Potato leaf disease detection through ensemble average deep learning model and classifying the disease severity

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ABSTRACT

The varying crop species, symptoms of crop diseases, and environmental conditions make early detection of potato leaf disease difficult. Potato leaf diseases are difficult to identify in their early stages because of these reasons. An ensemble model is developed using the ResNet50V2 and DenseNet201 transfer learning algorithms in this study for identifying potato leaf diseases. For this work, 5,702 images were collected from the potato leaf disease dataset and the Plant Village Potato dataset. The datasets include valid, test, and train subdirectories, and the images are taken on 5 epochs. By including three more dense layers in each model and then ensemble that model, the performance of leaf classification may also be improved. Accurately and appropriately, the suggested ensemble averaging model identifies potato leaf phases. So, the accuracy of the suggested ensemble model is achieved with perfect precision. On the second level, the severity of the disorder is assessed using the K mean clustering algorithm. To determine the disease's severity, this system examines each pixel in the early and late blight images. It will be classified as severe if more than 50% of the pixels are damaged.

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1. INTRODUCTION

Worldwide food insecurity and deprivation are caused by plant diseases that damage leaves in addition to affecting crops [1]. The main reason for the scarcity of food and the rise in the expense of producing it is crop disease, which is estimated to cause a 16% yearly crop output loss worldwide [2]. Approximately 70% of the expansion in food production is needed to provide a stable food supply [3]. Disorders and diseases are the categories for the elements that impact plants and their products. In contrast, biotic factors that induce ailments [4]. Using the SVM approach, Haridasan *et al.* [5] was able to identify and categorize particular varieties of paddy plant diseases and achieve 0.914 validation accuracy. Kaya and Gürsoy [6] suggested a deep learning-based method for plant disease diagnosis in 2023. They achieved their accuracy and obtained low standard derivation using the PlantVillage dataset and the five-fold cross-validation technique. Yu *et al.* [7] suggested cross-channel feature learning and inception architecture to increase information richness, which is particularly advantageous for fine-grained feature learning. Over the past few decades, a variety of techniques have been developed to identify diseases in various crops [8]. The majority of solutions required applying image processing techniques to extract attributes from images, which were then fed into a classification algorithm. The foundation of smart farming involves integrating new tools, technology, and algorithms into agriculture through deep learning [9]. Tarik *et al.* [9] used a machine-learning technique in 2021 to categorize potato leaves. They employed a dataset with 2034 images of both healthy and diseased potato leaves for their research. To tackle difficult issues deep learning is frequently utilized [10]. Deep learning was employed by numerous studies to diagnose crop diseases [11]-[13]. Using 25% test data and 75% train data, the algorithm predicts with an accuracy of 99.23% among them. In order to extract relevant characteristics from the dataset, Divyansh Tiwari used the pre-trained model VGG19 in [14]. Fuzzy logic and image processing were used by Dorado *et al.* [15] to categorize tomatoes. They categorized their tomatoes as either damaged or healthy in their work. They also categorized the tomatoes as being underripe, ripe, and overripe in their work. They utilize mathlab and the fuzzy logic toolbox in their work. A. J. Rozaqi proposed CNN in [16] and achieved 92% validation accuracy in classifying potato leaf disease. In 2021, Deepa and Nagarajan provided a method for identifying illnesses in plant leaves [17]. The authors first applied the Kuan filter to minimize noise before retrieving the data using a Hough transformation. A reweighted linear program boost classification was used to categorize the plant leaf disease. Saeed *et al.* [18] used two pre-trained models, Inception V3 and ResNet V2, to classify tomato leaves as healthy or unhealthy. Their accuracy was 99.22%, and loss was 0.03. To establish code-free cloud-based systems, Korot *et al.* [19] proposed a model and examined the operations of Google, Apple, Amazon, and Microsoft. A real-time unidentified aerial vehicle (UAV) recognition system was proposed by Sehree and Khidhir [20]. They were able to obtain good accuracy in this effort, and their model has a long detection range. Ahmed *et al.* [21] identified 26 leaf diseases and a few unusual harvests in 2022 using the ResNet model. Gining *et al.* colleagues. used image processing techniques in [22] to categorize the images of mango leafs. They employ the feature extraction technique to identify the images after converting RGB to HSI. Sehree and Khidhir [20] categorized cases of olive trees in 2022 using a deep convolutional neural network. Five distinct neural network architectures were compared in this work: VGG16, Resnet50, MobileNet, Xception, and VGG19. 50% accuracy was attained by Resnet50 using those models. Based on these previous studies, it can be concluded that there is a chance of being misled by a limited number of images if it relies only on one transfer learning model. Apart from these, it is also unable to categorize images with severe or light damage from these existing works.

The main goal of this work is to classify potato leaves using two distinct transfer learning techniques, ResNet50V2 and DenseNet201. After that, the output from the two models is ensembled and the average method is applied to find the result. This proposed potato leaf categorization model is more precise and accurate. To determine the severity of the disease, images that the model has classified as early or late blight will be given to the k-mean clustering approach in the second phase. Using k-mean clustering for the affected leaves, our model will be utilized to determine the disease's severity. Our model is applied to each leaf, k=3. Each leaf image is thus divided into three clusters: the background, the damaged area, and the healthy area. Lastly, we get the fraction of damaged pixels by counting the pixels of healthy and damaged areas. The proportion will be deemed severe by our system if it exceeds 50%.

2. METHOD

2.1. Platform utilized

The laptop utilized in the paper has hardware specifications including an Intel(R) Core(TM) i5-8250U CPU 1.60 GHz and 8 GB RAM. Graphs are plotted that describe the performance of the model using the Matplotlib package for data visualization. Keras library and TensorFlow are used for machine learning. Google Colab is used for this implementation and the GPU process is applied for running this work.

2.2. Images of potato leaf, the datasets

The Kaggle website provided the dataset that was used in this study. The dataset is called the “Potato Leaf Disease Dataset” and “Plant Village Potato Dataset”. This dataset covers Early-Blight, Late-Blight, and Healthy leaves. To prepare, approve, and test information, it is divided into three organizers train, validation, and test. Every organizer (train, test, valid) has three sub-organizers: Healthy, Early Blight, and Late Blight. The training and testing data consists of 5,702 images (1,939 of Early Blight, 1,824 of Healthy, 1,939 of Late Blight), and the validation data consists of 1,282 images (436 of Early Blight, 410 of Healthy, 436 of Late Blight). Table 1 describes the dataset and Figure 1 shows three samples for Figures 1(a)-(c) Early Blight; Late Blight and Healthy potato leaf images.

2.3. Preprocessing state

In image classification applications, reducing the high dimensionality of the images without losing feature information is the primary goal of neural networks. According to the dataset’s specifications, the image resolutions range from 712×439 pixels to 2,338×2,025 pixels. The images have been resized to

224x224. A large-scale image dataset is necessary for the extensive iterative training to reduce the possibility of overfitting and besides this, an elimination process is conducted for duplicate images.

2.4. Data augmentation

The method of image augmentation is used to expand the number of training images and finally obtain eight thousand images to train this model. Table 2 displays the data augmentation parameters. By using data augmentation, the number of images is increased.

Table 1. Description of the dataset

Label	Train set	Validation set	Test set	Total
Potato early blight	1939	436	49	2,424
Potato late blight	1939	436	49	2,424
Healthy	1824	410	46	2,280

(a) (b) (c)

Figure 1. Samples of data from the dataset: (a) early blight, (b) light blight, and (c) healthy

Table 2. Augmentation configuration

Rotation	Zoom
Probability 0.7	Probability 0.3
Max_left_rotation 10	Min_factor 1.1
Max_right_rotation 10	Max_factor 1.6

2.5. Proposed model

This study suggests deep learning frameworks to categorize diseases of potato leaves (early blight and late blight). The suggested method's algorithm is explained in Algorithm 1.

Algorithm 1: Disease detection algorithm from potato leaf image

```
1. Collect data from the datasets. Upload the datasets to Google Drive. In Google Colab,
   merge the datasets and eliminate the duplicate images from this dataset. Train, test,
   and validation sets are the different sets for the datasets.
2. Apply augmentation to increase the training samples.
3. To increase the learning rate of the model, obtain images with batchsize 32 from the
   train, test, and validation directories.
4. Resnet50 and Densenet201 models are used to develop ensemble model for classifying the
   images as healthy, early blight or late blight.
5. Following the ensemble of the two models' outputs, the average method is applied for the
   final result.
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To obtain accurate and correct classifications, potato leaf images are applied to two pre-trained models: ResNet50V2 and Densenet201. In each model, global average pooling is applied for downsampling. Dropout 0.4 is used to reduce overfitting. The output of these models is then combined and the average result is counted. A set of pretrained images of potato leaves is input into many deep learning models, including ResNet50V2 and Densenet201. The layers of this proposed model were adjusted to increase accuracy. These models (X, Y) are applied to all of the potato leaf images in the dataset, where X is the set of N images, each with a size of 224 x 224, and Y has equivalent labels. Split the training set (Xtrain, Ytrain) into smaller groups, with 32 batch sizes. When testing, the suggested model makes use of layering to combine the results of every individual model and produce a consistent output for predicting the class label of the unseen sample. The benefits of several models are combined by the ensemble averaging approach to increase performance. The models compile with the Adam optimizer to reduce loss. The loss function is Sparse Categorical Crossentropy. By doing this, our model completes its first stage and distinguishes between healthy, early blight, and late blight potato leaves. The suggested model is shown in detail in Figure 2. Table 3 provides the configuration information and several parameters for the suggested model.

2.6. Detecting the severity of the disease

The image of the potato leaf is used to determine the disease's severity if it is classified as early blight or late blight. There are two stages to the entire process.

Phase 1:
- Transforming the image into an RGB (2-dimensional) array of pixels.
- Convert to float type.
- For k mean clustering set k as 3 and calculate the distance from each point to cluster center.
- The iteration procedure will end when the accuracy of our algorithm approaches 1.0 or the maximum number of iterations (10).
- This allows for the acquisition of center and label data, which can then be transformed into a one-dimensional array using the flatten function.
- Ultimately, obtain a segmented image.

Phase 2:
- Calculate the pixels of each segment.
- From the number of pixels of each segment measure the disease severity.

The process of measuring the disease level is shown in Figure 3.

Here, the total amount of pixels for every level is found in this Figure 3. Here, number of pixels for background is 19,668, for affected is 14,938, and for healthy is 9,503. The percentage of affected pixels are also classified and when the value is more than 50% then system will recommend as severe otherwise mild. The overall architecture of the proposed model is described in Figure 4.

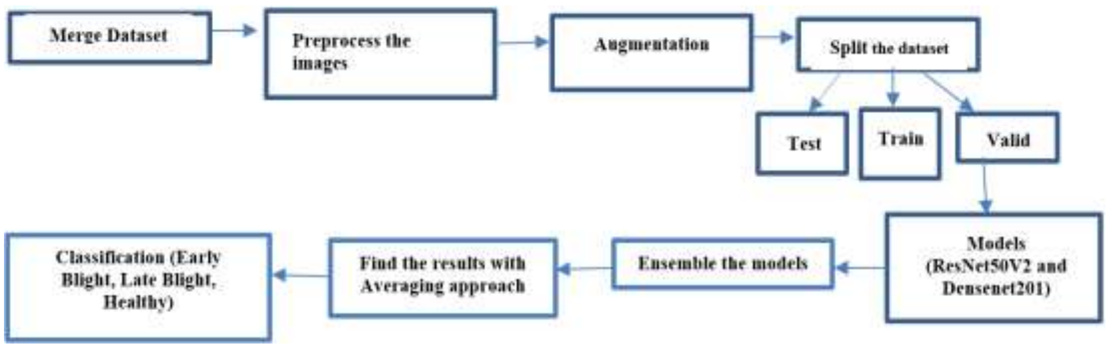


Figure 2. Flow diagram for the suggested model

Table 3. Model's parameters

Parameters	Values
Epoch	5
Validation step	1
dropoout	0.4
Optimizer	Adam
Loss function	Sparse categorical crossentropy
Batchsize	32
Hidden layers	512
Output layer	Softmax

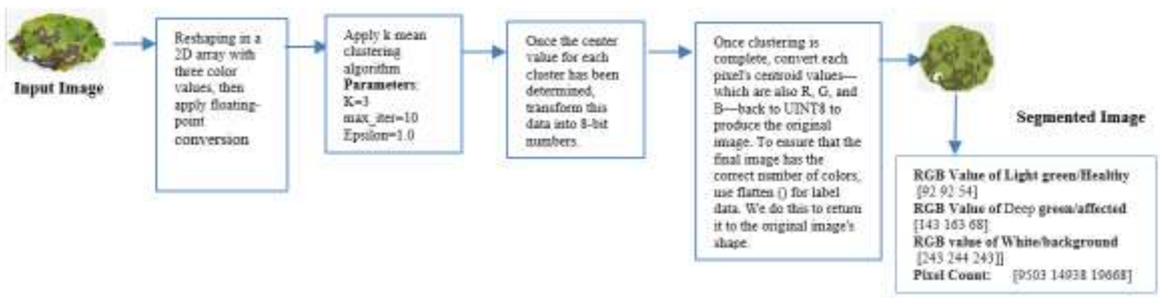


Figure 3. Detecting the severity of diseases

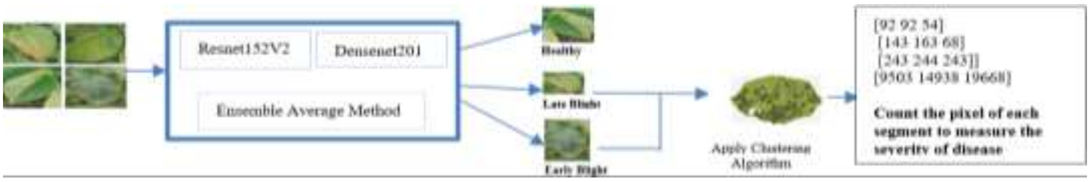


Figure 4. Architecture of the proposed model

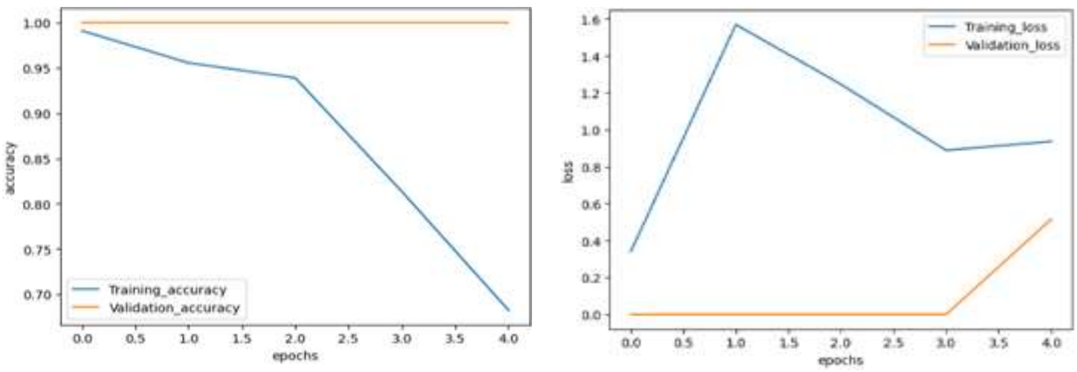
3. RESULTS AND DISCUSSION

Python programming, the Keras open-source libraries, and the TensorFlow framework were employed to carry out the proposed approach experiments. The following were the main findings of the suggested model:

– Identifying diseases from leaf images.
– Measure the severity of the disease after classification of the image.

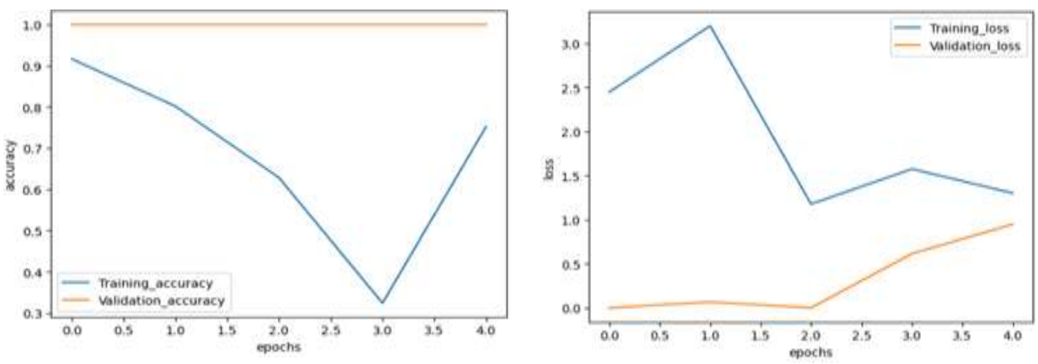
3.1. The suggested model's performance on the dataset

In order to achieve more accuracy, here utilized the Densenet201and ResNet50V2 models in this work and then ensemble those models. Figure 5, describes the performance analysis for the Densenet201 model. In order to expand the dataset's image count and thereby improve accuracy, here the data augmentation technique is applied in this study. 8,000 images were obtained after augmentation, and the models were trained using these images. We applied five epochs and obtained more accurate val_accuracy from this model, as can be seen in Figure 5(a). In addition, a minimal value is displayed in Figure 5(b) by validation loss. It appears from this graph that there is no overfitting. The performance of Densenet201 is illustrated on Figure 5. Figure 6 describes the performance of the ResNet50V2 model. Figure 6(a) makes it evident that the val_accuracy is nearly accurate, which is satisfactory, and that the val_loss is also at a minimum amount, indicating that no overfitting has occurred shown in Figure 6(b).



(a) (b)

Figure 5. Performance analysis of densenet201 model (a) accuracy graph (b) loss graph

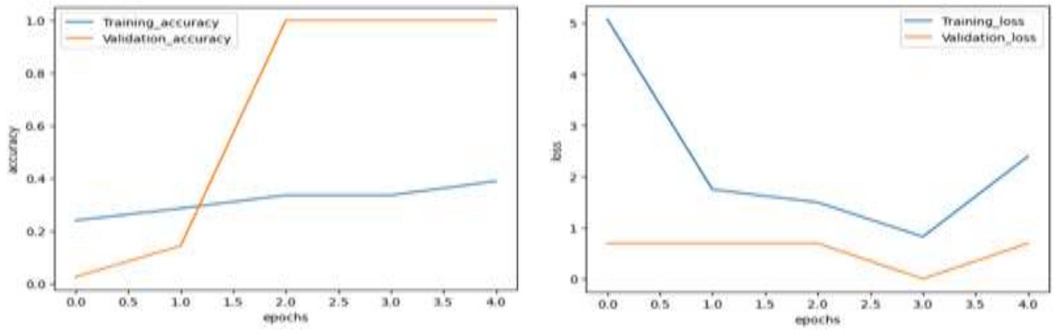


(a) (b)

Figure 6. Performance analysis of ResNet50V2 model (a) accuracy graph (b) loss graph

Figure 7, describes the performance of the ensemble model. Figure 7(a) clearly illustrates how the val_accuracy gradually increases from 0 to 1, changes abruptly from epoch 1 and achieves val_accuracy 1, and displays val_accuracy 1 for each of the 4 epochs. Figure 7(b) also demonstrates that the val_loss is steadily decreasing.

ROC curve analysis is another tool used to assess the performance of the suggested ensemble approach. Early blight is shown by light blue, late blight by orange, and a healthy zone by deep blue. The ensemble model performs exceptionally well in classifying data from the validation and test sets for all classes with a greater area (almost 100%) under the curve. Figure 8, describes the ROC curve of the proposed model. Upon comprehensive analysis of all the data, it can be concluded that the suggested approach performed better in identifying potato leaf disease than the current models.



(a) (b)

Figure 7. Performance analysis of ensemble model (a) accuracy graph (b) loss graph

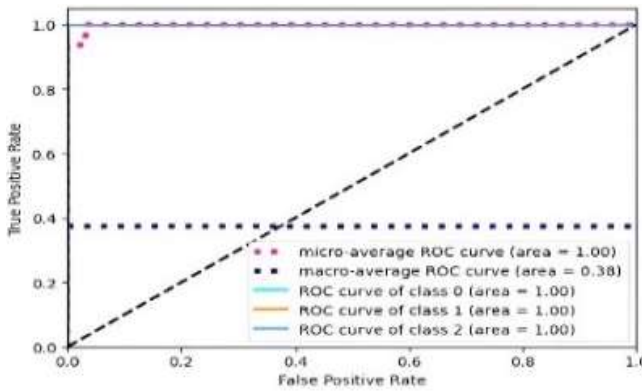


Figure 8. ROC curve of the suggested system

3.2. Analysis of the disease severity process's performance

Classifying the disease severity for the affected images is another method used in this work. Here, segmentation is accomplished by applying the K-mean clustering algorithm's result. Pixels are counted in the segmented image to determine the severity of the condition. More than 50% of the pixels will be considered affected, if not, mildly. Two images are used as examples in the Table 4, and the segmented image portion shows that the image is divided into three clusters: the background, the affected area, and the healthy area. In order to gauge the severity, counting is finally performed for each split component. Here, the RGB values of the healthy portion—labeled in light green—are [92 92 54] and [123 146 108] regarding Samples 1 and 2. The affected regions' rgb values for samples 1 and 2 are represented by [143 163 68] and [42 56 28]. The background pixels' RGB values are [181 186 183] and [243 244 243]. In order to determine the percentage of affected and healthy pixels, count the number of pixels for each RGB value area to measure the disease level. When it came to identify the disease severity, the suggested strategy fared better than the current models. Table 4, shows the two results of this algorithm.

Table 4. The proportion of infections and the related actions

	Sample 1		Sample 2	
Sample image		Green/healthy [92 92 54] Deep green/affected [143 163 68]		Green/healthy [[123 146 108] RGB value of deep green/affected [42 56 28]
Segmented image		White/background [243 244 243]] Pixel count: [9503 14938 19668]		RGB value of White/background [181 186 183]] Pixel count: [7889 31897 25750]
Result	Severe [(AP/TP)*100 >50) [14938/24441 * 100 = 61.12%]		Mild [(AP/TP)*100 <50 [7889/39786 * 100=24%]	

3.3. Comparing the suggested approach to current research

The performance of the suggested strategy is evaluated with the existing approaches to illustrate the generalization of the proposed approach, as shown in Table 5. When compared to the latest approach, it was found that the suggested deep learning model performed well.

Table 5. Comparative analyses of similar works and the suggested architecture

Related works	Method	Accuracy
[21]	CNN	98.7%
[22]	Image processing	68.8%
[23]	CNN	97.2%
[24]	fuzzy set	----
[25]	Image processing	94.5%
Proposed model	Ensemble transfer learning to detect early blight, late blight, and healthy. K-means clustering is used to measure the severity of the disease.	More accurate and precise

4. CONCLUSION

This research proposed an ensemble deep-learning architecture to categorize potato leaves. To detect the types of disease from the potato leaf, an ensemble transfer learning approach is used. In this way, our model achieves higher accuracy than the existing works. Besides this, the data augmentation process increases our dataset and our dataset finally contains 8,000 images, which are also responsible for this accuracy. Here, a model is also designed with k mean clustering to analyze the disease level (mild or severe). This work has nearly perfect precision for both approaches. Future developments for this research would include the ability to identify several diseases on a single leaf, localize the illnesses, determine the severity of the illnesses, develop an IoT system, make a website, and publish a mobile application.

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