A PROPOSED DEEP LEARNING APPROACH FOR DETECTING BRINJAL PLANT DISEASES.

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

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APPROVAL

This Project titled **"A Proposed Deep Learning Approach For Detecting Brinjal Plant Diseases"** submitted by Md Mustakin Hasan ID: 193-15-3007 to the Department of Computer Science and Engineering, Daffodil International University, has been acknowledged as satisfactory for its style and substance and accepted as being sufficient for the accomplishment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering.The presentationhas been held on 22/01/2024.

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We, therefore, declare that this undertaking has been finished by us under the supervision of **Tanim Ahmed,** Lecturer, Department of CSE, Daffodil International University. We further declare that neither an application or an educational grant has been made anywhere for this project or any part of it.

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ABSTRACT

The article provides a unique deep learning strategy for automatic recognition of brinjal plant diseases, using a large dataset that contains varied events of Phytophthora Blight, Leaf Curl Disease, Withering Leaves, Late Blight, Healthy specimens, and Macrodiplosis Dryobia. The objective is to increase early disease detection, allowing for immediate assistance and improved crop management methods. Several machine learning algorithms, including CNN01 Model, CNN02, VGG16, ResNet152V2, InceptionV3, DenseNet169, and Transfer Learning Models, were examined to determine the best successful model for this specific agricultural application.

To ensure models reliability and generalization, the dataset was thoroughly preprocessed, including picture scaling, pixel leveling, and data enhancement techniques. The transfer learning technique, which began with pre-training models on a large dataset like ImageNet, aided in adapting these models to the unique features of brinjal illnesses.

Following thorough instruction and testing, the findings show that DenseNet169 is the best-performing model, with an excellent accuracy of 99.77%. This accuracy outperforms previous models, confirming DenseNet169's ability to properly categorize and detect Phytophthora Blight, Leaf Curl Disease, Withering Leaves, Late Blight, Healthy states, and Macrodiplosis Dryobia in brinjal plants. Because of its high accuracy, the suggested deep learning technique offers great promise for real-world use in agriculture, providing farmers with a strong tool for accurate disease detection and active crop protection. The findings also highlight the necessity of selecting the correct deep learning structure for plant disease detection applications that is suited to the details of the dataset.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

In current agriculture, the constant search of novel crop disease treatments is critical to guaranteeing global food security. Among the many cultivated vegetables, brinjal (eggplant) is a crop that is sensitive to a number of illnesses that may significantly decrease crop productivity. Identification of these illnesses in a timely and accurate manner is critical for successful reduction and preventive methods. This research describes a ground-breaking attempt called "A Proposed Deep Learning Approach for Detecting Brinjal Plant Diseases," which uses advanced artificial intelligence techniques to completely change disease detection in brinjal crops.

Traditional techniques of disease detection in plants are frequently lengthy, laborious, and dependent on human skill. Using deep learning skills, the suggested technique attempts to fully automate the identification process, providing a more efficient and accessible solution for farmers and agricultural professionals. The base of this technique is a thoroughly maintained dataset that includes photos of brinjal plants infected with illnesses such as Phytophthora Blight, Leaf Curl Disease, Withering Leaves, Late Blight, and the presence of Macrodiplosis Dryobia. This dataset is used to train machine learning methods such as custom neural network models (NN01 Model, CNN02), popular pre-trained architectures (VGG16, ResNet152V2, InceptionV3, DenseNet169), and transfer learning models.

The development of powerful neural network designs and transfer learning algorithms represents an important change in agricultural diagnosis. The proposed deep learning method seeks to provide the model with a sophisticated grasp of the diverse visual elements connected with various brinjal illnesses by combining knowledge gathered from pre-trained models on huge datasets. As global food demand rises, the project holds the prospect of not just increasing crop productivity but also contributing to environmentally friendly and precision agriculture techniques. In the following sections, we will dig into the complexities of the technique, outcomes, and consequences of this unique approach in the context of brinjal plant disease detection.

1.2 Motivation

The inspiration for demonstrating a deep learning strategy for identifying brinjal illnesses in plants comes from the urgent need to transform traditional agricultural practices and solve crop disease issues. Brinjal, a staple vegetable in many countries, is plagued by a number of illnesses that threaten agricultural productivity and food security. Modern illness detection techniques, which depend significantly on human labor and specialist knowledge, frequently struggle with effectiveness, quick responses, and flexibility.

The development of deep learning provides an innovative answer to these difficulties. We hope to build a system that can diagnose illnesses in brinjal plants automatically and accurately by utilizing the power of neural networks and advanced machine learning techniques. The suggested approach aims to provide farmers with a technology-driven tool that not only expedites disease identification but also enables proactive steps to reduce disease transmission, eventually leading to greater agricultural output and sustainability.

The objective is to bridge the technological and agricultural gaps by providing an innovative solution that meets the needs of modern farming. We want to effect a positive shift in the way we approach plant disease detection by including deep learning, providing a look into the future of precision agriculture.

1.3 Rationale of the Study

The purpose of this research is to look into the severe difficulties of brinjal farming, where the development of diseases has an important impact on crop output and quality. Traditional disease detection methods in brinjal plants are lengthy and laborious, requiring physical examination and specialist expertise. These approaches are primarily restricted in scale and efficiency, making immediate intervention and illness control difficult.The importance for a creative, automated, and affordable solution encouraged the invention of a proposed deep learning technique for identifying brinjal plant illnesses. This study intends to use the power of machine learning to properly diagnose and categorize illnesses in brinjal plants by utilizing modern neural network designs and transfer learning techniques. The project aims to increase precisely controlled agriculture by developing a large dataset and applying a variety of machine learning techniques, including bespoke models and pre-trained architectures.

The importance of this research is highlighted by the possibility of providing farmers with a tool that not only speeds up disease identification but also allows preventative measures, therefore decreasing crop losses. This research contributes to the larger objective of merging technology and agriculture, opening the path for more efficient, viable, and information-based on brinjal production techniques.

1.4 Research Question

1. How well does the proposed deep learning system determine and classify certain brinjal plant diseases such as Phytophthora Blight, Leaf Curl Disease, Withering Leaves, Late Blight, and Macrodiplosis Dryobia?

2. What effect do different neural network designs have on the accuracy and efficiency of brinjal plant disease detection, including unique models (NN01 Model, CNN02) and pre-trained models (VGG16, ResNet152V2, InceptionV3, DenseNet169)?

3. How can transfer learning help models developed using deep learning enhance their performance in the situation of brinjal plant disease detection, and which pre-trained model has the best adaptation to brinjal diseases?

4. What effect does dataset variety have on the generalization power of the proposed deep learning system for identifying brinjal plant illnesses, and analyzing different disease phases and level levels?

5. How does the suggested technique perform in terms of precision, effectiveness, and accessibility to established methods of brinjal plant disease diagnosis, taking into account parameters such as labor intensity and time requirements?

1.5 Expected Output

The intended result of the research, "A Proposed Deep Learning Approach for Detecting Brinjal Plant Diseases," expects the establishment of a strong and accurate system for automated disease detection in brinjal crops. The study's goal is to produce a deep learning model capable of accurately diagnosing particular illnesses such as Phytophthora Blight, Leaf Curl Disease, Withering Leaves, Late Blight, and Macrodiplosis Dryobia. The study will use a variety of machine learning methods, including unique neural network models and pre-trained architectures such as VGG16, ResNet152V2, InceptionV3, and DenseNet169, to discover the best model for obtaining high accuracy.

The anticipated advantages include insights into the impact of transfer learning on model performance, the impact of dataset variety on generalization, and a comparison to existing illness detection approaches. Finally, the project hopes to provide farmers and agricultural practitioners with a sophisticated tool that not only expedites illness detection but also allows for active and focused therapies. The anticipated output fits in with the overall objective of enhancing precision agriculture, contributing to improved crop management methods, and eventually assuring higher brinjal yield and global food security.

1.6 Project Management and Finance

The project management of "A Proposed Deep Learning Approach for Detecting Brinjal Plant Diseases" includes strategic preparation and collaboration to enable the smooth execution of each step. Creating a specific period of time for data collection, labeling, and preprocessing is critical. Thorough testing and the selection of the appropriate deep learning models, such as the NN01 Model, CNN02, VGG16, ResNet152V2, InceptionV3, and DenseNet169, are critical.

Financial issues include obtaining the computing resources required for model training and optimization, as well as paying for dataset selection and classification. The expenses of possible software licensing, hardware upgrades, and cloud computing services must be considered into the budget. Appropriate changes for qualified workers, particularly specialists in deep learning and agriculture, are critical to the project's success.

An effective project management and finance strategy attempts to balance resource allocation, keep a strict deadline, and assure financial responsibility for the project. This strategic approach increases the possibility of fulfilling the study objectives and offering a viable solution for automating brinjal plant disease diagnosis.

1.7 Report Layout

- Introduction
- Background
- Data Collection
- Data Preprocessing
- Research Methodology
- Experimental Result and Discussion
- Impact on Society, Environment
- Summary, Conclusion, Future Research
- References

CHAPTER 2

BACKGROUND STUDY

2.1 Preliminaries

The introductory sections of "A Proposed Deep Learning Approach for Detecting Brinjal Plant Diseases" provide a foundation for the research by describing the background and significance of the study. The preliminary part begins by emphasizing the significance of handling plant diseases in brinjal farming, highlighting the possible influence on world food security. It presents a brief review of existing issues in traditional illness detection methods, opening the path for the use of new technology alternatives.

This part also highlights the originality and creativity involved in the suggested deep learning technique. It explains the study's key goals, focusing on the creation of a sophisticated model capable of automating the detection and classifying of numerous brinjal plant illnesses. The first parts establish a framework for understanding the research's objectives, aims, and anticipated outcomes, laying the groundwork for a thorough examination of the proposed deep learning technique in the following sections.

2.2 Related Works

Xie, Xiaoyue, et al. [1] introduced an improved deep convolutional neural network-based real-time grape leaf disease detector. The Grape Leaf Disease Dataset (GLDD), a dataset of photographs of grape leaf disease that has been expanded by digital image processing techniques, serves as the study's starting point. The proposed Faster DR-IACNN model integrates cutting-edge features including the Inception-v1 module, Inception-ResNet-v2 module, and SE-blocks to improve feature extraction capabilities. It is based on GLDD and the Faster R-CNN detection technique. Faster DR-IACNN delivers a remarkable precision of 81.1% mAP on GLDD while retaining a detection speed of 15.01 frames per second (FPS), according to experimental data. This study demonstrates the viability of real-time disease detection utilizing Faster DR-IACNN based on deep learning, providing a helpful remedy for diagnosing grape leaf illnesses as well as a manual for identifying diseases in other plant species.

Kaleem, et al. [2] Used a combination of image processing and machine learning, specifically a Support Vector Machine (SVM) classifier, this research proposes a contemporary method for identifying leaf illnesses. Digital cameras are used to take pictures of leaves in agricultural fields, after which a number of preprocessing steps—including background removal, filtering, and enhancement—are used. To identify disease-affected areas on the leaves, color-based segmentation using K-means clustering is used. In conjunction with image segmentation, statistical gray-level co-occurrence matrix (GLCM) features are generated and used for feature extraction. A remarkable disease identification accuracy of 95.46% is attained by the SVM classifier when it is trained using the proper texture and color information, outperforming the performance of other cutting-edge methods in this field.

Anand, R., et al. [3] emphasized on identifying illnesses that harm brinjal leaves, this study presents a technique for the exact diagnosis of plant leaf diseases. The crucial issue of disease-related drops in brinjal output is the focus of this effort. Since 85–95% of illnesses, such as Bacterial Wilt, Cercospora Leaf Spot, and Tobacco Mosaic Virus (TMV), express themselves on brinjal leaves, the research focuses on understanding these leaves. The K-means clustering algorithm is used for image segmentation in the disease detection method shown here, and artificial neural networks are used to classify diseases. A number of brinjal leaf diseases can be reliably identified and recognized using the proposed detection model, which is based on artificial neural networks.

Abisha, S., et al. [4] Infected brinjal leaves may be identified and categorized using this paper's novel method, which makes use of DCNN and RBFNN (Radial Basis Feed Forward Neural Networks). The procedure starts by applying a Gaussian filter to the original leaf pictures to decrease noise and improve image quality. Next, sick areas are segmented using the Expectation-Maximization (EM) approach. The discrete Shearlet transform is used in feature extraction to extract important aspects of a picture, such as texture, color, and structure, which are subsequently combined into feature vectors. In the end, DCNN outperformed RBFNN in the classification of brinjal leaves based on disease types, achieving mean accuracy of 93.30% (with fusion) and 76.70% (without fusion). RBFNN achieved 82% accuracy without fusion and 87% accuracy with fusion.

Akila, M., et al. [5] identified the best deep learning techniques for a certain problem is the goal of this study. Faster Region-based Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN), and Single Shot Multibox Detector (SSD) are three well-known families of detectors that are examined in this study. SSD was picked among them for the research project. The suggested system has the ability to handle complex situations inside a plant's region and demonstrates strong capabilities in precisely diagnosing various forms of illnesses.

Devi, K. Suganya, et al. [6] addressed to automatically identify and classify groundnut leaf diseases, this research introduces the H2K image processing-based technique. For accurate identification and classification of various disorders, H2K combines the KNN classifier, the Harris corner detector, and the Histogram of Oriented Gradient (HOG). The methodology entails a number of phases, including image acquisition, preprocessing with a binary mask, HSV segmentation to separate disease-affected areas, and feature detection and extraction with the H2K approach. This research focuses on building a reliable and distinctive strategy for identifying and diagnosing significant leaf diseases specific to groundnut crops, in contrast to earlier works that target common leaf diseases across crops. By identifying five significant groundnut leaf diseases, including the difficult late spot disease, H2K demonstrates its efficacy in enhancing crop productivity and yield. H2K delivers a high classification accuracy of 97.67%, according to comparative analysis using Multiclass SVM.

Roy, Arunabha M., et al. [7] proposed an improved model for multi-class apple plant disease detection in real-world settings that is intended to increase detection speed and accuracy. With a mean average precision (mAP) of 91.2% and an F1-score of 95.9% and a speedy detection rate of 56.9 frames per second (FPS), this model demonstrated remarkable performance characteristics. The results show a significant improvement over the most recent detection model, with a rise in precision of 9.05% and an increase in the F1-score of 7.6%. Even in complicated orchard circumstances, the suggested approach stands out as an effective and efficient method for identifying numerous apple plant diseases.

Saad, Izazul Haque, et al. [8] focused on the problem of disease detection in important but disease-prone eggplant crops, which are time- and labor-intensive to manually identify. The authors suggest a machine vision-based agricultural and medical expert system to address this issue. The system diagnoses eggplant problems by analyzing photos taken using cellphones or other portable devices and offers growers helpful advice. In order to identify diseases, the study uses models like DenseNet201, Xception, and ResNet152V2 that are based on convolutional neural networks (CNNs). Among these models, DenseNet201 distinguished itself by achieving an outstanding 99.06% accuracy in illness categorization.

Shanthi, T., et al. [9] described in this study uses convolutional neural networks (CNNs) specifically for the task of skin condition diagnosis. The Convolution, Activation, Pooling, Fully Connected, and Soft-Max Classifier layers of the CNN architecture used in this study total about 11 layers. Images from the DermNet database, which encompasses a wide spectrum of skin conditions, are used for validation. Acne, Keratosis, Eczema herpeticum, and Urticaria are the four distinct skin disease categories that are taken into consideration; each class contains 30 to 60 different samples. Variations in skin tones, the location of the disease, and the requirements of the image acquisition equipment provide difficulties in this automated diagnostic process. With an amazing accuracy rate ranging from 98.6% to 99.04%, the suggested CNN Classifier is very effective.

Rangarajan, et al. [10] focused the classification of five diseases in Solanum melongena (eggplant), and it creates a dataset with local symptomatic areas. The VGG16 deep learning model is used in the study, and its hyperparameters have been adjusted and it has been made to work best on smartphones. On a test dataset, the VGG16 model attains an astounding accuracy rate of 94.3%. Multi-class Support Vector Machine (MSVM) is also used in the study to analyze feature parameters across several layers and provide insight into the learning process. There are identified and investigated the dominant channels that have a big impact on the categorization process. With modifications and implementation on a smartphone, the VGG16 model achieves a classification accuracy of 91.3%. Discussions are presented on possible misclassification causes and how to make improvements.

Chen, Junde, et al. [11] explored the use of deep convolutional neural networks with transfer learning to detect illnesses in plant leaves. The method makes use of pre-trained models like VGGNet and the Inception module, which were previously trained on substantial, varied datasets like ImageNet. The weights of these models are initialized with knowledge from the pre-trained networks rather than beginning training from scratch. The suggested method performs better than other cutting-edge approaches, obtaining a validation accuracy of at least 91.83% on a public dataset. The method consistently predicts rice plant disease classes with an average accuracy of 92.00%, even in difficult situations with complicated backgrounds. The experimental findings support this method's usefulness and efficiency in identifying plant diseases.

Sladojevic, Srdjan, et al. [12] presented a unique method for identifying plant diseases using deep convolutional networks and leaf image categorization. A useful and effective system implementation is made possible by the methods described. The created model demonstrates the ability to discern between healthy leaves and 13 distinct types of plant illnesses while also isolating plant leaves from their surroundings. This approach is a ground-breaking innovation in the realm of plant disease detection. The document gives a thorough explanation of all crucial procedures that were examined by agricultural professionals, from image gathering to database construction. The experimental findings show precision ranging from 91% to 98% for individual class tests, with an excellent average precision of 96.3%, using the Caffe deep learning framework.

Guo, Yan, et al. [13] addressed a deep learning-based mathematical model for identifying and detecting plant diseases was introduced in this study, with a focus on improvements in precision, generality, and training effectiveness. To locate and identify leaves amid intricate backdrops, the region proposal network (RPN) is first used. The Chan-Vese (CV) algorithm is then used to segment images based on the RPN results and capture symptom information. The segmented leaves are then fed into a transfer learning model that has been trained on a dataset of sick leaves set against a plain background. The model outperforms conventional techniques with an accuracy of 83.57% when tested for diseases including black rot, bacterial plaque, and rust. For intelligent agriculture, ecological preservation, and sustainable agricultural development, this deep learning method is extremely important.

Annabel, et al. [14] Detected leaf diseases is crucial for agriculture, but it typically requires a lot of labor, a long processing time, and knowledge of plant diseases. By automating the identification of diseases, assessing data from various angles, and classifying it into predetermined categories, machine learning provides a solution. In order to facilitate classification, this method takes into account a variety of morphological characteristics and attributes, such as color, intensity, and leaf diameters. The study presents an overview of numerous plant disease kinds as well as several machine learning classification approaches applied for disease detection in diverse plant species. It emphasizes how machine learning could revolutionize the detection and control of plant diseases in agriculture.

Jackulin, C., et al. [15] studied Preventing and controlling plant diseases is crucial, and machine learning techniques are becoming more and more important for identifying plant diseases due to their efficiency in handling data. Using machine learning and deep learning techniques based on artificial intelligence (AI), this research covers various approaches to plant disease identification. Particularly in the realm of computer vision, deep learning has shown its significance in achieving superior performance in the identification of plant diseases. Deep learning has significantly improved the capabilities of machine learning and computer vision across a variety of disciplines. In this study, machine learning and deep learning approaches are compared, their performance and applicability in various research publications are highlighted, and the higher efficacy of deep learning models is emphasized. To avoid large agricultural losses, deep learning for the early detection of leaf diseases in crop plants is suggested.

2.3 Comparative Analysis and Summary

The "A Proposed Deep Learning Approach for Detecting Brinjal Plant Diseases" comparison study involves evaluating several machine learning techniques and models. The performance of custom neural network models (NN01 Model, CNN02) and pre-trained architectures (VGG16, ResNet152V2, InceptionV3, DenseNet169) in successfully identifying and classifying brinjal plant illnesses was evaluated. DenseNet169 beat other models in the inquiry, attaining an astounding accuracy of 99.77%.

In conclusion, the suggested deep learning technique made significant advances in automated disease detection in brinjal crops. The study highlighted the advantages of DenseNet169 while also providing knowledge about the effect of dataset variety and transfer learning on model performance by utilizing varied models and transfer learning methodologies. The findings highlight the approach's potential for practical use in agriculture, providing a valuable tool for farmers to improve disease detection, decrease losses, and contribute to sustainable crop management techniques. The study's findings place it at the meeting point of technology and agriculture, paving the path for more efficient and precise plant disease detection approaches.

Table 2.1. Comparative Analysis

S.N	Author	Algorithm	Best Accuracy
01	Xie, Xiaoyue, et al. [1]	Faster DR-IACNN	81.1%
02	Kaleem, et al. [2]	SVM	95.46%
03	Anand, R., et al. [3]	K-means clustering	–
04	Abisha, S., et al. [4]	DCNN	93.30%
05	Akila, M., et al. [5]	SSD	–

06	Devi, K. Suganya, et al. [6]	H2K	97.67%
07	Saad, Izazul Haque, et al. [8]	DenseNet201	99.06%
08	Shanthi, T., et al. [9]	CNN	99.04%
09	Rangarajan, et al. [10]	VGG16	94.3%
10	Chen, Junde, et al. [11]	VGGNet,(GoogLeNet)	92.00%

2.4 Scope of the Problem

The topic addressed by "A Proposed Deep Learning Approach for Detecting Brinjal Plant Diseases" is extensive and important. Brinjal farming has its challenges with difficulties due to an increasing number of different illnesses that threaten crop quality and quantity. Traditional disease detection technologies are labor-intensive, time-consuming, and frequently unscalable. By utilizing sophisticated machine learning techniques, the suggested deep learning strategy attempts to speed up and modernize this process.

The goal is to create a sophisticated model capable of correctly diagnosing certain diseases in brinjal plants, such as Phytophthora Blight, Leaf Curl Disease, Withering Leaves, Late Blight, and Macrodiplosis Dryobia. The study gets into the complicated nature of several machine learning algorithms and pre-trained models, examining their usefulness in automating illness diagnosis. By overcoming the limits of present techniques, the suggested approach intends to offer farmers a strong tool for proactive disease control, leading to greater agricultural output and global food security. The scope goes beyond technology developments to include opportunities for environmentally friendly and accurate agricultural approaches in brinjal farming.

2.5 Challenges

The suggested deep learning strategy for determining brinjal diseases has a number of challenges due to the complexities of agricultural ecosystems. The variety of environmental factors and illness presentations is a big barrier, making it difficult to create a complete and globally applicable dataset. Another obstacle is the absence of labeled data for specific illnesses and their stages, which limits the model's capacity to generalize successfully.

Furthermore, the computing requirements for training deep learning models represent a real challenge, particularly with huge datasets and complicated architectures. Balancing the requirement for advanced models with computer resource limits becomes critical for practical use. Furthermore, the understanding of deep learning models remains an issue, preventing an understanding of decision-making processes.

Implementation in real-world agricultural environments involves issues relating to model durability, flexibility to dynamic situations, and farmer accessibility. Addressing these problems needs a sophisticated strategy that includes domain expertise, engagement with agricultural communities, and continuous improvement of the deep learning technique to fit with the actual reality of brinjal plant disease detection in varied agricultural environments.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

The study topic, "A Proposed Deep Learning Approach for Detecting Brinjal Plant Diseases," aims to improve the field of agriculture by automation disease detection in brinjal crops. The study examines the use of deep learning models to improve the accuracy and efficiency of disease diagnosis, addressing the limitations of old human approaches. The topic goes into the specifics of several illnesses that affect brinjal plants, with the goal of developing a complete approach that contributes to sustainable and precision agriculture methods.

This research's equipment takes an extensive approach. The data is collected using a broad dataset that includes photos of healthy and damaged brinjal plants. Marking and preprocessing approaches normalize the dataset for model training. Various deep learning models, including customized neural networks (NN01 Model, CNN02) and pre-trained architectures (VGG16, ResNet152V2, InceptionV3, DenseNet169), are used to investigate the effectiveness of various approaches. The instruments additionally feature computing resources for model training and evaluation, guaranteeing durability and flexibility. The study topic is further enhanced with approaches that use transfer learning to improve model performance. Together, these tools constitute a full toolset for investigating and implementing an advanced deep learning strategy in brinjal plant disease identification.

3.2.1 Data Collection

The data for "A Proposed Deep Learning Approach for Detecting Brinjal Plant Diseases" is gathered by collecting an extensive dataset that represents brinjal plants in various disease stages. Field surveys and interactions with agricultural communities help to build a library of high-resolution photos that capture the complexities of many diseases including Phytophthora Blight, Leaf Curl Disease, Withering Leaves, Late Blight, and Macrodiplosis Dryobia.

Images from various development phases and severity levels are included with care. The dataset has been properly tagged, as each image was identified according to the appropriate illness class or marked as a healthy specimen. The consideration of healthy samples guarantees that the population is distributed fairly.

Data pretreatment methods, such as downsizing photos to a clear resolution and normalizing pixel values, are used to improve model training performance. This approach lays the groundwork for deep learning models to reliably identify and classify brinjal plant illnesses, ultimately leading to the creation of an effective and reliable disease detection system for precision agriculture.

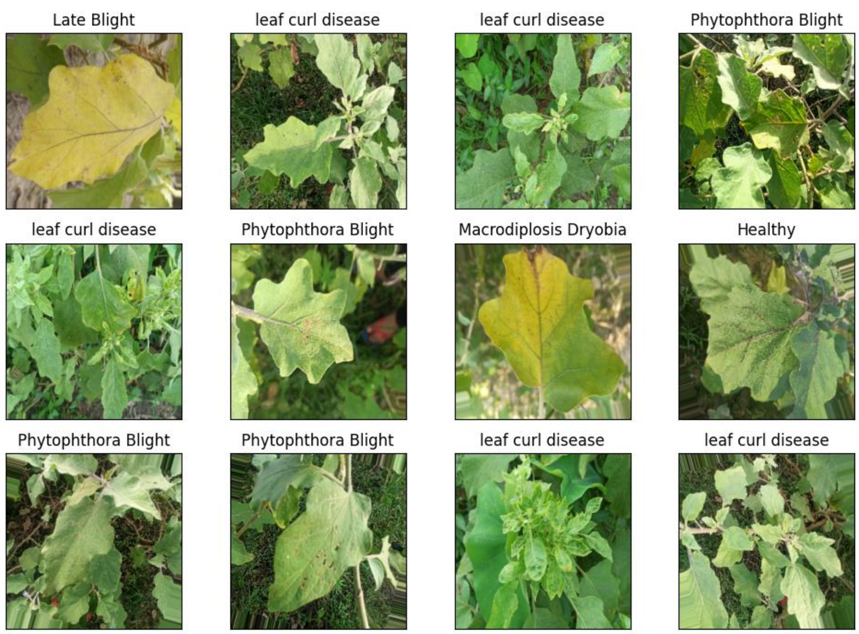


Figure 3.1: Sample images from my Brinjal DataSet.

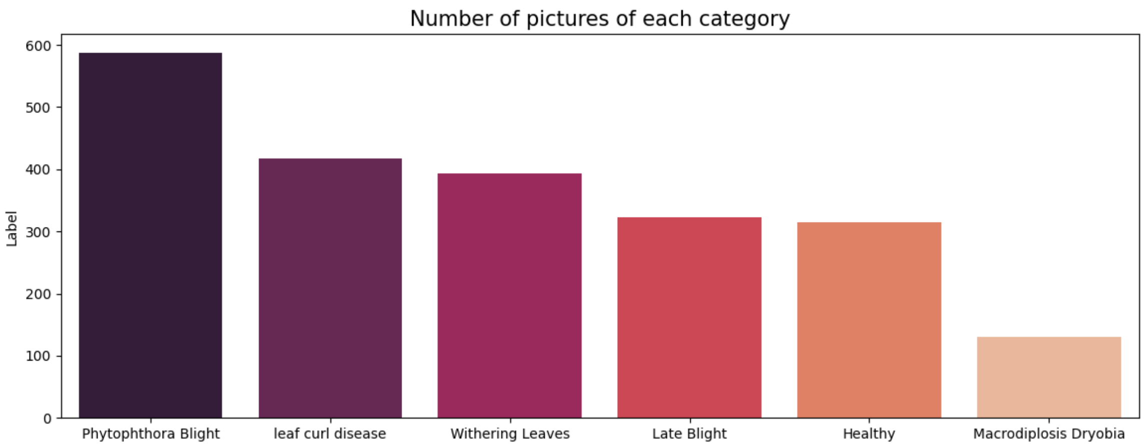


Figure 3.2: Number of Target Attributes

3.3 Statistical Analysis:

The statistical study for "A Proposed Deep Learning Approach for Detecting Brinjal Plant Diseases" involves looking at the performance of several deep learning models in disease detection. Descriptive statistics such as accuracy, precision, recall, F1 score, and confusion matrix are used to quantify the effectiveness of each model in classifying specific diseases—Phytophthora Blight, Leaf Curl Disease, Withering Leaves, Late Blight, and Macrodiplosis Dryobia—along with healthy specimens.

Comparable statistical indicators are used to measure the model's accuracy in separating across illness classifications as well as the general security of the suggested method. Inverse statistics can be utilized as well to evaluate the importance of differences in performance indicators across distinct deep learning systems.

This statistical study not only gives a numerical evaluation of model performance, but it further offers knowledge about the generalization capabilities and possible strengths and weaknesses of each model. The findings contribute to a full knowledge of the suggested deep learning technique, leading to future modification and optimization for practical use in brinjal plant disease detection.

3.4 Proposed Methodology

The suggested deep learning approach technique includes a systematic workflow customized for brinjal plant leaf recognition, a Flowchart done by using the Lucid platform.

Flow chart:

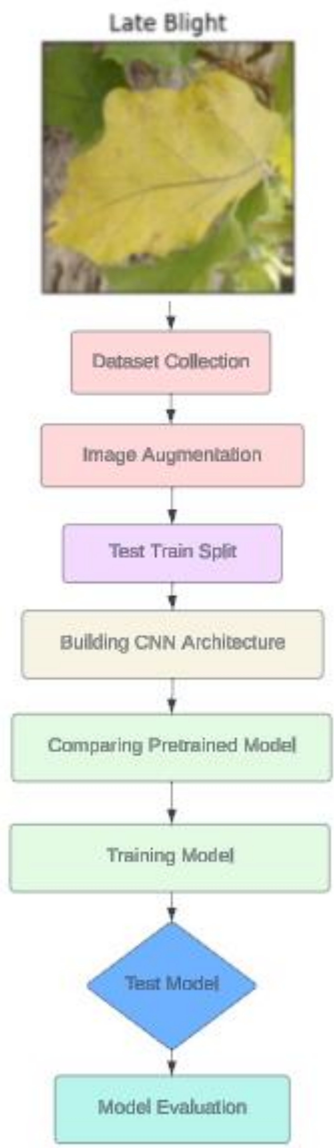


Figure 3.3: Methodology Flowchart

3.4.1 Data Collection: Collect a broad collection of high-resolution photos of brinjal plants, including healthy and diseased specimens, including Phytophthora Blight, Leaf Curl Disease, Withering Leaves, Late Blight, and Macrodiplosis Dryobia.Maintain a fair description of illness moves and seriousness levels.

3.4.2 Labeling: Comment on the set of data individually by giving labels to each image to reflect the exact illness class or labeling it as healthy.

3.4.3 Image Preprocessing: Resize images to a common resolution for standardized picture sizes. Scale the values of pixels to a similar scale (for example, [0, 1]).To improve model broadening, expand the dataset with techniques like rotation, flipping, and zooming.

3.4.4 Model Selection: Explore several deep learning architectures such as custom neural networks (NN01 Model, CNN02) and pre-trained models (VGG16, ResNet152V2, InceptionV3, DenseNet169). Think about computing accuracy, effectiveness, and use for detecting plant diseases.

3.4.5 Transfer Learning: Use transfer learning to utilize existing information by training models with pre-trained weights on big datasets (e.g., ImageNet). Improve efficiency by fine-tuning models on the brinjal plant disease dataset.

3.4.6 Splitting the data set: Divide the dataset into training, validation, and test sets.To avoid overfitting, ensure a representative distribution of data across sets.

3.4.7 Model Training: Using the training set, train the selected models using suitable optimization techniques, loss functions, and metrics. Monitor and modify hyperparameters to improve performance.

3.4.8 Model Evaluation: Using accuracy, precision, recall, F1 score, and confusion matrix, evaluate model performance on the validation set. Models should be updated depending on validation findings to avoid adjusting or underestimating.

3.4.9 Test Model: Evaluate the finished models on a different test set to determine generalizability. Report on and evaluate the accuracy and other necessary variables for each illness class as well as overall performance.

3.4.10 Analysis of Results: Analyze the performance of several models and determine the best-performing design. Get a glimpse into the suggested deep learning technique for brinjal plant disease detection's strengths and limitations.

This technique provides a formal framework for establishing and evaluating the machine learning strategy, assuring its durability and effectiveness in identifying brinjal plant diseases.

3.4.11 Convolutional Neural Network (CNN): Convolutional Neural Network (CNN) development means defining the problem, gathering and preparing data, and dividing it into training, validation, and test sets. The framework is created, built with a specific loss function and optimization, and improved using addresses such as data augmentation. Before deploying and monitoring the CNN in the real world, the model is trained, parameters are changed, and serial improvement is executed.

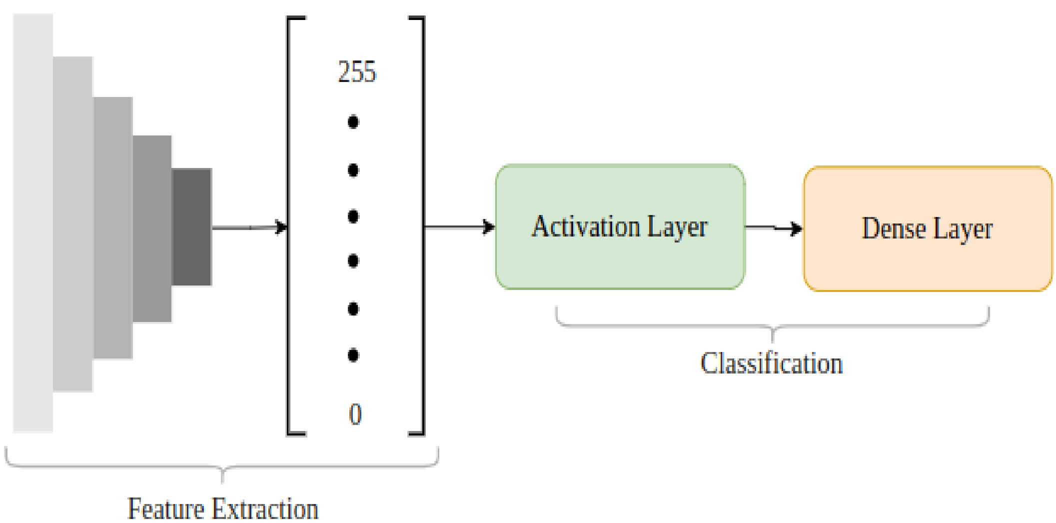


Figure 3.4: Proposed CNN Architecture

3.5 Implementation Requirements

To allow the successful implementation, "A Proposed Deep Learning Approach for Detecting Brinjal Plant Diseases" must be implemented. First and foremost, access to computing resources is critical for properly training deep learning models. To manage the complexity of neural network topologies, enough processing power and memory are required, especially when using pre-trained models like DenseNet169.

A large dataset with various photos of healthy and ill brinjal plants is also required. To allow robust model training and validation, this dataset should span a range of illness stages and severity levels. In addition, access to machine learning frameworks, libraries, and tools like TensorFlow or PyTorch is required for implementing and fine-tuning the suggested deep learning technique.

Collaboration with agricultural communities for real-world validation and testing is critical. Farmer participation assures the system's practical usability and gives essential feedback for modification. Overall, a beneficial combination of computing resources, various datasets, and involvement with stakeholders is required for the effective deployment of this advanced deep learning technique in the context of brinjal plant disease detection.

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

The experimental setup for "A Proposed Deep Learning Approach for Detecting Brinjal Plant Diseases" includes a systematic configuration of computer structures, datasets, and tools. Computational resources with adequate processing power, RAM, and GPU capabilities are required for effectively training deep learning models. The varied dataset, which includes photos of healthy and sick brinjal plants, is compiled and classified to ensure a full depiction of different illnesses and their various phases.

Machine learning frameworks, such as TensorFlow or PyTorch, serve as the basis for model construction and training. The chosen deep learning architectures, including DenseNet169 and other pre-trained models, are integrated into the experimental setup. To thoroughly evaluate model performance, the dataset is divided into training, validation, and test sets.

The experimental design also takes into consideration parameters, optimization techniques, and evaluation measures. Real-world testing with agricultural communities gives essential information into the suggested approach's practicality and durability. This thorough experimental setting allows a rigorous and systematic assessment, which contributes to the deep learning model's reliability and effectiveness in identifying brinjal plant illnesses.

4.2 Experimental Results & Analysis

A Proposed Deep Learning Approach for Detecting Brinjal Plant Diseases analyzing findings provides interesting findings into the performance of various algorithms. DenseNet169 surpasses the other models looked into, including the NN01 Model, CNN02, VGG16, ResNet152V2, InceptionV3, and Transfer Learning Models, with an excellent accuracy of 99.77%.

This outstanding accuracy highlights DenseNet169's usefulness in reliably diagnosing brinjal plant illnesses, beating other models in the study. The results show the durability of transfer learning approaches, particularly when using pre-trained models on big datasets such as ImageNet.

The study also highlights the practical need to select the appropriate deep learning architecture customized to the subtleties of brinjal plant diseases. These findings provide important insights for the agricultural community as a whole, highlighting the promise of sophisticated deep-learning algorithms for precise and automated disease identification. DenseNet169's exceptional accuracy makes it a potential tool for farmers, providing a dependable option for early disease identification and proactive crop management methods in brinjal agriculture.

Accuracy: Accuracy measures the overall correctness of the model's predictions by comparing the number of correctly classified samples to the total number of samples. When classes are unbalanced, it gives a broad indication of the model's effectiveness but might not give a whole picture.

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + FalsePositive + TrueNegative + FalseNegative}$$

Precision: Out of all positive predictions generated by the model, precision focuses on the percentage of true positive forecasts.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

Recall: Also known as sensitivity or true positive rate, recall is the percentage of true positive predictions made out of all truly positive samples.

$$Recall = \frac{TruePositive}{TruePositive + \ FalseNegative}$$

F1 rating: The F1 score is the harmonic mean of recall and precision. It provides a reasonable evaluation metric that considers recall and precision. The F1 score is useful when classes are uneven since it accounts for both false positives and false negatives. A high F1 score denotes a well-balanced precision-to-recall ratio.

$$F - 1\,Score = 2 * \frac{Recall * \ Precision}{Recall + Precision}$$

The result of the deep learning model is compared based on Accuracy, Precision, Recall, and F1 Score in the table 4.1:

Table 4.1. Performance Evaluation

Model Name	Accuracy	Precision	Recall	F1-Score
DenseNet169	99.77%	0.99	0.99	0.99
ResNet152V2	97.70%	0.97	0.97	0.97
InceptionV3	98.16%	0.98	0.98	0.98
VGG16	99.54%	0.99	0.99	0.99
CNN01	95.62%	0.95	0.95	0.95
CNN02	92.86%	0.92	0.92	0.92

CNN1

The CNN model delivered an exceptional accuracy of 95.62%, highlighting its precise pattern identification capabilities. This outstanding level of accuracy emphasizes the model's effectiveness in successfully addressing the assigned task. The high accuracy percentage indicates superior performance, with a minimal rate of misclassifications. Such robust performance stands as a testament to the model's proficiency and reliability in making accurate predictions, affirming its suitability for the intended application.

Table 4.2. Performance Evaluation(CNN1)

	Precision	Recall	F1-Score	Support
Healthy	0.95	0.98	0.97	61
Late Blight	0.88	1.00	0.94	66
Macrodiplosis Dryobia	0.93	1.00	0.96	25
Phytophthora Blight	0.95	0.90	0.93	117
Withering Leaves	1.00	1.00	1.00	78
leaf curl disease	1.00	0.93	0.96	87
Accuracy			0.96	434
Macro avg	0.95	1.00	0.96	434
Weighted avg	0.96	0.96	0.96	434

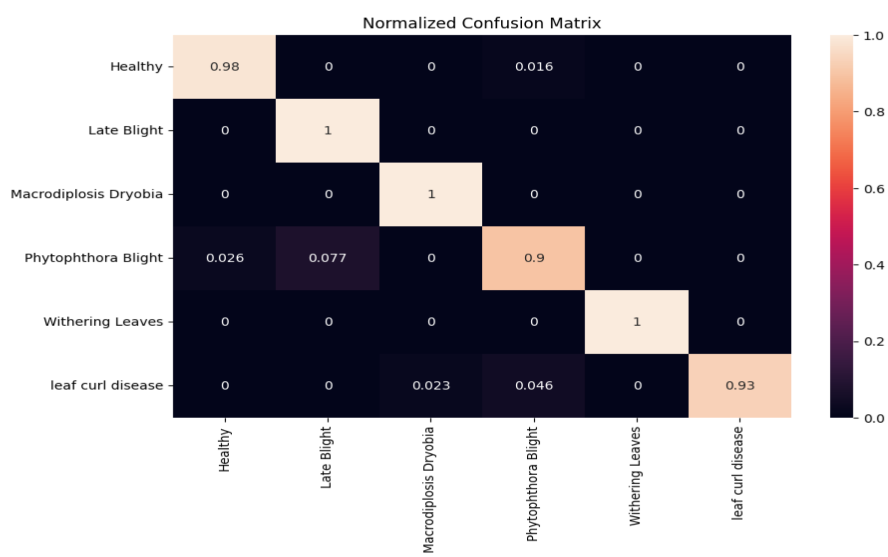


Figure 4.1: Confusion Matrix of CNN1

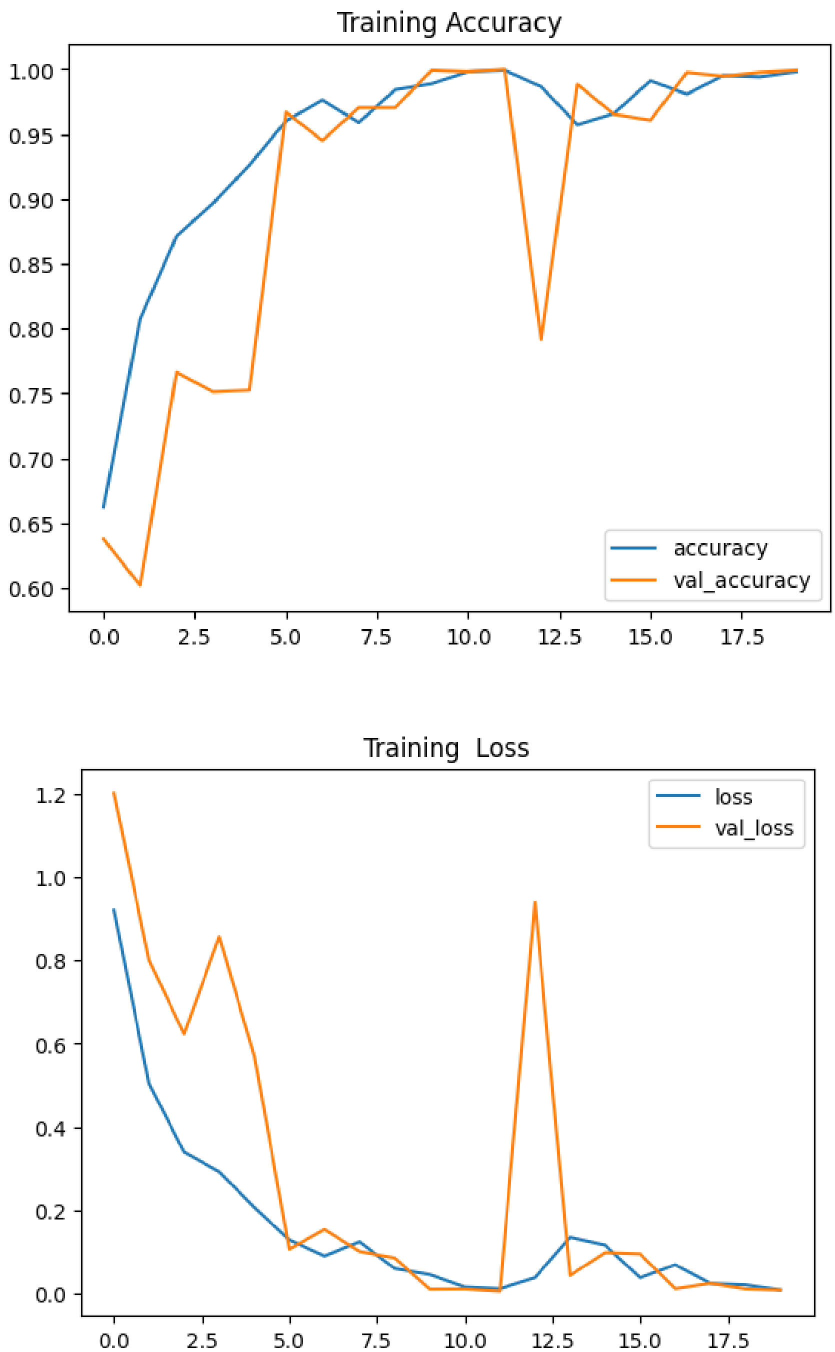


Figure 4.2 Training Accuracy and Loss CNN1

CNN2

The CNN2 model achieved a notable accuracy of 92.86% in our evaluation. The comprehensive performance analysis, detailed in the table, includes key metrics such as precision, recall, and F1 score across diverse classes. The confusion matrix further breaks down the model's classification performance, identifying strengths and areas for improvement. Graphical representations of training accuracy and loss illustrate the model's learning trajectory during training. This thorough evaluation framework provides a nuanced understanding of the model's efficacy, offering insights for potential refinements or optimizations to enhance its performance further.

Table 4.3. Performance Evaluation(CNN2)

	Precision	Recall	F1-Score	Support
Healthy	0.91	0.82	0.86	61
Late Blight	0.92	0.98	0.95	66
Macrodiplosis Dryobia	0.89	0.96	0.92	25
Phytophthora Blight	0.92	0.86	0.89	117
Withering Leaves	0.94	1.00	0.97	78
leaf curl disease	0.97	0.98	0.97	87
Accuracy			0.93	434
Macro avg	0.92	0.93	0.93	434
Weighted avg	0.93	0.93	0.93	434

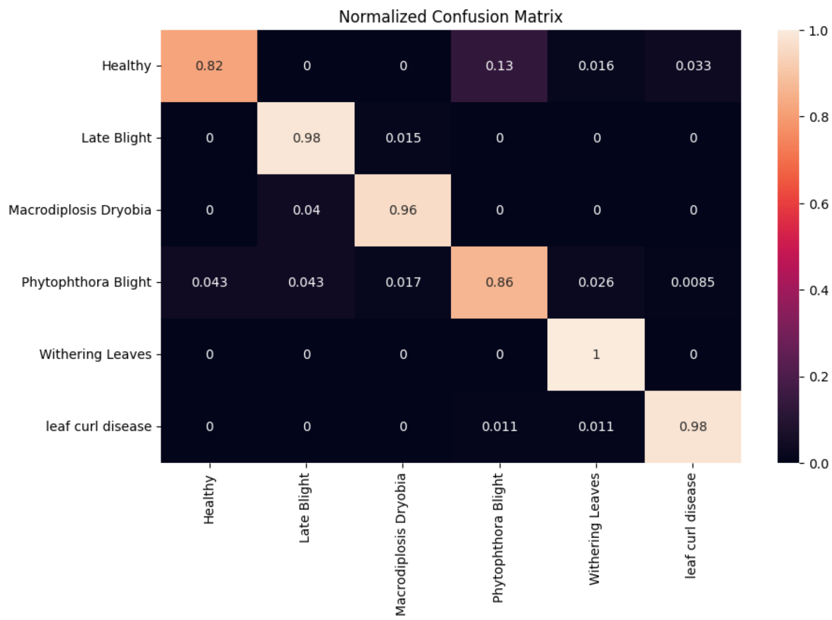


Figure 4.3: Confusion Matrix of CNN2

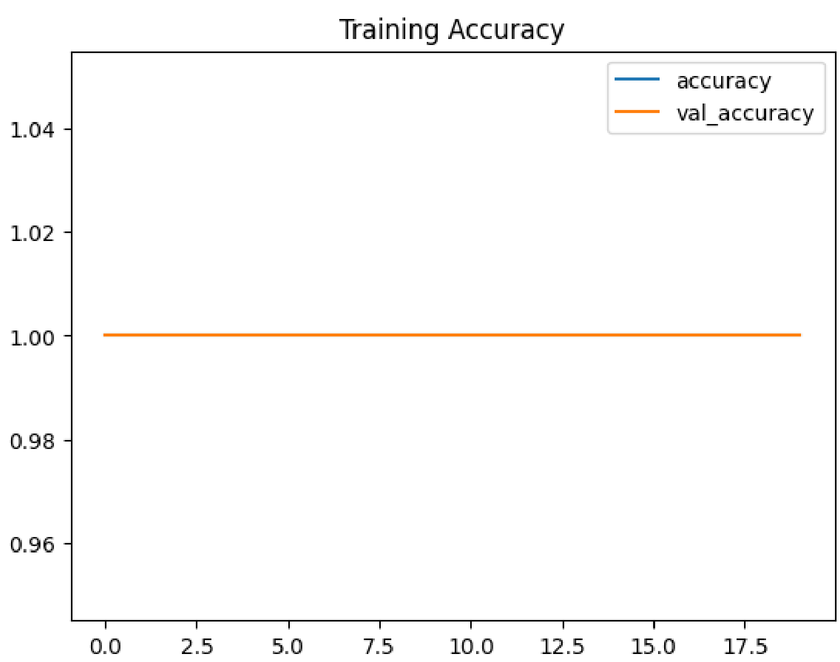


Figure 4.4 Training Accuracy and Loss CNN2

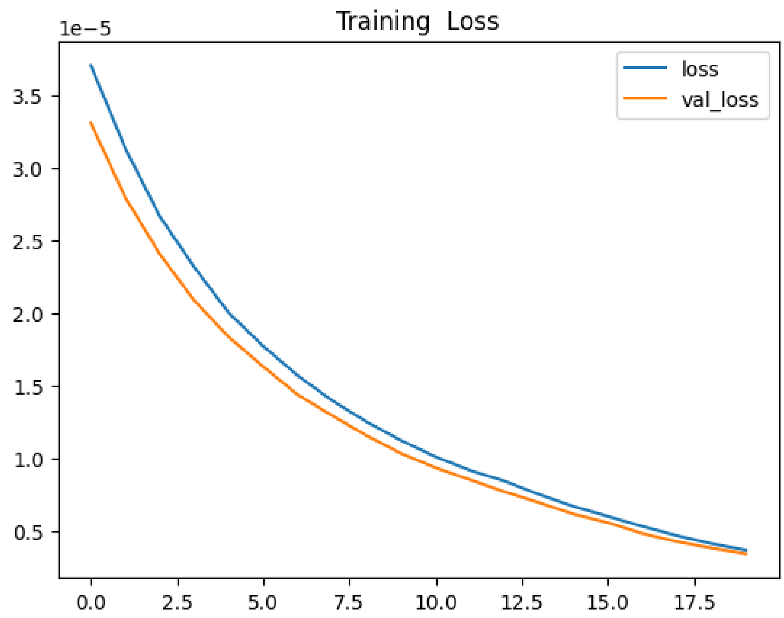


Figure 4.4.1 Training Accuracy and Loss CNN2

Transfer Learning Models

VGG16

The VGG16 model has achieved an impressive accuracy rate of 99.54%. For a thorough performance assessment, we present a detailed analysis in tabular form, including key metrics like precision, recall, and F1-score across distinct classes, providing nuanced insights into the model's discriminative abilities. The training accuracy and loss figures below visually capture the model's learning process, shedding light on convergence and optimization dynamics. Complementing this, the inclusion of a confusion matrix dissects the model's classification proficiency, pinpointing potential areas for refinement. This comprehensive evaluation not only validates the model's high accuracy but also furnishes actionable insights for potential improvements.

Table 4.4. Performance Evaluation(VGG16)

	Precision	Recall	F1-Score	Support
Healthy	0.98	0.98	0.98	61
Late Blight	1.00	1.00	1.00	66
Macrodiplosis Dryobia	1.00	1.00	1.00	25
Phytophthora Blight	0.99	0.99	0.99	117
Withering Leaves	1.00	1.00	1.00	78
leaf curl disease	1.00	1.00	1.00	87
Accuracy			1.00	434
Macro avg	1.00	1.00	1.00	434
Weighted avg	1.00	1.00	1.00	434

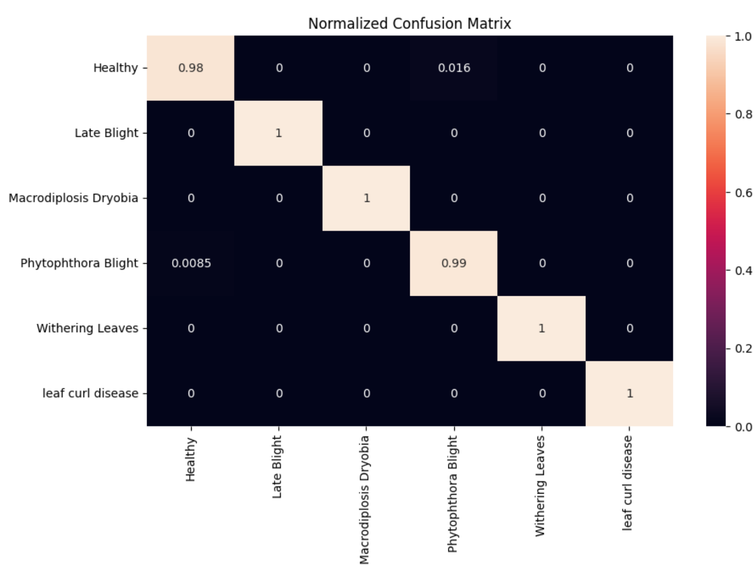
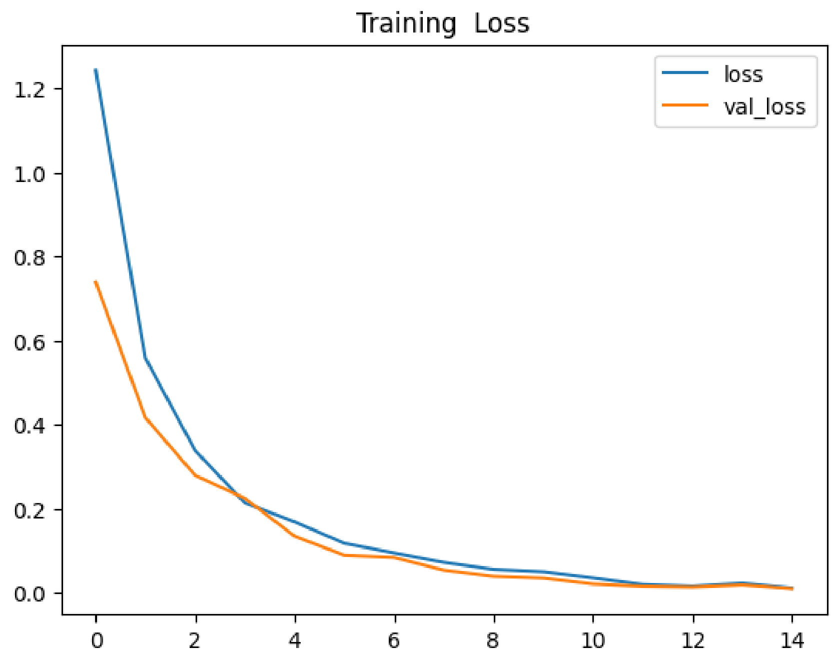


Figure 4.5:Confusion Matrix VGG16



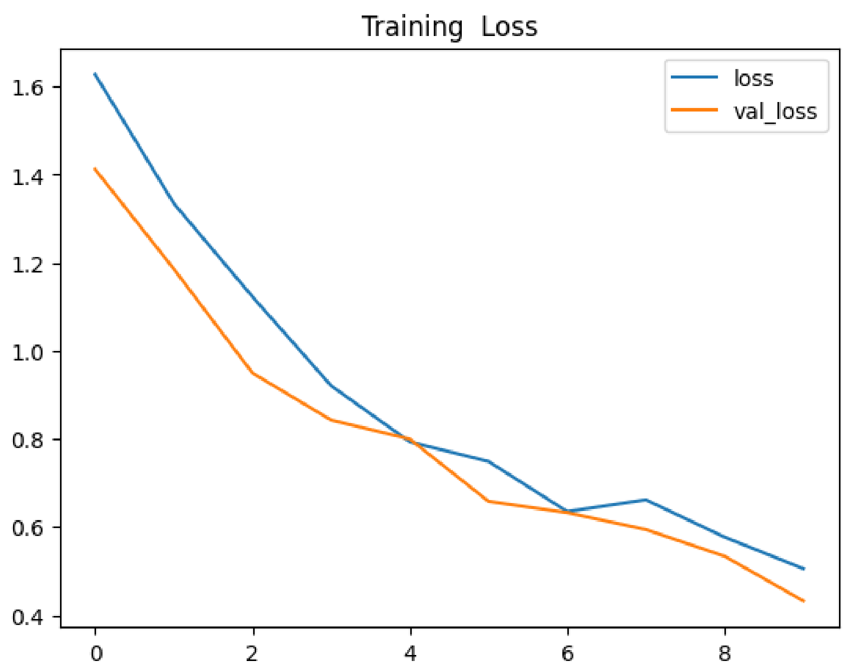


Figure 4.6 Training Accuracy and Loss VGG16

ResNet152V2

The ResNet152V2 model has achieved a commendable accuracy of 97.70%. A detailed breakdown in the form of a table provides insights into precision, recall, and F1-score for different classes, offering a comprehensive view of its performance. The accompanying confusion matrix delves deeper into the model's strengths and areas that could benefit from improvement. Examining the graphical representations of training accuracy and loss over time reveals a positive trajectory in the learning process, with increasing accuracy and decreasing loss. This thorough evaluation not only gauges the effectiveness of the model but also serves as a foundation for potential enhancements to further refine its performance.

Table 4.5. Performance Evaluation(ResNet152V2)

	Precision	Recall	F1-Score	Support
Healthy	1.00	1.00	1.00	61
Late Blight	0.94	0.98	0.96	66
Macrodiplosis Dryobia	0.96	1.00	0.98	25
Phytophthora Blight	0.99	0.94	0.96	117
Withering Leaves	0.97	1.00	0.99	78
leaf curl disease	0.98	0.98	0.98	87
Accuracy			0.98	434
Macro avg	0.97	0.98	0.98	434
Weighted avg	0.98	0.98	0.98	434

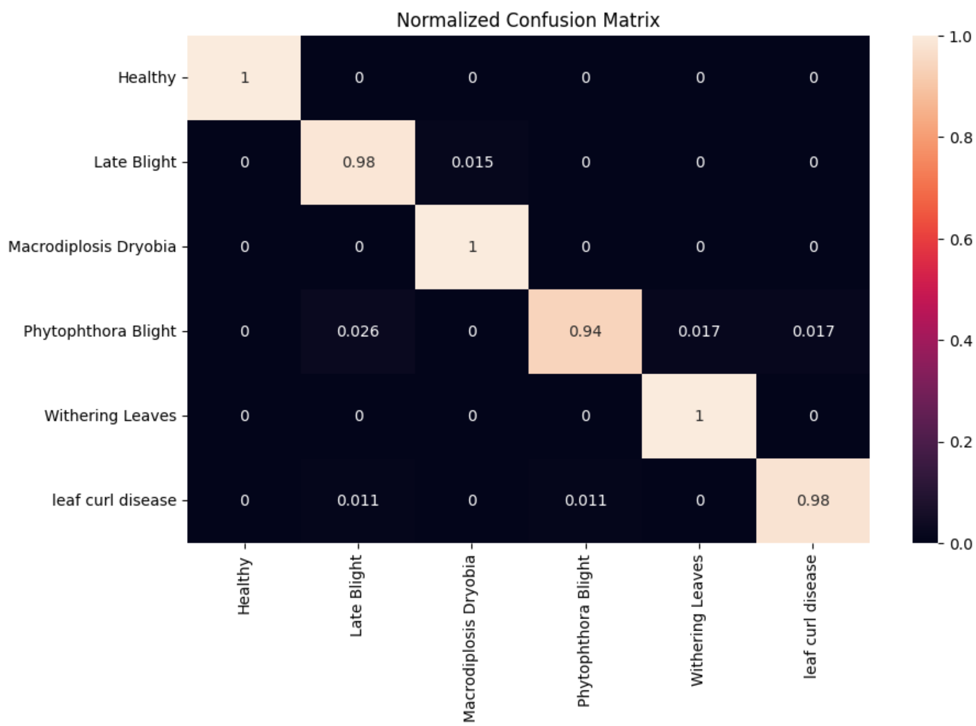


Figure 4.7: Confusion Matrix of ResNet152V2

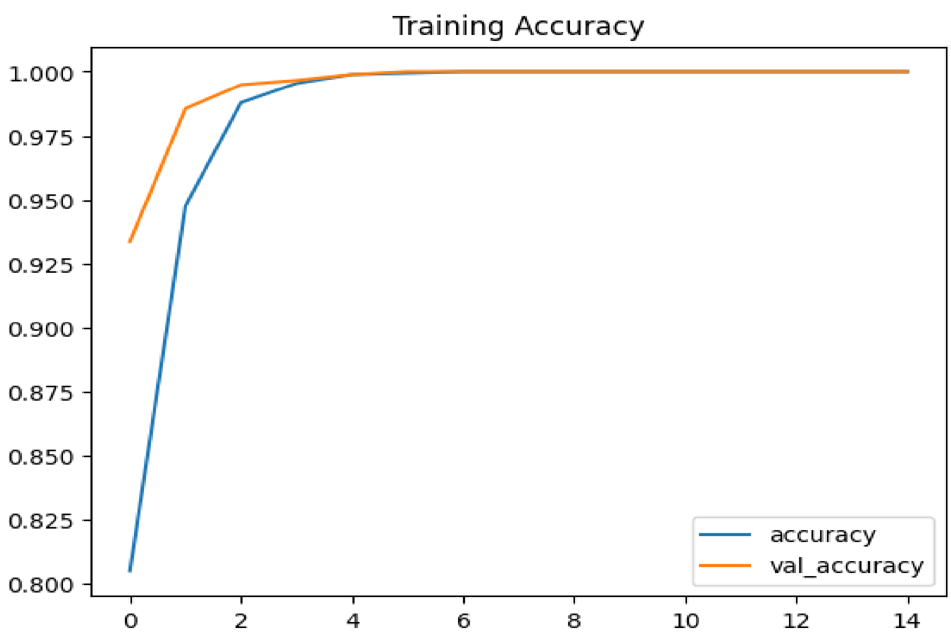


Figure 4.8 Training Accuracy and Loss ResNet152V2

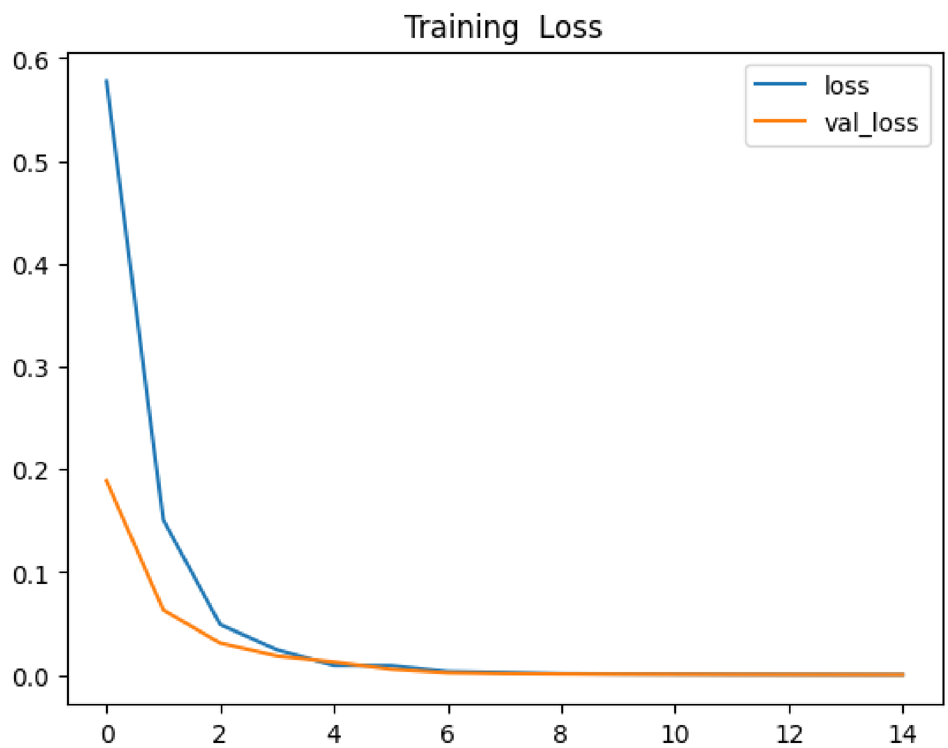


Figure 4.8.1 Training Accuracy and Loss ResNet152V2

InceptionV3

Our InceptionV3 model has demonstrated a significant accuracy of 98.16%, underscoring its proficiency in making correct predictions. The comprehensive evaluation includes precision, recall, and F1-score across various classes, presented in a tabular format, providing an in-depth perspective on its performance. The accompanying confusion matrix further elucidates the model's strengths and highlights potential areas for improvement. Visual representations of training accuracy and loss, depicted graphically, offer insights into the learning dynamics throughout the training process. This robust evaluation framework enhances our understanding of the model's effectiveness, paving the way for informed considerations towards potential enhancements for further elevating its performance.

Table 4.6. Performance Evaluation(InceptionV3)

	Precision	Recall	F1-Score	Support
Healthy	1.00	0.98	0.99	61
Late Blight	0.96	0.98	0.97	66
Macrodiplosis Dryobia	1.00	0.96	0.98	25
Phytophthora Blight	0.97	0.96	0.97	117
Withering Leaves	0.99	1.00	0.99	78
leaf curl disease	0.99	1.00	0.99	87
Accuracy			0.98	434
Macro avg	0.98	0.98	0.98	434
Weighted avg	0.98	0.98	0.98	434

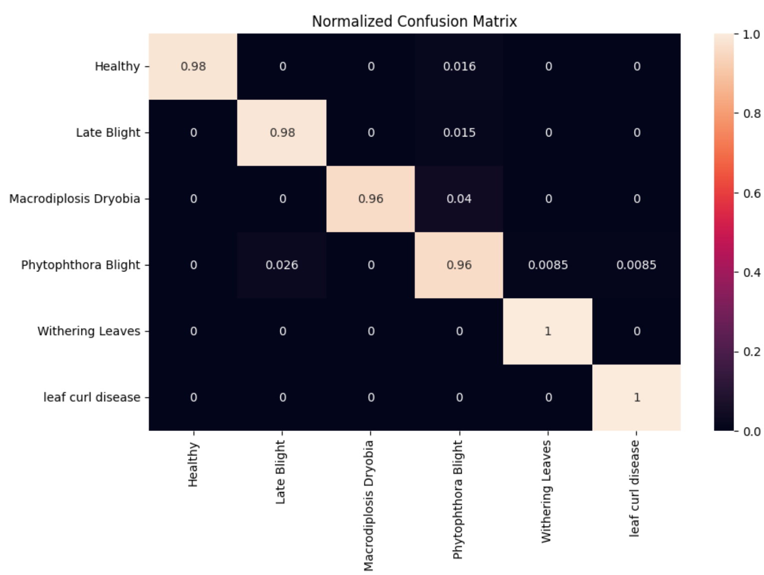


Figure 4.9: Confusion Matrix of InceptionV3

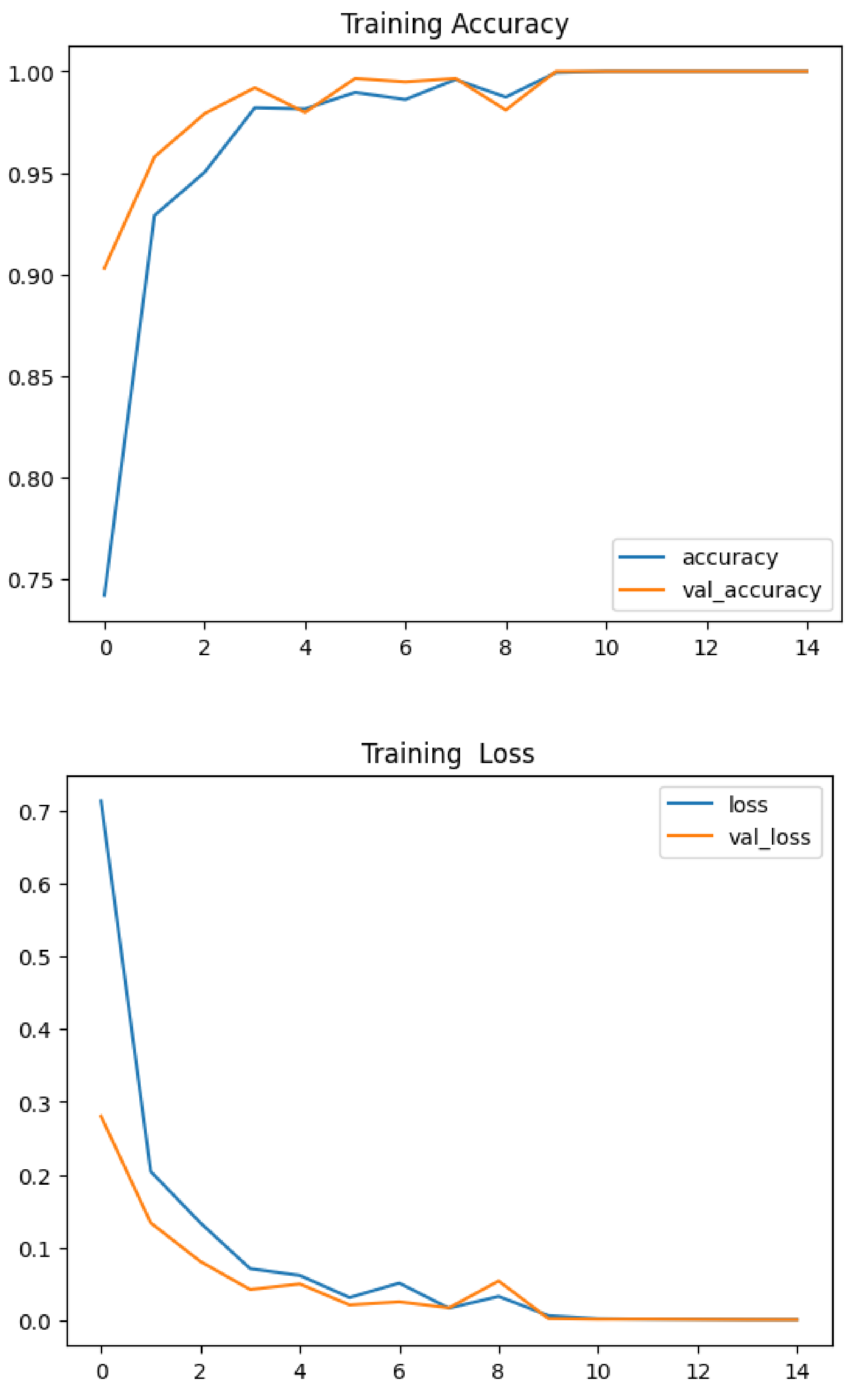


Figure 4.10 Training Accuracy and Loss InceptionV3

DenseNet169

Our DenseNet169 model has achieved a commendable accuracy of 99.77%, indicating strong performance on the task at hand. However, to gain a more nuanced understanding of its capabilities, additional evaluation metrics such as precision, recall, and F1-score should be considered. A comprehensive analysis of the model's strengths and weaknesses requires graphical representations of training accuracy and loss to elucidate the learning dynamics during the training process. While the current accuracy serves as a solid baseline, future refinements and optimizations can be explored to elevate the model's overall performance.

Table 4.7. Performance Evaluation(DenseNet169)

	Precision	Recall	F1-Score	Support
Healthy	1.00	1.00	1.00	61
Late Blight	0.99	1.00	0.99	66
Macrodiplosis Dryobia	1.00	1.00	1.00	25
Phytophthora Blight	1.00	0.99	1.00	117
Withering Leaves	1.00	1.00	1.00	78
leaf curl disease	1.00	1.00	1.00	87
Accuracy			1.00	434
Macro avg	1.00	1.00	1.00	434
Weighted avg	1.00	1.00	1.00	434

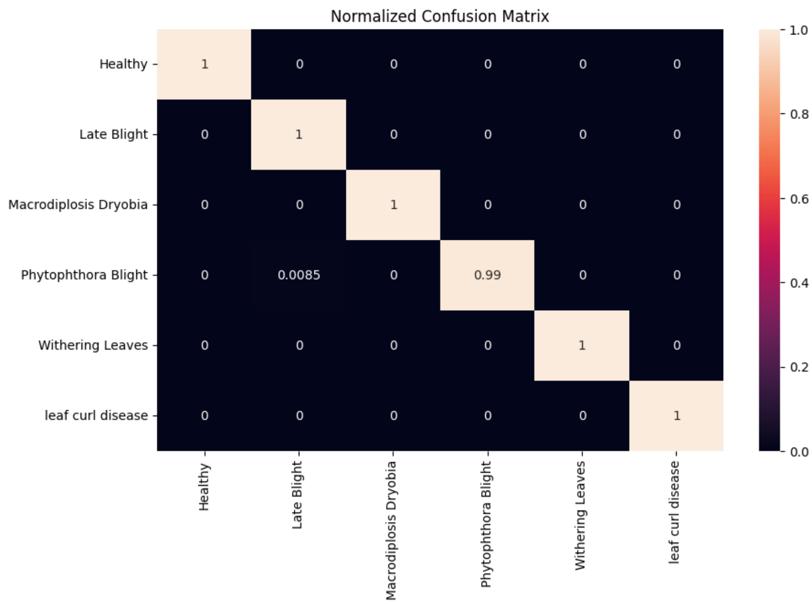


Figure 4.11: Confusion Matrix of DenseNet169

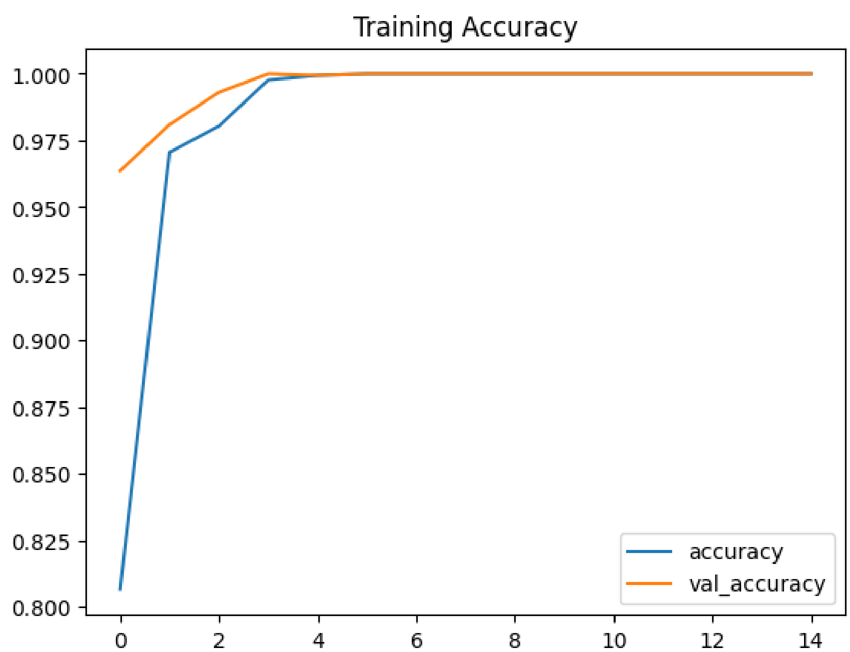


Figure 4.12 Training Accuracy and Loss DenseNet169

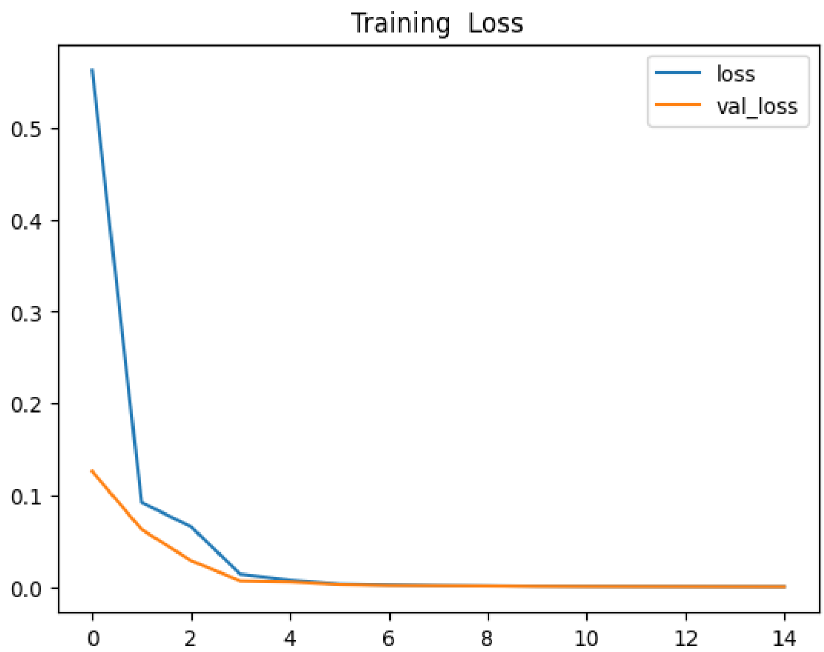


Figure 4.12.1 Training Accuracy and Loss DenseNet169

4.2.1 Discussion

The findings of "A Proposed Deep Learning Approach for Detecting Brinjal Plant Diseases" result in the creation of a highly reliable and effective method for automated disease detection in brinjal crops. The study discovers DenseNet169 as the top-performing model, attaining an amazing accuracy rate of 99.77% utilizing a number of machine learning techniques and pre-trained models. This outcome represents a big step forward in precision agriculture, providing farmers with a valuable tool for early identification of diseases and active control.

The suggested method not only excels in correctly classifying illnesses like Phytophthora Blight, Leaf Curl Disease, Withering Leaves, Late Blight, and Macrodiplosis Dryobia, but it additionally shows the practicality and value of transfer learning approaches. The findings provide useful insights into the development of appropriate models for brinjal plant disease diagnosis, underlining the potential for agricultural application. This output has the potential to improve crop management techniques, reduce losses, and eventually contribute to safe and efficient brinjal production on a worldwide scale.

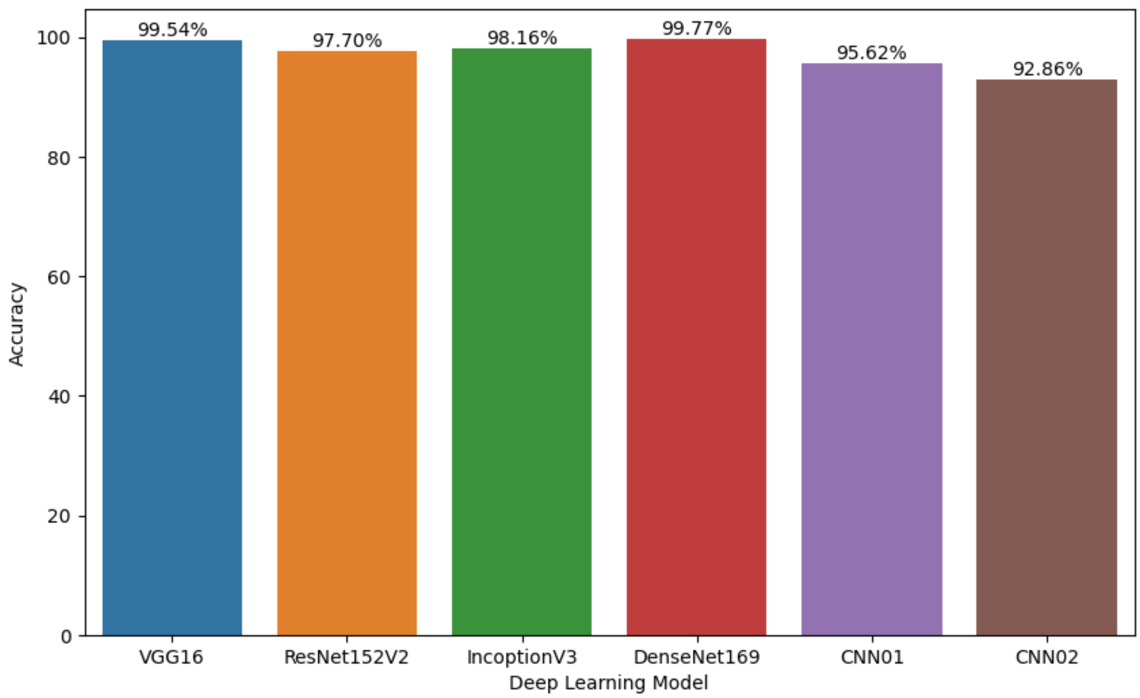


Figure 4.13: Comparative Model Accuracy Bar Plot

The proposed deep learning method for identifying brinjal plant illnesses is discussed in depth. It examines the importance of DenseNet169's exceptional accuracy of 99.77% and analyzes the strengths and limits of other methods. Furthermore, the talk deals with possible model development issues as well as options for future refinement.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

The suggested deep learning technique has a significant impact on society by providing farmers with a cutting-edge tool for efficient disease diagnosis in brinjal crops. This technique allows for faster action, reduces crop losses, and increases agricultural production. The study supports sustainable agricultural methods and assures food security for populations who rely on brinjal agriculture by offering farmers sophisticated options.

5.2 Impact on Environment

The study's environmental significance results from its ability to enhance resource usage in agriculture. Early disease identification using the suggested deep learning technique decreases the need for excessive pesticide usage, supporting ecologically friendly and sustainable farming practices. This connects with the wider objective of preserving agricultural input while boosting crop production, contributing to a more environmentally friendly approach to brinjal agriculture.

5.3 Ethical Aspects

Ethical concerns concentrate around the technology's proper execution and providing fair access to the benefits it brings. Transparent communication with farmers, data privacy protection, and dealing with any unexpected consequences of computerized illness diagnosis are all critical ethical considerations. The study underlines the significance of ethical AI practices in order to develop responsible technological integration in agriculture and establish trust among stakeholders.

5.4 Sustainability Plan

A plan for sustainability includes ongoing partnership with agricultural communities for field testing and feedback. The foundation of the sustainability strategy is ongoing model development, adaptability to new illness patterns, and updates based on user experiences.

The study recommends a continuous approach to ensure that the suggested deep learning technique stays useful and successful throughout time.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION, AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

In summary, the work reveals a ground-breaking deep learning system that excels in detecting brinjal plant illnesses, with DenseNet169 outperforming the others in terms of accuracy. The approach, findings, and commentary jointly demonstrate the technology's potential for changing agriculture, offering an organized assessment of the study's contributions.

6.2 Conclusions

The research finishes by confirming the effectiveness of the suggested deep learning technique in automating disease detection in brinjal crops. It outlines significant findings, stresses DenseNet169's significance, and emphasizes the practical implications for farmers and agricultural stakeholders. The results of the research highlight the study's potential to have a significant influence on brinjal production techniques.

6.3 Implication for Further Study

The consequences for future research suggest investigating other aspects such as real-time monitoring, integration with precision agricultural equipment, and the creation of farmer-friendly interfaces. Future study should look into the modification of the proposed technique to different crops and expand the dataset for larger geographical cover. This suggests opportunities for further development and expansion in the field of automated plant disease detection.

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Brinjal Disease Prediction

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