** A**

**Project Report**

on

**Plant Disease Detection using Convolutional Neural Networks**

submitted as partial fulfilment for the award of

**BACHELOR OF TECHNOLOGY**

**DEGREE**

SESSION 2024-25

in

**Computer Science and Engineering**

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(Formerly UPTU)

**May, 2025**

**DECLARATION**

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

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## CERTIFICATE

This is to certify that the Project Report entitled “**Plant Disease Detection Using Convolutional Neural Networks**” which is submitted by **Aashirwad, Ishika Jaggi and Ashutosh Kumar,**  in partial fulfillment of the requirement for the award of degree B. Tech. in the department of Information Technology of KIET Group of Institutions, Delhi NCR affiliated to Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

**Dr. Dilkeshwar Pandey Dr. Vineet Sharma**

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Finally, we acknowledge our friends for their contribution to the completion of the project.

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**ABSTRACT**

Detecting crop diseases is an important step in ensuring food security and enhancing agricultural productivity. Detecting diseases in time can help farmers take effective actions to prevent crop loss and improve yield. Earlier methods of disease detection, like visual inspections by agricultural intellectuals, are time-taking and sometimes inaccurate. With increasing developments in A.I. and deep learning, there’s a rapidly increasing interest in automating disease detection using image classification techniques and computer vision. This research paper provides a complete review of deep learning models which are used for detecting crop diseases, exploring the methods, challenges, and applications of these techniques in precision agriculture. The study also discusses various data sets, models, and tools utilized in this domain, providing insight into future directions for improving disease detection and management in crops.

**Keywords:** Crop Disease Detection, Deep Learning, Image Classification, Precision Agriculture, Neural Networks, Agricultural Automation.

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**LIST OF ABBREVIATIONS**

| **Abbreviation** | **Full Form** |
| --- | --- |
| CNN | Convolutional Neural Network |
| GDP | Gross Domestic Product |
| SVM | Support Vector Machine |
| HDF | Hierarchal Data Format |

VGG Visual Geometry Group

**CHAPTER 1**

**INTRODUCTION**

**1.1 INTRODUCTION**

Agriculture is essential to the global economy, providing food, jobs, and a source of income for many. In India, a significant amount of the people are engaged in agriculture, agriculture contributes approximately 18% to the national GDP and gives employment to around 53% of the workforce.

For past three years, there have been an increase of 17.6% to 20.2% in Gross Value Added to national economy. Given its economic importance, any decline in agricultural productivity due to plant diseases or pest infestations can have far-reaching consequences. Conventional preventive treatments often fall short in controlling epidemics, making timely detection and accurate recognition essential for minimizing losses and ensuring sustainable agricultural output.

Recognizing plant diseases early in time is critical for effective management. Diseased plants usually exhibit visible symptoms such as spots or lesions on leaves, stems, fruits, or flowers. Each disease and pest infestation tends to create distinct patterns, which can serve as indicators for identification.

However, traditional methods of diagnosis depend on intellectuals knowledge and human inspections, that can be time-taking, subjective, and occasionally inaccurate. Misidentifications may lead to improper treatments, negatively impacting both crop quality and environmental sustainability.

One majorly used dataset for detecting diseases is the Plant-Village dataset, developed by Pennsylvania State University. It comprises 54,305 RGB images categorized into 38 various disease classified across 14 plant species, with each species having both healthy and diseased leaf samples.

Since its release, this dataset is being used extensively in research to build and evaluate plant disease detection models. Despite the success of deep CNN architectures, training such models from the zero level is expensive and requires lots of data.

To address this challenge, researchers have increasingly adopted transfer learning, where already trained models like VGG-16, ResNet, DenseNet, and Inception are fine-tuned for plant disease classification. These models, originally trained on wide-ranged datasets like ImageNet, can effectively generalize to new datasets by leveraging their learned feature representations.

Transfer learning not only reduces training time but also enhances performance, even when datasets are relatively small. This study aims to improve plant disease diagnosis by leveraging transfer learning techniques with CNNs. We compare the performance of multiple existing deep-learning models on the PlantVillage dataset. The key contributions of this research include:

* Developing a model that uses deep learning to accurately identify diseases in plants.
* Evaluating the transfer learning approach that is most effective in multi-class disease diversification.
* Addressing labeling inconsistencies in recognizing diseases in plants by implementing a CNN based model which is multi-classed and multi-labeled.
* Applying data augmentation techniques to mitigate overfitting issues.

**1.2 PROJECT DESCRIPTION**

* This project focuses on developing a Convolutional Neural Network (CNN) model to automatically detect and classify diseases from medical or agricultural images. The goal is to create a robust deep learning model that can assist in early and accurate diagnosis based on visual patterns in the images.
* To ensure the reliability and generalization of the model, the original dataset is split into three parts: training, validation, and test sets. The training and validation sets are used to train and fine-tune the CNN model, while the test set is reserved for final performance evaluation.
* The trained model is then tested on unseen images to predict the presence of disease. Key performance metrics such as accuracy and F1-score are used to assess how well the model identifies and classifies diseases. This setup allows us to compare the actual and predicted disease labels for each test image, offering valuable insights into the model's practical utility.
* This project demonstrates the effectiveness of deep learning in automated disease diagnosis and highlights the importance of data preparation, model evaluation, and performance metrics in building reliable AI systems.

**CHAPTER 2**

**LITERATURE REVIEW**

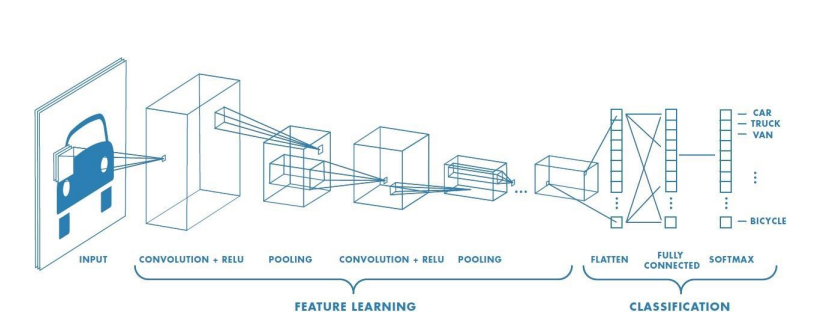
* In agriculture, overlooking the early indicators of plant diseases can result in substantial crop losses, which may have broader economic consequences. This section offers an deep analysis of latest developments in detection of leaf diseases.
* A CNN based deep learning model was designed to identify plant diseases accurately, as detailed in [13]. The training of the model was done with the help of a publicly accessible dataset containing 87,000 images. The workflow involved pre-processing, segmentation, and classification through the CNN. Accuracy of 93.5\% was attained using the same, it faced challenges in differentiating between specific disease categories, resulting in classification errors. Furthermore, its effectiveness was limited by the dataset’s lack of diversity.
* To increase accuracy, Narayanan [2] proposed a CNN model which is hybrid, tailored for banana leaves in detecting its diseases. Their approach preserved the original features of raw input images while keeping standard dimensions with the help of a median filter. A combination of CNN and a fusion support vector machine was employed, multi-class SVM identified the type of infection, and a separate SVM stage determined whether the leaves were healthy or diseased. This hybrid approach achieved a classification accuracy of 99\%. While CNNs demonstrated superior accuracy compared to traditional methods, these approaches still lacked diversity in training data.
* A CNN-based approach for detecting diseases in plants exists, utilizing a pre trained model such as Google-Net and Alex-Net to classify diseases in soybean plants. Although their model achieved promising results, its effectiveness was restricted by dataset limitations, making it challenging to classify multiple plant diseases. Many existing models prioritize the identification of specific diseases rather than creating a broad classifier capable of recognizing various plant diseases, primarily due to scarcity of diverse datasets required for training the deep learning models.
* Jadhav et al. [4] proposed an innovative histogram transformation technique to improve recognition accuracy synthetically generating images from test samples with low quality. Their approach enhanced leaf disease classification by using motion blurring, Gaussian blurring, and overexposure. To address the challenge of limited data in deep learning models, they adapted the MobileNetV2 architecture to train on these augmented images.
* To generate images of tomato leaves, Abbas et al. [7] used GAN(generative adversarial network), improving the efficiency and affordability of data collection. Similarly, a leaf classification model was proposed by Anh et al. [12], employing a pre-trained MobileNet CNN and achieving an accuracy of 96.58\%. Furthermore, a study referenced in [20] introduced a multi labeled CNN model to identify multiple plant diseases. This model incorporated transfer learning techniques with architectures such as Inception, Xception, ResNetDenseNet, MobileNet, and VGG. In particular, it was recognized as the initial study to classify 29 different plant disease categories using a multi-label CNN approach.

**CHAPTER 3**

**PROPOSED METHODOLOGY**

**3.1 Introduction to Convolutional Neural Networks**

* Convolutional Neural Networks (CNNs) are a specialized type of deep learning model particularly well-suited for analyzing visual data. They have become a powerful tool in image classification tasks due to their ability to automatically learn spatial hierarchies of features through convolutional layers. This makes CNNs especially effective in recognizing patterns, textures, and structures in images — key characteristics for identifying diseases in crops.
* In the context of agriculture, early and accurate detection of crop diseases is critical to minimizing yield loss and ensuring food security. Traditional methods rely heavily on manual inspection, which can be time-consuming, inconsistent, and dependent on expert availability. CNN-based systems offer a scalable alternative by enabling automated analysis of crop images, providing fast and reliable disease identification.

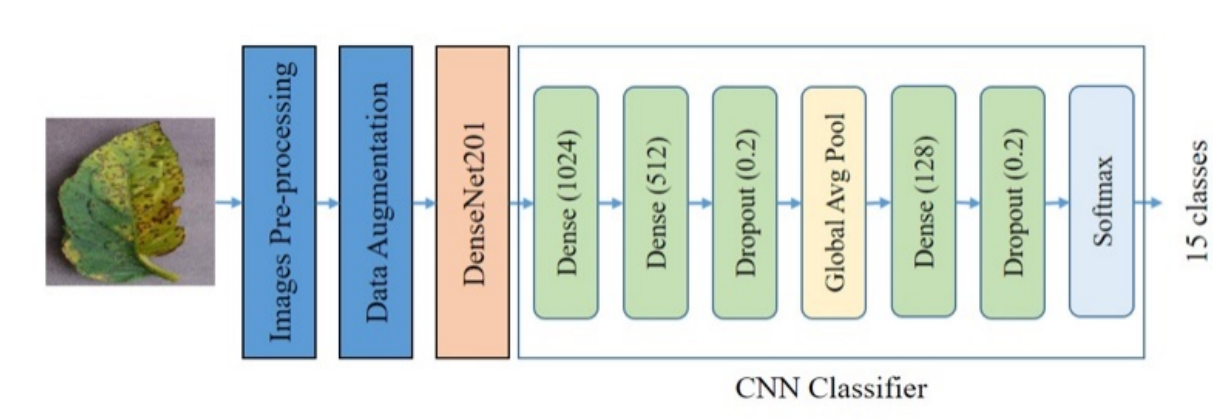


*Figure 3.1 Steps in CNN*

* A CNN model typically includes layers such as convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. By training the network on a large dataset of labeled crop images, the model learns to distinguish between healthy and diseased plants, as well as among different types of diseases.
* This capability makes CNNs a promising approach for building intelligent crop monitoring systems that support farmers and agricultural professionals in making informed decisions with greater efficiency and accuracy.

The proposed methodology uses a a model designed for plant diseases to be classified and predicted based on infected leaves’ images. The said approach integrates a model which is pre-trained with a CNN classifier for enhanced accuracy.

* We have used a dataset from Plant-Village dataset which contains around 22,930 images. The dataset has been divided into 3 parts, training, validation and testing with 75\%, 20\% and 5\% of data assigned respectively. Each image features a plant leaf that occupies most of the frame, serving as the primary focus while the background remains consistent.
* The data set is categorized into 15 distinct classes, including nine tomato disease classes along with a healthy tomato class, two potato disease classes along with a healthy potato class, and one pepper disease class along with a healthy pepper class. The 15 categories include: healthy tomato plants can be affected by various issues which are mentioned below in Fig. 3.
* To enhance the image data quality is done with the help of image pre-processing for performing classification by applying various adjustments, including rotation, scaling, and translation. During this process, the original image resolution of 256×256 pixels was reduced to 224×224 pixels. Regulating the size and resolution of the images is important to ensure consistency.
* To achieve optimal results, CNN requires substantial amount of training data (14). When only a limited dataset is available, image augmentation is commonly employed which helps in improving the performance of various CNN models. This technique enhances the dataset by introducing variations of existing images, which helps prevent overfitting. Overfitting occurs when the model memorizes specific data instead of recognizing general patterns within the dataset. Image augmentation provides more training samples using different transformations like flipping, rotation, blurring, adjusting lighting, and random cropping (13). In this study, we apply scaling, shearing, zooming, and horizontal flipping to augment the dataset.
* It is a technique used to enhance performance of a function by making small adjustments that improve the final outcome. Even minor modifications play a crucial role in the optimization process, significantly impacting computational convergence, time and speed and the required processing power. To increase the accuracy of our model, we applied the fine tuning process more than one time. Table I presents the training and fine-tuning parameters that yielded the best results. To see various parameters of training and fine tuning, refer to Table I.



*Figure 3.2 The Proposed Methodology*

**3.2 Architecture Overview**

* This model operates through five key phases, as illustrated in Figure 3.3.
* The first phase involves data pre-processing, followed by data augmentation in its second phase.
* The third phase emphasises on extracting various features, leveraging transfer learning with the architecture of DenseNet201.
* The extracted features are classified using a CNN to identify plant leaf diseases in the fourth phase.
* Lastly, the fifth phase involves performance evaluation and analysis. The processes of image pre-processing and data augmentation are conducted similarly.

A diagram of a data processing process

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*Figure 3.3 Steps in detecting and classifying plant leaf diseases.*

**3.3 Proposed Algorithm**

In this section, we are proposing algorithm for Crop Disease Detection Model using a CNN model.

This model operates through five key phases, as illustrated in Figure 3.3. The first phase involves data pre-processing, followed by data augmentation in its second phase. The third phase emphasises on extracting various features, leveraging transfer learning with the architecture of DenseNet201.

The extracted features are classified using a CNN to identify plant leaf diseases in the fourth phase. Lastly, the fifth phase involves performance evaluation and analysis. The processes of image pre-processing and data augmentation are conducted similarly.

Transfer learning in the third phase was done with the help of DenseNet201, enabling automatic feature extraction while using pre-trained weights from the dataset of ImageNet.

This approach significantly reduces computational workload. The DenseNet201 architecture facilitates the development of straightforward and efficient models by reusing features across layers, optimizing parameter efficiency, and enhancing efficiency in deeper layers.

The model follows a feed forward mechanism, where each layer connects to every other layer, leading to improved feature propagation.

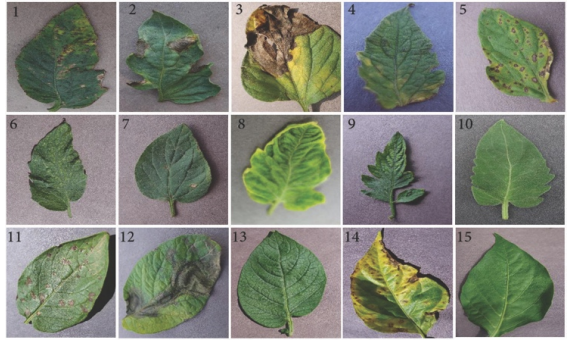
Additionally, it incorporates a pooling layer and bottleneck structure, which help reduce model complexity and parameters. Every layer within the DenseNet201 applies various nonlinear transformations, including convolution (Conv), pooling, batch normalization and rectified linear units.

A DenseNet201 network having L layers has L(L+1)/2 connections, as opposed to traditional architectures where each layer only connects to the next.

This means that outputs from all preceding layers serve as inputs to the subsequent layers. In this study, the implemented DenseNet201 model consists of 707 layers and approximately 21 million parameters.

The input layer processes images with dimensions of 224×224×3. Table 3 shows the parameters' count for the various models analysed, while illustrates the DenseNet201 architecture.

In the fourth phase, a 6-layer classification was designed by eliminating the O/P layers of classification of DenseNet-201.



*Figure 3.4 The ten categories for tomatoes include healthy, mosaic virus, yellow*

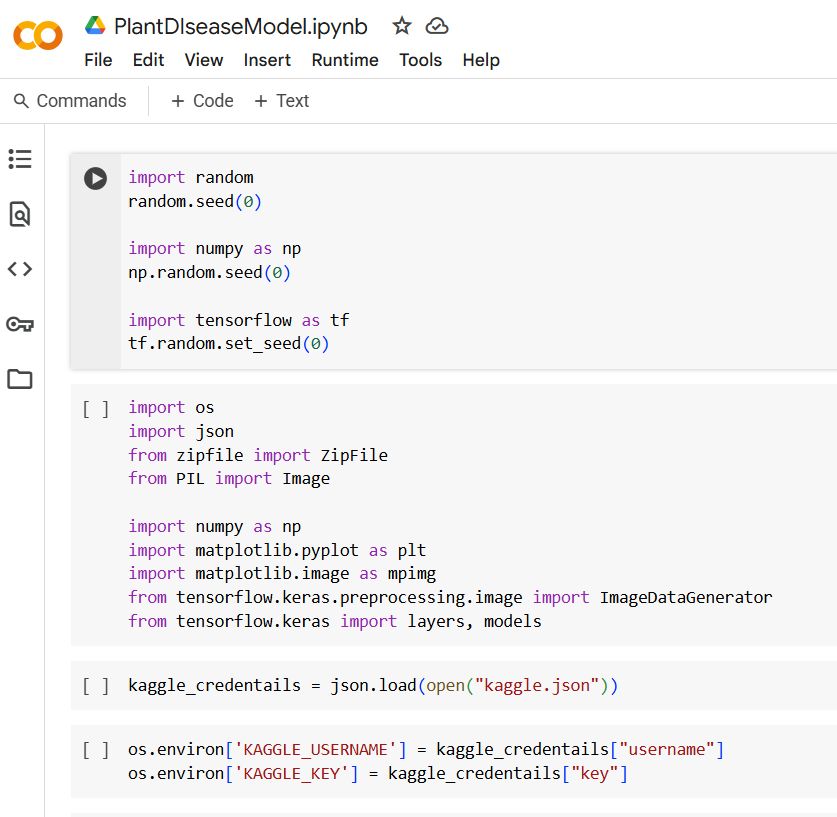
*leaf curl virus, target spot, two-spotted spider mites, septoria leaf spot, leaf*

*mold, late blight, early blight, and bacterial spot. Additionally, there are*

*categories for potatoes (healthy, late blight, early blight) and peppers (healthy,*

*bacterial spot)..*

**3.3 Sample Code**

****

**A screenshot of a computer

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**A green leaf with brown spots

AI-generated content may be incorrect.**

**A screenshot of a computer

AI-generated content may be incorrect.**

**A screenshot of a computer program

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**A screenshot of a computer

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**CHAPTER 4**

**RESULTS AND DISCUSSION**

**4.1 Experiments Performed**

* While experimenting, we began by resizing images from the dataset to 24 × 24 pixels. Following this, data augmentation was applied. To enhance training speed and accuracy, we utilized pre-trained ImageNet weights. We used softmax activation function with a batch size of 32 to train the model. The learning rate and hyperparameters were kept at their initial values.
* For plant disease classification, we implemented the following CNN models - Inception V3, VGG16, ResNet152V2 and DenseNet201 with the help of transfer learning technique. We then compared their performance with our proposed model. Figure 7 presents the loss and accuracy criteria for these models.

The table 1 showing access time for different element sizes using the Mondial Dataset.

**Table 4.1** Comparing Models’ performance

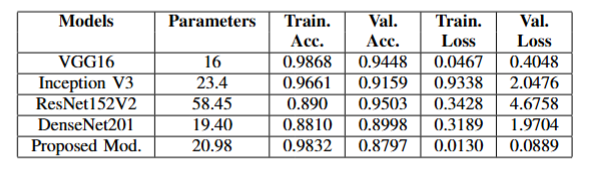
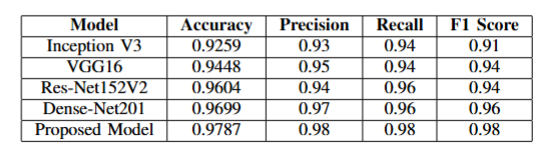


Table III presents the results of our tests, showcasing exceptional accuracy of our proposed model. It achieved a top accuracy with 99.31\% while training and accuracy of 97.96\% while performing validation.

**Table 4.2** F1 scores, Precision, Accuracy, Recall for various models



**4.2 Accuracy and Loss**

To further refine the outcomes, we analysed the results obtained from five different models. However, the model evaluation primarily considers two key factors: accuracy and the confusion matrix. It accuracy reflects how effectively the model we trained generalizes after arrival of new data.

Classification accuracy is a well-established metric for evaluating a classifier's performance. In this context:

false positives - incorrectly classified negative samples.

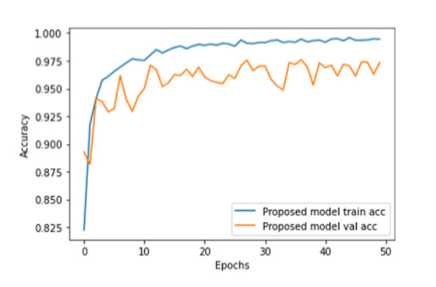
false negatives - incorrectly classified positive samples.

true negatives - identifies negative samples.

true positives - identifies positive samples.

Different performance evaluators include Classification Accuracy, Precision, F1-Score, and Recall are used to compare different models, as illustrated in Table IV. Figure 8 further visualizes the loss and accuracy trends of our model, revealing that the test dataset results closely align with those of the validation dataset.

For feature extraction in our tomato disease classification model, we utilized the DenseNet201 architecture, which demonstrated superior performance in transfer learning classification compared to alternative models. As indicated in Table III, DenseNet201 has lower number of trainable parameters than ResNet152V2, leading to improved accuracy while positively influencing model size and training duration.



*Figure 4.1 Accuracy of Proposed Model*

A graph of a graph showing the same model

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*Figure 4.2 Loss of Proposed Model.*

**4.3 Project Deployment**

The concluding trained and evaluated model was stored in H5 file format and utilizes the Hierarchical Data Format (HDF) to manage multidimensional scientific data. This file is later used in a prediction-based application.

We developed a mobile-app platform that loads trained model and allows farmers to upload images of diseased leaves. The application processes the uploaded image by converting it into the required format and resizing it to 224×224 pixels. The model then analyses image and predicts the disease class based on the detected symptoms.

**CHAPTER 5**

**CONCLUSION AND FUTURE SCOPE**

**5.1 CONCLUSION**

The following paper presents a comparative study aimed at identifying the most effective deep convolutional neural network (CNN) model to detect various diseases in plant leaves.

Four different deep CNN architectures—Dense-Net201, VGG16, Inception V3, and Res-Net15, evaluated using a dataset that included images of potato, tomato, and pepper leaves. Transfer learning techniques were employed during the models' training to enhance efficiency. The findings, summarized in Table III, highlight the performance of each model.

A novel classification approach was introduced that incorporates transfer learning using DenseNet201. In this model, DenseNet201 acts as the feature extractor, followed by a classifier based on a CNN.

The results tell us that this approach attains the most accurate results. Further enhancements were made by fine-tuning additional layers beyond just the top layer during the transfer learning process. The study also highlights variations in accuracy and parameter efficiency across five different CNN models, with the proposed model demonstrating superior performance.

Additionally, a web-based application was developed to assist farmers in diagnosing plant diseases. Users can upload images of affected leaves to receive an accurate diagnosis, suggested treatments, and relevant disease information. Future work aims to expand the study by exploring other CNN models trained for multi-classification, extending our model to cover more plant species and diseases, and enhancing the application by integrating crop state and weather data for improved disease diagnosis tailored to Indian farmers.

**5.2 FUTURE SCOPE**

Our application plays an important role in finding out the diseases in crop leaves and their causes. After it can generate suggestions to treat the disease.

This capability makes CNNs a promising approach for building intelligent crop monitoring systems that support farmers and agricultural professionals in making informed decisions with greater efficiency and accuracy.

After uploading the crops leaves, users can get the understanding of the diseases and their causes. Then the application can suggest the necessary aids in the form of fertilizers and whatever necessary.

The future scope of our application are as follows:

* Using the users location, we can provide a weather report which can be used by them in crop selection.
* We can also collect soil samples to do a thorough inspection which can be used by farmers to judge the fertility of their soil.
* Providing farmers with good connections to markets for selling their crops.

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**APPENDIX 1**

Project Outcome: Research Paper (Initial Page)

A document with text on it

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**APPENDIX 2**

Plagiarism Report (Initial Page)

A screenshot of a computer

AI-generated content may be incorrect.

**APPENDIX 3**

Acceptance Mail

A document with text and a red text

AI-generated content may be incorrect.

A screenshot of a web page

AI-generated content may be incorrect.

**APPENDIX 4**

Participation Certificate

![A white background with black and white clouds

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