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Late and Early Blight Diseases Identification of Potatoes with a Light Weight Hybrid Transfer Learning Model

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***Abstract*—Potatoes are one of the world's most important commodities, and leaf maladies such as early and late blight can substantially reduce their yield and quality. Hence, both farmers and researchers must prioritize quick and precise illness diagnosis. In our research, we propose a strategy based on transfer learning for classifying toxic and diseased potato leaf tissue. We specifically used our dataset of potato leaf photos to fine-tune the Mobile-Net model, which was a pre-trained convolutional neural network. To enhance the model's functionality, we also added a few more layers. Our study found that, in comparison to other state-of-the-art methods, our methodology outperformed them all by achieving a multi-class classification accuracy of 99%. Our method can be used to detect and monitor potato leaf maladies in real-world situations, which could eventually contribute to enhancing potato productivity and food security.**

***Index Terms*—Potato Disease, Deep Learning, Transfer Learning, MobileNet, Prediction**

I. Introduction

Millions of people depend on the potato as an important source of nutrition, as the potato is an important crop grown around the world. Unfortunately, many diseases, including late blight, early blight, etc., can cause significant yield losses and reduce the quality of potatoes produced, often making potato production difficult. In order to guarantee excellent agricultural yields and food security, it is crucial to identify and diagnose [1] these diseases early and precisely.

The automated identification and categorization of plant diseases has shown significant potential because to recent developments in computer vision and deep learning. Convolutional neural networks (CNNs) have been widely employed for this purpose as a result of their ability to extract complex characteristics from massive datasets. It has also been demonstrated that transfer learning, which starts with a shallow neural network [2] and refines it using a smaller dataset, is a successful method for classifying plant diseases.

Recent studies have focused on the automatic diagnosis and classification of plant diseases utilizing deep learning. For example, Mohanty et al. [3] presented an automated plant disease detection system based on deep learning with a 99.35% accuracy rate. Using a deep learning-based technique, Sladojevics et al. [4] detect grape leaf illnesses with 99.4% accuracy.

Numerous publications have also studied the application of disease detection and classification algorithms based on deep learning for potato foliar diseases. For instance, Javed et al. [5] presented a potato leaf image-based disease classification technique based on multi-level deep learning with a 99.75% accuracy rate. Similarly, Johnson et al. [6] developed an automated method for identifying potato leaf blight in the field using a Mask R-CNN and achieved 98% accuracy.

We describe a learning-based technique for categorising potato leaves as infected or healthy. Utilizing our potato leaf image dataset, we use our technique to train the MobileNet model as a pre-trained CNN. We also added more layers to improve the model's capabilities. Our findings demonstrate that our technique picks all existing modern approaches and achieves a multi-class classification accuracy of 99%. Our work adds to the advancement of practical knowledge of deep learning-based approaches for plant disease classification and demonstrates the efficacy of learning-based methods for diagnosing potato leaf diseases.

The most notable contributions of our study are:

- Utilized a custom dataset containing three specific classes of potato leaf diseases, allowing for accurate classification of these diseases.
- Preprocessed the dataset using data augmentation and normalization techniques to reduce noise and prevent overfitting.
- Proposed a transfer learning model was created using the pre-trained MobileNet architecture and fine-tuned by adding four additional layers.
- Achieved a 99% accuracy rate with transfer learning model for multi-class classification of potato leaf diseases.
- The methodology used in the study can potentially be applied to other types of plant diseases, leading to early detection and prevention of crop loss due to diseases.

The structure of the remaining research articles is as follows: Section II displays the work that is relevant to our study, and Section III outlines our technique. Section IV provides the findings and analysis, and Section V concludes the study.

II. Related Work

Studies on potato foliar diseases have been studied using a variety of methods. The availability of public data sets has facilitated the study of potato leaf diseases using several methods. Predictive models are often used for diagnostics, the method depends on the nature of the forecast. However, the complex and ever-changing nature of potato leaf disease requires accurate and up-to-date methods of detection and diagnosis. Deep learning techniques have emerged as a promising approach to provide more accurate plant representations and improve diagnostic accuracy in this context.

Kurundu et al. [7] used deep learning to identify potato leaf infections, achieving 97.89% accuracy with a fine-tuned VGG16 model. They proposed a three-level classification system and compared it to existing methods, using data augmentation to improve performance. Kang et al. [8] built a website using Django to identify potato foliar diseases with over 93% accuracy using a lightweight CNN model. They plan to improve their system by using more advanced vision structures and exploring graph matching and self-supervised learning [9].

Asif et al. [10] proposed in the study to detect diseases in potato leaves with 97% accuracy. The model analyzed images using five algorithms of deep learning models [11] (AlexNet, VggNet, ResNet, LeNet and their provided sequence model) and categorized leaves as normal or diseased. The research aims to implement a prediction system for potato leaf health.

Iqbal et al. [12] proposed an automated approach based on image processing and machine learning for identifying and classifying potato leaf diseases. This work uses seven classification algorithms to over 450 photos of healthy and sick potato leaves from the publicly accessible Plant Village database in order to detect and classify healthy and diseased leaves. The classification accuracy of Random Forest is 97%. Their suggested technology paves the path for the automated diagnosis of plant leaf diseases.

Barman et al. [13] trained a system to recognise potato diseases using augmented and unaugmented image datasets, achieving outstanding validation and training accuracies. For the unaugmented and enhanced datasets, the top validation accuracies of SBCNN are 96.98 and 96.75 percent, while the training accuracies are 99.71 and 98.75 percent. SBCNN surpassed MobileNet and was integrated into an Android app to detect potato leaf spot disease in real time.

Rashid et al. [5] developed using YOLOv5 segmentation and CNN achieves 99.75% accuracy on a dataset from Punjab, Pakistan, achieving improvements in both accuracy and computational cost compared to state-of-the-art models. Potential future applications include multi-disease detection, severity assessment and real-time monitoring systems.

Sholihati et al. [14] created an accurate classification system for diagnosing four potato plant diseases based on leaf situations using deep learning models, VGG16 and VGG19. The 91% average accuracy of the experiment validates the deep neural network procedure.

Tiwari et al. [15] proposed a modified method (transfer learning) for extracting key features from a dataset using a pre-trained model such as VGG19. In regards to classification accuracy for the test data set, logistic regression performed better than the other classifiers, attaining 97.8%.

Joe et al. [6] used Mask R-CNN to detect Fusarium wilt on potato leaves under field conditions using transfer training on a dataset of 1423 images. The model is able to distinguish between diseased and healthy points and achieves an overall accuracy of 98% on complex backgrounds by converting the raw RGB data into another color space.

Tarik et al. [16] introduced an ML-based system to identify potato leaf diseases with 99.23% accuracy using pre-trained models on 2,034 images from the Plant City dataset, surpassing previous methods.

III. Methodology

A. Outline of the Architecture

"Collecting leaf dataset" is the first stage in our workflow. This entails assembling a collection of leaf pictures for use in training the deep CNN model [17]. The dataset is then "augmented" in the next step. Data augmentation is producing new training data by applying various transformations on the given dataset, for as rotating or flipping photographs. This procedure increases the quantity of data available for training and may enhance the model's accuracy. After data augmentation, the dataset is separated into three sets: "Train," "Test," and "Validation." On the training set, the CNN model is trained, and on the test set, its efficacy is evaluated. The validation set is used to calibrate the hyperparameters of the model. After splitting the datasets, the CNN model is developed and trained using the training dataset [18]. The workflow for collecting, preprocessing, training, and classifying a dataset involves a series of steps that include data collection, data preprocessing such as labeling, augmentation till model training, and model evaluation as in the given fig.1.

This procedure entails configuring the neural network's architecture and modifying its weights based on the training data. Following training, the CNN model serves as a "CNN classifier," which means it can categorize new leaf pictures into the many disease categories it was trained on. The "Model Prediction" step begins when a new leaf picture is given into the model for categorization. Based on the training data, the model analyses the input image and guesses which class it belongs to. Finally, the "Result" of the prediction is generated, which contains information on the disease existing in the leaf. This finding may be used to assist producers in implementing the necessary measures to prevent the disease from spreading further.

B. Data set Explanation

For our study on potato leaf disease, we utilized the PlantVillage dataset [19], which contains over 54,000 leaf images categorized by species and disease. From this extensive

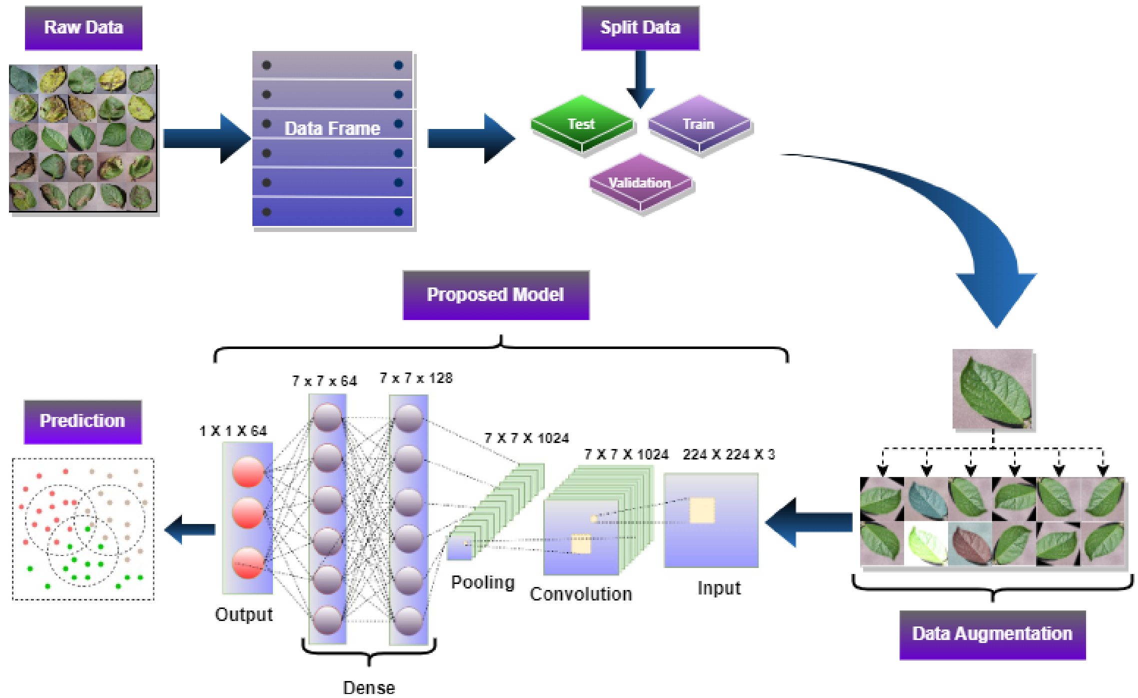

Fig. 1: Work flow of the proposed architecture for early and late blight classification

dataset, we narrowed our focus to three categories of potato leafs: late blight (3131 images), early blight (3149 images), and healthy (2006 images). In total, we selected 8286 images and created a data frame with corresponding labels. The dataset was then partitioned into three sub groups: 49% for training, 30% for validation, and 21% for testing. This allowed us to effectively train and evaluate our models for the accurate detection of potato leaf disease. Figure 2 shows the graphical representation of potato leaf dataset.

C. Neural Network

Convolutional Neural Networks (CNN/ConvNet) are a kind of deep neural network used in deep learning for image processing [2]. When we think about neural networks, we see matrix multiplication, not ConvNets. Utilize folders. A convolution is a mathematical procedure that produces a third function indicating how one function is altered by another. ConvNets, which resemble the network of interconnected neurons in the human brain, were inspired by the visual cortex's architecture. Individual neurons react solely to stimuli within their receptive fields, which are minute regions of the visual field. A set of comparable fields of vision may be stacked to encompass the complete field of view [18].

ConvNets may effectively capture spatial and temporal correlations in pictures using the right filters. Due to the decreased number of involved parameters and the re-use of weights, the architecture is more suited to picture datasets. In other words, the network may be taught to identify picture complexity more accurately.

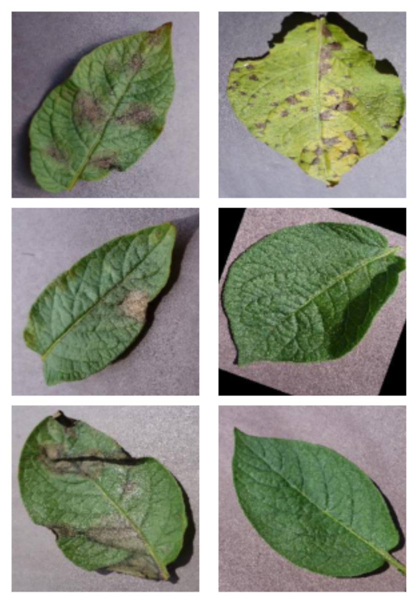

Fig. 2: Example of Potato Leaf Images from 3 classes

D. Proposed Model

The MobileNet architecture uses depthwise separable convolutions to reduce the number of parameters and computational complexity while maintaining high accuracy on image classification tasks. A depthwise convolution is followed by a pointwise convolution in depthwise separable convolutions. The depthwise convolution applies a single filter per input

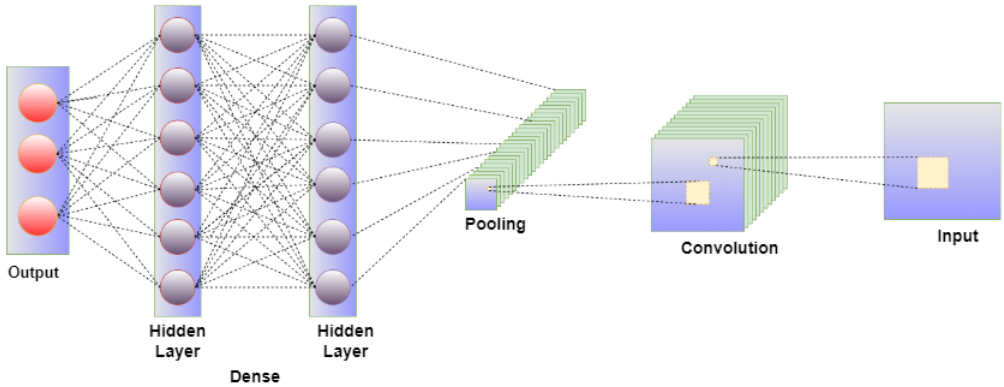

Fig. 3: Proposed modified CNN Architecture

channel, while the pointwise convolution combines the depthwise output using 1x1 filters. Fig. 3 depicts the modified CNN structure while Figure 4 shows the full architecture of our proposed model MobileNet.

Our model is a deep neural network specifically developed for picture categorization tasks. It comprises of an input layer that accepts a 224 × 224 x 3 pixel image as input. This is followed by a MobileNet convolution layer that extracts features from the input image using the MobileNet architecture. This layer's output has a dimension of 7 x 7 x 1024. After the convolutional layer are two dense layers with 128 and 64 neurons, respectively, with ReLU activation. Then, there is a global average pooling layer that calculates the mean of each feature map throughout its whole spatial range. A three-neuron output layer employs the softmax activation function to generate a probability distribution across the classes. Overall, the model is well-suited for image classification tasks due to its capacity to extract picture characteristics and generate reliable classification results.

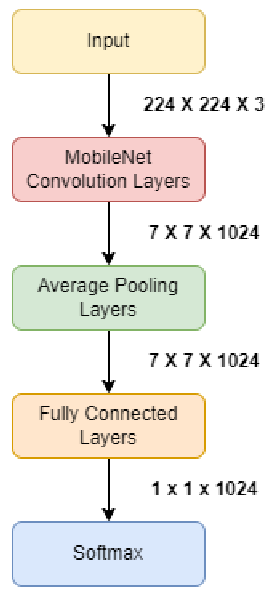

Fig. 4: MobileNet Architecture

E. Compiling the model

After constructing the model, we employed an optimizer, a loss function, and accuracy measures performance evolution to compile the model as we need to make sure the imbalance issue [20] of dataset. The root-mean-square propagation (Rmsprop) used in this model is an optimization procedure that adaptively changes the learning rate based on the root-mean-square value of the previous gradients. This method divides the rate of weight acquisition by the moving average of the size of the final gradient of the weight. The goal is to improve convergence speed and performance for non-stationary or noisy gradient problems.

And for the loss function [21], categorical-crossentropy is used for multi-class classification tasks where the output variable is a categorical variable. It measures the difference between the true and predicted class probabilities. It is calculated as the negative log-likelihood of the true class. The goal is to minimize this loss function during training. The "accuracy" metric option specifies the evaluation measure that will be used to assess the model's performance during training and testing [2]. Additionally measure the percentage of photos with valid classifications. It is obtained by dividing the number of photos that were successfully categorised by the total number of images.

F. Training and Testing

In the course of the model's training, the number of "Epochs" is set to 50. This value takes into account the number of times the model is trained using the whole dataset. The "Batch Size" option was set to 32, which sets the number of training samples utilized in each batch. In addition, the "callbacks" argument was utilized, which is a list of functions that can save the model's weights, stop training under certain conditions, or adjust the learning rate [22]. Specifically, the "Checkpoint Model" callback was used to save the model's

weights at certain intervals for resuming training or choosing the best model, while the "Early Stopper" callback was used to stop training early if validation loss did not improve

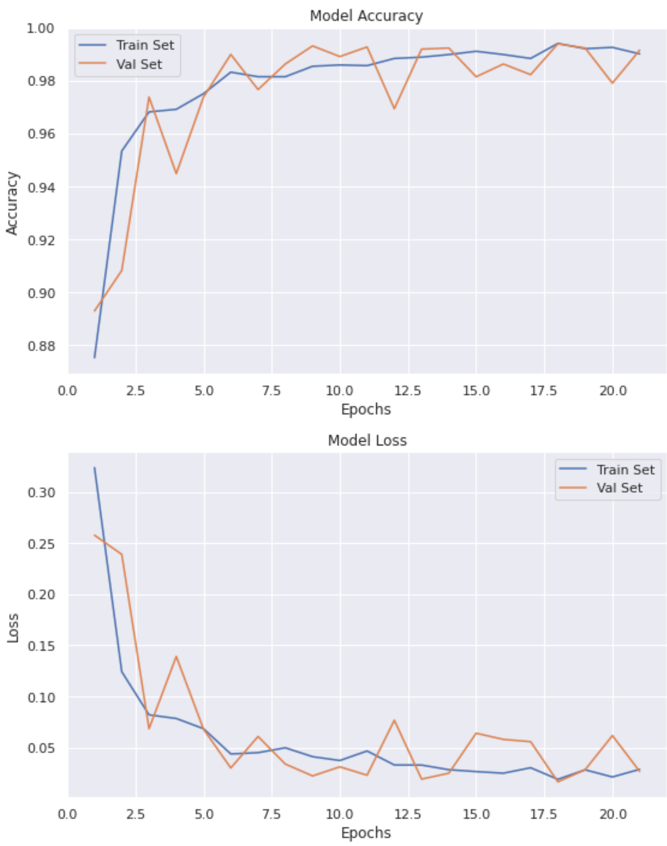

Fig. 5: The graphical representation of Accuracy and Loss

after a certain number of epochs, thereby preventing overfitting and improving generalization. These arguments and responses are essential components of the training process and can aid in enhancing the model's performance. After the model training is completed, the next step involves model evaluation to assess its performance.

IV. Empirical Evaluation

When evaluated on the test data, the model achieved a very low loss of 0.0173 and a high accuracy of 0.9954, showing that it performs exceptionally well on unknown data. This indicates that the model has learned to categorize the target variable appropriately based on the input information. After 50 epochs of training, the model had a validation accuracy of 99.4%. The training process lasted roughly one and a half hours, and the final model had a validation loss of 0.0166 and a training accuracy of 99.4%. The model's excellent validation accuracy indicates that it is capable of accurately classifying photos of potato leaf diseases. The fact that validation accuracy is greater than training accuracy shows that the model has not been overfitting to the training data.

Transfer learning is one possible explanation for the model's outstanding performance. Utilizing a pre-trained model as a starting point permitted the model to acquire knowledge from a much larger dataset than would have been possible with the training data provided. Moreover, the use of data

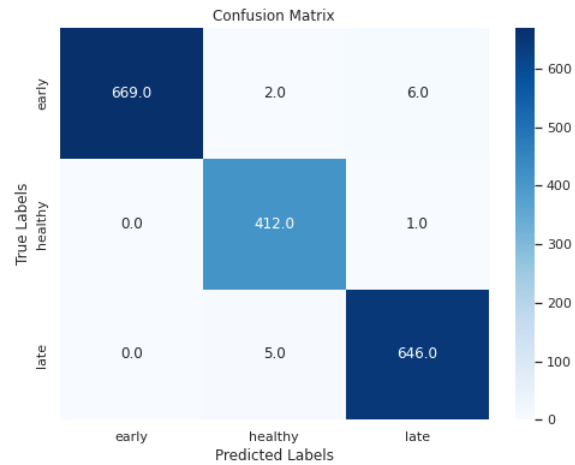

Fig. 6: Performance Evaluation Matrix

augmentation techniques likely improved the capacity of the model to generalize to new data. Fig. 5 shows the accuracy and loss graph of our work.

The confusion matrix gives information regarding how accurately the model predicted the classes and Fig. 6 depicts the confusion matrix of our work. It indicates the number of examples correctly and wrongly categorized for each class. In this instance, the model accurately identified 669 instances as "late," 412 instances as "healthy," and 646 instances as "early." Two cases of the "late" class, one instance of the "healthy" class, and five occurrences of the "early" class were mistakenly classified. In terms of correctly identifying the occurrences, the model looks to have performed well overall. Precision indicates the fraction of instances classed as a certain class that are in reality true positives. At the same time, recall provides the proportion of genuine positive instances that were correctly recognized by the classifier. The F1-score is the harmonic mean of accuracy and recall and assesses the classifier's overall performance [23]. From Table I, we can see that early blight and late blight are classified with 0.99 accuracies for our proposed model. In terms of healthy blight, we got 0.98 accuracy. F1-scores of three classes are 0.94 (Early Blight), 0.96 (Late Blight), and 0.91 (Healthy Blight). For our proposed model, it is evident that late blight outperforms the other regarding the F1-score.

TABLE I: Results of our proposed method in all classes

Class Label	Accuracy	Precision	Recall	F1-Score
Early Blight	**0.99**	0.98	0.97	0.94
Late Blight	**0.99**	0.97	0.98	0.96
Healthy Blight	0.98	0.98	0.93	0.91

Table II depicts the comparison of all the performances of different leaf disease recognition methods. Iqbal et al. [12] proposed a method with a random classifier in the same dataset and get the result of 97%. In a different paper [24], the author presented Fuzzy C-means clustering and Back Propagation

TABLE II: A Comparison of the Performance of Several Leaf Disease Recognition Methods

Reference	Methods	Disease affected plants	Accuracy
Iqbal et al. [12]	Random forest classifier	Potato	97%
Tiwari et al. [15]	Logistic Regression	Potato	97.8%
Biswas et al. [24]	Fuzzy C-means clustering and Back Propagation Neural Network	Potato	93%
Pinki et al. [25]	K-means clustering and Support Vector Machine (SVM) classifier	Paddy	92.06%
Hossain et al. [26]	Image processing with Support Vector Machine (SVM) classifier	Tea	90%
Proposed Method	**MobileNet**	**Potato**	**99%**

Neural Networks to identify Early and Late Blight, achieving a 93% detection rate. Pinki et al. [25] proposed a clustering using a K-means and the SVM predictor and the disease-affected plant, paddy, with an accuracy of 92.06%. The paper [26] discussed image processing using SVM classifier, and the impacted plants in this case are tea, yielding a 90% accuracy rate. Although our suggested approach MobileNet is 99% accurate.

V. Conclusion

The classification of potato leaf diseases into multiple classes was accomplished with the aid of a MobileNet-built transfer learning model. The validation and test accuracies of the model came in at a remarkable 99.4% and 99%, respectively. The performance of the model was extraordinary. The model was not overfitting to the training data, and it most likely benefitted from the use of pre-trained weights and data augmentation processes. The model did not become overfit to the training data. There is no indication that the model inappropriately fits the training data. According to the confusion matrix, the model was able to effectively forecast the classes, with just a few instances of wrong classification occurring overall. In general, the results of our study indicate that the model that was built is capable of properly classifying potato leaf diseases and has the potential to be utilised in the field as a diagnostic and management tool. This was backed by the fact that we were able to show its effectiveness, which demonstrates how effective it is.

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