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DSCNN: A NOVEL DEPTHWISE SEPARABLE DEAP LEARNING APPROACH FOR AUTOMATIC POTATO LEAF DISEASE CLASSIFICATION

MUHAMMAD USMAN SAEED*

Department of Computer Science, Central South University, Changsha 410083, Hunan, China.
Email: usmansaeed534@csu.edu.cn

GHULAM ALI

Faculty of Computing Department of Software Engineering, University of Okara, Okara Pakistan.
Email: ghulamali@uo.edu.pk

MEHWISH RASHEED

PhD Scholar, Lecturer, Department of Computer Science and Information Technology, Superior University Lahore, Faisalabad, Pakistan. Email: mehwishrasheed.fsd@superior.edu.pk

TUBA MANSOOR

Lecturer, Department: Ripha School of Computing and Innovation, Riphah International University Lahore, Pakistan. Email: tubamansoor786@gmail.com.

AGHA WAFA ABBAS

Lecturer, Department of Computer Science, University of South Asia, Lahore, Pakistan.
Email: wafa.abbas@usa.edu.pk

QURATULAIN MANSOOR

Software Engineer, Department of Computer Science and Information Technology, Superior University Lahore, Lahore, Pakistan. Email: quratulain.mansoor@gmail.com

Abstract

Machine learning and artificial intelligence have been more essential in recent years in areas of agriculture including the diagnosis and forecasting of plant diseases. Because symptoms, field crops, and climatic conditions all vary, it can be difficult to identify plant diseases early on. The quality and quantity of potatoes are affected by a number of diseases, including late blight and early blight. The manual diagnosis of potato leaves disease is a laborious and complicated operation. To diagnose the condition, a specialist with good abilities is needed. Therefore, a technique that can identify the illnesses affecting potato leaves must be automated and effective. In order to extract the deep features from the dataset, a unique convolutional neural network model is developed in this study. On the Plant Village dataset and the Plant Leaf Disease dataset, the model is assessed. The outcome demonstrates that the suggested model outperforms the earlier work in terms of efficiency and outcomes.

Keywords: Convolutional Neural Network; Patato Leaf Disease; Digital Image Analysis; Plant Pathalogy.

1. INTRODUCTION

Diseases are a naturally occurring phenomenon that can have serious effects on plants, lowering productivity, product quality, and overall production levels. The primary

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component for assessing a plant's illness is its leaf. To prevent agricultural losses, one must be able to quickly identify and classify leaf diseases. Different plant leaves transmit various illnesses.

The three primary categories of plant leaf diseases are caused by bacteria, fungus, and viruses. The most common plant diseases are Alternaria Alternata, Anthracnose, Bacterial Blight, Cercospora Leaf Spot, Powdery Mildew, Downy Mildew, and Rust.

Figure 1 illustrates how the potato leaf disease early blight creates circular marks on the borders and in the centres of the leaves (a). This leaf disease, which results in the enlargement of these spots and the browning of the leaf's hue, is caused by the fungus Alternia solani. Furthermore, late blight, a particular potato leaf disease that can harm plants, is mostly brought on by the bacterium Phytopthora infestans de Bary. Figure 1 (b) shows a leaf with late blight, which is identified by the emergence of lesions on the leaves and continues to reproduce [1].

Figure 1: The Potato Leaf disease (left) Early Blight (right) Late Blight

This analysis can serve agricultural operators in providing effective and efficient care of unhealthy or atypical plants. Many digital image studies in agriculture have been conducted to discover diseases and identify good agricultural production. For the purpose of identifying leaf diseases, several researchers in the fields of computer vision and image processing have employed LBP [2] and K-means clustering [3].

Both plant and human illnesses may be detected and categorised thanks in large part to machine learning. Using a machine learning model helps in detection and classification and can achieve robust and efficient performance. For the categorization of plant leaf diseases, a variety of machine learning models including PDDCNN [4], VGG19, VGG16 and Inceptionv3 with Logistic Regression [5], VGGNet [6], and SVM [7] were utilised.

Due to the enormous number of trainable parameters, these models demand more processing power and training time. The study's suggested model is a simple convolutional neural network for identifying and categorising potato leaf diseases. The dataset is divided into three classes: early blight, late blight, and healthy. Convolutions in the model are depth-wise separable, which lowers the computational burden while preserving greater accuracy outcomes.

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The following are the main goals of this study:

- To develop a novel machine learning model that classify potato leaf disease
- To extract deep features that can perform well during classification process
- To introduce an efficient machine learning model that can reduce computational cost
- To use depth wise convolutions which can extract important features and reduces the trainable parameters

2. LITERATURE REVIEW

There are several ways to spot plant diseases, and different researchers have offered different strategies for spotting potato leaf diseases in published works. Multiple methods, including X-ray ultrasounds, RGB pictures, multispectral and hyperspectral technologies, have been developed to effectively monitor and identify crop illnesses [8]. A technique of detecting potato leaf disease utilising pre-trained VGG19 for feature extraction was put out by Divyansh et al. [5]. Multiple classifiers were then employed to assess the performance. The model was trained and validated using the Plant Village dataset. With an accuracy of 97.8%, the logistic regression outperforms the other classifiers. Rizqi et al. [6] proposed a further deep learning method for the identification and categorization of potato leaf diseases. The VGG16 and VGG19 network models that made up the model, known as VGGNet, were combined. On the test dataset, which was the Plant Village dataset, the model had an average accuracy of 91%.

Deep learning was suggested [9] to automatically identify plant leaf diseases and evaluate several models. With the Plant Village dataset, MobileNet, VGG16, ResNet, and VGG19 were initially chosen and trained. In comparison to other models, VGG16 performs well and obtained 92.69% accuracy. Using the tweaking principle, the VGG16 model's performance was further improved. After adjustments, this model classified early blight, late blight, and healthy leaves with an accuracy of 97.89%. A machine learning-based strategy for the categorization of potato leaf disease was proposed by Sakhshi Sharma et al. [10]. For the categorization of potato leaf diseases, our system combined image processing techniques with machine learning techniques.

Using several machine learning methods including Support Vector Machine, Naive Bayes, and Decision trees, two potato leaf diseases—early blight and late blight—were classified. The dataset photos were first filtered with a Gaussian filter, and then the k-means clustering technique was used to identify the region of interest. When compared to the other classifiers, the Support Vector Machine performs best, with an accuracy rate of 92.9%. Using several image processing techniques, Asif et al. [11] presented a comparison methodology for potato leaf disease diagnosis. The design of the convolutional neural network was chosen because it excels in classification tasks. The model was trained using a sizable number of datasets. According to the findings, the proposed strategy performed 97% more accurately than the other methods that used image processing techniques. The model was trained using a sizable number of datasets.

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According to the findings, the proposed strategy performed 97% more accurately than the other methods that used image processing techniques.

Khalid et al. [12] proposed a CNN model in which many CNN models were employed to determine the effectiveness of the algorithms. The sequential CNN model, AlexNet, VGGNet, LeNet, and ResNet were employed. On a binary classification of normal and pathological plant leaf dataset, the model had a precision of 97%. A potato leaf disease diagnosis method based on texture feature extraction and distinctive colours was proposed by Ungsumalee et al. [13]. First, the RGB to L*a*b colour space conversion of the image's colours. K-means clustering was utilised to distinguish between normal and aberrant leaf components. To classify potato leaves using Euclidean distance, these colour characteristics were coupled with statistical information. Using the Plant Village dataset for evaluation, the model had an average accuracy of 91.67%. Trong et al. [14] presented a further CNN method for the categorization of potato leaf diseases.

This model is very effective and shows superior classification of potato leaf disease with lower computing cost and accuracy. To improve the quality of the data for subsequent processing, an image database was developed utilising image processing techniques. The dataset from Plant Village was utilised to assess the suggested model. Cross-entropy and the Adam optimizer were used to analyse the model. The outcomes demonstrated that the CNN model has a 99.53% accuracy rate. The convolutional neural network model presented in this article is a simple model for the differentiation of healthy, early blight, and late blight potato leaf diseases. The dataset is first preprocessed using the histogram equalization and linear contrast enhancement techniques. Then, augmentation techniques are used to expand the input data, which can enhance the model's training process. The depth wise separable convolutions are then added to the model, which improves accuracy while using less processing power. In comparison to state-of-the-art techniques, the suggested model behaves well with fewer trainable parameters and produces results with greater accuracy.

3. METHODOLOGY

3.1. Plant Village Dataset

The first dataset utilised in this study is called "Plan Village" and is open source and freely accessible at [15]. About 54,306 photos from 14 distinct crop species make up the dataset. The categorization of the potato leaves is the primary goal of this study. The potato species dataset, which has a total of 2152 photos and includes images of leaves with early blight, late blight, and healthy leaves, is taken from this database. Additionally included in Figure 2 are the example pictures from this collection.

Table 1: Number of images in Plant Village Dataset

Labels	Images
Early Blight	1000
Late Blight	1000
Healthy	152
Total	**2152**

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Figure 2: The potato leaf images from Plant Village Dataset (a) Healthy leaves (b) Early blight (c) Late blight

3.2. Plant Leaf Disease Dataset

The second dataset that was used in this investigation was created by Javed et al. [4] to track down agricultural leaf diseases in Pakistani regions. The real-time dataset was gathered in district Okara in Pakistan's central Punjab province using a variety of tools, including digital cameras, cell phones, and drones. The pictures were taken under various lighting and weather situations. As shown in Table 2, the dataset includes 1020 healthy leaf photos of potatoes and 1628 images of early, 1414 images of late, and 1628 images of early blight. Figure 3 also displays the dataset's sample photos.

Table 2: Number of images in Plant Leaf Disease Dataset

Labels	Images
Early Blight	1628
Late Blight	1414
Healthy	1020
Total	**4062**

Figure 3: The potato leaf images from Plant Leaf Disease Dataset (a) Healthy leaves (b) Early blight (c) Late blight

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3.3. Evaluation Metrics

Various assessment criteria are available to assess the performance of the machine learning models. Below are the assessment measures that were employed in this study to assess the suggested model.

3.3.1. Accuracy

The accuracy is determined by dividing the total number of correct positive predictions by the total number of forecasts. The following is the mathematical formula for calculating accuracy:

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

3.3.2. Precision

The initial It is the proportion of all positively expected observations to those that were successfully predicted. The following is the equation for calculating precision:

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

3.3.3. Recall

It is a statistic that measures the proportion of accurate positive predictions out of all possible positive forecasts. The mathematical formula for calculating the recall is given below:

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

3.3.4. F1 Score

The initial by calculating the harmonic mean of a classifier's accuracy and recall, the F1-score integrates both into a single statistic. The following equation represents the F1 score:

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

3.4. Model Training Parameters

The datasets are split into 80-20 divisions, with 80% of the data utilised for training and 20% for testing. With a learning rate of 0.001, 100 training epochs are used to train the proposed network. During training, the 32-image batch size and the Adam optimizer are both employed. If the model's performance on validation data does not improve after 5 epochs, the training process is immediately halted. If there is no improvement in the validation loss, the learning rate is multiplied by 0.4.

3.5. Proposed Methodology

Deep learning is a sort of artificial intelligence and machine learning that mimics how people learn specific types of information. With developments in a variety of industries, including fraud detection [16], virtual assistants [17], the internet of things [18], face

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recognition systems [19], plant disease detection [20], and medical picture analysis [21], deep learning applications have developed. Convolutional Neural Networks are used to handle image-based challenges (CNN). Deep networks are used to extract the key characteristics from the datasets. The PLDD model, as seen in Figure 4, uses a CNN model to categories the illness of potato leaves.

The second iteration of the proposed model is a more sophisticated iteration that includes depthwise convolutional layers to increase accuracy while lowering computing costs. Figure 5 depicts the whole architecture of the final suggested model.

Figure 4: The PLDD model for potato leaf disease detection

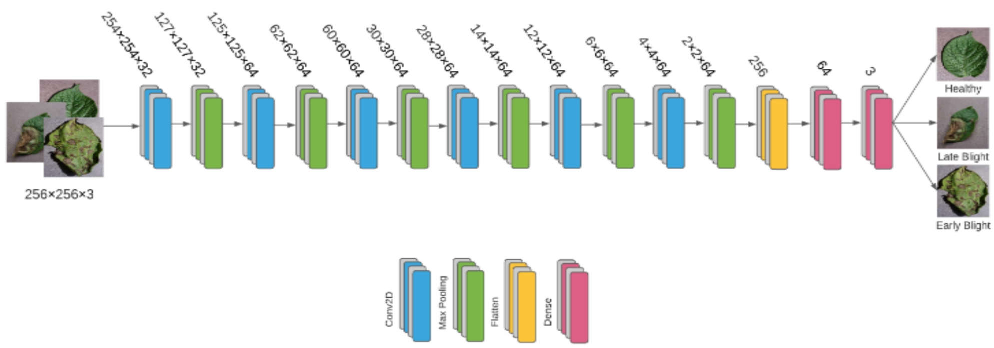
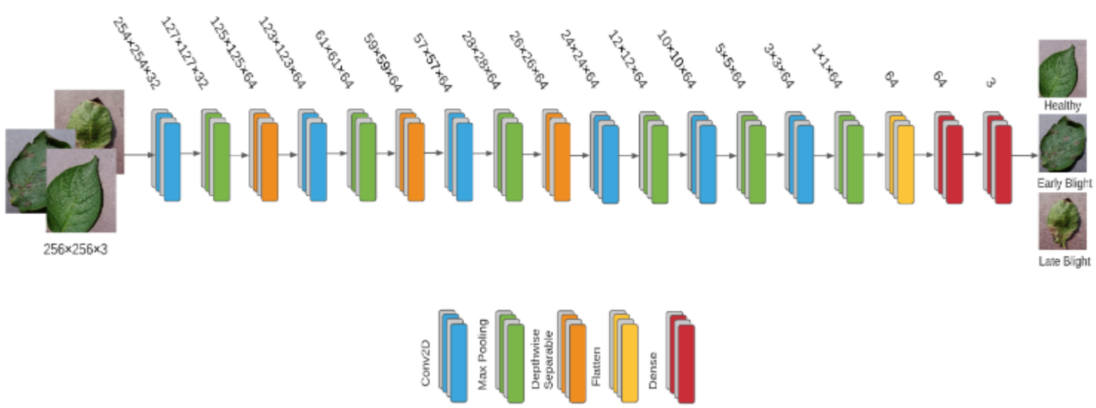


Figure 5: The proposed model for potato leaf disease detection



4. EXPERIMENTAL RESULTS

The findings on the Plant Village dataset and the dataset for Potato Leaf Disease using the proposed convolutional neural network are explained in depth. To enhance the suggested model, several tests are carried out. First, both datasets are used to train the model without using any pre-processing or augmentation methods. Table 3 presents the findings for both datasets. The outcomes demonstrate that the suggested model performs better on the Plant Village dataset than it does on the Plant Leaf Disease dataset.

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Table 3: The results of the PLDD model on Plant Village Dataset and Plant Leaf Disease Dataset

Dataset	Parameters	Accuracy	Precision	Recall	F1 Score
Plant Village	483,747	89.26	91.82	91.59	90.14
Plant Leaf Disease	483,747	88.03	90.26	91.44	90.25

4.1. Image Enhancement Methods

4.1.1. Histogram Equalization

The contrast of the photos is enhanced using the image enhancement technique known as histogram equalisation. This enables the low-contrast region to acquire high contrast values. Let f be an input picture with pixel intensities ranging from 0 to L-1 represented as a m(r) by m(c) matrix, where L is the total number of intensity values. Let P stand for the histogram off adjusted to each conceivable intensity.

$$P_n = \frac{\text{Total no. of Pixels with Intensity N}}{\text{Total Pixels}}$$

The output image of histogram equalization is obtained by:

$$g_{i,j} = \text{floor}((L-1)\sum_{n=0}^{fi,j} P_n)$$

Where floor () rounds down to the nearest number. The images of both the datasets after applying histogram equalization are given in Figure 6 and Figure 7.

Figure 6: The Plant Village dataset images after applying histogram equalization (a) healthy leaf, (b) early blight, (c) late blight

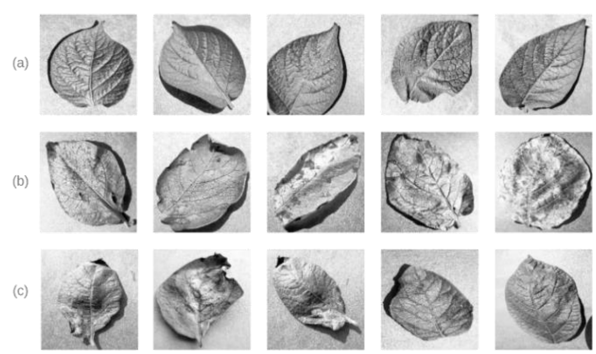

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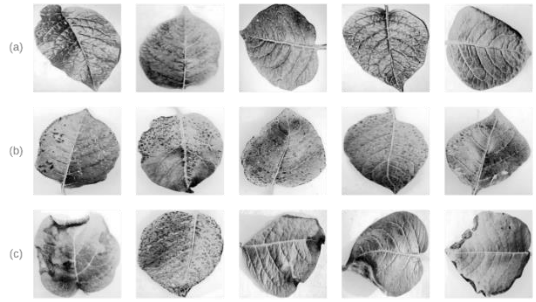
Figure. 7. The Plant Leaf Disease dataset images after applying histogram equalization (a) healthy leaf, (b) early blight, (c) late blight



4.1.2 Linear Contrast Enhancement

Another technique to enhance the image's contrast and brightness is linear contrast enhancement. Using X as the input picture, C as the contrast, and B as the brightness, the following equation may be used to create the new image:

$$\mathrm{Output} = \mathrm{X} \times \mathrm{C} + \mathrm{B}$$

The images of both the datasets after applying the linear contrast enhancement are given in Figure 8 and Figure 9.

Figure 8: The Plant Village dataset images after applying linear contrast enhancement (a) healthy leaf, (b) early blight, (c) late blight

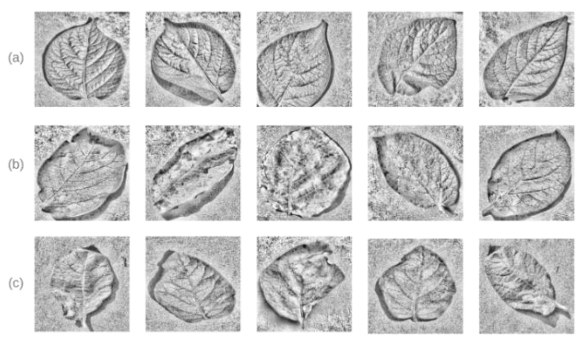
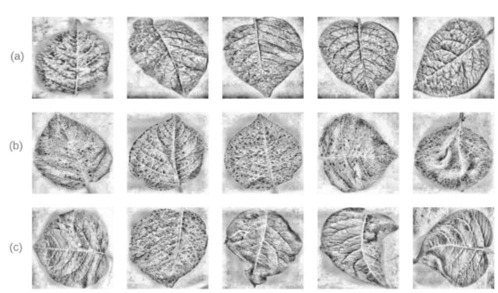


Figure 9: The Plant Leaf Disease dataset images after applying linear contrast enhancement (a) healthy leaf, (b) early blight, (c) late blight



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The results obtained after applying the histogram equalization and linear contrast are given in Table 4. The performance of the proposed model improves due to image enhancement techniques.

Table 4: The results of the proposed model on Plant Village Dataset and Plant Leaf Disease Dataset with histogram equalization and linear contrast enhancement

Dataset	Trainable Params	Pre-processing	Accuracy	Precision	Recall	F1 Score
Plant Village	483747	LC	92.15	94.65	93.79	94.14
		HE	94.87	95.26	96.35	96.56
Plant Leaf Disease	483747	LC	92.45	94.12	95.79	94.67
		HE	94.26	95.65	95.47	96.38

4.2. Data Augmentation

Data augmentation techniques are used to provide fabricated instances of real-world data in order to produce more input samples for model training. To provide a more reliable dataset for the classifier during training, data augmentation is used for datasets with sparse data. This is often advantageous for training models with limited data. By minimally altering the current data, data augmentation methods are used to expand the amount of input data. The many enhancement methods employed in this study are listed below:

4.2.1 Scaling and Rotation

Important deep characteristics can be learned by deep neural network models utilising a scaled-down training set. The scaling factors for the X and Y directions are represented by Gx and Gy in the operation G, which can be done in a variety of directions. Scaling can produce usable augmented pictures for training since tumour sizes vary. In order to retain the dimensions of the supplied image, scaling is coupled with cropping. Only the essential portions of a picture can be cropped.

$$Z = \begin{pmatrix} G_x & 0 \\ 0 & G_y \end{pmatrix}$$

4.2.2 Flip and Rotation

The original image is mirrored along the axes when randomly flipped. Natural pictures may often be flipped along the horizontal axis but not the vertical axis because up and down components of an image are not always "interchangeable." A brain comprises two hemispheres in the axial plane, and the brain is typically thought of as anatomically symmetrical. This characteristic also applies to MRI brain scans. When you rotate along the horizontal axis, the left and right hemispheres are switched, and vice versa. A picture can be usefully rotated in this situation around the centre pixel. After that, the original picture size is fitted using the proper interpolation. When zero padding is employed to fill

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up the gaps between pixels, the rotation operation Z is widely utilised in:

$$G = \begin{pmatrix} \cos\alpha - \sin\alpha \\ \sin\alpha \cos\alpha \end{pmatrix}$$

The results given in Table 5 shows that the augmentation technique improves the performance of the proposed model for both datasets.

Table 5: The results of the proposed model on Plant Village Dataset and Plant Leaf Disease Dataset with augmentation, histogram equalization and linear contrast enhancement

Dataset	Trainable Params	Pre-processing	Accuracy	Precision	Recall	F1 Score
Plant Village	483747	LC	97.56	98.59	98.49	98.76
		HE	98.85	99.54	99.12	99.61
Plant Leaf Disease	483747	LC	96.01	98.68	98.91	98.12
		HE	97.66	98.92	99.12	98.56

4.3. Depth wise Separable Convolution

The final model is an updated version of the proposed CNN model in which depth wise separable convolution layers are added. A single convolutional layer is applied to each channel of the input image separately. Regular convolutional layers require more computational cost due to higher number of trainable parameters; however, the depth wise separable convolutions contain less trainable parameters. Low computational resources are required during the training process which makes it cheaper and faster. The results after adding the depth wise separable convolution layers are given in Table 6. From there, we can conclude that these layers increase the performance of the proposed network with less computational cost.

Table 6: The results of the proposed model on Plant Village Dataset and Plant Leaf Disease Dataset with augmentation, histogram equalization, linear contrast enhancement and depth wise separable convolution

Dataset	Trainable Params	Pre-processing	Accuracy	Precision	Recall	F1 Score
Plant Village	483747	LC	99.56	99.59	100	99.86
		HE	99.79	100	99.89	99.61
Plant Leaf Disease	483747	LC	99.51	98.88	99.91	99.72
		HE	99.86	99.89	99.92	99.56

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4.4. Comparison of the proposed model with other CNN models

The depth wise separable convolution neural network was used to create the suggested CNN model. The number of trainable parameters has a significant impact on the amount of processing time and resources required to train the model. The goal of this study is to create a lightweight model that uses the fewest resources possible while producing effective outcomes. Table 7 displays the findings from several models used to categorise plant leaf disease.

Table 7: The results of the proposed model on Plant Village Dataset and Plant Leaf Disease

Reference	Dataset	Total Params	Accuracy
[22]	ILSVRC-2012	14,716,227	40.05
[23]	Plant Village	6,812,995	92
[24]	Plant Village	16,407,395	96.98
[5]	Plant Village	143,667,240	97.80
[25]	Plant Village	10,089,219	99
[7]	Plant Village [LAB]	-	95
[6]	Plant Village	-	91
[4]	Plant Leaf Disease, Plant Village	8,578,611	99.75, 96.71
[5]	Plant Village	-	97.8
Proposed Model	Plant Leaf Disease, Plant Village	183,747	99.86, 99.79

Karen et al. [22] looked at the impact of network depth on its accuracy. The accuracy of the suggested model, which has a total trainable parameter count of 14,716,227, has been improved by employing a modest filter size of 3x3. The model was tested on different datasets and showed that the depth of the CNN models can improve the results. The Plant Village dataset's healthy, early blight, and late blight leaf pictures were classified using a deep learning algorithm [23]. The dataset was split into training and testing portions of 70% and 30%, respectively. Results from this model's test dataset with learnable parameters of 6,812,995 were 92% accurate.

Utpal et al. introduced an SBCNN model in [24] that was evaluated both with and without augmentation. The assessment of this model utilises the Plant Village dataset. With 16,407,395 trainable parameters, the accuracy on the augmented and non-augmented datasets was 96.98% and 96.75%, respectively. The model was also used to identify potato leaf diseases in real time in an android application. A pre-trained VGG19 with precise adjustment was employed by Divyansh et al. [5] to extract the key characteristics from the input photos. Then, these characteristics are fed to several classifiers, with logistic regression showing good performance with a 98.7% accuracy and 143,667,240 trainable parameters. For effective categorization of potato leaf diseases, a convolutional neural network [25] was suggested. Initially, the dataset was improved using image processing techniques. Softmax's activation feature was combined with the Adam optimizer. The model had 10,089,219 trainable parameters and a 99 percent accuracy.

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Monzurul et al. [7] proposed an automated machine learning and image processing technique for the diagnosis of potato leaf disease. The performance of the model was verified using the Plant Village dataset. Over 300 photos, this model's accuracy was 95%. In order to provide an effective outcome, [6] introduced another deep learning model that combines the VGG16 and VGG19 models. The accuracy of this model, which was trained using data from Plant Village, was 91 percent. A multi-level deep learning model for classifying potato leaf diseases was described in [4]. Initially, the YOLOv5 segmentation approach was used to remove the potato leaves. The convolutional neural network was then given these photos of leaves to classify them into healthy, late blight, and early blight images. The model was evaluated using data from Plant Village and a self-generated dataset from Pakistan's Central Punjab. On the self-generated dataset, the model's accuracy was 99.75 percent and its total trainable parameter count was 8,578,611.

In this work, a CNN model is suggested for categorising potato leaf diseases. Convolutional, max pooling, and depthwise separable convolutional layers make up the model. The suggested model is evaluated using the Plant Village and Plant Leaf Disease dataset. On the datasets for Plant Leaf Disease and Plant Village, the model had accuracy rates of 99.86 and 99.79 percent, respectively. The proposed model has 183,747 total trainable parameters that are derived from cutting-edge deep learning models of potato leaf diseases and need less computation and training time.

5. CONCLUSION

As a source of energy, plants are seen as being crucial to human existence. Any time between planting and harvest, plant diseases can damage the leaf, causing major losses in crop output and market value. As a result, the diagnosis of leaf diseases is crucial in the field of agriculture. However, it needs a greater amount of computer power, processing time, and knowledge of plant diseases. The categorization of potato leaves into healthy, early blight, and late blight is accomplished in this study through the use of an automated, lightweight convolutional neural network. The proposed model is tested on two datasets, Plant Village and Plant Leaf Disease, and it obtains accuracy precision, recall, and f1 scores of 99.79%, 100%, 99.89%, and 99.61% for Plant Village and 99.86%, 99.89%, 99.92%, and 99.56% for Plant Leaf Disease, respectively. In order to increase performance and minimise the number of trainable parameters, which in turn lowers the computing cost, depthwise separable convolutions are utilised. When compared to the earlier approaches, the suggested model produces better outcomes with fewer resources.

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