Deep Transfer Learning Technique for Potato Leaf Diseases Classification

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***Abstract*—Potato, a globally significant food crop ranking as the fourth largest by production, is cultivated in various regions worldwide. However, potato crops are notably susceptible to fungal infections, leading to the occurrence of early blight and late blight diseases. Timely disease control and management measures are pivotal in augmenting crop yields and mitigating agricultural losses for farmers. The capacity to automatically discern diseased crops holds substantial promise for farmers. Consequently, this research endeavors to present the power of transfer learning in SoTA Convolutional Neural Network (CNN) architecture ResNet-50v2 and DenseNet-201 which are finetuned to the task of potato disease detection. In our experimental endeavors, we employed three distinct datasets, and in each instance, we attained state-of-the-art results.**

***Index Terms*—potato leaf disease, classification, image processing, deep transfer learning, machine learning.**

I. Introduction

The agriculture industry is under a lot of pressure to boost crop output and maximize yields since the world's population is expected to expand to 10 billion people by the year 2050. Two possible solutions to the issue of impending food shortages have been identified: increasing land usage and implementing large-scale farming, or embracing novel techniques and utilizing technological breakthroughs to increase production on currently farmed land [1].

Farming productivity should take into account agricultural technologies. Utilizing contemporary technology helps farms produce more. The computer automation system continually supports farmers in their decision-making [2]. Potato farming is one sort of agriculture used in Bangladesh. During the winter, most potato farms are located in Munshiganj, Bogura, Rangpur, and Dinajpur. Potato farms should be situated on productive, sunny land with enough soil moisture. November's first two weeks are wonderful. However the yield has decreased because of potato diseases.

You might become sick by eating potatoes' fruits and leaves. Late blight (Phytophthora infestans), the most pervasive and destructive fungus disease infecting solanaceae crops in Bangladesh, is so named. Potatoes, tomatoes, and other Solanaceae crops are among those it impacts [3].

In this work, we focused on diseases of potato leaves. Farmers routinely visit plant pathology specialists to diagnose illnesses. To assist in making decisions, a computer automation system might be used to identify potato leaf disease. We proposed a deep transfer learning base model to classify potato leaf disease. Our proposed model is a combination of DenseNet201 and ResNet50V2. To validate our proposed model we collected three different datasets from different sources.

We organized this paper as follows, we discussed previous potato leaf disease classification-related works in Section II and in Section III we discussed the dataset. In Section IV we discussed our proposed methodology. We analyzed our results and compared our work with previous works in Section V. We concludes this work in section VI.

II. Literature Review

Studies on agricultural growth, using deep learning models and computer vision, aim to promote economic progress and create a safe environment. This section is a compelling summary that provides information about earlier studies.

Barman et al. proposed a self-build CNN (SBCNN) for detecting potato disease in 2020. The SBCNN algorithm is applied to enhance and un-enhance potato leaf datasets for testing and training images. The model achieves the highest validation accuracy (96.48% and 96.75%) and training accuracy (99.71% and 98.75%). Without overfitting, it performs well with an enhanced dataset. The model is determined to be the best model for creating smartphone apps when its performance is compared to MobileNet architecture [4].

Lee et al. used a convolutional neural network (CNN) design to identify potato diseases. The model uses image processing, cross-entropy analysis, Adam optimization, and the Softmax judgment function. The convolution layer maintains low resource usage and good accuracy. Experimental results show a parameter utilization of 10,089,219 and 99% accuracy in disease judgment under the preset model [5].

In order to refine previously trained models like VGG19, Tiwari et al. offered a model. When various classifiers were

(a) Early Blight (b) Late Blight (c) Healthy

Fig. 1: Images of Potato Leaf.

used to analyze the findings, logistic regression outperformed them all, and got 97.8% accuracy throughout the test dataset [6].

Mohamed et al. proposed system's main tactic is to employ a Convolution Neural Network (CNN)-based diagnosis and detection system to detect plant illnesses early and minimize production losses from the plant. For classification purposes, we employed CNN to extract the illness features from the provided training dataset's input photos. 1700 photos of potato leaves were utilized to train the model; 300 images were used for testing; and 100 images were used for parameter calibration and fine-tuning against biased data. Comparing our suggested CNN architecture to other methods used on the same dataset, it achieves an accuracy rate of 98.2% [7].

Nishad et al. proposed K-means clustering segmentation, several data augmentation approaches, and a deep learning algorithm to identify and categorize potato leaf illnesses. VGG16 outperformed other approaches in terms of performance, achieving 97% accuracy [8].

III. Dataset

For this work, we collected potato leaf disease datasets from three sources (TABLE VII) that are publicly available. These three datasets contained a total of 5,210 potato leaf images divided into three classes (Early_blight, Late_blight, and Healthy). In Fig. 1 we illustrated three classes of potato leaf images. Where Fig. 1(a) is the early blight, Fig. 1(b) is the late blight, and Fig. 1(c) is the healthy leaf images.

TABLE I: Potato Leaf Dataset.

Soruce	Dataset Name	Total
[9]	Potato Leaf Diseases	1558
[10]	Potato Leaf	1500
[11]	PlantVillage (Potato)	2152
		5210

IV. Methodology

In this research work, we used the deep transfer learning model to classify potato diseases from potato leaf images. We collected the potato leaf dataset from three different sources. After analyzing the data we applied some image processing techniques on those data. In Fig. 2 is our proposed workflow diagram.

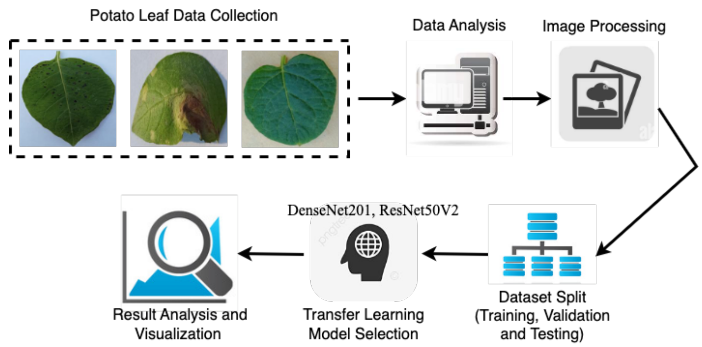

Fig. 2: Our Proposed Workflow Diagram

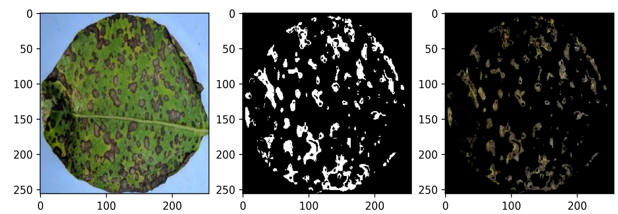

Fig. 3: Segmented Early Blight Leaf

A. Data Analysis

We performed color channel intensity analysis of potato images to check all images were RGB images. Mainly, we focused on RGB color channel analysis.

B. Image Processing

In the image processing step at first, we normalized the input image by down-scaling its size and fixed the size 224×224 pixels. Then the color space transformation process was applied to these normalized images. In this transformation process, we converted BGR input images into RGB format, and in the final step, we transformed the RGB images to the HSV color space, which was crucial for the segmentation process. We used a technique for segmentation that relies on building masks with the help of color information, color intensity, and HSV color space brightness. It may be simple to identify early blight, late blight, and healthy leaf samples using the attributes of a correctly segmented image. Green areas of a leaf image indicate the healthy leaf sign and brown or dark sections indicate the disease-affected sign. In Fig. 3 we showed the segmented early blight leaf output and in Fig. 4 the segmented late blight leaf output.

C. Feature Extraction

For extracting features, we used Global Feature Descriptors (GFD) to complete the classification task. GFD is commonly used as a shape descriptor. The shape of the image object is qualified by Hu Moments, descriptor texture features are

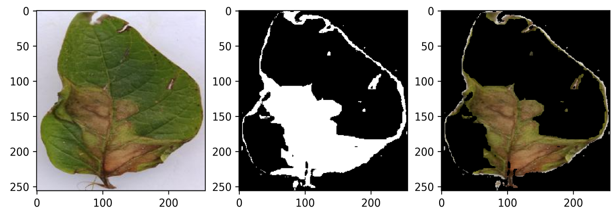

Fig. 4: Segmented Late Blight Leaf

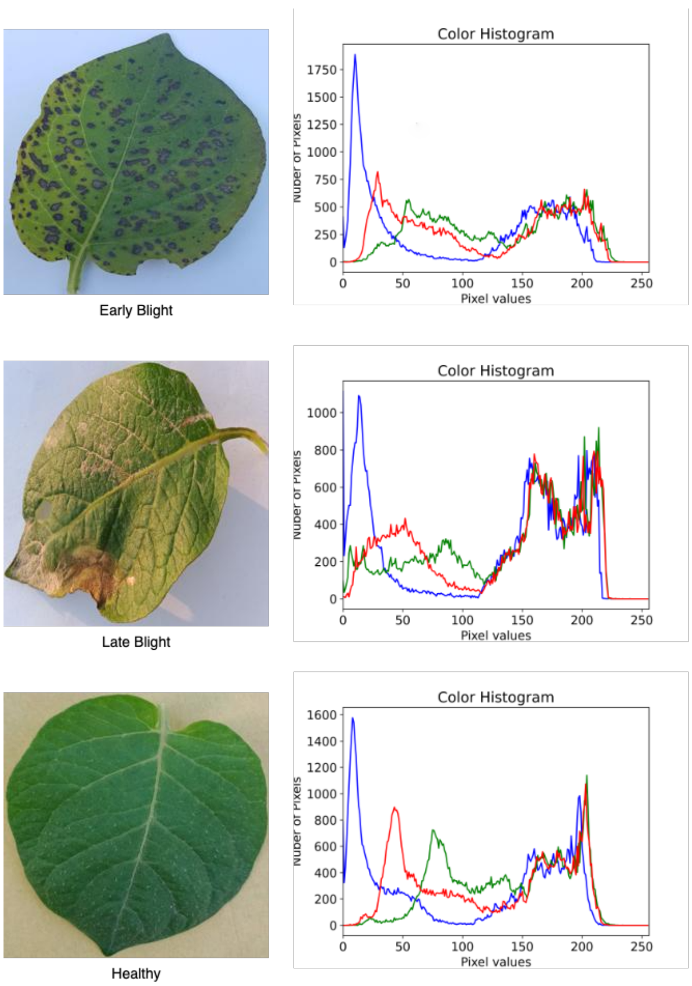

Fig. 5: Color channel intensity analysis histogram of Basak et al. dataset.

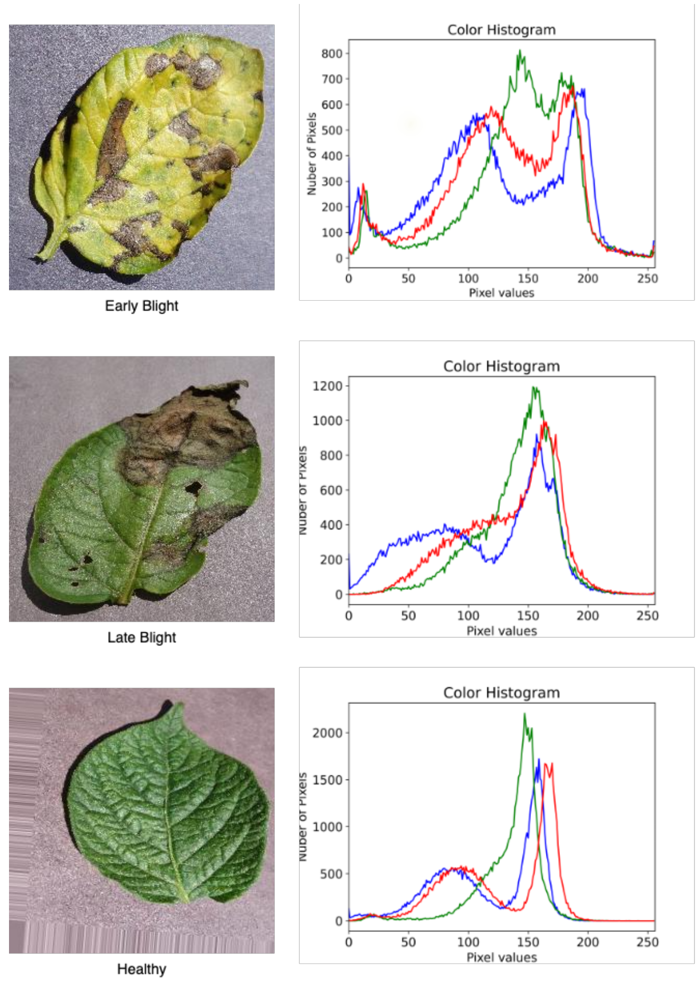

Fig. 6: Color channel intensity analysis histogram of Putra et al. dataset.

extracted by the Haralick Texture feature, and the Color Histogram represents the color distribution and number of pixels of an image. We showed potato early blight, late blight and healthy leaf images color channel intensity analysis histogram of Basak et al. [9] dataset in Fig. 5, Putra et al. [10] dataset in Fig. 6, and G. G. et al. [11] dataset in Fig. 7.

D. Dataset Split

For this work, we split all datasets into three groups training, validation, and testing. We kept 60% of the data in the training group, 20% of the data in the validation group, and 20% of the data in the testing group.

E. Deep Transfer Learning Model

We developed a Deep Transfer Learning model to address our potato disease classification work. Our proposed model is a combination of DenseNet201 and ResNet50V2. We also added some extra layers to these models.

1) DenseNet201: In 2016, Huang et al. [13] developed Densely Connected Convolutional Networks (DenseNet). Every layer of this DenseNet network is connected with every

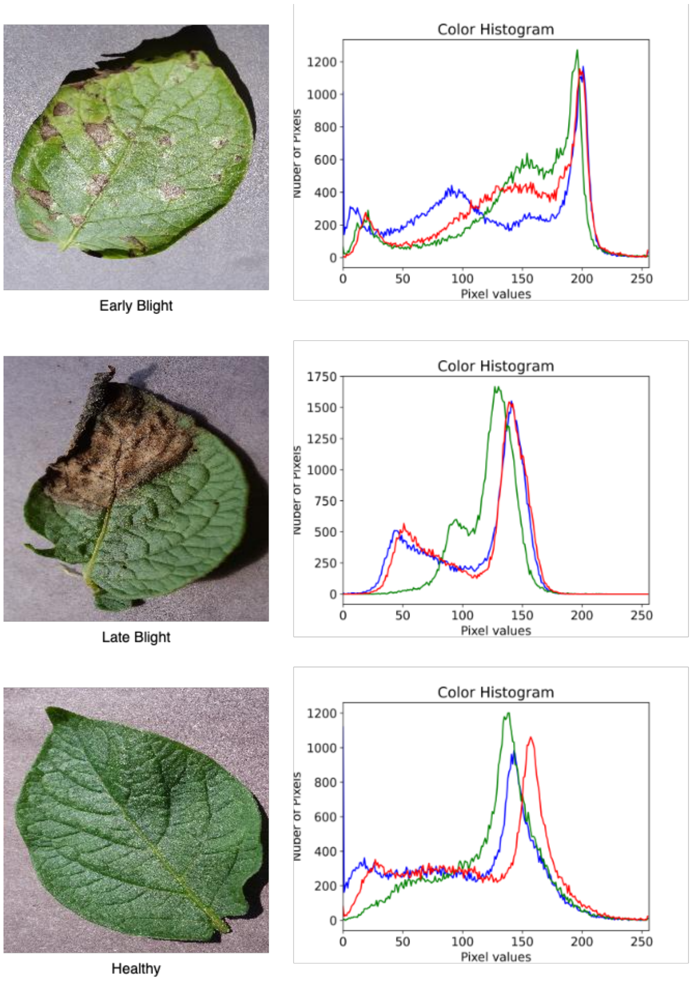

Fig. 7: Color channel intensity analysis histogram of G. G. et al. dataset.

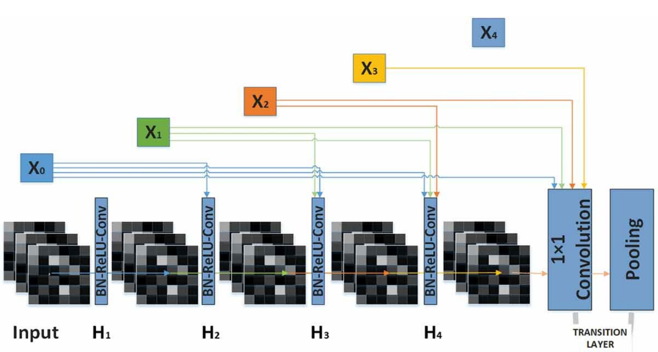

Fig. 8: Dense block and Transaction layer structure of DenseNet201 [12]

layer. In DenseNet201, there are 201 layers deeper layers of the network. A pre-trained Densenet201 can categorize photos into 1000 different object categories. In Fig. 8 we illustrated the DenseNet201 model's submodule layers structure. In order to jointly affect the output layer, a Regularized random vector functional link combines the hidden layer and the input layer. We added a fully connected layer after the base model output layer and used the Softmax (1) as an activation function.

$$\sigma(x_j) = \frac{e_j^x}{\sum_i e_i^x} \tag{1}$$

2) ResNet50V2: He et al. [14] introduced Residual Network (ResNet) in 2016 and ResNet50V2 is the modified version of the deep CNN model. It performs better for the ImaheNet dataset. Mainly in ResNetV2, the propagation formula of connection blocks was modified. As with as DenseNet201 model modification here We added a fully connected layer after the base model output layer and used the Softmax (1) as an activation function.

F. Result Analysis and Visualization

We used 60% data of all datasets to train the model, 20% for the validation process, and the remaining 20% data for evaluating the model. We analyze our proposed method performance by calculating the Precision, Recall, F1-score, and Accuracy (2) of each model relative to each dataset.

$$Accuracy = \frac{T_1 + T_2}{T_1 + T_2 + F_1 + F_2} \tag{2}$$

Where:

- T_1 = True Positives
- T_2 = True Negatives
- F_1 = False Positives
- F_2 = False Negatives

G. Experiment Environment Setup

To implement this research work we used Python v 3.11.5, Tensorflow v 2.13.0, and Keras v 2.14.0. All experiments were done in a Kaggle environment with 16GB GPU P100.

TABLE II: Accuracy and Losses of Our Model.

Dataset Name	**Deep Transfer Learning Model**			
	DenseNet201		**ResNet50V2**	
	Accuracy(%)	Loss(%)	Accuracy(%)	Loss(%)
Potato Leaf Diseases	99.80519	0.22194	99.93507	0.21924
Potato Leaf	99.98723	0.23946	98.33334	0.26323
PlantVillage (Potato)	99.30723	0.23527	97.67981	0.26799
Merged Dataset	99.36248	0.22293	99.08925	0.21082

V. Result & Discussion

To train, validate and test our proposed model we used three datasets ([9], [10], & [11]) separately and used a combined dataset of three datasets. Using these datasets we obtained better results than DenseNet201 and ResNet50V2.

TABLE III: Performance Measures of ResNet50V2 Model Using Potato Leaf Diseases [9] Dataset.

	Precision	Recall	F1-Score	Support
Early Blight	0.99	0.99	0.99	148
Late Blight	0.99	0.97	0.98	61
Healthy	0.99	0.99	0.99	103
accuracy			0.99	312
macro avg	0.99	0.99	0.99	312
weighted avg	0.99	0.99	0.99	312

TABLE IV: Performance Measures of DenseNet201 Model Using Potato Leaf [10] Dataset.

	Precision	Recall	F1-Score	Support
Early Blight	1.00	0.99	1.00	156
Late Blight	1.00	1.00	1.00	58
Healthy	0.96	0.99	0.97	86
accuracy			0.99	300
macro avg	0.99	0.99	0.99	300
weighted avg	0.99	0.99	0.99	300

In TABLE II we illustrated DenseNet201 and ResNet50V2 models accuracy and losses.

Using the Potato Leaf Diseases dataset, we get the best accuracy by the ResNet50V2 model (Accuracy: 99.93507, Loss: 0.21924), DenseNet201 model (Accuracy: 99.98723, Loss: 0.23946) for the Potato Leaf dataset, DenseNet201 model (Accuracy: 99.30723, Loss: 0.23527) PlantVillage Potato dataset, and DenseNet201 model (Accuracy: 99.36248 Loss: 0.22293) for the merged dataset). In TABLE III, IV, V, and VI we showed the performance measures results of DenseNet201 and ResNet50V2 model.

In TABLE VII, we compared our proposed model's accuracy with previous researchers' model's accuracy.

VI. Conclusion

In this study, we have delved into the potential of transfer learning to attain state-of-the-art outcomes. Nevertheless, we aspire to extend our investigation further. Specifically, we aim to explore cross-dataset evaluation to assess the model's ability to generalize beyond its initial training data. To facilitate this assessment, we intend to leverage eXplainable Artificial Intelligence (XAI) algorithms. Once we have achieved satisfactory levels of generalization, our subsequent objective is to optimize the model by pruning and compressing it, thereby preparing it for deployment in resource-constrained edge computing environments.

TABLE V: Performance Measures of DenseNet201 Model Using PlantVillage Potato [11] Dataset.

	Precision	Recall	F1-Score	Support
Early Blight	0.96	0.99	0.97	189
Late Blight	0.97	0.99	0.98	104
Healthy	1.00	0.99	1.00	137
accuracy			0.99	430
macro avg	0.99	0.99	0.99	430
weighted avg	0.99	0.99	0.99	430

TABLE VI: Performance Measures of DenseNet201 Model Using Merged Dataset.

	Precision	Recall	F1-Score	Support
Early Blight	1.00	0.99	1.00	422
Late Blight	0.97	0.99	0.98	213
Healthy	1.00	0.99	0.99	407
accuracy			0.99	1042
macro avg	0.99	0.99	0.99	1042
weighted avg	0.99	0.99	0.99	1042

TABLE VII: Result Comparisons with Previous Works.

Soruce	Models or Mehtods	Accuracy (%)
Our Model	Deep Transfer Learning Model (DenseNet201, ResNet50V2)	99.98723 99.93507 99.36248 99.30723
[4]	SBCNN	96.48, 96.75
[5]	Deep CNN	99.00
[6]	VGG19	97.80
[7]	Inception V3	98.70
[8]	VGG16	97.00
[15]	YOLOv5	99.75
[16]	Mask R-CNN	94.24
[17]	Inception V3	90.00
[18]	VGG16 and VGG19	91.00
[19]	K-means	95.99

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