

A Lightweight Convolutional Neural Network Framework for Efficient Plant Leaf Disease Classification Using Image Processing

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ABSTRACT

Plant diseases are a serious problem in agriculture as they can cause a loss of yield and product quality. Early detection can enable farmers to take any necessary action before the disease is spread. But normally the diagnosis will be made by visual inspection, which can be time consuming and may require expert staff. Using images of the leaves of plants enables the automation of this process by using image processing and deep learning. In this paper a light weight CNN is designed for Categorization of plant leaf diseases. Here, the method proposed is based on the PlantVillage dataset containing images of various categories of healthy and diseased plants. The images are first resized to a standard size of 224x224 pixels and then standardized to give uniform input to the network during training. The CNN consists of multiple convolutional blocks with Batch Normalization and Max Pooling, followed by a Global Average Pooling and fully connected layers for the final classification. Sparse Categorical Crossentropy loss and the Adam optimizer are used to train the model. The Accuracy, Precision, Recall, F1-score, Classification Report, and Confusion Matrix are used to measure the performance of the model. The proposed model gave an accuracy of 93.69% on the validation set. The weighted Precision, Recall, and F1-score were 94.04%, 93.69%, and 93.50%, respectively. It is also observed from the confusion matrix that the most of the samples were correctly classified, but there still exists some degree of confusion between similar disease classes in terms of visual similarity. Overall, the obtained results suggest that the proposed lightweight CNN may be useful in the automated diagnosis of plant disease in smart agriculture with a relatively simple network to achieve reliable classification of plant diseases.

Keywords: Plant Leaf Disease, Image Processing, Convolutional Neural Network, Lightweight CNN, Deep Learning, PlantVillage Dataset, Image Classification, Precision Agriculture

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I. INTRODUCTION

Agriculture directly impacts on food availability, livelihoods of people in rural areas, and economy. A major problem of the farmers is the occurrence of plant

diseases. Bacteria, viruses, fungus and other pathogens can cause diseases, which can damage crops, cause a loss in yield, and affect the quality of agricultural products. Early diagnosis is therefore significant as appropriate management measures can be implemented if the disease is detected early [1], [2].

Disease diagnosis is still based on visual inspection of leaves for most agricultural situations. This approach may be effective when an experienced professional is available, but can be challenging if a large number of plants are required to be evaluated. The diagnosis can also be subjective and depend on the experience of the person doing the diagnosis. Sometimes, too,

various diseases may give similar symptoms, so there is a great need for early identification. All these have spurred researchers to look into automatic disease detection through image processing and artificial intelligence [2], [10], [21].

The use of deep learning algorithms has opened up image-based plant disease classification to practicality. In comparison to other deep learning techniques, Convolutional Neural Networks are more successful as they are able to learn useful visual features directly from pictures. Unlike feature-selection, CNNs detect patterns (e.g., edges, textures, shapes, disease related patterns, etc.) while they are training [3], [4] and [9]. VGG, ResNet, MobileNetV2, EfficientNet, and DenseNet are promising models for image classification, and have been explored for plant disease detection [2] [6] [16] [23].

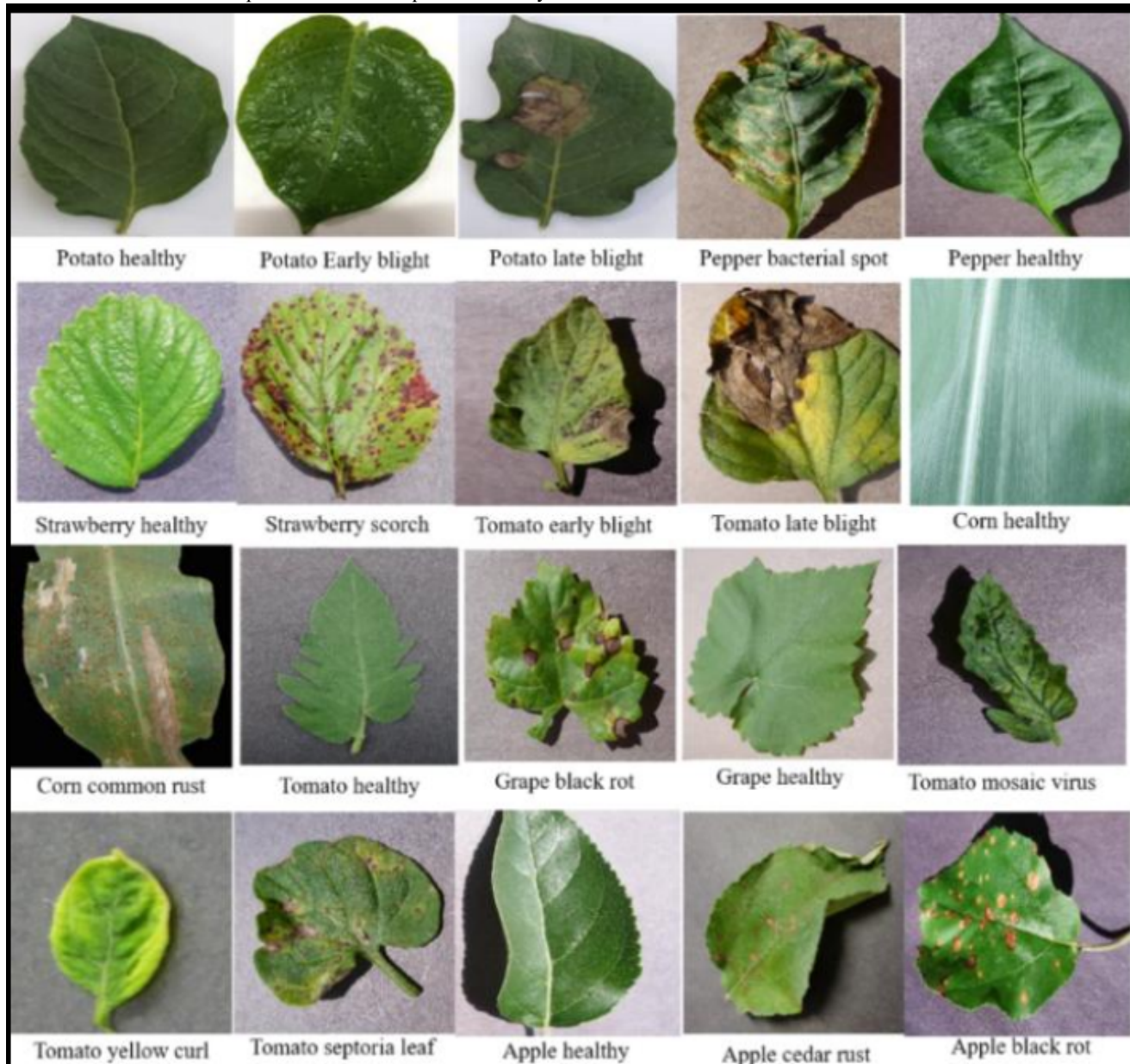
However, deep CNNs often require more computations. Some large models can have millions of parameters and consume significant memory and computational resources. This can be a problem if the model is required on mobile phones, embedded

systems or on edge computers where it is typically not as compute intensive as it is on a desktop or cloud system [5, 6, 17]. Another key component of an automated disease classification system is image preprocessing. Leaf images can vary in size and intensity across the dataset, which can cause variations in how the network is trained. The leaf images may have different sizes and pixel intensities in the dataset, leading to variations in training the network. Sometimes the resizing and normalization operations are performed prior to CNN-based classification and can help for stable model learning [10].

Due to these issues, lightweight CNN architectures have garnered more and more interest. Improve the model's performance by

choosing a size that is reasonable for both classification accuracy and computational demands. Compact models have been shown to be effective in various practical applications, such as recent work on efficient CNNs, mobile applications, and edge based plant disease detection [26, 28, 35].

With this motivation, the present study proposes a lightweight CNN framework for plant leaf disease classification in multi-class classification problem. The basic image preprocessing is implemented with a custom CNN architecture that is learned to detect the features of the disease from the images of the leaves. Model development and evaluation is carried out using Plant Village dataset and there are 38 disease classes in the experiment.



Representative healthy and diseased leaf images from the PlantVillage dataset.

In Figure 1, representative images of leaves from various categories of the PlantVillage dataset are shown: healthy and diseased leaves. The diversity of the visual patterns used for the automated plant disease classification is reflected by the visible differences in the color, texture, and disease symptoms of the leaves.

This work is the main contribution:

1. A custom lightweight CNN is designed for multi-class plant leaf disease classification.
2. The leaf images are preprocessed for classification by image resizing and image normalization.

3. To keep the network relatively small, Global Average Pooling and Dropout are added to the network.

4. Accuracy, Recall, F1-score, Precision, Classification Report, and Confusion Matrix are used for evaluating the model.

The proposed model is able to validate the dataset with an accuracy of 93.69%.

II. LITERATURE REVIEW

The use of deep learning for recognition of plant disease has grown considerably over the last ten-year. New developments in this area have been the PlantVillage dataset introduced by Hughes and Salathé [1] and the recent release of the Plant Photo

Database in April 2018. The dataset made it possible for researchers to have a common set of labelled images of plant leaves, and to compare different approaches. Later, Mohanty et al. [2] used leaf images to show that deep learning can be used effectively to recognize plant diseases.

CNNs are used in this problem because of their automatic learning of image features. Various architectures have been explored to classify plant diseases such as VGG [3], ResNET [4], MobileNetV2 [5], EfficientNet [6] and DenseNet [16]. For instance, Geetharamani and Pandian [8] created a CNN with nine layers to identify diseases in plant leaves. Ferentinos [23] also explored the deep learning models for plant disease recognition and found that CNN based models found useful for recognising various disease categories.

The classification performance may also be influenced by the quality and uniformity of the input images. To enhance the quality of the image prior to training the model, image preprocessing techniques like noise removal, contrast adjustment, normalization, and resizing are often used [10]. Resizing makes the images identical in size and normalization scales the pixel values to a range appropriate for the learning algorithm.

Recently, there has been a focus on models that are able to yield good classification performance without demanding large network resources. A number of researchers have proposed efficient CNN architectures for plant disease detection and efficient scaling strategy for CNN models in general [6, 7].

Rizwan et al. [28] studied a computationally efficient CNN, and Reddy et al. [29] studied a mobile application that is developed for the automated detection of disease. Various recent studies have suggested lightweight or edge-based models for practical deployment [30]–[35].

The studies demonstrate the importance of lightweight architectures for plant disease applications, particularly. However, most of the studies that have been done have concentrated on the classification accuracy with comparatively less effort given to the simplicity of the model. A model that is accurate but has significant computational requirements may not be easy to use in a field application.

Hence the present study aims at implementing a custom lightweight CNN that strives to achieve good classification accuracy with a relatively simple architecture. The proposed method is based on image preprocessing, convolutional feature extraction and a lightweight classification stage. This makes it a good foundation to explore lightweight plant disease classification using the PlantVillage dataset.

III. PROPOSED METHODOLOGY

The proposed system is a simple pipeline which starts from the PlantVillage dataset and ends with multi-class disease prediction. The key steps include dataset preparation, image preprocessing, feature extraction using CNN, classification, and evaluation of performance.

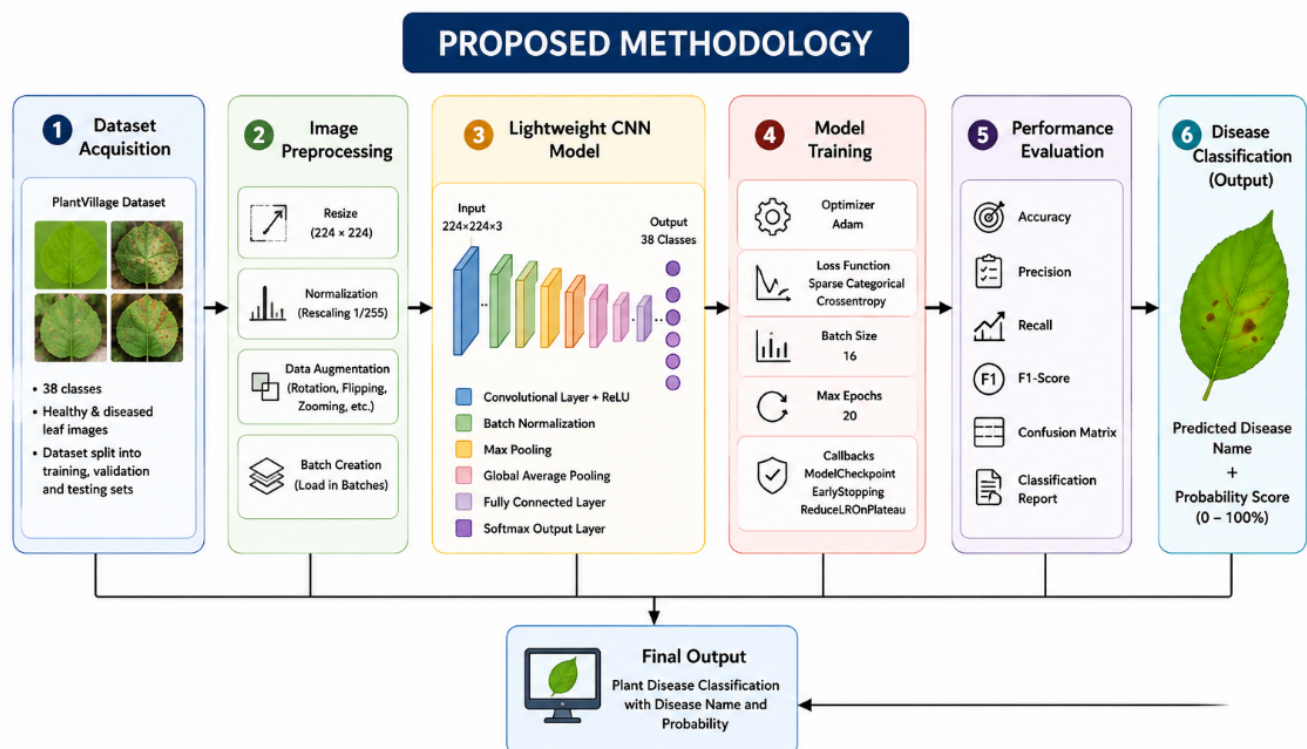


Fig. 2. shows the overall process of the proposed system starting from the PlantVillage dataset and preprocessing.

The preprocessed leaf images will then be fed into the lightweight CNN which will extract the features and classify the disease. Finally, the trained model is tested on the standard performance measures to calculate the classification efficiency.

A. Dataset Acquisition

The Plant Village dataset was used for developing and evaluating the proposed model. It is made up of RGB images of healthy and diseased leaves of various crop species and disease categories [1] [2]. For this study, there were 38 classes in the classification task. There was a validation dataset to check the trained model that included 10,861 images.

B. Image Preprocessing

All images were resized to 224×224 size before being given to CNN. This made sure that all samples were of the same spatial size. The images were rescaled by using a Rescaling layer, followed by a normalization using a scale of $1/255$. Consequently the original pixel values were normalized to be in a range which helped to keep the model training stable. The data has been loaded into the dataset with integer class label using the `image_dataset_from_directory()` function of TensorFlow.

C. CNN Architecture Lightweight

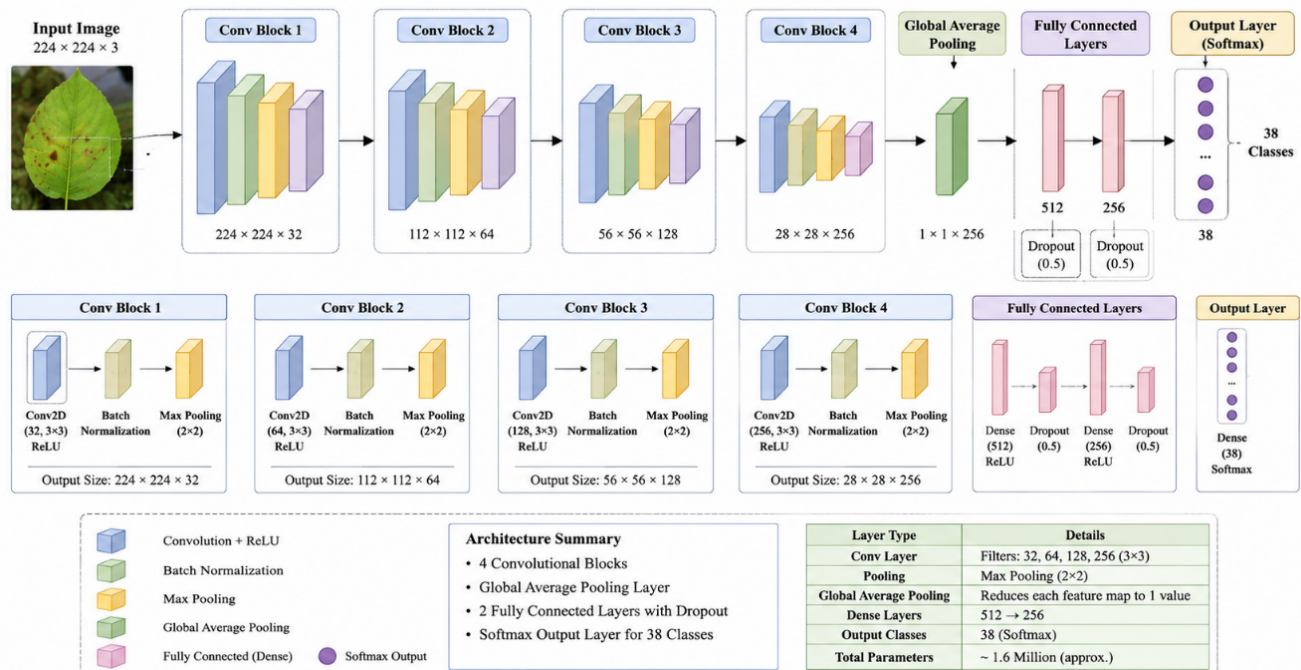
A custom CNN was designed for the classification problem of 38 classes.

There are four convolutional blocks in the network. Each block consists of a Conv2D, Batch Normalization and Max Pool layer.

Global Average Pooling (GAP) was used after the last convolutional layer to reduce the spatial feature maps to a small feature representation. This representation is then passed to fully connected layers with ReLU activation and Dropout layers for

improved learning and avoiding overfitting. Last, the learned features are transformed into probability scores, using the Softmax layer, for the 38 disease classes, allowing the model to detect the most probable disease class.

Architecture of the Proposed Lightweight CNN Model



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C. CNN Architecture Lightweight.

A custom CNN was designed for the classification problem of 38 classes. There are four convolutional blocks in the network. Each block consists of a Conv2D, Batch Normalization and Max Pool layer. The convolutional layers learn more complex visual

patterns of the leaf images as the image passes through the network.

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IV. EXPERIMENTAL SETUP

A. Experimental Environment

Implementation was done in Python 3.12 with TensorFlow/Keras. The training and evaluation was carried out in a Jupyter Notebook environment on a Windows based system. Preprocessing was done using NumPy, visualization was done using Matplotlib and performance analysis was done using Scikit-learn.

B. Description of the Dataset.

The PlantVillage dataset comprises RGB images of healthy and diseased plant leaves and is widely used as a standard dataset for plant disease classification studies. In this work, 38 different classes were taken into account and all the images have been resized to the same dimensions of 224×224 to have a uniform input dimension. For the validation set, 10,861 images were allocated and tested the performance and generalization capability of the trained model.

C. Experimental Configuration

TABLE I
EXPERIMENTAL CONFIGURATION

Parameter	Value
Dataset	PlantVillage

Parameter	Value
Number of Classes	38
Image Type	RGB
Image Size	224 × 224
Programming Language	Python 3.12
Framework	TensorFlow / Keras
Libraries	NumPy, OpenCV, Matplotlib, Scikit-learn
Optimizer	Adam
Learning Rate	0.001
Loss Function	Sparse Categorical Crossentropy
Batch Size	16
Maximum Epochs	20
Activation Functions	ReLU, Softmax
Callbacks	ModelCheckpoint, EarlyStopping, ReduceLROnPlateau

Table I summarizes the main configuration used for training and evaluating the proposed lightweight CNN. The parameters define the image input, training strategy, optimization settings, and supporting software environment used in the experiment.

V. PERFORMANCE EVALUATION

The model was evaluated using several commonly used classification measures. Accuracy gives an overall view of the predictions, while Precision, Recall, and F1-score provide additional information about classification behavior. The Confusion Matrix was used to examine errors among individual disease classes.

1) ACCURACY

Accuracy represents the overall percentage of correctly classified samples among the total number of test samples.

$$\text{Accuracy} = \frac{TN + TP}{TP + FP + TN + FN}$$

where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

A higher accuracy indicates better overall classification performance.

2) PRECISION

Precision represents the proportion of true positive predictions among all instances that the model classifies as positive.

$$\text{Precision} = \frac{TP}{FP + TP}$$

A high precision value indicates that the model produces fewer false positive predictions.

3) RECALL

Metric	Value
Validation Accuracy	93.69%
Validation Loss	0.1927
Precision	94.04%
Recall	93.69%
F1-Score	93.50%

The performance of the proposed CNN is shown in the overall validation results in Table II on the PlantVillage validation set. The model was consistent for all the evaluated disease classes

Recall, also known as Sensitivity, measures the ability of the model to correctly identify all positive samples.

$$\text{Recall} = \frac{TP}{FN + TP}$$

Higher recall indicates that fewer diseased leaves are incorrectly classified as healthy.

4) F1-SCORE

The F1-score is the harmonic mean of Precision and Recall. It provides a balanced measure when the dataset contains class imbalance.

$$\text{F1-Score} = \frac{2 \times (\text{Recall} \times \text{Precision})}{\text{Recall} + \text{Precision}}$$

A higher F1-score indicates better overall classification reliability.

5) CONFUSION MATRIX

The Confusion Matrix compares actual and predicted labels for all disease classes. It provides a direct view of correct classifications as well as the classes that are more frequently confused with one another.

VI. RESULTS AND DISCUSSION

A. Overall Classification Performance

The proposed CNN was validated with the Plant Village validation set which includes 38 disease classes. The model performed well in validation with an accuracy of 93.69% and a loss of 0.1927. Weighted Precision was 94.04%, Recall was 93.69% and F1-score was 93.50%. The near equality of the values suggests that the model's performance was similar for the categories assessed.

TABLE II

OVERALL PERFORMANCE OF THE PROPOSED CNN

and showed an accuracy of 93.69%, a Precision of 94.04%, and a Recall of 93.69% and a F1 of 93.50%.

B. Performance Metrics

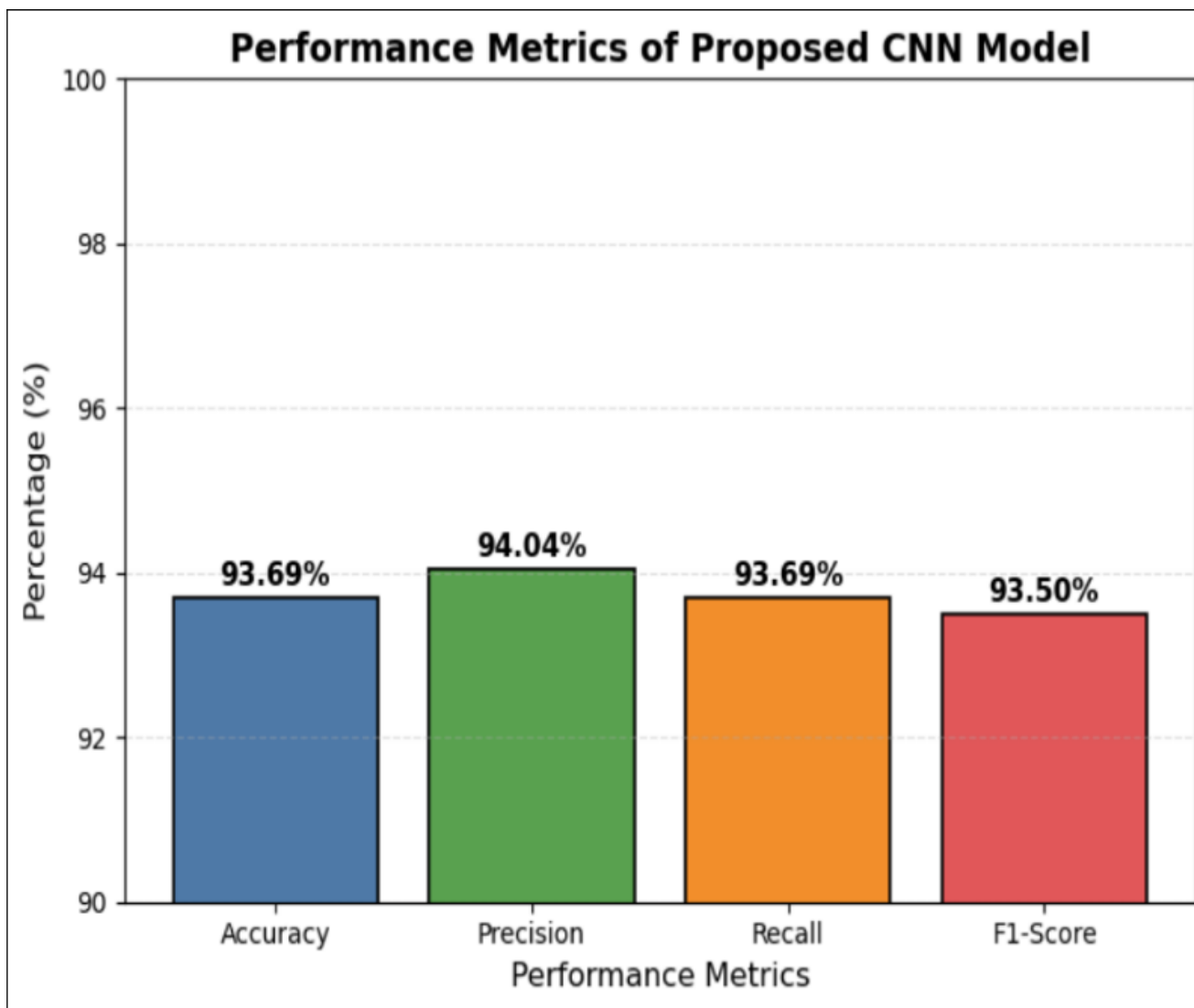


Fig. 3. Comparison of performance metrics achieved by the proposed CNN model

The performance of the proposed CNN model is compared with the Accuracy, Precision, Recall and F1-score in terms of these metrics as shown in figure 3. The model achieved 93.69% Accuracy, 94.04% Precision, 93.69% Recall, and 93.50% F1-score. The metrics are close, suggesting that classification results

are similar for the different classes of plant diseases. The spread in values is rather low for the four evaluation measures. Both Precision and Accuracy/Recall are at 94.04% which is slightly higher. The F1-score is 93.50%. The fact that these two values are similar indicates that the difference in precision and recall does not have much influence on the performance of the model.

C. Confusion Matrix

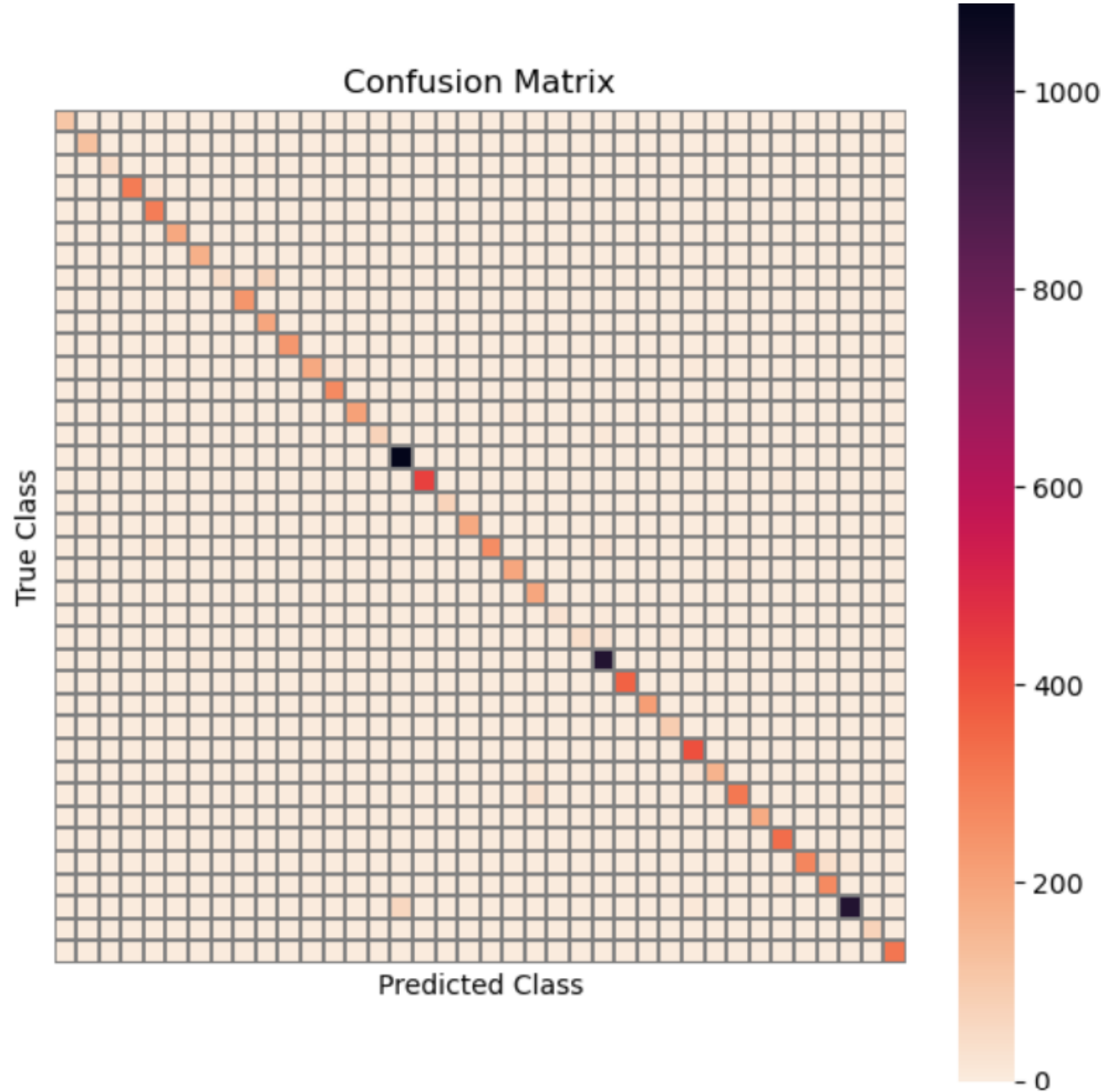


Fig. 4. The proposed CNN model's confusion matrix computed using the PlantVillage validation dataset.

The confusion matrix for the 38 classes of plant diseases assessed on a validation set is shown in figure 4. The majority of the predictions are focused along the main diagonal from which it can be seen that most of the images of the leaves were identified correctly. The values off the diagonal are the classifications of misclassified instances, primarily between the groups of disease with similar visual characteristics. The confusion matrix depicts that the majority of predictions are along the main diagonal, indicating that most samples were classified into their corresponding classes. The small number of numbers off the diagonal means that the samples were allocated to a different

class. There is likely to be some overlapping of diseases with similar symptoms. Despite this, the distribution of predictions is generally consistent with the results of the other evaluation instruments.

D. Classification Report

The classification report provides a more detailed view of the model's performance. The weighted Precision, Recall, and F1-score were **94.04%**, **93.69%**, and **93.50%**, respectively.

TABLE III
SUMMARY OF CLASSIFICATION REPORT

Metric	Weighted Average
Precision	94.04%
Recall	93.69%
F1-Score	93.50%

The weighted classification results of the CNN model proposed in this work is summarized in table III. The F1-score, Precision and Recall values are all kept above 93%, signifying that the model maintains a steady level of classification accuracy for each class of the plant disease evaluated.

The results show that the model is consistent over the categories evaluated. The poor performance for some individual classes can be attributed to commonalities in the visual appearance of some of the diseases.

E. DISCUSSION

From the experimental results, it is observed that the proposed lightweight CNN can learn useful disease related pattern information from plant leaf images. An accuracy of 93.69% was obtained and the Precision, Recall and F1-score were above 93%. The confusion matrix also indicates that the majority of the samples were correctly classified. The remaining errors are mainly associated with classes that have similar visual characteristics. The findings indicate that the image preprocessing and custom CNN is a good approach to the multi-class plant disease classification. A compact design of CNN is one beneficial part of the proposed approach. The network is not very deep, but consists of four convolutional blocks, followed by Global Average Pooling and fully connected layers. This approach may be applicable where resources for computational requirements are scarce. During this time the results should be viewed within the limits of the data set employed. The PlantVillage images are taken in controlled conditions and, thus, performance can vary if the model is presented with images taken directly in an agricultural field.

VII. CHALLENGES AND LIMITATIONS

There are several limitations in this study that should be taken into account in the interpretation of the results. The first limitation is related to the dataset. PlantVillage is helpful data set, but the images were captured under relatively controlled conditions. Changes in illumination, background or weather, occlusion and image quality are possible in real field images. These may impact the model's performance when it's used outside of the dataset context.

The second constraint is the existing system is based on RGB leaf images only. This did not include details of temperature, humidity, soil moisture or nutrient status. The factors may be helpful in the diagnosis of plant health in field situations. Another drawback is the compromise between model size and classification performance. If a deeper or more complex model is able to better identify some of the more complex disease classes, then it may require more computational resources. Last but not least, there is no explainability aspect in the current work. Future research can be explored to determine which areas of a leaf image are significant to the model's prediction, for example, using Grad-CAM.

VIII. FUTURE SCOPE

To test the model with field images the next step in this work would be. The images in the field are not controlled, and may have complex backgrounds, non-uniform lighting, occlusion, etc. Field images may have complicated backgrounds, non-uniform lighting, occlusion, etc. that is not controlled like the images in PlantVillage. Such tests would give a better indication of the model's performance in a real agricultural situation. The proposed CNN can also be compared to the light weight transfer learning models, such as MobileNetV3 and EfficientNetV2. This comparison would be useful to assess if the classification accuracy can be further enhanced while retaining the benefits of the small model size. An alternate approach is to deploy on mobile phones, edge devices, or IoT agricultural systems. In such environments, the lightness factor is particularly relevant as it can help to lessen reliance on costly computing resources. The system may be expanded by adding leaf images, environmental data like temperature, humidity, soil moisture, and nutrient condition. This might give a more accurate idea of plant health than would image information. Furthermore, future experiments can be conducted using Grad-CAM or other explainability methods for easier interpretation of predictions.

IX. CONCLUSION

The aim of this work is to employ image processing technique to design a light weight Convolutional Neural Network (CNN) for automated plant leaf disease classification. The model was tested against 38 classes of plant diseases from the PlantVillage dataset.

Before feeding to CNN for training, images were resized to 224×224 and normalized. The proposed model with validation accuracy of 93.69% is proposed. The weighted Precision, Recall, and F1-score were 94.04%, 93.69%, and 93.50%, respectively. The confusion matrix revealed that the prediction accuracy was high for most samples, and the misclassification of samples was primarily between similar diseases in the visual category. The results suggest that the CNN is able to perform a reliable multi-class plant disease classification using a relatively small CNN. The proposed framework is thus a good starting point for automatic diagnosis of disease without relying on a complex network architecture. Still, more experiments using images obtained in a field environment would require for the implementation in practice. The system could be enhanced with the use of lightweight transfer-learning models, mobile or edge deployment, environmental sensor data, and explainability methods, thus providing a more robust and practical system for real agricultural applications.

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