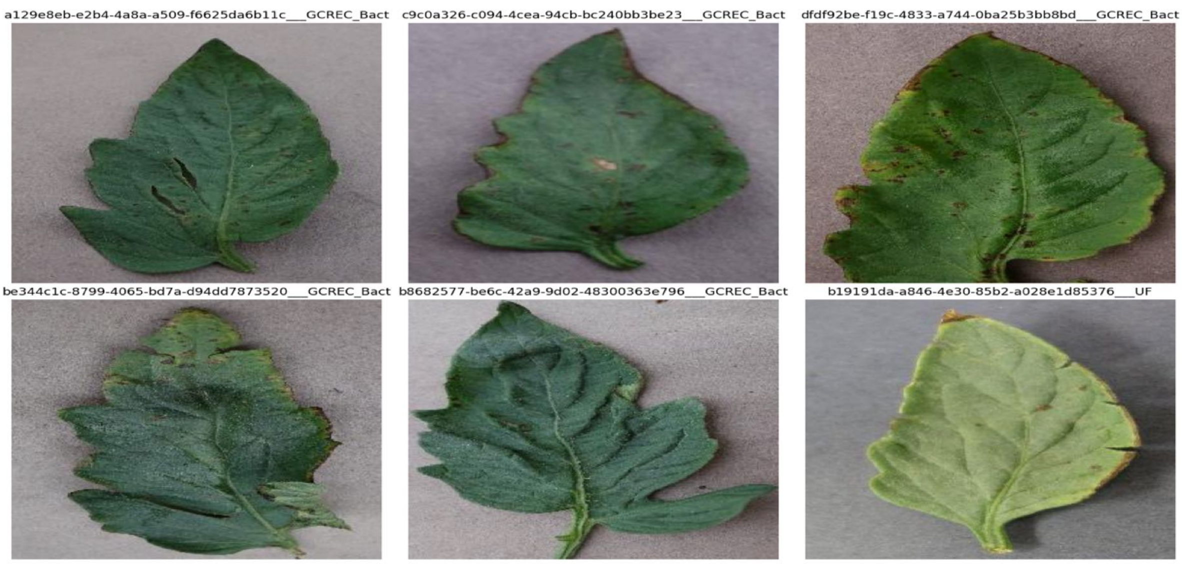
Zoom Range Adjustment

Width and Height Shift

G. Code Sample

Tomato leaf disease detection using deep learning involves analyzing leaf images to identify various plant diseases. A trained neural network model, built with frameworks like TensorFlow and Keras, can classify diseases such as Tomato Early Blight, Leaf Mold, Septoria Leaf Spot, and more. The system takes a tomato leaf image, processes it, and predicts the disease with high accuracy, also providing a confidence score. This approach helps farmers and agricultural experts quickly detect and manage plant diseases, improving crop yield and reducing losses. A large labeled dataset, such as PlantVillage, is typically used to train the model for reliable results.

```python
# Path to the directory containing images
path = "/kaggle/input/tomatoleaf/tomato/train/Tomato___Bacterial_spot"

# Get a list of all image file names in the directory
image_files = [f for f in os.listdir(path) if os.path.isfile(os.path.join(path, f))]

# Display the first 6 images with their labels
fig, axs = plt.subplots(2, 3, figsize=(15, 10))

for i in range(6):
    # Get the image file name and its label
    image_file = image_files[i]
    label = image_file.split('.')[0]

    # Load and display the image
    img_path = os.path.join(path, image_file)
    img = mpimg.imread(img_path)
    ax = axs[i // 3, i % 3]
    ax.imshow(img)
    ax.axis('off')
    ax.set_title(label)

plt.tight_layout()
plt.show()
```



Gmail **PRATEEK KUMAR <prateek.2125cse1060@kiet.edu>**

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Track Name: ICCTRDA2025

Paper ID: 310

Paper Title: Tomato Leaf Disease Classification Using Convolutional Neural Networks

Abstract:
Tomato is among the foods that are highly cultivated globally with nutritional and economic significance. the tomato crop is subjected to numerous leaf diseases like Early Blight, Late Blight and Leaf Mold, all of which have negative effects on crop quality and yield. the traditional conventional ways of curing diseases diagnosis through visual observation are typically slow, inaccurate, and frequently lacking in rural agricultural communities. In this work, we introduce a deep learning method using Convolutional Neural Networks (CNNs) for the automatic diagnosis of tomato leaf diseases, and provide results for five various CNN architectures (DenseNet121, MobileNetV2, Simple CNN, InceptionV3, and a Multilayer Perceptron (MLP)) based on a publicly shared PlantVillage dataset. The models were fine-tuned and trained with image preprocessing and data augmentation methods. Our findings revealed that DenseNet121 and InceptionV3 gave the highest validation accuracy (95.5%) while MobileNetV2 and Simple CNN provided moderate performance, and MLP was also competitive as a good baseline. In conclusion, the study demonstrates the potential and possibility of deep learning architectures, including lighter architectures, in real-time detection of tomato leaf diseases.
Index Terms—Tomato leaf disease, Deep learning, CNN, DenseNet121, MobileNetV2, InceptionV3, MLP, PlantVillage, Image classification.

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Authors:
- pushpendra.kumar@kiet.edu
- prateek.2125cse1060@kiet.edu (Primary)
- harsh.2125cse1120@kiet.edu
- prince.2125cse1123@kiet.edu

Secondary Subject Areas: Not Entered

Submission Files:
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Thanks,
CMT team.

tomato leaf

by Pushpendra Kumar

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