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A Transfer Learning-Based Efficient Model for the Detection of Plant Leaf Diseases

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ABSTRACT
Plant disease control is necessary in agriculture since it can result in considerable crop yield losses. To reduce damage, quick diagnosis and categorization of plant leaf diseases is required; unfortunately, this process takes a lot of time and needs human efforts. To deal with these issues, a novel computerized approach for fast observation and categorization is required. There exist methodologies based on Deep Learning (DL) techniques that make use of an easily accessible dataset, namely The Plant Village Dataset. However, they may fail to recognize the diseases on unseen data due to less diverse feature extraction. Therefore, this research proposed a plant disease detector based on Deep Learning model using images of leaves and can identify several plant diseases. First, we perform image preprocessing operations. Second, Convolutional Neural Network (CNN) having several convolution and pooling layers is employed and the results are evaluated with existing DL models with varying hyper-parameters. After training, the model is carefully evaluated to validate the findings. We conducted several trials using the proposed model and attained testing accuracy of 97.6%.

Keywords: Transfer Learning; CNN; Plant Diseases; Agriculture

1. Introduction

The population of the entire globe might rise dramatically by 2050, according to the Food and Agriculture Organization (FAO) of the United Nations, which estimates 9.1 billion people. Food consumption will increase exponentially as a result of this expanding population (Bruinsma 2009). While this is happening, the lesser number of farmland and insufficient availability of clean water hamper the growth of nutritional value. The major supply of food, raw resources, and fuel, all of which contribute to a country's economic prosperity depends on agriculture. Agriculture is straining to fulfil the requirements of a fast-growing global population. Changing climate, crop diseases, pollinator decrease, shortage of irrigation, and similar factors threaten food security. Plant diseases cause damage on agricultural productivity as well as food quality. Therefore, it is a great challenge to save plants against diseases to improve crop quantity and quality (Altieri 1995).

Plant diseases cause serious crop damage by drastically lowering agricultural productivity. Accurate and timely detection of plant diseases is critical for ensuring food security and the sustainability of agricultural ecosystems. The early identification of plant illness is most demanding domain in agriculture (Hasan et al. 2020). Computer vision and machine learning are helping almost in every region since they can predict significant outcomes at minimum cost (Haffner et al. 2024). For improvement in this area, the agriculture industry is starting to depend on DL based solutions (Cap et al. 2020). Deep learning has significantly transformed the field of computer vision and perform a variety of tasks, including automated plant disease detection (Hidayatuloh et al. 2018), predicting crop production, predicting rainfall, and managing soil fertility (Howlader et al. 2019). To guide farmers and increase plant productivity, the automated diagnosis of plant diseases used several Deep Learning-based solutions (Liu et al. 2020; Saleem et al. 2019).

Early disease detection and the use of the appropriate treatment to stop the spread of the illness are the foundation of a successful safety measures (Shah et al. 2022). Several automated research have proposed that CNNs can be applied to recognize and analyze illnesses in plants (Brahimi et al. 2017; Kawasaki et al. 2015). However, high accuracy alone is not sufficient for the categorization of plant diseases. Moreover, the automated models must be trained in the diagnosing process and the signs present in particular crops using diverse datasets. More precisely, this can be achieved by segmentation methods to focus on the diseased areas of a leaf (Hughes & Salathé 2015). Three groups of object identification algorithms have been employed for locating the impacted regions in the plant: Single Shot Multibox Detector (SSD), Faster Region-based Convolutional Neural Network (Faster R-CNN), and Region-based Fully Convolutional Network (R-FCN) (Fuentes et al. 2015). A real-time object recognition technique called You Only Look Once (YOLO) has been also utilized to detect crop diseases and pinpoint the exact location of damaged areas (Katumba et al. 2020), (J. Liu & Wang 2020a), and (J. Liu & Wang 2020b). Although, the object detection-based models provide high detection accuracy, however they require high computational resources and time for training.

Therefore, our goal is to provide a new and efficient model that utilizes minimum computational resources while providing significant classification outcomes. The associated goals of this work is summed up as follows:

– To suggest a light-weight CNN model to classify plant diseases with maximum accuracy.

– To illustrate the efficiency of the suggested model, a thorough assessment is achieved using a large and complex database that contains samples of 54303 unhealthy and healthy leaf images.

– To evaluate the accuracy of the ResNet50, Xception and VGG-16 pre-trained CNN models using the un-processed and processed plant images.

– Employing various hyper-parameters and assessing their impact on the classification accuracy.

– Extensive comparison with segmentation, and classification-based existing methods to validate the performance of suggested model.

2. Related work

Following the studies, the authors used visualization tools to comprehend the symptoms and identify disease-prone leaf regions. This method outperformed the existing approaches, according to the authors, with 99.18% accuracy. As a result, farmers may practice it in real-time to protect their crops from disease proposed by Brahimi et al. (2017). However, the technique only focused the tomato leaves and identifies symptoms. Brahimi et al. (2019) developed a classification and visualization method as Teacher-Student (T-S) architecture depends on combined learning of two deep classifiers. T-S is a deep learning framework in which a large, complex model (the Teacher) transfers learned knowledge to a smaller, more efficient model (the Student). This distillation improves accuracy and model compression simultaneously, enhancing deployment feasibility without sacrificing interpretability or performance. A deep interpretable architecture categorizes the illness and imagines its signs.

The authors presented a deep learning algorithm for identifying fruit illnesses, particularly affecting apples (Chao et al. 2020). The goal is to assist in developing an automated or semi-automatic system that will be more economical and efficient than manual methods monitoring diseases, which could be time-consuming and necessitate the assistance of experts. According to Afsharpour et al. (2024) and Albahar (2023), DL models improve the diagnosis of fruit illnesses and increase the yield in the agricultural industry. The method proposed by Albahar (2023) was more robust for fruit decay detection. The proposed system overcame the effects by varying conditions such as image obstructions and lighting.

As noted by Huang et al. (2023) introduced the combined form of inception module and the state-of-the-art EfficientNetV2 to create the suggested neural network, which improved multi-scale extraction of features and illness detection of citrus fruits. To improve the network's segmentation performance, the Visual Geometry Group (VGG) was employed in place of the U-Net backbone. Segmentation is a process of dividing an image into meaningful regions to isolate disease-affected areas on leaves, thereby enabling more accurate diagnosis and feature extraction. The Inception module and the state-of-the-art EfficientNetV2 were combined to create the suggested neural network, which improved multi-scale extraction of features that refers to the model’s ability to capture information at various levels of granularity by using filters of different sizes for illness detection of citrus fruits. This technique enhanced the model’s performance by allowing it to detect subtle as well as broad disease patterns present in leaf images.

Lokesh et al. (2024) suggested an artificial intelligence method for detecting leaf illness using generative adversarial networks (GAN) and deep learning models. The strategy outperformed current techniques with a better classification accuracy for healthy and diseased leaf pictures. GANs can generate diverse synthetic data, aiding in class imbalance, while DenseNet and EfficientNetV2 offer better feature propagation and computational efficiency. However, GANs are computationally expensive and difficult to train, and complex architectures like EfficientNetV2 may overfit on small datasets without careful tuning.

Tari Priyank et al. (2024) suggested a method for swiftly identifying plant illnesses using DL architectures like CNN and RNN, based on plant disease data. This strategy can increase food security in a progressive climate, promote sustainable farming methods, and reduce social and economic effects.

In order to detect plant leaf diseases, Bajpai et al. (2023) suggested a DNSVM method that combines DenseNet-201 with Support Vector Machine (SVM), outperforming the prior DenseNet-121-based model with 97.78% accuracy.

SVM was employed by Thilagavathi et al. (2020) to detect sugarcane leaf disease with achieving a 95% classification accuracy. Anand et al. (2016) employed Artificial Neural Network (ANN) and k-nearest neighbors (KNN) techniques to create a model for detecting and classifying cassava leaf disease.

Harakannanavar et al. (2022) identified leaf disease in tomato samples including six types of illnesses. Image processing includes resizing samples for uniformity, using Histogram Equalization (HE) and K-means clustering for quality, and contour tracing to extract boundaries. SVM, KNN, and CNN are some of the machine learning techniques used for feature classification and model performance.

Demilie et al. (2024) discussed current advances in plant disease classification and detection utilizing deep learning (DL) and machine learning (ML) approaches. They emphasized enhanced performance and speed of various methods, finds the optimal Deep Learning approaches for multi-class illness diagnosis, and suggested multi-label DL techniques, multi-class for real-world use.

Katafuchi et al. (2020) provided a procedure for plant illness identification on images based using unsupervised algorithm. They suggested a cutting-edge system that uses a conditional adversarial network called pix2pix to identify plant illness. The aim of this study was to reduce the efforts to gather labeled in supervised deep learning approaches. The results attained on The Plant Village dataset showed that the newly suggested system performs better than the previous AnoGAN technique relating to accuracy and computing efficiency.

Wang et al. (2021) discussed plant disease identification and how to rise the diversity and size of data by conducting pixel processing and spatial transformations on the primary dataset. For plant leaf detection, they presented a DBA_SSD network model by adding 1x1 convolution, attention mechanism, and residual network in the SSD algorithm to overcome the issues of low accuracy and poor recognition rate of the SSD model. Further, they evaluated many traditional selected detectors and validated the usefulness of the DBA_SSD method in detecting plant diseases. The outcomes demonstrated that a proposed method called DBA_SSD, achieved better accuracy up to 92.20% while also being resilient and fast.

To create the image data, 330 images of rice plant leaves were used (Kalra et al. 2023). 40% was utilized for testing, and 60% was used for training. They segmented the leaf areas employing a hybrid strategy that combines the Otsu and Global threshold methods. 76.59% of the cases were classified correctly when the KNN classifier was used. These hybrid approaches improve focus on diseased regions, thereby enhancing precision. However, real-world conditions—like occlusion, inconsistent lighting, or complex backgrounds—can hinder segmentation accuracy, affecting overall classification performance.

Pandian et al. (2022) developed a unique DCNN model for detecting 42 leaf illness in 16 types of plants. To gain the better accuracy of the illness detection, they employed hyper-parameter and data augmentation tuning strategies. A deep convolutional neural network technique was trained using 58 well and damaged plant leaf sets. To maximize the value of the most frequent hyper-parameters, random finding with the coarse-to-fine approach was applied.

3. Methodology

The steps involved in the proposed model illustrated in Figure 1. We tested three previously trained models, such as (ResNet50, Xception, and VGG-16), on the plant's dataset. These models are used due to their proven performance in image classification tasks (Mahum et al. 2023). These models were chosen because they have demonstrated robust accuracy in detecting patterns and features in complex datasets (Mahum et al.2023). However, pre-trained models often fail to generalize well in the plant pathology domain due to domain shift from ImageNet-trained features to agricultural imagery. Their high parameter count also leads to longer training and inference times. The proposed model addresses these limitations by being tailor-made for plant disease features, thus achieving better performance with lower computational costs.

The unprocessed and pre-processed both type of mages were utilized for training and classification. To determine whether or not pre-processed images enhance the accuracy of the models, we compared the findings. Our results demonstrate that the proposed model outperforms conventional models in terms of classification accuracy, especially after applying image pre-processing and transfer learning techniques. These findings emphasize the effectiveness of the approach in achieving higher accuracy.

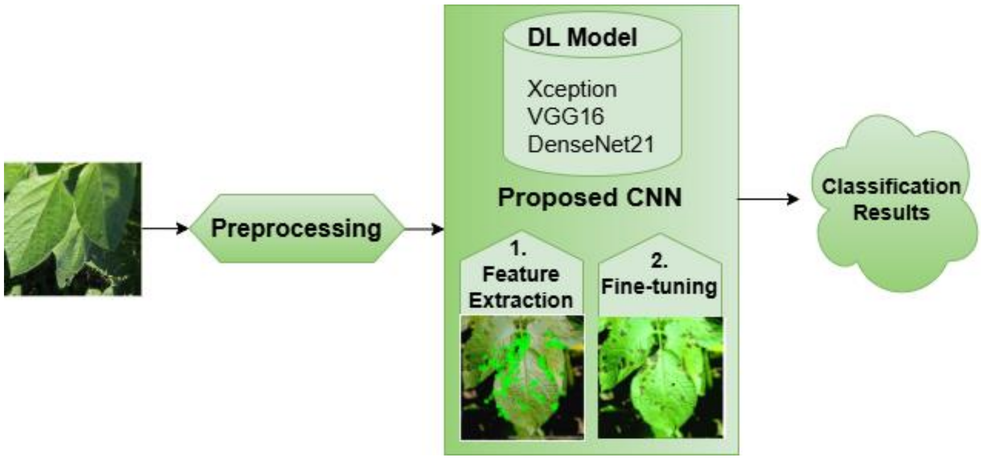

Figure 1- Flow diagram of proposed model

3.1. Data gathering

The plant leaves images were initially gathered from an openly accessible dataset titled The Plant Village Dataset. It contains 54 303 unhealthy and healthy leaf images including 38 classes that cover 14 different crop species, each labeled with either a specific disease (fungal, bacterial, or viral) or a healthy condition. The study's primary goal is to evaluate the effectiveness of deep learning models in accurately classifying these diseases, with an emphasis on improving agricultural practices and disease management.

3.2. Image Pre-processing

In this step, we pre-process images to reduce noise and enhance their contrast and quality. These operations are used for non-uniform intensity correction and image normalization and improve the correctness of the subsequent processing path. Figure 2 depicts the samples having varying diseases from the Plant Village Dataset.

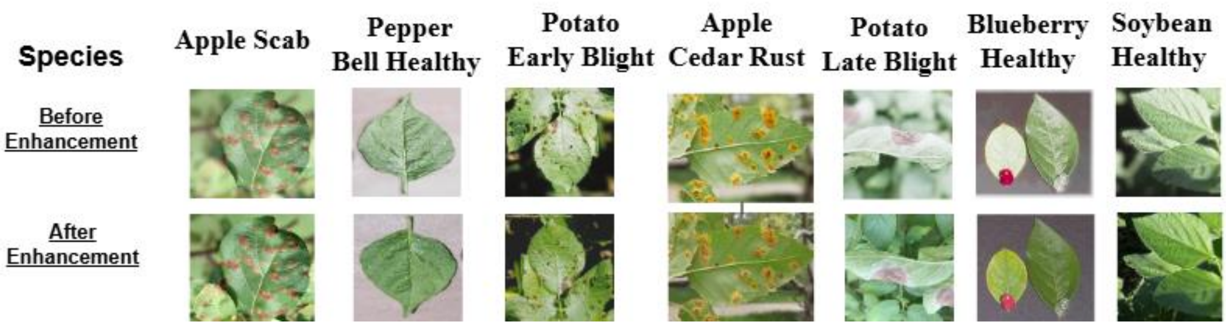

Figure 2- Some samples of diseased plants

3.2.1. Image Enhancement

It is a method of improving the plant images so that they can be analyzed more effectively. It entails eliminating noise, sharpening, or brightening photos to find important characteristics. Examples of morphological filtering include denoising, linear contrast adjustment, histogram equalization, median filtering, decorrelation stretch unsharp mask filtering and contrast-limited adaptive histogram equalization (CLAHE). The process of image enhancement is shown in Figure 3.

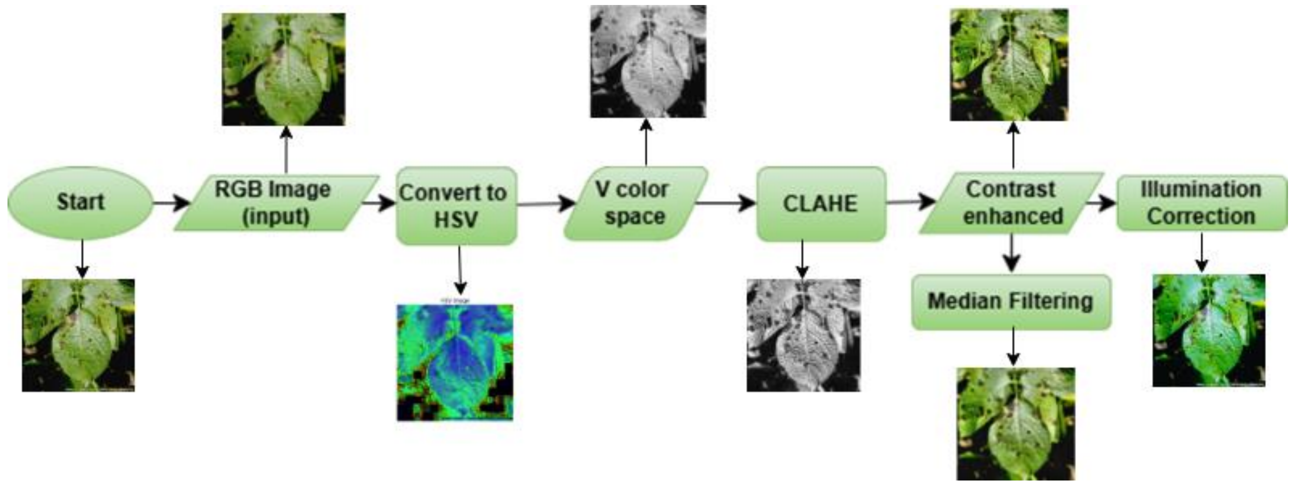

Figure 3- Steps for Image Enhancement

3.3. Transfer Learning

In this study, we apply plant image categorization using CNN-based transfer learning. We investigated CNN transfer learning methods that have been pre-trained to give the best classification outcomes.

For image classification, the idea of transfer learning is that a network may efficiently train for a specific goal, which includes some labeled instances than the training on dataset from the scratch (for example, ImageNet).

Pre-trained models will be altered in two ways in this paper:

I. **Feature extraction**: the process of using characteristics from the source images to draw out pertinent features. To alter the feature maps that were initially learned for the sample, we introduced a new network that can be guided to scratch out the features to top of the pre-trained models.

II. **Fine-tuning,** restoring some of the freezing layers of the frozen network and mutually training the n recently added network layers and the final layers of the base network. This aids in fine-tuning the base network's higher-order character demonstration so that they are more suited to the intended job. To achieve image categorization, we enhance three pre-trained CNN like (VGG-16, DenseNet21, and Xception) in Table 1.

Transfer learning accelerates training and improves feature learning on limited datasets. However, it may not capture task-specific features effectively without extensive fine-tuning, which can be computationally intensive and require large labelled datasets.

The comparative plot is displayed in Figure 4. The model performances, as shown in Top 1 and Top 5, are quite similar across the models, with Xception performing slightly better than the others. It is important to note that these results were obtained after applying the proposed changes, such as pre-processing techniques and transfer learning.

The suggested CNN model offers comparable or improved classification accuracy with significantly reduced computational costs due to less parameters and memory usage. It is lightweight, making it ideal for real-time applications and edge deployment scenarios, unlike the heavier pre-trained models.

Table 1- The details of some existing deep learning models

Model	*Depth***	*Parameters*	*Top-1 accuracy**	*Top-5 accuracy**	*Size*	*Reference*
Xception	126	22 910 480	0.790	0.945	88 MB	Chollet (2017)
VGG16	23	138 357 544	0.713	0.901	528 MB	Simonyan & Zisserman (2014)
DenseNet21	--	8 062 504	0.750	0.923	33 MB	Huang et al. (2017)

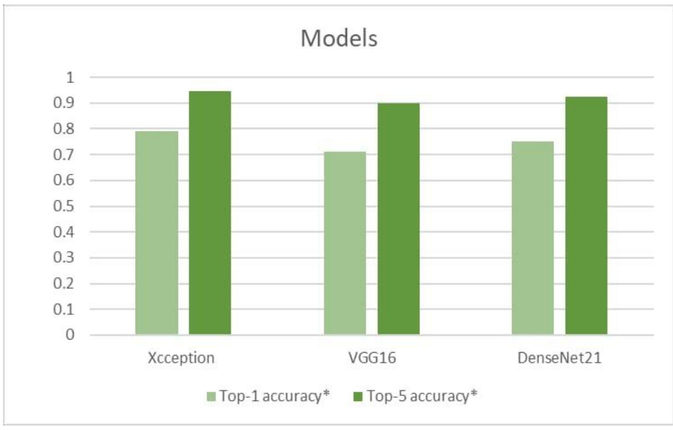

Figure 4- The performance evaluation attained by XceptionNet, VGG16, and DenseNet21

3.4. Proposed CNN Model

CNNs are the most often used deep learning methods for training plant images to recognize diseases. This is explained by the fact that CNN maintains distinguishing characteristics when evaluating input images. Figure 5 depicts the overall structure of CNN, while Table 2 lists the chosen hyper-parameters. The hyper-parameters for the CNN model, including learning rate, batch size, and epochs, were selected based on prior research and experiments. Hyper-parameter tuning is critical. A properly chosen learning rate ensures stable convergence; dropout prevents overfitting, and batch size affects training efficiency and model stability. These collectively influence the model's ability to generalize across unseen data.

The model was trained for 50 epochs to prevent overfitting, and the learning rate was optimized for faster convergence. The computational cost of training was estimated based on time and resources, with training taking place on a machine with 16 GB RAM and an NVIDIA GPU. This suggested CNN model has five convolution layers and uses a 244x244 plant images as its input. The optimizer was Root Mean Square Propagation (RMSprop) due to its adaptive nature for handling image classification tasks in deep networks (Seyyarer et al. 2023).

Table 2- The proposed CNN's hyperparameters

A1 Model	***A2 Epoch***	***A3 Image size***	***A4 Mini batch size***	***A5 Initial learning rate***	***A6 Optimizers***	***A7 Cross-validation***	***A8 Loss function***
CNN	100	224*224	32	3e-4	RMSprop	10-fold	*BCE

*: BCE—binary cross-entropy

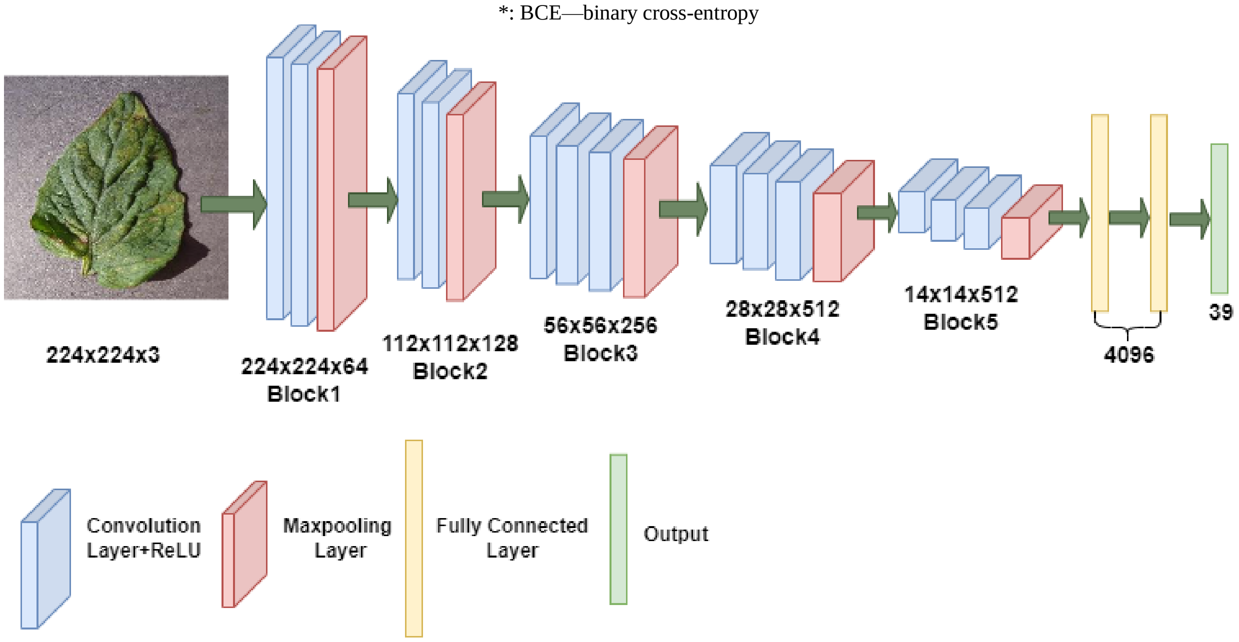

Figure 5- The architecture of the proposed CNN

A total of 64 of these filters are used in the first convolution layer employing 5 x 5 x 3 kernel filters with a stride of 1. The input shrunk to half of its original size (112 x 112) in the following layer, which obtained the output from the first layer having 2x2 stride on max-pooling layer. Then, the result of the pooling layer goes through the ReLU activation. The nonlinear result is gained, provided to the following convolution layer, which has 5x5x64 accompanied by 128 filters and the same stride value of 1 x 1. The output was then passed through a max-pooling layer using the same 2 x 2 strides, which once more cut the input in half to 56 x 56.

Following ReLU activation, the output is fed into the third convolution layer, which has 256 filters and a kernel size of 5x5x128 with a stride of 1. After the output is passed through a max-pooling layer, a tensor with the dimensions 28x28 is produced. Once more, the output is activated by ReLU and fed into the fourth convolution layer, which has 512 filters, a kernel size of 5 x 5 x 256, and the same stride of 1 x 1. The fourth convolution's result is max-pooled to a 14 x 14 size. After activating ReLU, the data is passed to the fifth convolution layer, which has 512 filters and a 14 x14x512 kernel size to accommodate all of the filters from previous convolution layers. The result of that layer is then max-pooled with a stride of size 2 x 2, producing an output with the dimensions 14 x 14. The resulting tensor is now 77 512 in shape. Here, values are dropped using the dropout layer to manage network overfitting. In our research, we used a training dropout rate of 0.5. The choice of a 0.5 dropout rate is based on empirical results from deep learning practice, where a rate between 0.2 and 0.5 is often found to strike a good balance between regularization and model performance. A higher dropout rate (e.g., 0.8) might result in underfitting, where the model is too simple, while a lower rate (e.g., 0.2) may not sufficiently prevent overfitting. A dropout rate of 0.5 was chosen to prevent overfitting, a common problem where the model memorizes the training data and fails to generalize to new, unseen data. Overfitting occurs when the model becomes too complex and learns noise or irrelevant patterns. The dropout technique randomly disables half of the neurons during training, helping to improve generalization and reduce the likelihood of overfitting. The result is enhanced with ReLU activation after the fully connected layer reduces the tensor from 25 088 to 64.

4. Experimental Evaluation

The proposed model has been evaluated using a variety of metrics to determine whether the illness identified in the images was correctly or incorrectly classified. The details of Dataset and experiments is given below.

4.1. Dataset

A complete set of 54,303 healthy and unhealthy leaf images are available in The Plant Village Dataset. We used the ratio of 20% and 80% for testing and training respectively. The pre-processed and resized images are used for training and classification. Some samples from all 38 classes are displayed in Figure 6.

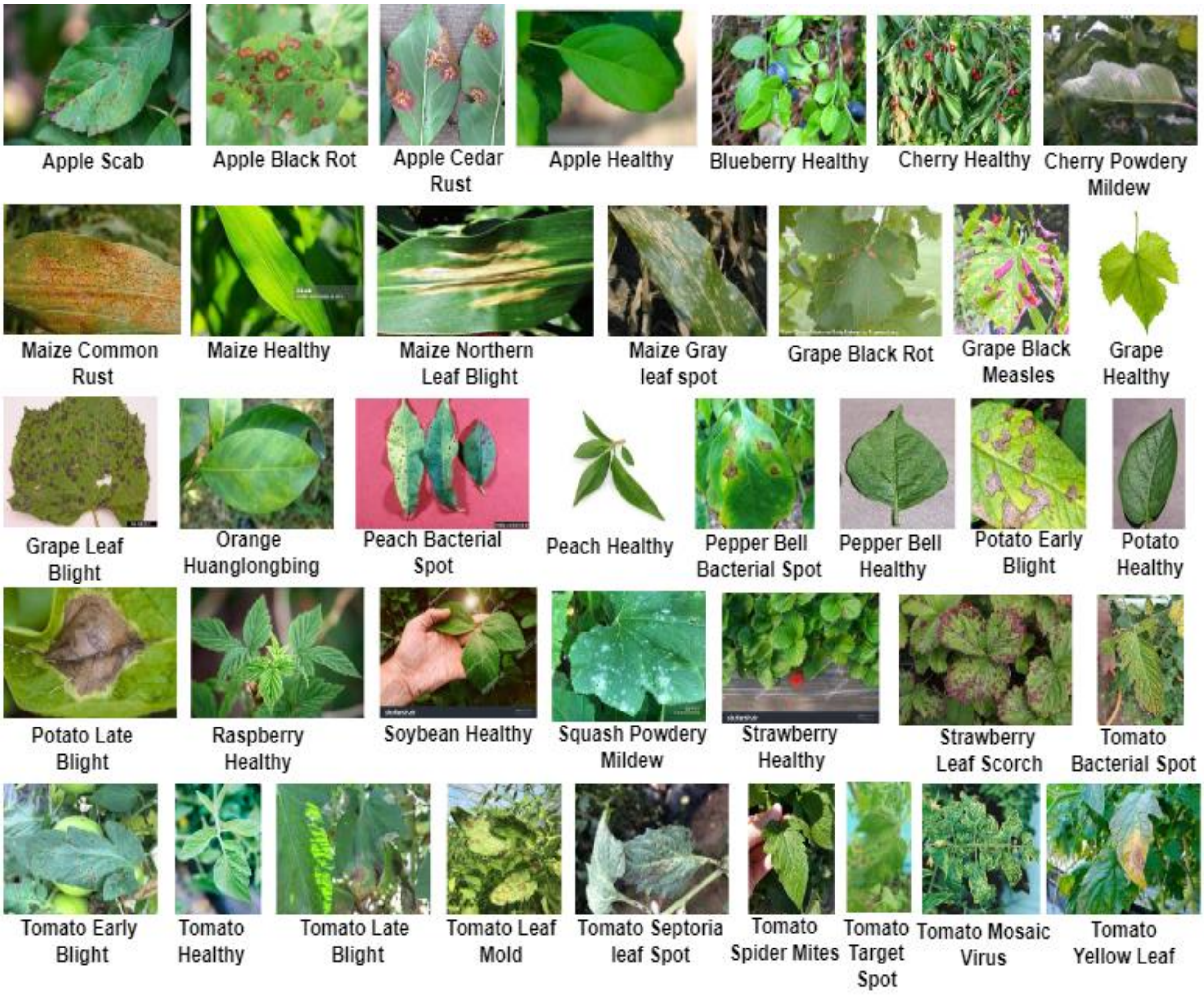

Figure 6- Sample of the Plant Village dataset

4.2. Evaluation parameters

We divided the data into testing and training sets from the plant village dataset at random to achieve the maximum efficiency of the suggested method. We used NVIDIA GM107GL Quadro and a Windows computer with an IntelVR Xeon(R) CPU E3-1226 v3 running at 4 GHz on each core and 4 GB of RAM, for the experiments to be carried out.

The values for the hyperparameters were as follows: 32 batch size, 100 epochs, and 0.001 learning rate. The Python framework and The Keras v0.1.1 library was used for all of the experiments. We also examined the performance of the suggested model with varying image size. However, it is noted that results with an image size of 224x224 are more accurate. Figures 7 and 8 show the plots for precision, accuracy, and recall of the proposed model, focusing on the recall metric. Recall is an important measure as it highlights the model's ability to correctly identify diseased plants. A higher recall value suggests that the model is effectively detecting a large number of diseased plants and minimizing false negatives. This is particularly significant in plant disease detection, where failing to identify diseased plants could have serious consequences. As the number of epochs rises, accuracy improved.

Metrics: True Negative (TN), False Negative (FN), True Positive (TP), and False Positive (FP) are used to analyze the proposed model’s performance. If there is a plant leafroll (PLR) disease and the prediction is PLR, it will be counted as TP. Similarly, TN is a measure of the likelihood that a prediction of an image does not associate to a specific class is true. For instance, if a leaf is healthy, ~~and~~ the suggested system does not predict it to be an image of a diseased leaf. FP refers to the incorrect prediction by system to the positive class. For example, if the prediction is potato late blight however it does not have any disease. FN is the estimation that an image does not belong to a negative class, but it is expected as if it belongs to, i.e., a leaf has an illness, and it is expected as negative. The confusion matrix that will be used to present the analysis of the results was constructed using these four ratios. Suppose that *x* illustrates the actual class and the other one *y* illustrates the expected class. Below, where *M* stands for the matrix, are the confusion metrics components for each class.

$$TP_x = M_{xx} \tag{1}$$

$$FP_x = \sum_{i=1}^{n} M_{ix} - TP_x \tag{2}$$

$$FN_x = \sum_{i=1}^{n} M_{xi} - TP_x \tag{3}$$

$$TN_x = \sum_{i=1}^{n} \sum_{j=1}^{n} M_{ij} - TP_x - FP_x - FN_x \tag{4}$$

In addition, the classification performance is evaluated using the four metrics accuracy, precision, recall, and F1 score. The confusion matrix for all 38 classes attained is displayed in Figure 9, The confusion matrix is plotted using the cross-validation estimator (Sokolova & Lapalme 2009). Accuracy is a measure of how many accurate predictions were made using the suggested model. It is calculated as the entire number of estimates made with the suggested model split by the number of accurate predictions. Equation 5 shows the mathematical form of *Accuracy*.

$$Accuracy = \frac{TN+TP}{TP+FP+FN+TN} \tag{5}$$

The number of images that the suggested model correctly classifies is known as *Precision*. The calculation method is, to divide the entire number of positive class images expected by the suggested system by the number of positive class images that exist. The formula is provided in Equation 6.

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

The proportion of images that the model remembered to be unhealthy is *Recall*. The calculation of Recall is the percentage of all positively categorized samples to correctly classified positive samples.

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

F1 score shows the harmonic mean of recall and precision. It illustrates how reliable the classifier is. The equation for the F1 score is displayed in Equation 8.

$$F1\ score = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{8}$$

Table 3 displays the outcomes achieved for every disease by the proposed system.

Table 3- The outcomes attained for each disease of plant

Sr.no	*Classes*	*Accuracies*	*Recall*	*Precision*
1	Apple Scab	99.91	99.91	99.87
2	Apple Black Rot	99.94	99.94	99.92
3	Apple Cedar Rust	91.97	99.97	99.91
4	Apple Healthy	99.98	99.98	99.98
5	Blueberry Healthy	99.93	99.93	99.93
6	Cherry Healthy	91.97	99.97	99.94
7	Cherry Powdery Mildew	99.91	99.91	99.89
8	Maize Common Rust	91.91	99.91	99.78
9	Maize Healthy	100	100	100
10	Maize Northern Leaf Blight	91.29	99.92	100
11	Maize Gray leaf spot	90.14	99.94	99.74
12	Grape Black Rot	99.2	100	99.89
13	Grape Healthy	100	100	100
14	Grape Black Measles	100	100	100
15	Grape Leaf Blight	99.15	100	99.81
16	Orange Huanglongbing	100	100	100
17	Peach Bacterial Spot	99.01	99.97	99.97
18	Pepper Bell Bacterial Spot	99.77	99.89	99.77
19	Peach Healthy	100	100	100
20	Pepper Bell Healthy	97.07	100	100
21	Potato Early Blight	100	100	100
22	Potato Healthy	100	100	100
23	Potato Late Blight	99.71	99.96	99.84
24	Raspberry Healthy	91.93	99.93	99.93
25	Soybean Healthy	91.84	99.94	99.94
26	Squash Powdery Mildew	100	100	100
27	Strawberry Healthy	99.09	99.93	99.89
28	Strawberry Leaf Scorch	91.94	100	99.94
29	Tomato Bacterial Spot	99.36	99.92	99.36
30	Tomato Target Spot	100	100	99
31	Tomato Early Blight	91.04	99.99	99.83
32	Tomato Septoria leaf Spot	100	100	99.89
33	Tomato Healthy	100	100	100
34	Tomato Late Blight	91.09	100	99.69
35	Tomato Leaf Mold	99.17	100	99.87
36	Tomato Spider Mites	93.7	100	99.94
37	Tomato Mosaic Virus	91.95	99.94	99.89
38	Tomato Yellow Leaf	99.97	99.92	100

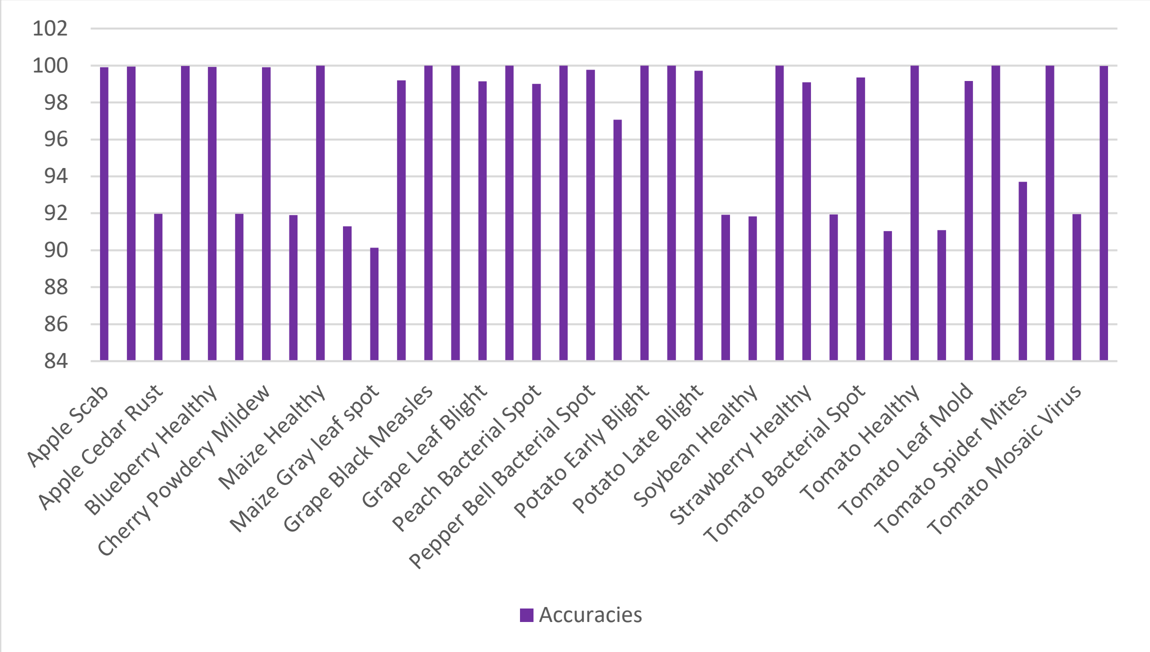

Figure 7- The plot for accuracy attained for each plant disease

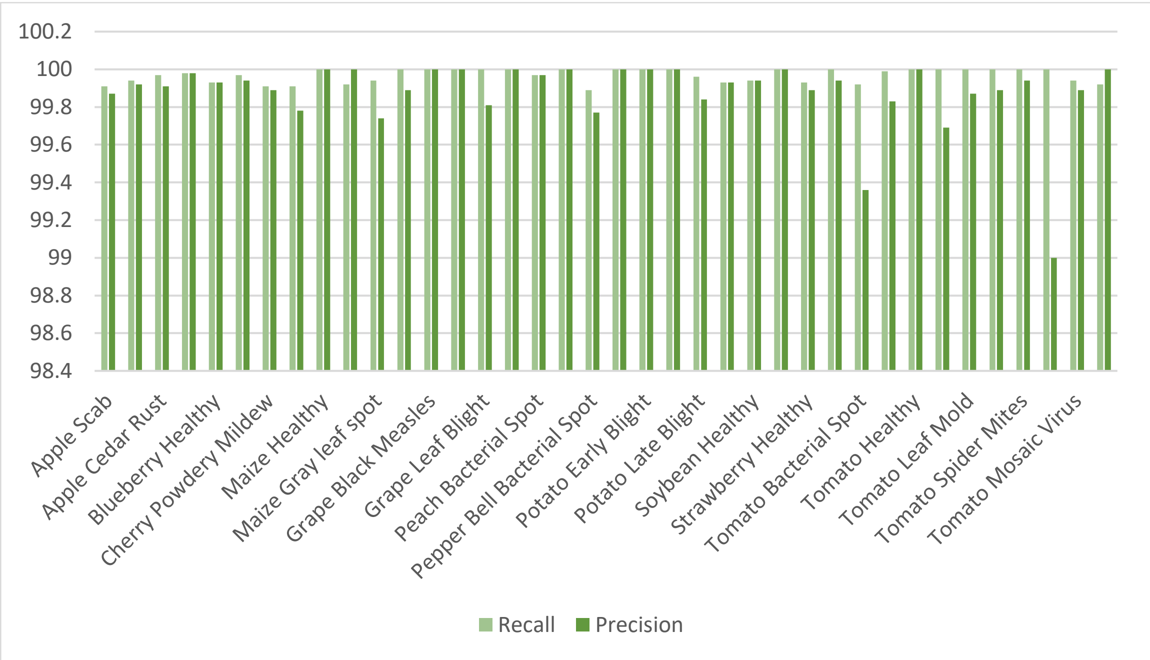

Figure 8- The plot for recall and precision attained for each plant disease

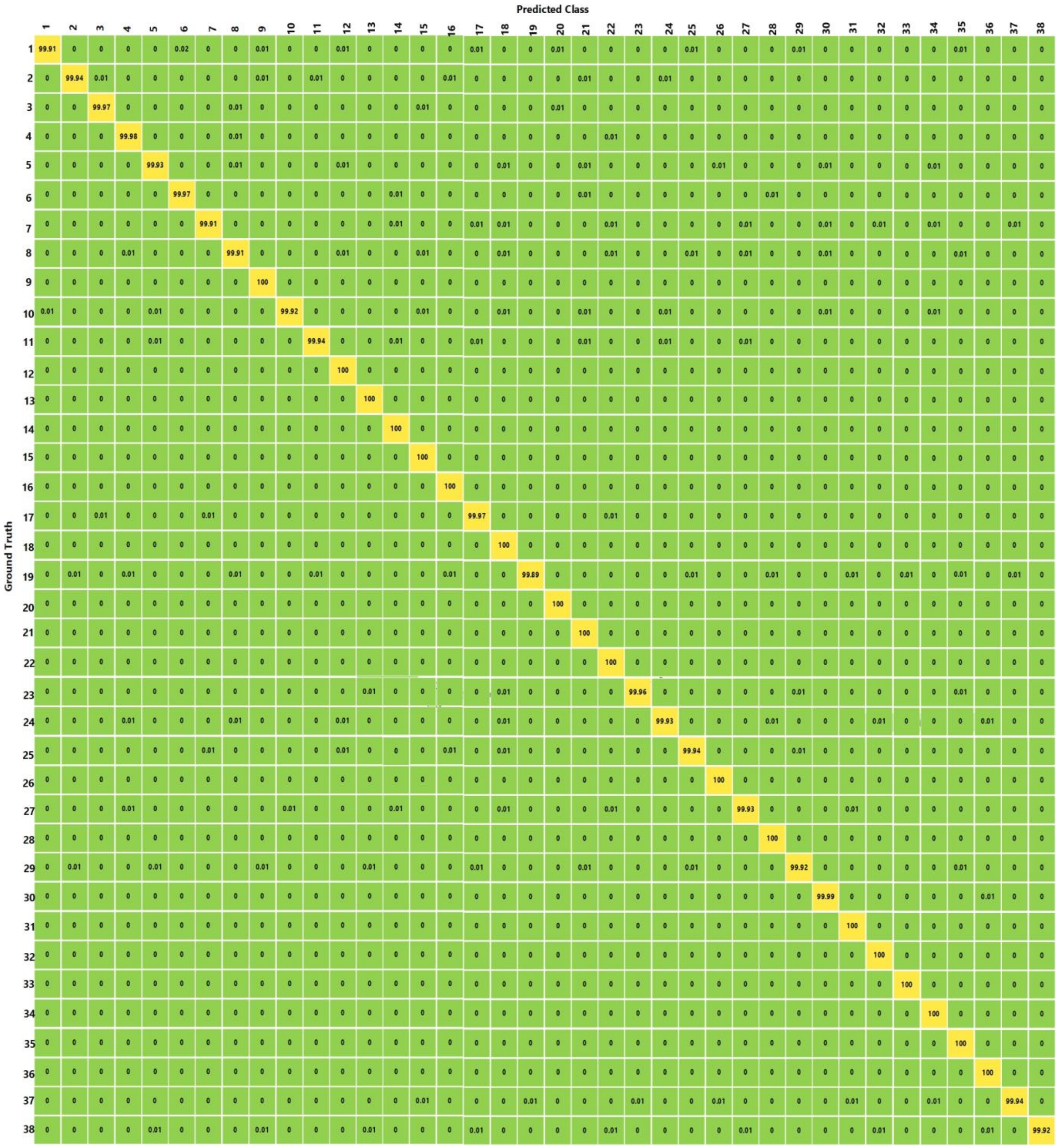

Figure 9- The confusion matrix attained for 38 diseases of plants

4.3. Results on processed and Un-processed images

The proposed model achieves significantly better performance on pre-processed images compared to original images, as shown in Tables 4, 5, and 6. The accuracy for the pre-processed images is consistently higher across all disease types, which suggests that the pre-processing steps contribute to enhancing the model's overall performance. Pre-processing significantly improves the model’s performance by enhancing image clarity and reducing noise. This leads to higher accuracy, sensitivity, and precision, thereby making the classification results more reliable.

Table 4- The VGG16 model's average performance on preprocessed images

Disease	*Model*	*Accuracy (%)*	*Sensitivity (%)*	*Precision (%)*
Fungal	VGG 16	84.43	86	78
Bacterial	VGG 16	89.13	85	96
Viral	VGG 16	88	95	90

Table 5- The new proposed model's average performance on original images

Disease	Model	Accuracy (%)	Sensitivity (%)	Precision (%)
Fungal	CNN	63.43	53	61
Bacterial	CNN	82.13	83	82
Viral	CNN	80	81	83

Table 6- The new suggested model's average performance on preprocessed images

Disease	Model	Accuracy (%)	Sensitivity (%)	Precision (%)
Fungal	CNN	93	100	99
Bacterial	CNN	96	95	95
Viral	CNN	98	100	100

4.3. Comparative evaluation with CNN-based existing techniques

For spotting illness in leaves, there exist numerous methods. Due to the backpropagation strategy used to cut costs, convolutional neural networks outperform traditional ML based methods for classification. Table 7 compares the suggested model with current CNN-based method to evaluate performance. For this experiment, we specifically used potato diseased images form the Plant Village Dataset. The samples included leaves from three categories: early blight, late blight, and health class. The detection and classification of plant illnesses into late blight, early blight, and healthy, Tiwari et al. (2020) proposed the code based on VGG19 with CNN. Although they achieved 97.8% accuracy, our suggested approach has a 98.6% accuracy rate for identifying the three illnesses. An approach of deep learning has been suggested for the identification of stress in vertical photographs of potato plants by Butte et al. (2021). According to the study, the suggested model achieved 93% accuracy to identify the stress level of one illness, late blight. More specifically, our system is more robust and extorts the disease's most elusive features as it achieves better accuracy on unseen images.

Table 7- Comparative analysis with available potato disease detection models

Reference	*Their suggested Models*	*Accuracy (%)*
Tiwari et al. (2020)	Convolutional neural Network+ VGG 19	97.8
Butte et al. (2021)	Faster R-CNN	89
Biswas et al. (2014)	Back Propagation Neural Network+ Fuzzy C-Means	93
The proposed model	CNN	98.6

4.4. Comparison according to Machine Learning techniques

As compared to our suggested technique, which is based on Deep Neural Network (DNN) architecture, typical ML algorithms need customized feature extraction for detection and classification.

Additionally, machine learning-based techniques use small datasets for training while DL-based system need large datasets. However, generalization is a problem for machine learning-based algorithms. Generalization means the ability of a model to perform well not only on the training data but also on new, unseen data. When a model is overfitted to the training dataset, it may not generalize well, resulting in lower performance on test or real-world data. The authors have identified five banana leaf diseases in (Singh & Misra 2017). They used the SVM classifier for training by collecting 60 digital camera photos. The algorithm's accuracy was 95.7%.

Using pictures captured by the camera, the writers of (Zhang et al. 2015) used the k-nearest neighbors method to identify the five illnesses affecting corn leaves. They managed to attain a 90% accuracy rate. Okra leaves were divided into groups of healthy and damaged leaves using the Nave Bayes (NB) method (Mondal, Chakraborty, Kole & Majumder, 2015). Despite using 79 photos, they only utilized 49 to train the system and 30 to assess it. With 87% accuracy, the system categorized the leaves.

Wheat leaves had four illnesses that were identified utilizing 50 photos for testing and 150 photos for training (Tian et al. 2011). They suggested the use of multiple classifier system and achieved accuracy of 95.1%. Table 8presents a thorough analysis. It is shown that our suggested method, which is built on CNN-based, successfully categorizes plant illness.

Table 8- Comparison with Machine Learning-based techniques

Reference	*Plant Type*	*Year*	*Algorithm*	*Total Images*	*No. of illness*	*Testing Images*	*Training Images*	*Accuracy (%)*
Singh & Misra (2017)	Banana	2017	SVM	106	5	46	60	95.7
Zhang et al. (2015)	Corn	2015	KNN	100	5	10	90	90
Mondal et al. (2015)	Okra	2015	NB	79	2	39	40	87
Tian et al. (2011)	Wheat	2010	SVM	200	4	50	150	95.1
Our proposed model	Different plants	2023	Efficient DenseNet	54303	38	10860	43442	97.6

4.5. Comparison with classification-based DL models

In this section, we make a comparison with different classification models for detecting plant disease. We used the same dataset for different models. Moreover, we utilized the same training and testing parameters for all models. Table 9 represent the comparative results.

Table 9- A comparison with classification-based model

Models	*Accuracy (%)*
MobileNet	91.3
ResNet	90.8
AlexNet	94.5
The proposed model	97.6

4.6. Comparative analysis with segmentation-based methods

In this portion, we perform the effectiveness of our strategy for detecting leaf illness by contrasting it with other segmentation-based methods. The process of segmentation involves breaking the sample up into several pieces and extracting the damaged area from the picture. In Table 10, there exist several segmentation-based methods for contrasting the suggested model. The two-stage approach for illness detection was proposed by the authors in (Soni & Chahar 2016). First, the color intensity characteristics from the photos have been extracted using the segmentation technique based on the ring. Second, they used a Probabilistic Neural Network (PNN) classifier to categorize plant leaves in binary form with 90% accuracy. Using the dataset gathered from Nagpur's fields, cotton plants have been classified in (Rothe & Rothe 2019). To start, they used a filter to sharpen the corners of the leaves. In addition, they used the Otsu segmentation technique to exclude the damaged area from the photos.

Table 10- Comparative analysis among segmentation-based methods

Reference	*Classifier*	*Testing and Training*	*Features*	*Segmentation*	*Number of Disease*	*Accuracy (%)*
Soni & Chahar (2016)	Neural Network	NA	Color and Intensity	Ring	NA	90
Rothe & Rothe (2019)	Neural Network	70,30	Color, Shape, and Texture	Ostu	3	95.48
Singh et al. (2019)	SVM	NA,500	Wavelet	Binary Threshold	1	89.6
Iqbal &Talukder (2020)	RF	450-100	Humoment, Histogram and Haralic	Color Threshold Method	3	97
Khirade & Patil (2015)	Multiple Linear Regression	NA	Color, Texture, and Shape	Improved Histogram	NA	90
Masazhar & Kamal (2017)	SVM	NA	Color, Texture, and Shape	K-means	2	95
The Proposed model	Efficient DenseNet	3852-1326	Automatic	NA	38	97.6

Then, four form characteristics, 22 texture features, and nine color features were retrieved and supplied into the FFN (feed-forward neural network). The accuracy of the system was 95.48%.

The pea plants have been evaluated to divide them into classes of healthy and ill plants (Singh et al. 2019). First, noise from pictures is removed during pre-processing using Gaussian filters. The Gaussian filter smooths the image, removing highfrequency noise and preserving important features in the image, which is crucial for effective disease classification. A log modify was also used to improve the photographs. Log modify refers to applying a logarithmic transformation to the image, which is a common technique in image processing to improve contrast. Finally, the segmentation was done using binary threshold approach. This method was chosen due to its simplicity and effectiveness in cases where there is a clear intensity difference between foreground and background. Ultimately, segmented pictures' derived wavelet characteristics were sent to the SVM classifier, which achieved an accuracy of 89.6%.

Three potato leaf illnesses have been identified using seven distinct ML techniques (Iqbal & Talukder 2020). First, the color threshold segmentation approach was used to pre-process and segment 450 photos. Later, characteristics were retrieved using the Humoment, Histogram, and Haralic techniques, and they used seven algorithms for categorization. The Random Forest (RF) achieved 97% maximum accuracy.

To identify the quantity of plant diseases, a novel model depends on Multiple Linear Regression (MLR) has been developed (Khirade & Patil, 2015). An enhanced histogram technique has been proposed to determine the value of threshold after pre-processing. Following the removal of the damaged area, characteristics based on texture, color, and form were retrieved. MLR was ultimately used to categorize the leaves, and it had a 90% accuracy rate.

Additionally, a SVM classifier has been applied to separate pictures of healthy and unhealthy palm oil leaves (Masazhar & Kamal 2017). The illness part of the leaf was then separated using the k-means segmentation technique. After that, the categorization was done with the use of 13 characteristics, including form, color, and texture, and it was 95% accurate.

As a result, it is abundantly obvious from the study that our suggested method performs better than the current segmentation-based strategies in terms of detection accuracy.

The proposed compact CNN model delivers high classification accuracy while substantially lowering computational overhead. By utilizing a streamlined architecture with reduced layers and parameters, the model ensures faster inference and lower memory usage. This efficiency makes it particularly well-suited for deployment in real-time agricultural monitoring systems and resource-constrained edge devices.

The model handles large datasets effectively via batch processing and data augmentation. Scalability to diverse crop species and environmental conditions remains a challenge, but can be mitigated through domain adaptation techniques and training on varied datasets.

Moreover, the proposed CNN model is end-to-end and bypasses the need for explicit segmentation, resulting in lower computational overhead. Although segmentation offers spatial localization, it adds complexity and is sensitive to variations in real-world imagery, whereas CNNs offer robustness and efficiency due to its simple and easy to implement architecture.

5. Conclusions

- This study proposed novel and a general approach for identifying plant disease. This model is simple to use for classification that makes use of CNN-based feature extraction.

- Several experiments have been performed to validate the performance of the suggested classifier. On publicly available dataset i.e., The Plant Village Dataset, the system's testing accuracy has been overall 97.6%. The accuracy leads to the conclusion that CNN is well suited for plant recognition and diagnosis automatically.

- On the other side, the proposed work also analyzed the performance using un-processed and pre-processed leaf images and it is noticed that the model achieves better performance on pre-processed images.

- Integration of image pre-processing and augmentation techniques significantly enhanced classification performance and robustness.

- Compared to segmentation-based and traditional machine learning methods, the proposed CNN model provided an end-to-end, efficient, and scalable solution.

- Although, our proposed classifier is simple and efficient to use for plant disease detection, however, due to lack of resources we were unable to assess it in real world scenarios. Therefore, in future, the model may be combined with a drone or any other technology to identify plant illnesses in real time scenarios to inform farmers about the locations of the suffering plants so that they can be treated appropriately.

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