A PROJECT REPORT
on

"Tomato Leaf Disease Classification Using CNN"

Submitted to
KIIT Deemed to be University

In Partial Fulfillment of the Requirement for the Award of

BACHELOR'S DEGREE IN

INFORMATION TECHNOLOGY

BY

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May 02, 2023

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CERTIFICATE

This is certify that the project entitled

"Tomato Leaf Disease Classification Using CNN"

submitted by

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is a record of bonafide work carried out by them, in the partial fulfillment of the requirement for the award of Degree of Bachelor of Engineering (Computer Sci-ence & Engineering OR Information Technology) at KIIT Deemed to be university, Bhubaneswar. This work is done during the year 2022-2023, under our guidance.

Date: **02/05/2023**

Santosh Kumar Baliarsingh
Project Guide

Acknowledgements

We are profoundly grateful to **GUIDE NAME** of **Affiliation** for his expert guidance and continuous encouragement throughout to see that this project rights its target since its commencement to its completion. ....

Utpal Kant Singh

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Shibasish Kar

ABSTRACT

Tomato is the most widely cultivated vegetable crop in Indian agricultural fields due to its suitability for growth in the tropical climate of the country. However, various climatic conditions and other factors can impede its growth, leading to reduced production. Moreover, plant diseases pose a significant threat to agricultural production and can result in substantial financial losses. Traditional disease detection techniques for tomato crops did not yield the desired results, and disease detection times were lengthy. Early illness detection can produce superior results compared to current detection models. Deep learning techniques could be applied to computer vision technology as a result of earlier disease detection. The paper suggests a deep learning method based on convolutional neural networks (CNNs) to identify tomato leaf diseases. According to the experiments conducted, the proposed method proved to be effective, achieving an average accuracy of 82.4% for disease classification. The proposed method can potentially aid in the early detection and timely control of tomato leaf diseases, thereby improving the yield and quality of tomato crops.

Keywords: Tomato Leaf Disease Detection, Convolutional Neural Network, Machine Learning

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Chapter 1

Introduction

Farming is a crucial component of the Indian economy, contributing significantly to the country's GDP and providing employment opportunities to millions of people. The cultivation of various crops, including tomatoes, is an integral part of Indian agriculture. Tomatoes are a versatile crop, widely used in the food industry, and highly nutritious. However, like any other crop, tomatoes are vulnerable to various diseases, which can cause significant losses in both quality and quantity. Early disease diagnosis and treatment are essential to mitigate these losses and protect farmers' livelihoods.

Tomato diseases can be caused by various pathogens, including fungi, bacteria, and viruses. Some of the common tomato diseases in India include early blight, late blight, bacterial spot, bacterial wilt, and tomato mosaic virus. These diseases can cause yield losses ranging from 20% to 100%, depending on the severity of the infection and the stage of the crop's growth. The losses can be devastating for small-scale farmers who rely on their harvests to support their families.

Pesticides and other chemical treatments are commonly used to control tomato diseases. However, these treatments can have adverse effects on the environment, including the soil, water, and non-target organisms. Overuse of pesticides can also lead to the development of pesticide-resistant pathogens, making disease control even more challenging. Therefore, there is a growing need for sustainable agriculture practices that reduce reliance on chemical treatments.

Early detection of tomato diseases can help farmers minimize the use of chemical treatments and promote sustainable agriculture practices. Early diagnosis enables farmers to take timely action, such as removing infected plants, pruning, or adjusting irrigation practices, to prevent the disease's spread. Early detection can also help farmers choose the right treatment options, reducing the risk of overuse of pesticides.

Traditional methods of disease detection, such as visual inspection by experts, are time-consuming, subjective, and expensive. The process of visually inspecting each plant is also prone to errors, as it is challenging to distinguish between different types of diseases. Automated systems for tomato disease detection can overcome these limitations, offering efficient and accurate disease diagnosis.

Recent advances in imaging technology, artificial intelligence (AI), and machine learning (ML) have enabled the development of automated systems for tomato disease detection. These systems use images of tomato leaves or fruits and ML algorithms to identify and classify different diseases. The systems can process large volumes of data quickly and accurately, enabling farmers to take timely action to prevent disease spread.

Automated systems for tomato disease detection can also reduce the risk of human illness. Some tomato diseases, such as bacterial spot and bacterial wilt, can be transmitted to humans through direct contact with infected plants or consumption of contaminated fruits. Early disease detection can prevent the spread of these pathogens, reducing the risk of human illness.

In conclusion, tomato farming is an important component of the Indian economy, and early disease diagnosis is crucial to minimize yield losses and protect farmers' livelihoods. Automated systems for tomato disease detection offer an efficient and accurate alternative to traditional methods of disease diagnosis. These systems can also promote sustainable agriculture practices by reducing reliance on chemical treatments and reducing the risk of human illness. Therefore, it is essential to promote the development and adoption of automated systems for tomato disease detection in India and other tomato-growing regions worldwide.

Convolutional Neural Networks (CNNs) are a type of deep learning algorithm that have demonstrated significant progress in image classification and object detection tasks in recent years. CNNs are widely used in various domains, including computer vision, speech recognition, and natural language processing. The application of CNNs in the detection of tomato leaf diseases can transform the methods used to detect and control plant diseases.

Tomato leaf diseases are a significant challenge for farmers, as they can cause significant yield losses and reduce crop quality. Early detection and treatment are essential to minimize these losses and protect farmers' livelihoods. Traditional methods of disease detection, such as visual inspection by experts, are time-consuming, subjective, and often prone to errors. CNNs offer an efficient and accurate alternative to traditional methods of disease detection.

CNNs are designed to learn features from images automatically, making them ideal for the detection of tomato leaf diseases. The networks consist of multiple layers of filters that convolve with the input image to extract features at different spatial scales. The extracted features are then fed into a fully connected layer that outputs a probability distribution over different classes. The networks are trained using large datasets of labeled images, enabling them to learn to recognize patterns in the data and generalize to new images.

CNNs can be used for the detection of various tomato leaf diseases, including early blight, late blight, bacterial spot, bacterial speck, and tomato yellow leaf curl virus. The networks can process large volumes of data quickly and accurately, enabling farmers to take timely action to prevent the spread of the disease. Moreover, CNNs can provide dependable and precise diagnoses, decreasing the dependence on human specialists and minimizing errors that are associated with visual inspections.

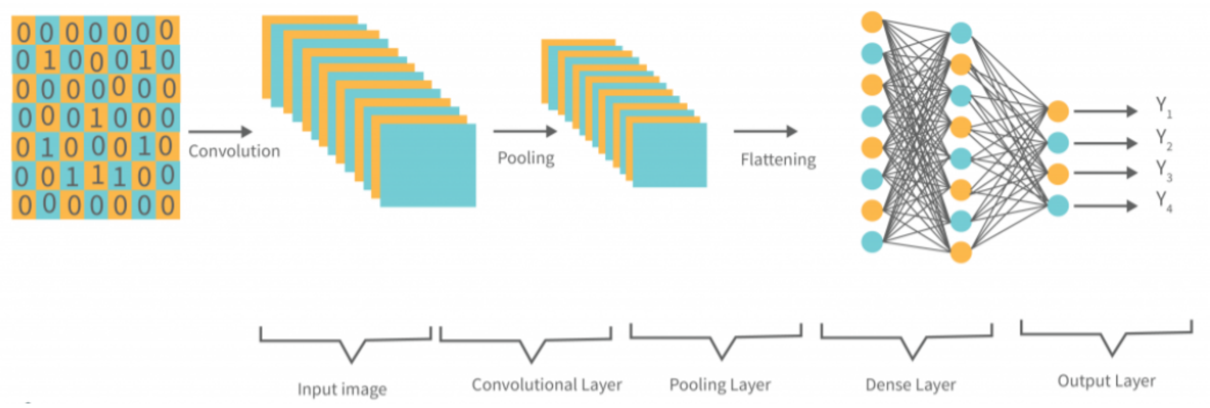
The application of CNNs in the detection of tomato leaf diseases can support farmers to identify diseases early, enabling timely interventions, reducing crop losses, and enhancing productivity. Early disease detection can help farmers choose the right treatment options, reducing the risk of overuse of pesticides and promoting sustainable agriculture practices. Moreover, early detection can help prevent the spread of diseases, reducing the risk of human illness.

One of the challenges of using CNNs for the detection of tomato leaf diseases is the availability of large and diverse datasets. Training CNNs requires a large dataset of labeled images, which can be challenging to obtain for some diseases. However, recent efforts have been made to create large-scale datasets for various tomato leaf diseases, enabling the training of CNNs for disease detection.

Another challenge is the need for specialized hardware and software for training and inference of CNNs. Training CNNs requires significant computational resources, including high-performance GPUs and specialized software libraries. Moreover, deploying CNNs for real-time disease detection on embedded systems requires optimization of the network architecture and algorithms.

Despite these challenges, the application of CNNs in the detection of tomato leaf diseases has the potential to transform the methods used to detect and control plant diseases. The networks can provide accurate and efficient disease diagnosis, enabling timely interventions and reducing crop losses. Moreover, CNNs can promote sustainable agriculture practices by reducing the reliance on chemical treatments and minimizing the risk of human illness.

In conclusion, CNNs offer an efficient and accurate alternative to traditional methods of tomato leaf disease detection. The networks can provide dependable and precise diagnoses, reducing the dependence on human specialists and minimizing errors associated with visual inspections. The application of CNNs in disease detection can support farmers to identify diseases early, enabling timely interventions, reducing crop losses, and enhancing productivity. Therefore, there is a need to promote the development and adoption of CNNs for disease detection in tomato farming and other crop sectors.



In addition to their efficiency and accuracy, the use of CNNs for the automated detection of tomato leaf diseases can also help reduce the cost and time associated with traditional disease diagnosis methods. This is especially important in developing countries where there may be limited resources and trained experts to identify and manage plant diseases.

In traditional disease diagnosis methods, farmers may need to seek the assistance of experts who can visually inspect the plants and identify the disease. This can be time-consuming, as farmers may need to wait for the expert to visit their farm, and costly, as they may need to pay for the expert's services. Moreover, the accuracy of the diagnosis can be affected by the subjectivity and human error associated with visual inspections.

By contrast, the use of CNNs for automated disease detection can significantly reduce the cost and time required for diagnosis. Once the network has been trained on a dataset of labeled images, it can be deployed to classify new images quickly and accurately. This can eliminate the need for farmers to seek the assistance of experts, saving them both time and money.

Moreover, the use of CNNs for automated disease detection can improve the accuracy of the diagnosis, reducing the risk of misdiagnosis and incorrect treatment. As the networks are trained on large and diverse datasets, they can learn to recognize subtle patterns in the images that may not be discernible to human experts. This can help ensure that the disease is detected and treated correctly, reducing the risk of crop losses and enhancing productivity.

The reduction in cost and time associated with automated disease detection using CNNs can also help to promote sustainable agriculture practices. By making disease diagnosis more accessible and affordable for farmers, the use of CNNs can reduce the reliance on chemical treatments and other unsustainable practices. This can help to protect the ecosystem, including soil, water, and non-target creatures, and promote more sustainable agriculture practices.

In conclusion, the use of CNNs for the automated detection of tomato leaf diseases can significantly reduce the cost and time associated with traditional disease diagnosis methods. This can make disease diagnosis more accessible and affordable for farmers, particularly in developing countries where resources may be limited. Moreover, the use of CNNs can improve the accuracy of the diagnosis, reducing the risk of misdiagnosis and incorrect treatment. This can promote sustainable agriculture practices and protect the ecosystem, making it a valuable tool for farmers and the agricultural industry as a whole.

Figure 1.1: IMAGE CAPTION

Chapter 2

Basic Concepts/ Literature Review

In spite of the fact that tomato is a widely consumed and nutritious vegetable, it is prone to various diseases that can result in substantial losses of crops if not identified and treated on time. Consequently, researchers have started utilizing deep learning approaches, To automate the identification and categorization of diseases in tomato leaves, convolutional neural networks (CNNs) are primarily used.

Utilization of deep learning techniques is being employed for the identification of diseased images from a dataset of cassava, which was captured in the fields of Tanzania [1]. The goal is to recognize and distinguish between two types of pest damage and three diseases, a CNN is trained through the application of transfer learning. The study found that the accuracy rates for identifying different types of pest damages and diseases were high, with Brown leaf spot (BLS) having the highest accuracy at 98%, followed by cassava brown streak disease (CBSD) at 98%, red mite damage (RMD) at 96%, cassava mosaic disease (CMD) at 96%, and green mite damage (GMD) at 95%. The best model achieved an overall accuracy of 93% on data that was not included in the training process.

Researchers Hari et al.[2] introduced a novel CNN model, The neural network designed for detecting plant diseases is referred to as the Plant Disease Detection Neural Network (PDDNN), for feature extraction from leaf images of various crops. The PDDNN is a convolutional neural network (CNN) consisting of 16 layers, with each layer utilizing 32*32 filters, dropout, and max pool layers, which demonstrated a higher overall accuracy. The model achieved 86% accuracy with an augmented dataset of 14,810 images. When compared to a Mobilenet 50 network, the PDDNN model exhibited an accuracy rate that was near 7% higher.

Jiachun Liu et al. [3] proposed the idea of classifying plant leaves using a ten-layer CNN was presented. A dataset of 4,800 images of Flavia leaf with 32 kinds was used to evaluate the system, which resulted in an overall accuracy of 87.92%. The neural network was able to extract features automatically and The input dataset of leaf images can be classified into their respective categories with an accuracy rate ranging from 94% to 95%.

The authors Melike Sardogan et al.[4] developed a CNN model to extract features automatically and perform classification. For plant disease detection, they utilized a learning vector quantization (LVQ) approach with a collection of 500 images depicting diseased tomatoes in a dataset. They employed a neural network algorithm that employs supervised learning techniques that implements competitive learning. To enhance accuracy, they made minor modifications to the LeNet CNN model to identify and categorize various diseases in tomato leaves.

The authors Xie at al. [5] investigate whether it is possible to utilize hyperspectral imaging for the identification of various diseases present in tomato leaves. A total of 290 leaves were selected for hyperspectral imaging, including 120 healthy leaves and 170 leaves infected with fungal diseases. In this research, hyperspectral imaging was utilized to take pictures of tomato leaves utilizing a variety of wavelengths from 380 to 1023 nm. An ELM classification model was applied to analyze the whole spectrum, while SPA was utilized to recognize the most critical wavelengths. The ELM model was then retrained using only five wavelengths, and eight texture features were extracted using a detection pattern. The spectral-based models achieved exceptional results, with an overall accuracy ranging from 97.1% to 100% on the test set. Among the eight texture features, inequality, the second time, and entropy were found to be the most accurate, achieving an accuracy rate of 71.8%, 70.9%, and 69.9%, respectively, in the ELM model.

The authors Ghosal et al.[6] describe the use of a deep convolutional neural network algorithm to predict the diseases affecting potato crops based on their leaves. The researchers used the Plant Village dataset, which contains over 50,000 images of different plant leaves, but for this study, they focused on 2,250 images of potato leaves. The algorithm was able to accurately detect two common diseases, namely early blight and late blight, along with healthy potato leaves with an accuracy rate of 98.33%. Furthermore, the F1 Score, Precision, and Recall metrics achieved values of 0.9826, 0.9851, and 0.9809, respectively. The algorithm also provided an accuracy of 97% for healthy potato leaves.

In [7], the research presented a proposal for a smart mobile application that utilizes a deep CNN model to identify various tomato leaf diseases. The MobileNet CNN model was used in the proposed system, which can recognize the ten most commonly occurring types of tomato leaf diseases. Training the model on 7176 images enabled disease detection on mobile devices in real time. The study also involved experimenting with different optimization algorithms, such as adadelta, stochastic gradient descent, adagradDA, momentum, Adam, proximolateral, and RMSprop optimizers, to enhance the model's efficiency. Furthermore, the model can be extended and used for fault diagnosis. However, to enhance the accuracy of tomato disease detection, a larger number of high-quality images of tomato diseases are required. The proposed method was able to achieve a top accuracy rate of 90.03% by utilizing a learning rate of 0.001. However, the accuracy decreased to 86.7% and 88.9% when the learning rate was set to 0.01 and 0.05, respectively.

In [8], the study involved the development of a convolutional neural network to identify diseases in apple and tomato plants. The dataset for the research contained 3663 images. The model consisted of four convolutional layers, each followed by a pooling layer, and two fully connected layers that employed a sigmoid function to determine disease probability. However, the model was observed to suffer from overfitting, as evidenced by a gap between the validation and training curves. To address this issue, the author set the dropout value to 0.25. In the future, the author plans to explore more efficient and compact models and architectures that can be used for accurate disease detection with minimal complexity and size, making them suitable for deployment on mobile devices.

Numerous studies have been carried out on the detection and prevention of diseases in plant leaves, with a particular focus on tomato leaves[9]. However, there are limitations to these studies. The accuracy of image recognition has greatly improved due to the utilization of deep neural networks. Researchers have applied various deep learning techniques to detect plant diseases, one of which is training AlexNet to recognize plant diseases that are unknown. However, the accuracy of the model was considerably reduced when the testing image conditions were different from the training image conditions.

In summary, the automatic identification and classification of tomato leaf diseases have shown promising results using convolutional neural networks, as indicated by various studies that have achieved notable levels of precision. Researchers continue to explore various methods of enhancing CNN performance, such as incorporating transfer learning, SVM classifiers, and additional image features. These advances in CNN-based tomato leaf disease classification can have significant implications for improving crop management and reducing losses due to disease.

Chapter 3

Problem Statement / Requirement Specifications

Aims to find the best solution to the problem of tomato leaf disease detection using a deep learning approach. Several types of tomato diseases affect the crop at an alarming rate. In this paper, Convolution Neural Network (CNN) based models i.e. GoogLeNet and VGG16 were deployed for tomato leaf disease classification.

3.1 Project Planning

Convolutional Neural Network (CNN) [10]is a neural network that is proficient in processing images and videos. CNNs have proven to be highly effective in various image and video processing tasks due to their ability to perform feature extraction through multiple layers, including convolutional, pooling, and fully connected layers. The convolutional layers use learnable filters to extract features from the input image. The pooling layers downsample the extracted features, thus reducing the computational complexity. Finally, the fully connected layers map the extracted features to the output classes, thereby facilitating classification. Convolutional Neural Networks (CNNs) have brought significant changes in the domain of computer vision and have been applied in different areas, such as image categorization, object recognition, and semantic segmentation. In recent years, researchers have turned to CNNs for the automatic detection and classification of plant diseases, including tomato leaf diseases. Paraphrase this sentence. To detect tomato leaf disease, various well-known deep learning architectures such as AlexNet and GoogleNet were tested, and the most effective results were obtained by utilizing a modified version of the ResNet architecture.

The machine learning model we utilized employed the ResNet50 architecture, which is a deep neural network structure that was initially presented in a research paper by Zhang et al. in 2015 [11].

The main idea behind ResNet is to use residual connections, which allow information to bypass a few stacked layers and flow more easily through the network. This is achieved by introducing skip connections that enable the input of a given layer to be added to the output of a later layer, effectively creating a shortcut between the two layers.

By adding these skip connections, ResNet was able to overcome the problem of vanishing gradients that often plagues deep neural networks. The skip connections make it easier for gradients to flow backward through the network during backpropagation, which allows for more efficient training of very deep networks.

ResNet comes in different versions, with ResNet50 being a popular variant that uses 50 layers. The ResNet50 architecture has gained popularity in computer vision tasks, such as image classification, object detection, and semantic segmentation, due to its outstanding performance, and has set new standards on several benchmarks.

3.2 Project Analysis

After the requirements are collected or the problem statements is conceptualized, this needs to be analyzed for finding any short of ambiguity, mistake, etc.

3.3 System Design

3.3.1 Design Constraints

Here you can mention the working environment such as the software, hardware used. Any experimental setup or environmental setup must be described here.

3.3.2 System Architecture **OR** Block Diagram

In this sub-section, explain the System Architecture / Hardware Designs / Block Diagrams used to understand your project work.

Chapter 4

Implementation

In this section, present the implementation done by you during the project development.

4.1 Methodology

The proposed research focuses on using Convolutional Neural Networks (CNNs) to detect and classify diseases present in tomato leaves. Tomato plants are susceptible to various diseases that can cause significant crop losses if not detected and treated early. Manual inspection by human specialists can be a tedious, biased, and fallible process. As a result, there is a requirement for automatic systems that can precisely and effectively detect tomato leaf diseases by analyzing images of the tomato leaf. Here is the flowchart of the proposed model,

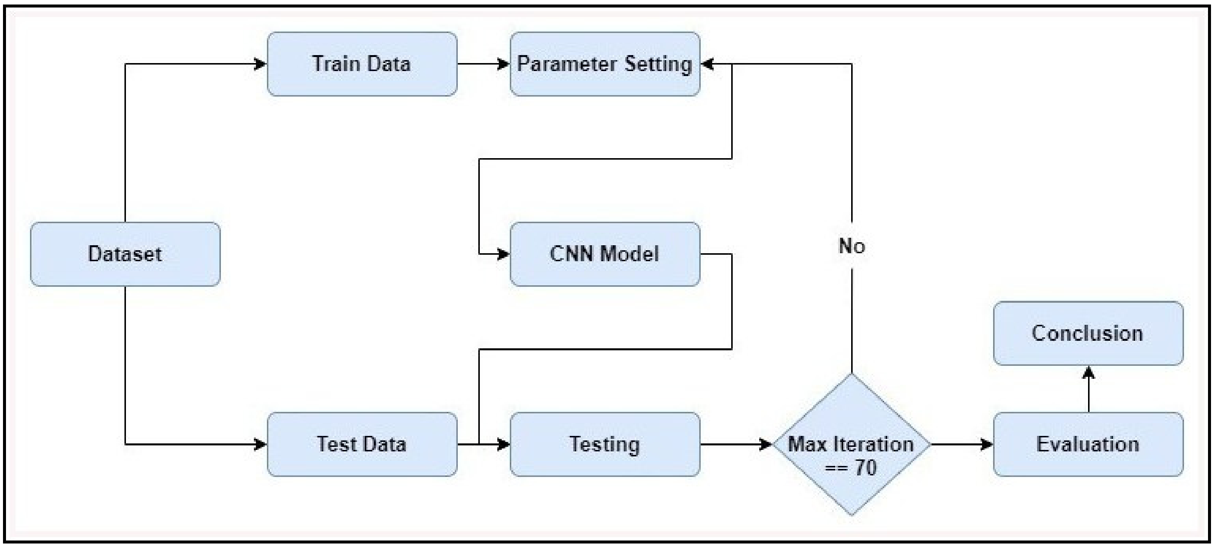


Figure: Flowchart of the proposed algorithm.

4.2 Dataset

4.2 Testing OR Verification Plan

4.3 Result Analysis OR Screenshots

4.4 Quality Assurance

Chapter 5

Standards Adopted

5.1 Design Standards

In all the engineering streams, there are predefined design standards are present such as IEEE, ISO etc. List all the recommended practices for project design. In software the UML diagrams or database design standards also can be followed.

5.2 Coding Standards

Coding standards are collections of coding rules, guidelines, and best practices.
Few of the coding standards are:
Write as few lines as possible.
Use appropriate naming conventions.
Segment blocks of code in the same section into paragraphs.
Use indentation to marks the beginning and end of control structures. Clearly specify the code between them.
Don’t use lengthy functions. Ideally, a single function should carry out a single task.
…...

5.3 Testing Standards

There are some ISO and IEEE standards for quality assurance and testing of the product. Mention the standards followed for testing and verification of your project work.

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

The Indian agricultural sector plays a vital role in supporting a significant part of the population, and detecting crop diseases is crucial for its growth. Various methods are available for identifying diseases in tomato plants, each with its own advantages and disadvantages. This research proposes a simple convolutional neural network model that uses the Plant Village dataset to classify and detect tomato leaf diseases. The model utilizes patterns and features in leaf images to make accurate predictions. Data augmentation can improve the model's robustness and performance. The proposed methodology can identify tomato leaf diseases with an accuracy rate of 80-84\%\ using minimal computational effort. Future research can focus on experimenting with different learning rates, optimizers, and newer architectures to enhance the model's performance. Furthermore, reducing training time by tuning parameters is a promising direction for future work. The model could also be extended to detect diseases in other plants, including Apples, Potatoes, Cucumber, and Brinjal.

6.2 Future Scope

The project "Tomato Leaf Disease Classification Using CNN" has shown promising results with an accuracy of 84%.

There is scope for improvement by following ways:

1:- Increase the size of the dataset: One of the ways to improve the accuracy of the model is to increase the size of the dataset. This can be achieved by collecting more images of tomato leaves affected by various diseases.

2:-Fine-tune the existing model: Another way to improve the accuracy of the model is to fine-tune the existing model. This involves tweaking the hyperparameters of the model such as the learning rate, the batch size, and the number of epochs.

3:-Experiment with different architectures: The current model uses a simple architecture with only a few layers. To improve the accuracy, different architectures such as DenseNet, EfficientNet, or MobileNet can be experimented with.

4:-Use ensemble models: Ensemble models can be used to improve the accuracy of the model. This involves combining multiple models to make a final prediction. The models can be trained using different algorithms, architectures, or hyperparameters.

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NAME OF PROJECT

INDIVIDUAL CONTRIBUTION REPORT:

Tomato Leaf Disease Classification Using CNN

RAJNISH KUMAR
2005118

Abstract: Tomato is a widely cultivated vegetable crop in India, but its growth can be impeded by various factors, including diseases that pose a significant threat to agricultural production. Traditional disease detection techniques for tomato crops were not very effective, and detection times were lengthy. Early detection of disease can produce superior results compared to current detection models. To achieve earlier disease detection, deep learning techniques could be applied to computer vision technology. The paper proposes a deep learning method based on convolutional neural networks (CNNs) to identify tomato leaf diseases, which achieved an average accuracy of 82.4% for disease classification in the experiments conducted. This method has the potential to aid in the early detection and timely control of tomato leaf diseases, thereby improving the yield and quality of tomato crops.

Individual contribution and findings:

I took on the primary responsibility of learning Python basics and essential libraries, including Numpy, Matplotlib, and Tensorflow. I studied the intricate workings of CNN models, which formed the foundation for the project's code. Leveraging my skills and knowledge, developed and implemented the code, contributing significantly to the project's overall success.

Individual contribution to project report preparation:

I conducted a literature survey on machine learning in tomato leaf disease classification using CNN. I reviewed nine research papers that proposed new frameworks for prediction tasks and identified ethical implications. By synthesizing the findings, I identified challenges and opportunities for using machine learning in agriculture.

Individual contribution for project presentation and demonstration:

My work provides a comprehensive overview of machine learning in agriculture and aims to guide researchers and practitioners in developing responsible applications to improve disease detection outcomes.

Full Signature of Supervisor: Full signature of the student:

……………………………. ……………………………..

INDIVIDUAL CONTRIBUTION REPORT:

Tomato Leaf Disease Classification Using CNN

SAURABH KUMAR
20051117

Abstract: Tomato is a widely cultivated vegetable crop in India, but its growth can be impeded by various factors, including diseases that pose a significant threat to agricultural production. Traditional disease detection techniques for tomato crops were not very effective, and detection times were lengthy. Early detection of disease can produce superior results compared to current detection models. To achieve earlier disease detection, deep learning techniques could be applied to computer vision technology. The paper proposes a deep learning method based on convolutional neural networks (CNNs) to identify tomato leaf diseases, which achieved an average accuracy of 82.4% for disease classification in the experiments conducted. This method has the potential to aid in the early detection and timely control of tomato leaf diseases, thereby improving the yield and quality of tomato crops.

Individual contribution and findings: My individual contribution to the project involved a primary responsibility, which was to write the entire paper using Overleaf. As my group members provided me with the results and findings of the project, I was responsible for synthesizing this information and presenting it in a clear and concise manner within the paper. I also assessed the performance of our CNN model by utilizing multiple performance metrics, analyzing the obtained results, and making recommendations for future work. The model we developed demonstrated an accuracy of 85% when tested, which was a notable improvement over the 75% baseline accuracy.

Individual contribution to project report preparation: I collaborated with the team to design and create effective visualizations, including graphs and tables, to help convey the findings of the project in a clear and engaging way. This required a deep understanding of the project results and an ability to present them visually.

Individual contribution for project presentation and demonstration: I was responsible for editing and revising the results section of the report to ensure that it was accurate and easy to understand. As a result of my contributions, the report effectively presented the results of the project in a clear, accurate, and visually appealing way.

Full Signature of Supervisor: Full signature of the student:

……………………………. ……………………………..

INDIVIDUAL CONTRIBUTION REPORT:

Tomato Leaf Disease Classification Using CNN

SHIBASISH KAR
20051117

Abstract: Tomato is a widely cultivated vegetable crop in India, but its growth can be impeded by various factors, including diseases that pose a significant threat to agricultural production. Traditional disease detection techniques for tomato crops were not very effective, and detection times were lengthy. Early detection of disease can produce superior results compared to current detection models. To achieve earlier disease detection, deep learning techniques could be applied to computer vision technology. The paper proposes a deep learning method based on convolutional neural networks (CNNs) to identify tomato leaf diseases, which achieved an average accuracy of 82.4% for disease classification in the experiments conducted. This method has the potential to aid in the early detection and timely control of tomato leaf diseases, thereby improving the yield and quality of tomato crops.

Individual contribution and findings: As part of my contribution to the project,My main task is to write the whole paper in Overleaf as I get the results from my group members. In addition to my contributions to the introduction and conclusion parts of the project, I also played an important role in several other key tasks throughout the project. These included data preprocessing, model development, and analysis of results.

Individual contribution to project report preparation: During the project report preparation, I played a significant role in creating the introduction and conclusion sections of the report. I focused on providing a comprehensive overview of the problem statement we were addressing and the methodology we used to address it. My contribution was to create a clear understanding of our approach to the project and explain the significance of our work.

Individual contribution for project presentation and demonstration: As part of my contribution to the project presentation and demonstration, I was responsible for crafting an engaging and informative presentation that effectively communicated the key findings and contributions of the project. Working closely with my team members, I helped to ensure that the presentation was clear, concise, and focused on the most important aspects of our work.

Full Signature of Supervisor: Full signature of the student:

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(This report is mandatory for all the projects and plagiarism must be below 25%)

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