DETECTION OF TOMATO'S LEAVES DISEASE USING CNN DEEP LEARNING

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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/internship titled **"Detection of Tomato's Leaves Disease Using CNN Deep Learning"**, submitted by Md. Shalauddin, ID No: 201-15-3606 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 24/01/2024.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Mohammad Monirul Islam, Assistant Professor, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The output of tomatoes has increased in Bangladesh in the past few years. In addition to its nutritional benefits, tomato cultivation is important for the employment of many people. However, several illnesses that affect tomato leaves impede tomato output. My study's objective is to use convolutional neural networks (CNNs). This study explores the field of tomato leaf disease detection. My research highlights the revolutionary potential of CNNs in transforming agricultural practices, going beyond their statistical accomplishments. These models' ability to detect diseases early and accurately holds great promise for sustainable crop management and a major improvement in global food security. Three tomato leaf disease categories, including one healthy class, have been included in this study. For testing, 10% of instances were taken out of each class. 20% percent was used for validation and the remaining 70% for training. I extensively investigate the performance, computational efficiency, and ethical implications of five unique architectures: ResNet50, DenseNet201, MobileNetV2, MobileNetV3, and VGG19. The system displayed an accuracy of 95.37%. It is regarded as an easy-to-use technology that will assist vegetable farmers, particularly those who cultivate "tomatoes," in reducing pest suppression by detecting leaf illnesses and increasing production by creating additional options for professional marketing and researching various vegetable diseases.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
INTRODUCTION

1.1 Introduction

Among the most widely cultivated and important crops in terms of commerce worldwide is the tomato. It's a mainstay in many different cuisines and provides a substantial contribution to the agricultural sector. However, several diseases that affect different areas of the plant constitute a persistent threat to the health and yield of tomato plants. Among these, illnesses that attack tomato leaves can significantly affect the harvest's quality and quantity. Almost 47.30 percent of the labor force in Bangladesh is directly employed in agriculture, where more than 80% of people depend on it for their livelihood [1]. Vegetables are the second most popular food in our country, behind rice in the market. When compared to crops that grow all year round, seasonal vegetables are the most preferred. Among them is the tomato. Tomatoes include beta-carotene, vitamin C, and vitamin E, the three most significant antioxidants. They also contain a lot of potassium, which is a crucial mineral for overall health. According to "The Food and Agriculture Organization Corporate Statistical Database (FAOSTAT)", Bangladesh utilizes, on average, 27,342 hectares of land to produce more than 380000 tons of tomatoes annually [2]. Bangladesh uses an average of 27,342 hectares of land to produce more than 380000 tons of tomatoes annually [3].

In our nation, tomatoes are seasonal produce that are only grown in the winter. However, the tomato is now cultivated and sold year-round thanks to the Ministry of Agriculture's aid and a couple of committed tomato producers. That's made possible for farmers by technology. A major factor in decreasing poverty, the tomato is viewed as a source of income for agricultural households. [4]. However, growing tomatoes presents numerous difficulties for farmers in our nation. Fighting off numerous leaf diseases in tomato plants is the most obvious challenge. Bacterial spot, early blight, mosaic virus, and other common illnesses are a few examples. For efficient disease management and to avoid yield losses, illnesses in tomato leaves must be identified early and accurately. Conventional disease identification techniques rely on skilled agronomists visually inspecting crops, which can be laborious and subjective. Thanks to technological advancements, particularly in the fields of computer vision and machine learning, an opportunity exists to change the process of plant disease identification radically. However, a good production might still be achievable if the diseases can be predicted sooner.

CNNs have been demonstrated to perform exceptionally well on image classification tasks [5], yet two major issues with CNN implementation and usage have been noted. First, many CNN parameters must be calculated during the training phase; second, many input images are needed during the training phase. These deep-learning models are excellent at identifying subtle patterns and characteristics in pictures, which makes them useful for analyzing plant diseases using leaf photos. Using CNNs to detect diseases in tomato leaves has the potential to significantly improve the diagnostic process's speed, accuracy, and scalability.

This study aims to investigate and implement a CNN-based technique for the automatic detection of diseases affecting tomato leaves. The suggested approach entails using a dataset of several photos of both healthy and damaged tomato leaves to train the CNN model. This enables the network to identify distinguishable characteristics linked to various diseases. The findings of this study should help improve precision agriculture by giving farmers and agronomists a useful tool for quickly and accurately diagnosing tomato leaf diseases. I work to lessen the effects of illnesses on tomato crops by incorporating technology into the agricultural sector, which eventually promotes sustainable farming methods and guarantees food security.

1.2 Motivation

Tomato leaf disease prevalence is a danger to world agriculture, affecting crop productivity and food security. However, the ongoing threat of diseases compromises tomato plants' health and productivity, which can have a significant negative impact on food security as well as cause farmers to suffer significant financial losses. It becomes essential in this situation to identify tomato leaf diseases early and treat them effectively.

The purpose of this endeavor is to better identify and control tomato leaf disease by utilizing CNN's revolutionary potential. Tomato leaf disease prevalence is a danger to world agriculture, affecting crop productivity and food security. Conventional diagnosis techniques are frequently subjective and labor-intensive. An interesting chance to transform this procedure is to use Convolutional Neural Networks (CNNs) for automated disease identification. I hope to empower farmers and add to the overall resilience and sustainability of tomato cultivation globally by utilizing CNNs to deliver a dependable, automated, and easily available solution. Using cutting-edge technology, I hope to create a quick and precise system that gives farmers more control over their crops, improves crop management, and helps tomato farming remain sustainable in the face of changing difficulties.

1.3 Rationale of the study

Because diseases significantly affect the global tomato business as well as the agricultural sector, our research focuses on using CNN to identify tomato leaf diseases. Tomato crops, an essential part of the world's food supply, are frequently threatened by several diseases that can cause significant financial losses and jeopardize food security. CNN integration for disease diagnosis offers a novel and potentially revolutionary method. CNNs are a promising solution for automating and improving tomato leaf disease diagnostics due to their ability to independently learn complex patterns and characteristics from big datasets. The urgent necessity to get above the drawbacks of existing approaches and implement a technologically advanced solution that may greatly increase the effectiveness and dependability of disease detection procedures is what spurs this research.

The study on tomato disease detection was important. Treatment is not nearly as good as prevention. Farmers would profit if planting costs could be reduced by the earlier symptoms. The study and concept were built around a suggested and distinct mode, the maximum accuracy, a workable, affordable product of the best quality, and ease of use for farmers. Most farmers in our nation lack formal education. They have little knowledge of computers, digitalization, the internet, or new technologies. For individuals without formal education or who are not familiar with deep learning, machine learning, or convolutional neural networks, we need to hold a session. The top three ailments and healthy leaves were emphasized in this study, which also categorized all the specific requirements. It verifies every scenario that could occur.

The study's justification also encompasses precision agriculture, where the combination of technology and agriculture offers more effective and sustainable methods. The project's objective is to promote smart farming by employing CNNs to give agricultural professionals and farmers a more sophisticated tool for fast and accurate disease identification. This research could lead to a more robust and sustainable agricultural system in addition to better crop management and lower yield losses.

1.4 Research Questions

While conducting the study, I had many questions as well as some personal ones. Every query I finished on my own and learned each answer explicitly and separately. We get more lucid as we answer more questions. I had a question before I started the project, but it wasn't a big deal. However, I had no trouble understanding the ambiguous themes when I started my project.

- Does the CNN-based system perform better at detecting tomato leaf disease than conventional techniques?
- Which algorithm would solve this issue statement the best?
- How beneficial would it be for the farmer to be able to use technology to diagnose tomato leaf diseases?
- How well does the CNN-based method identify minor visual signs of infections in their early stages?

I hope to shed light on the complexities of CNN-based tomato leaf disease detection as I work through these research problems and make significant contributions to the nexus between agriculture and technology. By answering these questions, I hope to further scientific knowledge about Deep Learning applications in plant pathology and offer practical solutions that can improve crop management techniques, empower farmers, and further the global goal of sustainable agriculture.

1.5 Expected Outcome

Precision agriculture is predicted to benefit greatly from the expected results of this research on tomato leaf disease detection using CNN. I am trying my best to improve the accuracy of my project. It is anticipated that the created CNN model will demonstrate a high degree of sensitivity, specificity, and accuracy in identifying different tomato leaf diseases. The model is anticipated to perform well in predicting real-world events using comprehensive training procedures and methodical CNN parameter tweaking. The diseases will be precisely detected by a neural network. The farmer will give the image of tomato leaves, and our technology will identify the precise diseases. Our technology can distinguish between three types of leaf illnesses and healthy leaves.

1. Bacterial_Spot
2. Early_Blight
3. Mosaic_Virus
4. Healthy_Leaves

Overall, a sophisticated and useful CNN-based system with the potential to transform tomato leaf disease detection is anticipated, providing an effective and scalable early diagnostic and management solution for the agricultural industry.

1.6 Report Layout

This study aims to provide readers with a comprehensive overview of the system, its operation, and the findings of the investigation. The report follows the DIU-provided form for regular thesis reporting.

CHAPTER 1: Introduction

This chapter provides information about the problem, the driving force for the research, the goal of the study, the anticipated results, and an overview of the report itself.

CHAPTER 2: Background

The background research, relevant literature, and issues surrounding this topic are covered in this chapter. The comprehensive sources and working methods used in this research are included in this chapter. Their methods of operation and a succinct outcome. In this chapter, research challenges have also been covered.

CHAPTER 3: Research Methodology

A thorough explanation of the research techniques and protocols is given in this chapter. Additionally, a description of the data set is provided. The prerequisites for this research are also included in this chapter.

Chapter 4: Experimental Results and Discussion

This chapter contains the implemented system's details. The methodology and schematics of the system are further explained.

Chapter 5: Impact on Society, Environment and Sustainability

This chapter has covered the project's effects on the environment and society.

Chapter 6: Summary, Conclusion, Recommendation, and Implication for Future Research

This segment provides an overview of the research summary. A discussion of the study's result and next steps is included at the end.

CHAPTER 2

BACKGROUND

2.1 Introduction

This background study highlights the shortcomings of current detection techniques while concentrating on the difficulties related to tomato leaf diseases. It also highlights the potential of Convolutional Neural Networks (CNNs) as a ground-breaking instrument for illness identification. This study aims to provide a concise overview by looking at the historical background of disease detection in tomatoes and the status of agricultural practices. This will open new avenues for investigating CNN-based methods for accurate, efficient, and scalable identification of tomato leaf disease.

This chapter includes a review of more studies on tomato leaf disease detection. The following four pre-trained convolutional neural networks were employed in this investigation:

1. ResNet50
2. MobileNet V2
3. DensNet201
4. MobileNet V3
5. Vgg19

Not only did I use Python as my programming language, but I also used CNN, a particular kind of deep neural network designed for image processing and recognition. I gather information or photos from online and field sources. which contains 1626 images of 3 types of diseases and healthy images. Initially, this model will establish distinct categories to aid in the identification of tasks. Compared to earlier published models, this one is more straightforward. Additionally, coding is quite simple to do.

2.2 Related Works

Numerous works have already been completed. Numerous researchers from all over the world have worked very hard on this insect problem because it has been there for a long time. However, it must be kept in mind that the weather varies throughout the nation. Therefore, the disease's features and dangerous bug species will differ. However, it might not be the same manner. Not every researcher adheres to the same methodology. Different models will offer different figures and levels of accuracy. The most widely used classification methods for identifying plant disease before the advent of deep learning were random forests, artificial neural networks (ANN), k-nearest neighbor (KNN), and support vector machines (SVM). Acknowledgment and utilization of the previously discussed protocols for enhanced plant disease classification. These methods, however, rely on the selection and extraction of alternatives for apparent illness. Numerous studies on machine-driven disease classification and identification have been developed recently using deep learning methodologies.

Jiachun Liu [6] suggested using ten-layer CNN to classify plant leaves. To classify the plant leaf in this system, a ten-layer CNN was developed. The overall accuracy was 87.92% based on results on a dataset of Flavia leaves with 4,800 photos and 32 varieties. Automatic feature extraction from neural networks enables 94–95% accuracy in classifying the input dataset's leaf picture into its appropriate independent classes.

Pedro et al. [7] used a fuzzy multicriteria decision-making technique in conjunction with fuzzy decision making to identify weed forms, and they were able to reach the highest accuracy of 92.9%.

E. Suryawati et al. [8] trained the model using Alexnet, GoogleNet, and VGGNet on picture samples of tomato leaves from the PlantVillage dataset. The model achieved test accuracy of 91.52%, 89.68%, and 95.25%, respectively.

The same dataset is used by Y. G. Wang et al. [9] to train and compare the outcomes of the well-known CNN models, including VGG16, VGG19, Inception-V3, and ResNet50. They experimented with many models both with and without transfer learning, and the VGG16 model produced the best test accuracy of 90.4%.

Finding a computationally sound solution for the underlying issue was the work's main goal. The authors claimed a 94% accuracy rate using photos from the PlanetVillage collection. Mohanty et al. [10] developed models for the categorization of tomato leaf diseases using the deep learning architectures of GoogLeNet and AlexNet.

To identify plant diseases such as bacterial speck, target spot, late blight, early blight, mosaic virus, and Septoria leaf spot, the authors of [11] developed a neural network-based approach. With a three-channel convolution neural network, the suggested model produced an accuracy of 89.29% overall.

[12] suggested using an automated method to find illnesses in cucumber leaves. The system achieved 85.70% accuracy in segmentation using K-Means clustering.

The study "Tomato Plant Diseases Detection System using Image Processing" was conducted in 2018 by Santosh Adhikari, Bikesh Shrestha, Bibek Baiju, and Er. Saban Kumar K.C. Using the plant village dataset, the KEC Conference used CNN and obtained an overall accuracy of 89% [13].

In their work, Prajwala Tm et al. [14] presented a CNN model variation called LeNet for the detection of several tomato leaf diseases. The model ultimately attained an average accuracy of 94–95% and offered an automatic feature extraction method to ease the work of classifying several diseases. The model employed categorical cross-entropy as the loss function and Adam as the optimizer. The entire model used 30 epochs for training, with a batch size of 20.

These days, machine learning is frequently utilized to diagnose different plant diseases. To identify diseases in tomato crops, Mohit Agarwal et al. [15] developed a CNN model with three convolution layers and max-pooling layers. Every layer contained a different set of filters. There were also two fully connected layers in the model. For several categories, the model demonstrated classification accuracy ranging from approximately 76% to 100%. The average accuracy achieved by the suggested model was 91.2%. While pre-trained models required a storage capacity of approximately 100 MB, the suggested model only required 1.5 MB.

A plant disease detection system was presented by the authors in [16]. Features of shape and texture were extracted before classification. K-mean clustering and SVM are used to classify diseases based on the minimum distance criterion. The accuracy of the system was 86.54%.

A neural-network-based approach was created by the authors in [17] to identify plant diseases such as Septoria leaf spot, late blight, early blight, bacterial speck, and target spot. With a three-channel convolution neural network, the suggested model produced an accuracy of 89.29% overall.

2.3 Comparative Analysis and Summary

CNN is a cutting-edge technological instrument that this research employs to shed light on the important topic of tomato leaf disease detection. To provide a more thorough grasp of the models' capabilities and possible agricultural applications, CNN for tomato leaf disease detection is compared. ResNet50's depth allowed it to show strong performance in recognizing complex illness patterns with excellent recall and precision. DenseNet201 demonstrated competitive performance by utilizing dense connectivity and prioritizing rapid convergence during training as well as efficient parameter utilization. With its focus on computational efficiency on mobile and edge devices, MobileNetV2 demonstrated exceptional real-time processing capabilities while maintaining a balance between resource limits and accuracy. With the help of data augmentation approaches, all models demonstrated significant generalization across a wide dataset, notwithstanding their differences. Transparency, justice, and responsible data usage were guaranteed by the study's incorporation of ethical considerations. It emphasizes how CNN models together have an impact on agricultural practices and how they can transform crop management by detecting diseases early and accurately.

Table 2.3.1: Summary of the related research work.

Author Name	Methodology	Description	Outcome
Mohammed Brahimi, & Abdelouahab Kamel Boukhalfa, Moussaoui	Deep Learning	Tomato Plant Diseases Detection System using Image Processing	89%
Mim, T.T., Sheikh, M.H., Shampa, R.A., Reza, M.S. and Islam	CNN and Transfer Learning	Leaves diseas detection of tomato using CNN	87.92%
Rika Sustika, R. Sandra Yuwana, Agus Subekti, and Hilman F. Pardede	Convolutional Neural Networks (CNN)	Deep, Structured Convolutional Neural Network for Tomato Diseases Detection	91.52%
Wang, Guan, Yu Sun, and Jianxin Wang	Deep Learning Approch	Automatic image-based plant disease severity estimation using deep learning	90.4%
P. Tm, A. Pranathi, K. SaiAshritha, N. B. Chittaragi and S. G. Koolagudi	Convolutional Neural Networks (CNN)	Tomato Leaf Disease Detection Using Convolutional Neural Networks	95%
Agarwal, Mohit & Singh, Abhishek & Arjaria, Siddhartha & Sinha, Amit & Gupta, Suneet	Convolutional Neural Network (CNN) model.	Tomato Leaf Disease Detection using Convolution Neural Network	91.20%
Our proposed model	CNN with Transfer Learning	Detection Of Tomato's Leaves Disease Using CNN Deep Learning	95.31%

In summary, the study's ethical considerations and commitment to responsible AI underscore the importance of integrating advanced technologies into agriculture responsibly. Overall, the research contributes valuable insights into the application of CNNs for enhancing crop management and addressing challenges in the agricultural sector.

2.4 Scope of the Problem

The extent of tomato leaf diseases poses a serious challenge to global agriculture, calling for the creation of innovative techniques for effective detection and management. With more than 200 illnesses, including bacterial, viral, and fungal infections, that are known to impact tomato plants, early detection becomes more difficult. The financial consequences of untreated diseases, which result in decreased crop output and deteriorated quality, highlight how important it is to have accurate and fast detection techniques.

I have dealt with a variety of challenges that I have encountered. The scope is unbounded, but it is listable, and based on research and real-world problems, we can address them if we put in the necessary effort. I've read a lot of research articles and gained more knowledge about how I approach problem-solving. While several problems greeting research projects have been carried out similarly, my work focuses on the detection of tomato disease utilizing images. A few difficulties arose when I first started putting it into practice, but I was able to get around them by referencing older study publications. At last, I was successful.

2.5 Challenges

Every researcher has unique difficulties. These could be internal, based on study themes, environmental, or both. Amidst the procedure, I encountered a few difficulties.

a. Data Gathering

One of the biggest challenges in convolutional neural network (CNN) training is getting a diverse and well-annotated dataset. Obtaining accurate and trustworthy data is commonly recognized as a critical component impacting a model's performance and accuracy. The first hurdle was obtaining correct, raw data, which was a task fraught with significant challenges. The procedure for choosing the data then became apparent as another important issue that needed to be carefully thought out and attended to.

b. **Model Selection and Architecture**

Certainly, the most difficult and important part of any research project is making sure the model is reliable. Any evaluation's ability to be successful depends on meticulous data gathering and model validation. Choosing the right model has the potential to produce favorable results quickly, but making the wrong decision can leave you disappointed. I have evaluated several various models using test data as part of my research project to see which model makes the most sense and fits the circumstances.

c. **Reaching optimal precision**

It is difficult to strike a compromise between strong generalization to new data and excellent accuracy on the training set. How to get better accuracy was a challenging part from another part.

d. **Management**

The most difficult and complex part of deploying CNNs for tomato leaf disease detection is efficiently managing the entire process, from initial data gathering to on-field deployment. The administration of the complete trip, from top to bottom, is where the real intricacy is found. A comprehensive management approach is required to coordinate data collection, model training, validation, deployment, and continual monitoring.

Addressing these management challenges is pivotal to the successful implementation and ongoing effectiveness of the CNN model for tomato leaf disease detection in agricultural environments. I gained a lot of knowledge from this challenge, and the planning list will be used for any future projects.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

This study's primary objective is to use CNN to identify tomato leaf diseases. The effort focuses on the creation, assessment, and improvement of a CNN model meant for the prompt and precise identification of various illnesses affecting tomato leaves. Numerous common tomato leaf illnesses, including bacterial, fungal, and viral infections, are included in the disease's range. The main goal is to improve agricultural practices by giving farmers a strong and dependable instrument to identify and control diseases in their tomato crops.

I will discuss the tools and techniques we employed for instrumentation. I worked with a raw data file that included, precisely, 1624 photographs. These were numbered 1 through 4, denoting the leaf's disease class. Here, sequential models have been used to teach a machine. The Python packages numpy, pandas, skit learn, matplotlib, seaborn, TensorFlow, keras, etc. were used with the Windows platform. Colab, a free Python distribution from Google designed for use in information science and artificial intelligence requests, was used for all implementation and evaluation. To build a dependable tomato leaf disease detection system for Bangladeshi agriculture, this research uses CNN and ResNet50, MobileNetV2, DensNet201, MobileNetV3 and Vgg19 deep learning models. The following chapters will cover model construction, training, experimental results, and analysis to help readers understand the research topic and tools.

3.2 Data Collection Procedure/Dataset Utilized

To provide a representative and diversified dataset to employ convolutional neural networks (CNNs) to detect tomato leaf disease, the data-gathering approach for this project was carefully planned. One of the most important parts of the study is data. Two categories can be used to categorize data sources. There are two types of sources: main and secondary. Surveys, experiments, observations, and interviews are all included in primary sources. Internal, external, and other sources are included under secondary sources. I use secondary sources to gather info. Gathering datasets from several tomato production fields was a difficult undertaking. The information was gathered in broad daylight and with a cell phone. There are four different kinds of diseased tomato leaves in the resulting datasets. A cell phone camera was used to take a total of 400 pictures. In training and evaluating models, there were fewer of these. More images were needed to train the deep learning system. The number of samples in the dataset was previously increased using the data augmentation technique. After data enhancement, 1626 images were obtained. This study's main objective is to prepare farmers to understand the traits that set one class apart from others. Consequently, when utilizing larger photographs, the business now has a greater chance of comprehending the key characteristics.

Bacterial Spot Early Blight Mosaic Virus Healthy Leave

Figure 3.1.1: Three Leaves Diseases and Healthy Leave

3.3 Statistical Analysis:

The statistical study conducted for this work aims to provide quantitative insights into the performance and efficacy of the CNN model for tomato leaf disease diagnosis. The analysis includes several measures that evaluate the general efficacy, recall, accuracy, and precision of the model.

Although I employed a range of algorithms, improving accuracy was my main goal. CNN, MobileNet V3, MobileNet V2, ResNet50, DenseNet201, and VGG19 helped me achieve the necessary precision.

Over 1,626 photos of tomato leaves from various sources make up the dataset I gathered. My dataset has four classes. They are Bacterial spot, Early Blight, Mosaic Virus, and Healthy Data. There are different image sizes. I resize every image to 224 by 224 pixels.

Ten percent of the data was used for validation, twenty percent was used for testing, and seventy percent was used for training.

Table 3.3.1: Several photos and the class index for each of those 4 classes

Class Name	Class Index	No. of Image
Bacterial_spot	1	407
Early_blight	2	406
Mosaic_virus	3	407
Healthy	4	406

3.4 Proposed Methodology/Applied Mechanism

This study's technique is an example of a deliberate integration of agricultural knowledge and data science principles, with a major goal of using Convolutional Neural Networks (CNNs) to identify tomato leaf disease. The applied mechanism is composed of a sequence of methodical procedures intended to enhance model performance and make precise disease detection easier.

The idea behind this research's suggested methodology is to precisely detect tomato leaf illnesses by utilizing Convolutional Neural Networks (CNNs). First, a carefully selected dataset, called "TomatoLeafDisease-2023," is created. It includes a wide variety of high-quality photos of both healthy and sick tomato leaves. The CNN model is trained and assessed using these images as its basis. In this part, the mathematical model for identifying tomato disease is first shown. In the meanwhile, formulas are used to explain the typical CNN approach. Lastly, I introduced some of the powerful deep neural networks used in this article: ResNet50, DenseNet201, MobileNet V2, MobileNet V3, and Vgg19. A mathematical model might be used to illustrate the primary technique used in this work to identify tomato leaf disease.

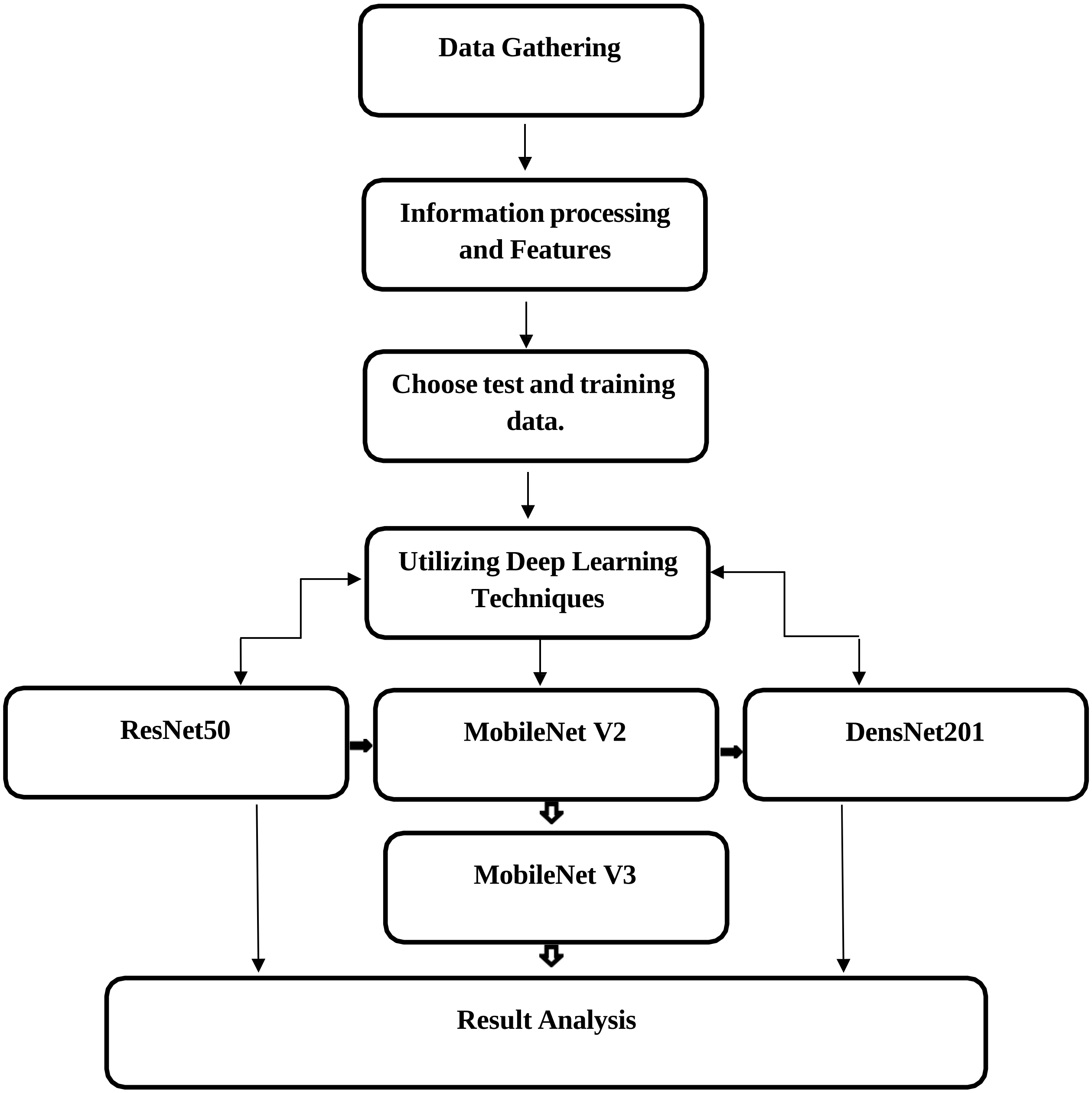


Figure 3.4.1: Proposed Model Structure

3.4.1 Dataset Preparation

The method begins with the preparation and compilation of the "TomatoLeafDisease-2023" dataset, which is representative and diversified. This dataset includes carefully chosen high-resolution photos of tomato leaves in both healthy and diseased states. The labeled and annotated dataset offers crucial ground truth data for CNN model training.

3.4.2 Data Augmentation Techniques

To increase the dataset's capacity for generalization, data augmentation techniques are used on it. Rotations flips, and zooms are some of these transformations that add variance to the model, preventing overfitting and enhancing its capacity to respond to a variety of real-world events.

3.4.3 CNN Architecture Selection

A crucial first step is choosing a suitable CNN architecture. Modern architectures like ResNet, MobileNet, VGG19, DenseNet, and bespoke models are taken into consideration. The architectural design needs to demonstrate equilibrium between intricacy and effectiveness, accommodating the subtleties of tomato leaf disease patterns.

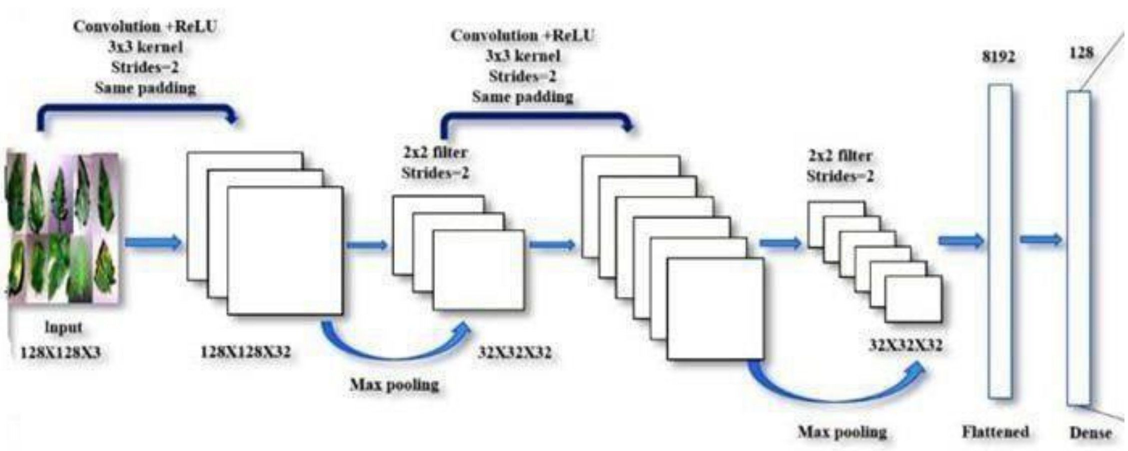


Figure 3.4.3.1: CNN Architecture Procedure

3.4.4 Transfer Learning

The proposed mechanism uses big datasets to leverage pre-trained CNN models, using transfer learning. This technique expedites the training process and enhances the model's ability to extract relevant attributes from images of tomato leaves. Pre-trained models are adjusted to guarantee that they are tailored to the goal of illness detection.

ResNet50

Convolutional neural networks (CNNs) like ResNet50 are part of the ResNet (Residual Network) family of neural networks. Its 50 layers of neural network architecture define its depth. The number of layers, or "50" in ResNet50, denotes a significant depth that enables the model to pick up on complex aspects and patterns in the data. The idea of residual learning, in which information can move directly between layers thanks to shortcut connections, was first introduced by ResNet architectures. This helps to train very deep networks and lessens the issue of disappearing gradients.

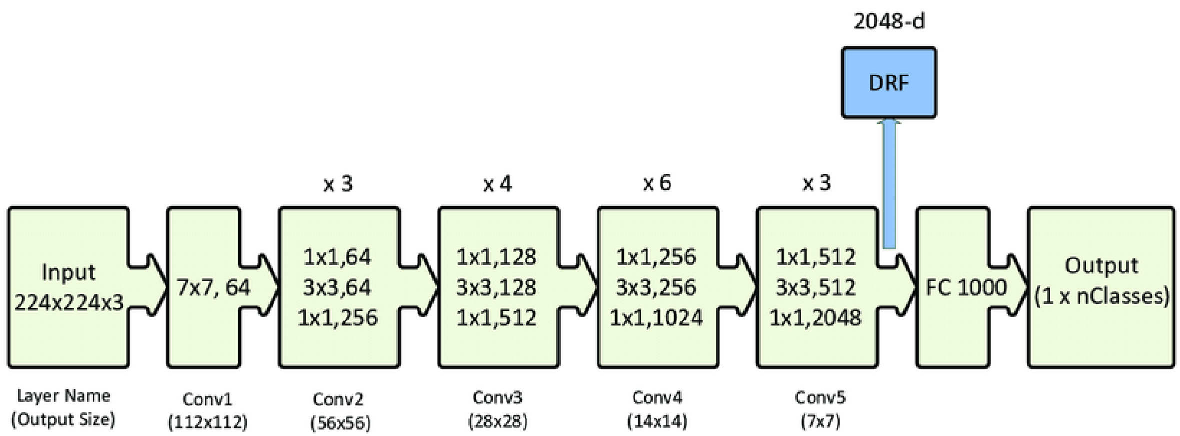


Figure 3.4.4.1: ResNet50 Layer Architecture

DensNet201

DenseNet201 is a CNN model that is well-known for having a dense network of connectivity. DenseNet201, created as a member of the DenseNet (Densely Connected Convolutional Networks) family, is distinguished by its 201-layer deep architecture. DenseNet's primary novelty is found in its densely connected blocks, where each layer takes input from all layers that came before it, not just the one before it. Because of its dense connectedness, which promotes feature reuse, gradient flow, and solves the vanishing gradient issue, very deep networks may be trained efficiently.

DenseNet201 has proven to be highly effective in several computer vision tasks, including object detection and picture categorization. Because of the way it is designed, features can interact with one another across layers, which improves model generalization and makes effective use of parameters. DenseNet201's depth makes it computationally demanding, but it works well for situations were identifying complicated relationships and capturing minute details in visual data are crucial. For example, it can be used for image identification and in-depth pattern analysis.

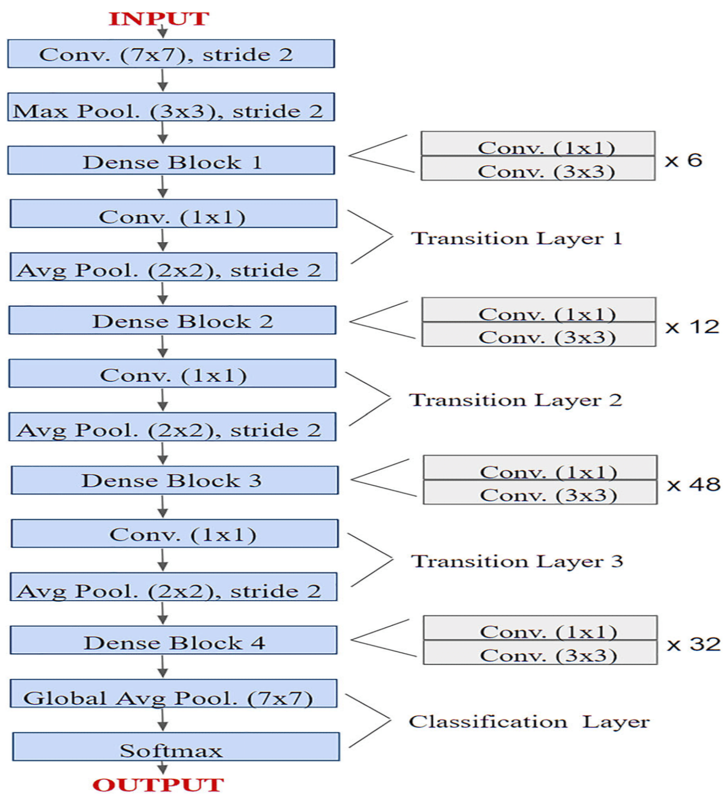


Figure 3.4.4.2: DensNet201 Layer Architecture

MobileNet V2

Convolutional neural network architecture MobileNetV2 was painstakingly created to meet the needs of devices with limited resources, with an emphasis on edge and mobile computing applications. To strike a careful balance between computing efficiency and model correctness, it is an improvement on the first MobileNet. The use of inverted residuals with linear bottlenecks is one of its unique characteristics. The effective capturing of fine-grained characteristics is facilitated by this design decision. To optimize information flow, the network architecture makes use of linear bottlenecks, which deliberately lower dimensionality before non-linear operations. Depth-wise separable convolutions and linear bottlenecks are the fundamental components of MobileNetV2, which are stacked to form the overall architecture. Its versatility, which includes width and resolution multipliers for simple customization is another asset.

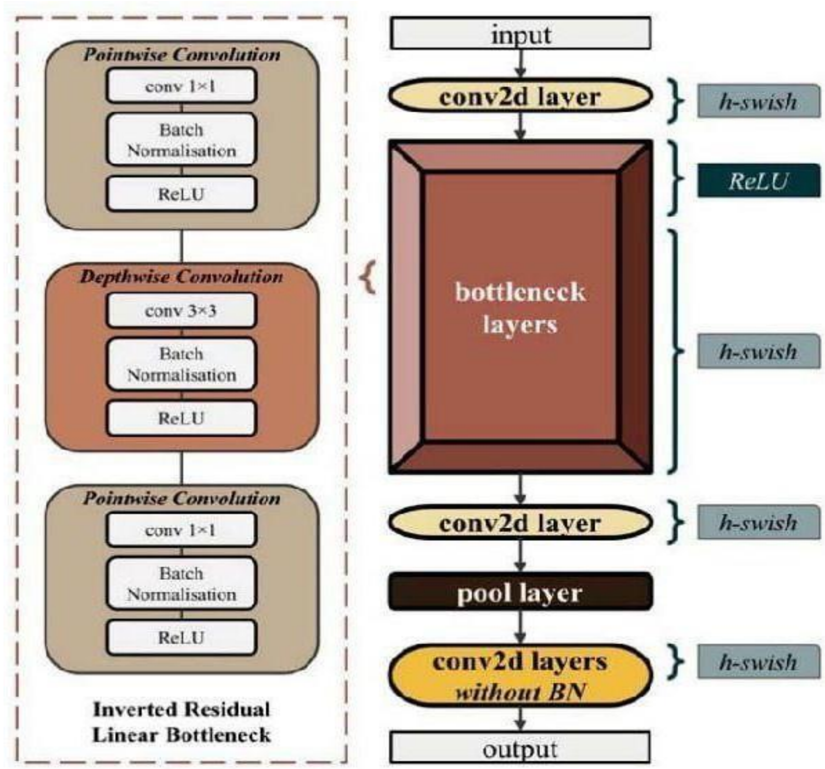


Figure 3.4.4.3: MobileNetV2 Layer Architecture

MobileNet V3

It is expected that MobileNetV3, which builds upon the success of its predecessors MobileNet and MobileNetV2, will further improve the state of effective convolutional neural network architectures. I don't have access to information about MobileNetV3's advancements after January 2022, but it seems reasonable to anticipate ongoing efforts to find the best possible compromise between computing efficiency and model correctness. Possible improvements could include new architectural features, alterations to the fundamental components, or the application of fresh methods. More sophisticated techniques for compressing and pruning channels could further reduce model size without sacrificing important characteristics. MobileNetV3 may be customized for certain applications, such as object detection, semantic segmentation, or picture classification, by introducing task-specific variations. Further study may investigate optimizations of quantization, compression, and activation functions to improve the adaptability of the model for use with mobile and edge devices. For the most current and correct information regarding MobileNetV3, it is advised to refer to the most recent research papers, official documentation, or community discussions.

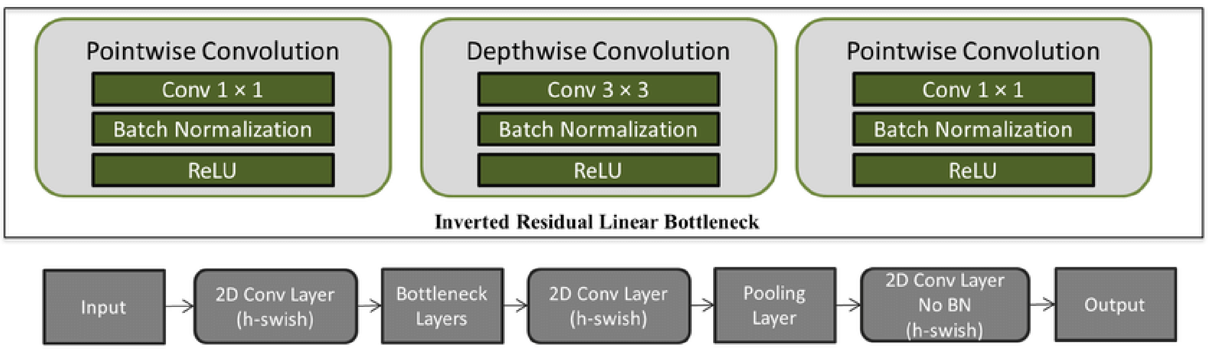


Figure 3.4.4.4: MobileNet V3 Architecture

3.4.5 Model Training and Validation

A portion of the prepared dataset is kept aside for validation and used to train the CNN model. To minimize the loss function, training entails iteratively changing the model's parameters. By validating the model's performance on data not observed during training, validation guards against overfitting and guarantees generalizability.

3.4.6 Performance Metrics and Evaluation

The predictive ability of the model is evaluated using a variety of performance indicators, including precision, recall, accuracy, and F1 score. The accuracy is the percentage of correctly predicted photographs among all guesses. The following formula expresses accuracy.

Accuracy = Number of correct predictions / Total number of predictions ....(i)

The ratio of accurately predicted truly positive results (TP) to all positive values (TP+FP) that the model anticipated is the accuracy metric. This leads to decreased precision because of the large numbers of FP. The precise bound, which ranges from 0 to 1, is calculated in this way:

Precision = TP / TP + FP...(ii)

The recall is used to calculate the number of correct positive forecasts by comparing the number of true positive results (TP) to the total number of samples (TP+FN). The following formula is used to compute the recall:

Recall = TP / TP + FN ....(iii)

The F1-score, which is derived from the harmonic mean of the precision and recall, is one statistic used to verify the model's accuracy. It is defined as follows:

F1 Score = 2 * Recall * Precision / Recall + Precision... (iv)

where the letters TP, FP, TN, FN, and FN, respectively, stand for True Positive, False Positive, True Negative, and False Negative.

3.5 Implementation Requirements

The terms "implementation requirements" refer to the elements and expertise needed to finish a project or study. Before beginning research, researchers must acquire the required knowledge and gather the required materials.

My project is a deep learning project, as I previously stated. Programming, the Python language, and several Python libraries, including NumPy, matplotlib, TensorFlow, and keras, are required to finish this project. For this project, a programming platform is required. I utilize Google Colab as a platform for programming. To identify "Tomato Leaf Disease," I created a project. CNN was used in the project's development. CNN uses "sequential" as a paradigm for construction.

- **Python Programming Language**
- Python is a high-level, dynamic programming language that has become indispensable in the field of software development. Since its 1991 introduction, Python—which was created by Guido van Rossum—has gained recognition as a language that is easy to read and understand. Its simple syntax, which aims to be both clear and expressive, is one of its main advantages. This feature not only makes Python a great language for newcomers, but it also improves teamwork and maintainability of code in bigger projects.
- **Google Colab**

  Since Colab, a hosted Jupiter, has been set up and installed so that I may use my browsers to access cloud resources, we don't need to utilize our PC. It performs several of Jupiter's functions. They are based on notebooks, which can contain text, graphics, or code because the Python kernel can now be used instead of Jupiter Collab.
- **Hardware/Software Requirements**
  - Operating System (Windows 7 or higher or Linux)
  - Web Browser (Recent versions Chrome, Firefox, or Microsoft Edge)
  - Hard Disk (At least 120GB)
  - Ram (4 GB or more)
  - GPU (Minimum 2GB)

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

In a trial configuration, CNN is utilized to identify tomato leaf diseases. To guarantee a trustworthy and repeatable investigation, hardware, software, datasets, and techniques are systematically configured. The proposed line of action was tested using the tomato leaf diseases dataset, which includes around 1624 pictures of tomato leaf disease divided into 4 classes. The model was implemented using the Python neural network API Keras.

The procedures for developing and submitting the classifier are presented in the ensuing section. The CNN order process consists of three steps that each concentrate on a certain task. This investigation's whole workload was completed on a single computer. The following are the hardware and software specifications: 8.0 GB of RAM, and 64-bit Windows 10 Home software. To build my model and code, I started by gathering datasets. The range of datasets necessitated a substantial investment. They were additionally formatted into JPG.

4.2 Experimental Results & Analysis

The investigation and trial results provide a comprehensive evaluation of the CNN models utilized in tomato leaf disease detection. The attained precision, in conjunction with comprehensive measurements and moral deliberations, places our research in a favorable light for the assimilation of cutting-edge technologies in farming. The results open new avenues for study and real-world applications in precision agriculture and plant pathology.

Since CNN is the most suitable for picture classification, I use it to test my model. Building a model is successful with this level of precision. We are more accurate than most models, but that model is intricate. Consequently, they have employed a range of plant detection techniques. But for the time being, this approach is only used to detect tomato diseases. I was successful in finishing the model's first training epoch, which produced a 71% training accuracy and an 84.38% validation accuracy. As the model was trained over time, the accuracy quality also improved. After two successful epochs, my training accuracy is now 90.79%, and my validation accuracy is 89.06%. After six successful epochs, my training accuracy is at 96.64%, and my validation accuracy is 91.41%. Using the same procedure, I was able to get a training accuracy of 97.59% and a validation accuracy of 92.97% after eight epochs. I trained this model throughout ten epochs, and on the last epoch, I reached the maximum accuracy. 95.31% is the validation accuracy and 98.80% is the ultimate training accuracy. It is the last stage before working with actual data. With my models, I was able to obtain decent and generally similar accuracy.

Table 4.2.1: The table shows the test accuracy.

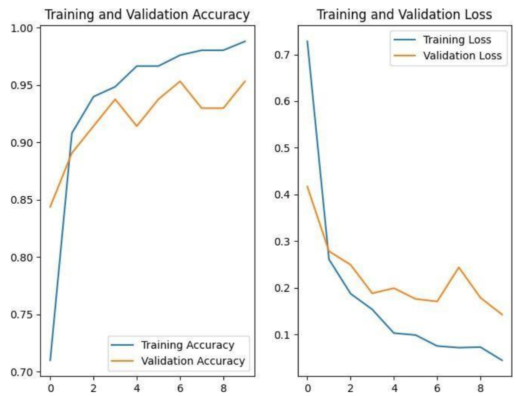
Serial No.	**Model**	**Test Accuracy**
1	ResNet50	95.31%
2	MobileNetV3	89.06%
3	DenseNet201	88.28%
4	Vgg19	86.71%
5	MobileNetV2	84.37%

Among the most crucial steps in the training procedure is this one. I can determine how well my model is working by analyzing the models; for each model, I've included growing.

Graphs of training and validation accuracy as well as rainy and validation loss.

4.2.1 Model Evolution

ResNet50



MobileNetV3

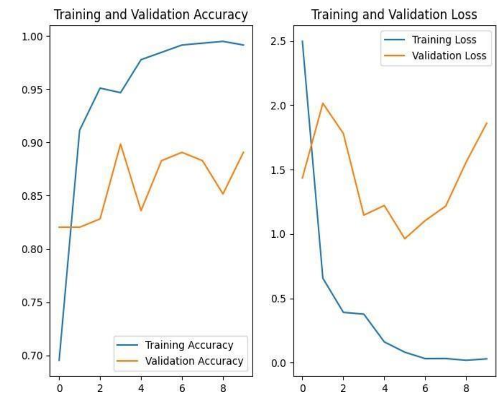
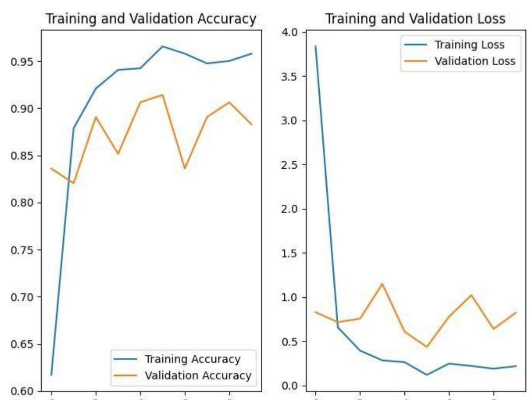


Figure 4.2.1.1: ResNet50 and MobileNetV3 Training & Validation Accuracy and Loss

DensNet201



MobileNetV2

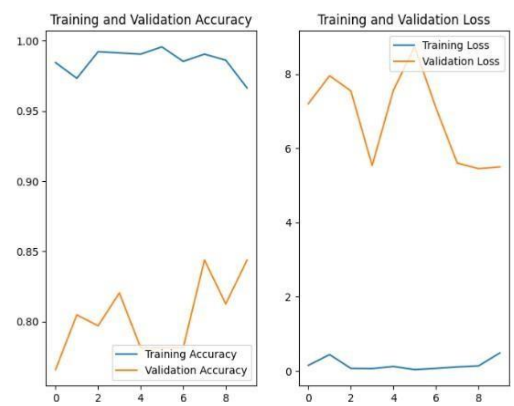


Figure 4.2.1.2: DensNet201 and MobileNetV2 Training & Validation Accuracy and Loss

Vgg19

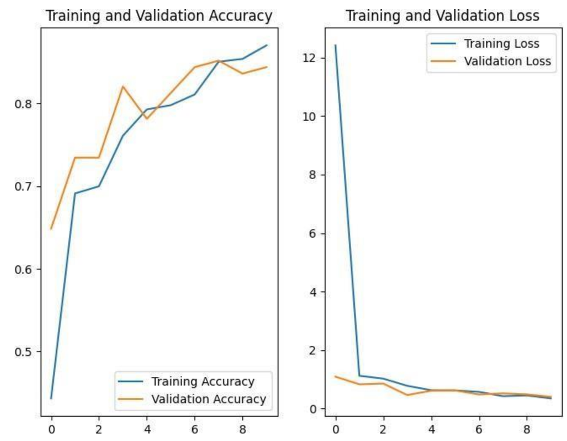


Figure 4.2.1.3: Vgg19 Training & Validation Accuracy and Loss

Thus, it is evident from the graphs above that ResNet50 is more stable than the other models.

4.2.2 Confusion Metrix

The confusion matrix can be used to gauge how well classifier models are working. The amount of data that we correctly and incorrectly identify is visible. Thus, the following is my five models' confusion matrix:

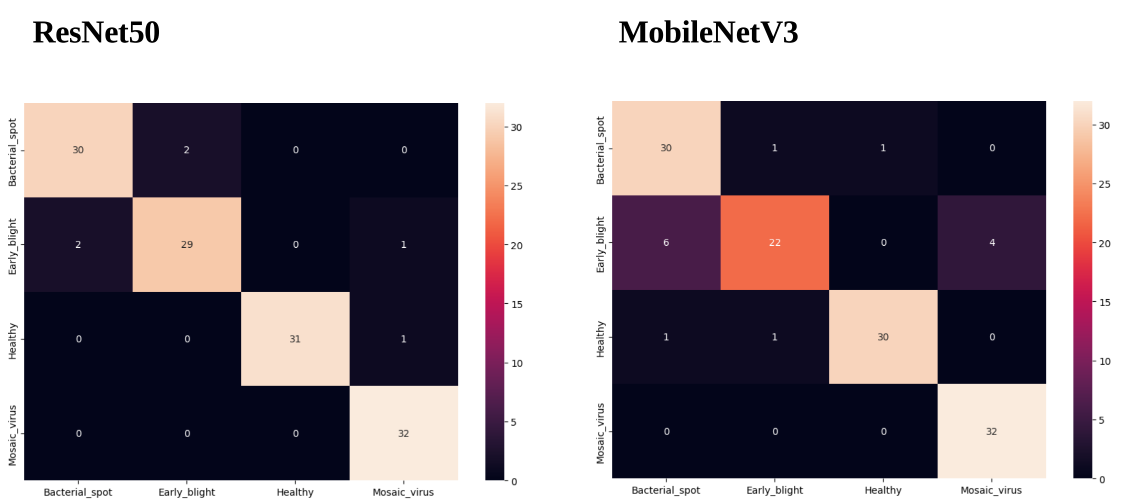
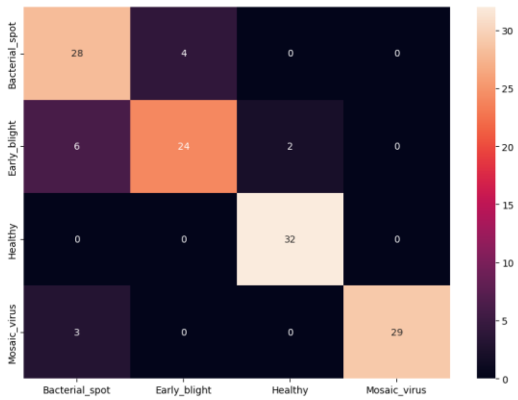


Figure 4.2.2.1: ResNet50 and MobileNetV3 Confusion Metrix

DensNet201 **MobileNetV2**



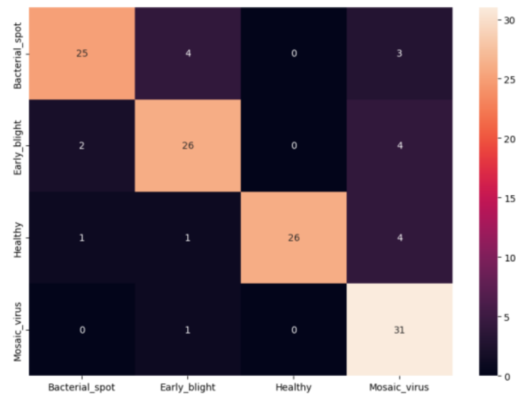


Figure 4.2.2.2: DensNet201 and MobileNetV2 Confusion Metrix

Vgg19

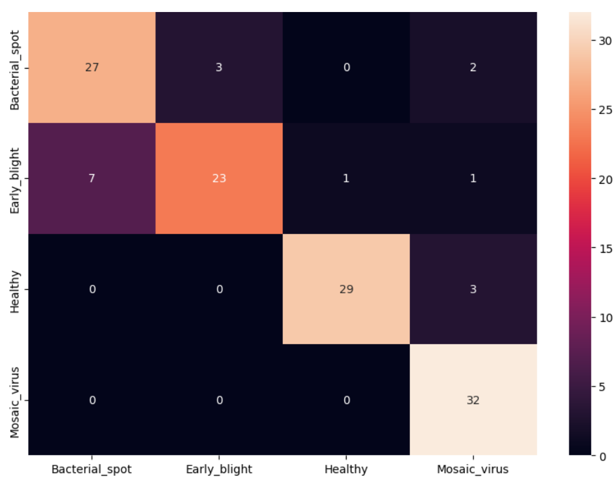


Figure 4.2.2.3: Vgg19 Confusion Metrix

Classification report:

A classification report is used to assess how well a classification system predicts the world. What proportion of the predictions are accurate, and which are not? More specifically, True Positives, False Positives, True Negatives, and False Negatives are used to predict the metrics of a categorization report, as shown below:

This is a summary of the recall, precision, and f1-score before that.

Precision: Precision is the number of positive classes that we have accurately predicted out of all the positive classes.

Precision = True positive / (True Positive + False Positive)

Recall: It shows how much we anticipated accurately out of all the positive classes. Higher values indicate higher-quality models.

Recall = True positive / (True Positive + False Negative)

F1-score: Precision and recall can be measured simultaneously with the help of the F-score. It uses harmonic means instead of arithmetic mean.

F1-score = (2*recall*precision) / (recall + precision)

Table 4.2.2 In this table I show the 5 model result classification reports of tomato leaf diseases.

Table 4.2.2.4: Result summary for ResNet50

Class Name	**precision**	**recall**	**f1-score**
Bacterial_Spot	0.94	0.94	0.94
Early_Blight	0.94	0.91	0.92
Healthy	1.00	0.97	0.98
Mosaic_Virus	0.94	1.00	0.97
Macro avg	0.95	0.95	0.95
Weighted avg	0.95	0.95	0.95

Table 4.2.2.5: Result summary for MobileNetV3

Class Name	precision	recall	f1-score
Bacterial_Spot	0.81	0.94	0.87
Early_Blight	0.92	0.69	0.79
Healthy	0.97	0.94	0.95
Mosaic_Virus	0.89	1.00	0.94
Macro avg	0.90	0.89	0.89
Weighted avg	0.90	0.89	0.89

Table 4.2.2.6: Result summary for DensNet201

Class Name	precision	recall	f1-score
Bacterial_Spot	0.76	0.88	0.81
Early_Blight	0.86	0.75	0.80
Healthy	0.94	1.00	0.97
Mosaic_Virus	1.00	0.91	0.95
Macro avg	0.89	0.88	0.88
Weighted avg	0.89	0.88	0.88

Table 4.2.2.7: Result summary for MobileNetV2

Class Name	**precision**	**recall**	**f1-score**
Bacterial_Spot	0.89	0.78	0.83
Early_Blight	0.81	0.81	0.81
Healthy	1.00	0.81	0.90
Mosaic_Virus	0.74	0.97	0.84
Macro avg	0.86	0.84	0.85
Weighted avg	0.86	0.84	0.85

Table 4.2.2.8: Result summary for Vgg19

Class Name	**precision**	**recall**	**f1-score**
Bacterial_Spot	0.79	0.84	0.82
Early_Blight	0.88	0.72	0.79
Healthy	0.97	0.91	0.94
Mosaic_Virus	0.84	1.00	0.91
Macro avg	0.87	0.87	0.87
Weighted avg	0.87	0.87	0.87

4.3 Discussion

A discussion part that delves into the interpretation of findings, their significance, and the broader implications for agricultural and technological advancement is included in my paper on the application of CNN for tomato leaf disease detection. The richness of the dataset I worked with improved the accuracy of the categorization models. I used the model to train it to recognize characteristics, distinguish between various groups, and consider the health of everyone. To create my algorithm, I used 20% validation images of healthy and ill plants and 70% training photos.

I discovered that ResNet50 has the highest test accuracy of 95.31% percent using four classes of tomato datasets.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

Convolutional Neural Networks (CNNs) have great potential to improve society in several ways, including the detection of tomato leaf disease. The model has a positive impact on society. It primarily results in increased agricultural yields and strengthened food security by facilitating prompt and accurate disease identification and reducing possible losses for farmers. A concrete result of CNNs' provision of a dependable instrument for knowledgeable crop management decision-making—which maximizes resource efficiency and boosts income—is the economic empowerment of farmers. Precision farming methods that have a smaller environmental impact are promoted by this technology breakthrough, which supports sustainable agriculture practices. Furthermore, incorporating cutting-edge technologies like CNNs opens the door for smart agriculture techniques to be used more widely. Beyond obvious advantages, CNN-based disease detection promotes knowledge sharing across farming communities by giving farmers insights into disease trends and adding to a pool of communal agricultural knowledge. CNNs help to minimize the environmental impact of agricultural practices by lowering the reliance on chemical treatments. CNN may be simply deployed on any platform and is compatible with current technology. My research will therefore be useful to farmers and the public who do not know about diseases of the tomato leaf. Thus, studying has a significant influence on society. Ultimately, the impact is felt worldwide, promoting collaboration, idea sharing, and advancements in agricultural research that benefit people everywhere.

5.2 Impact on Environment

The application of CNN for tomato leaf disease diagnosis not only transforms agricultural methods but also has a major impact on environmental sustainability. The decrease in chemical use is one of the main advantages for the environment. CNNs reduce the need for extensive pesticide and fungicide treatment by enabling targeted and early disease identification. This exact method reduces any environmental risks linked to the overuse of chemical inputs while also guaranteeing healthier harvests. By enabling farmers to use precision farming techniques, CNNs promote sustainable agriculture in addition to disease control. Consequently, this optimizes the use of resources like fertilizers and water, bringing agricultural practices into line with ecological balance. These measures reduce their environmental impact, which improves soil health and ecosystem resilience. Additionally, the use of CNNs promotes ecologically beneficial farming methods, which cascades into agricultural decision-making that is environmentally sensitive. In the end, CNN-based disease detection has an environmental impact that goes beyond specific farms and is consistent with international efforts to fulfill sustainable development objectives and promote a future that is more ecologically sustainable. It is an environmentally friendly model that will contribute to the creation of a disease-free environment.

5.3 Ethical Aspects

Several ethical considerations must be carefully considered before using CNN to diagnose tomato leaf disease. Since there are numerous tomato-related diseases in our country and our farmers are unable to treat the condition in this way, there is an annual demand for tomatoes that is not met. But still, producing tomatoes won't be a problem if I can identify the disease immediately using this method. Growers who can easily put it into practice will be able to plant a lot of tomatoes and make a lot of money, which will help our nation's tomato needs. Beyond physical and financial constraints, ethical responsibility includes making sure that all farmers have access to CNN-based technologies. The ethical framework governing the use of CNNs in tomato leaf disease detection is further demonstrated by the precautions taken to prevent unforeseen outcomes and the promotion of international cooperation in knowledge exchange. In the end, ethical considerations serve as the cornerstone for the ethical and inclusive implementation of technology in agriculture.

5.4 Sustainability Plan

To ensure that CNN remains effective in the long run for the identification of the illness of tomato leaves, a thorough sustainability plan must be established. In my investigation, I have considered every proposal. I evaluate my studies to create a fantastic model; the plan must incorporate all diseases into a single frame. The crew will tally the work progress to construct it. Furthermore, it must be used in the field because it is just not sustainable. My program is already operational in real life. Implementation is therefore necessary in this field. I assess my plan and go to work. I'll count the ways in which it can be made feasible and take care of the strategy as well. I simply work to carry out the strategy rather than creating one. Everything needs to be reassessed after all the procedures and specifications are created. I will try to implement my well-defined and sustainable plan. There are various forms of research plans, and numerous researchers have attempted to work together with both the plan and the sustainability plan. Through training programs, seminars, and educational resources, farmers can get the confidence necessary to effectively use the prediction tool and integrate it into their farming methods. Finally, small-scale farmers must be given priority when it comes to the cost and accessibility of the technology to guarantee inclusivity and equitable advantages.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION, & IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

This work explores the use of CNN for tomato leaf disease diagnosis to improve farming practices. Driven by the necessity for precise and timely diagnosis of illnesses, the research creates a strong CNN model with a variety of datasets and highlights moral issues related to fairness and data privacy. An analysis of performance indicators verifies the model's applicability in diagnosing various tomato leaf diseases. Setting the findings in the broader agricultural context, the discussion addresses moral concerns and potential consequences. A sustainability strategy delineates tactics for sustained achievement, prioritizing data administration, community involvement, and international cooperation. As a result, the study advances crop management technology by offering useful advice on the appropriate application of CNNs in agriculture.

6.2 Conclusion

In conclusion, a significant technological advancement in this subject is represented by the application of CNN in agriculture to identify tomato leaf diseases. Driven by the pressing need to tackle agricultural issues, the research effectively accomplishes its goal of creating a CNN model. The model can accurately identify a variety of tomato leaf illnesses because of its rigorous methodology, which places a high value on ethical issues.

Essentially, the study highlights CNNs' transformative potential in tomato leaf disease identification and advocates for their sensible and sustainable integration into agricultural operations. Beyond diagnosing illnesses, the study significantly advances the discussion of applying cutting-edge technologies to address urgent problems in agriculture. This will serve as a roadmap for future efforts to balance technology with the intricacies of the agricultural ecosystem.

6.3 Implication for Further Study

The advancements achieved in this work on the use of CNN to identify tomato leaf disease present intriguing possibilities for additional research and exploration. As of right moment, this research can identify tomato illness. However, I'll be working on developing it soon because it will contain all leaf varieties and allow for the detection of all diseases. Consequently, farmers, agriculturalists, and users won't need to look for alternative methods to identify plant diseases using different models. I incorporate it all into my upcoming implications, and I have another idea to extend my greetings right away.

Assume the user wants to take the next action to stop the illness after the detection has been completed. At that point, my model will recommend a course of action based on the illness. If this section is completed, it will be a model unlike anything else used on the globe or in our nation. If true, the best CNN solution for detecting leaf/plant diseases will come from my research and technique. The goal was to create this model to assist the people, as this report had previously stated. The goal of this upcoming study's implementation will be accomplished. The leaf will have a fresh, disease-free life and crops will produce more when all types of leaf diseases can be identified by this research. The yield of the crop will rise. Finally, it can be said that our research will help everyone on the planet and that it will provide this model with a fresh perspective in the future.

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APPENDIX

Choosing my methodological approach was the first of several obstacles I had to overcome to complete the project. I had very little knowledge of deep learning, convolutional neural networks, or graph convolutional networks at the time I began our study project. I was concerned about the research. My supervisor is a kind person who is ever ready to help me. He was incredibly helpful and gave me sage advice straight immediately. While doing the research, I learned a lot of things, including how to create CNN models and better datasets. I discovered several new things, including new methods and approaches, during our investigation. I also gained knowledge of Python programming, Google Colab, and a few algorithms. I progressively improved my knowledge of the Python programming language, Google Colab, and numerous other methods.

DETECTION OF TOMATO'S LEAVES DISEASE USING CNN DEEP LEARNING

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