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Potato Blight Classification Android Application using Deep Learning

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Abstract: *Farmers who grow potatoes suffer from significant financial losses each year due several diseases that affect potato plants. The most common diseases are Early and Late Blight , caused by fungus and specific microorganisms, respectively. Early detection and appropriate treatment can save a lot of waste and prevent economic losses. However, traditional visual inspection methods are time-consuming and prone to errors. To address this challenge, we propose a Convolutional Neural Network (CNN) approach for plant disease diagnosis. CNNs are a type of deep learning algorithm widely used for image classification tasks. They can automatically learn features from input image data, making them well-suited for plant disease diagnosis. Our customized CNN has fewer trainable parameters, reducing computation time and minimizing information loss. We used several convolutional and pooling layers, followed by fully connected layers with the ReLU activation function. We also applied dropout regularization to prevent overfitting. In conclusion, accurate and efficient plant disease diagnosis is essential for preventing economic losses. Our customized CNN for plant disease diagnosis has the potential to be an effective tool for farmers. It can help them diagnose plant diseases quickly and accurately, leading to timely treatment and reduced loss.*

Keywords: Potato Blight, Disease detection, Convolutional Neural Network, Deep learning, Image Processing

I. INTRODUCTION

The potato industry faces a significant challenge in preventing crop losses due to diseases as Early Blight and Late Blight. Early detection and appropriate treatment of these diseases can help prevent economic losses for farmers. One promising approach to disease diagnosis is through the use of machine vision and deep learning techniques. However, there are challenges to overcome, such as accuracy and computation time. To address these challenges, a customized convolutional neural network (CNN) can be developed with trainable parameters, reduced computation time, and minimized information loss. This approach could lead to the development of more efficient mitigation strategies for small-scale farmers and enhance food security on a larger scale. Additionally, the accurate classification of plant diseases through deep learning could enable site-specific application of agrochemicals, providing economic and environmental benefits. Various algorithms have been proposed for disease detection using neural networks, thresholding and image segmentation models, and unsupervised color-based techniques. However, most of these methods are not feasible for real-time applications, as they require lengthy image processing times.

II. METHODOLOGY

In recent years, many researchers have developed models for various crops, including potatoes, but their focus has not been on detecting specific diseases affecting potatoes. For instance, Geetharamani and Pandian developed a deep CNN model to distinguish between healthy and unhealthy leaves of multiple crops. The model was trained using the PlantVillage dataset, which consists of images from a specific region in the US and Switzerland, and did not consider potato diseases in regions. Similarly, Ferentinos evaluated various deep learning architectures, including AlexNet, Overfeat, VGG, and GoogLeNet, to identify normal and abnormal plants using the PlantVillage dataset. Meanwhile, Rozaqi and Sunyoto developed a CNN model to detect early and late blight diseases and healthy potato leaves using the

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PlantVillage dataset. Additionally, Agrawal et al. used a pre-trained VGG19 model with multiple classifiers, such as KNN, SVM, and neural networks, to classify early and late blight diseases and healthy leaves of potatoes using the PlantVillage dataset. While these models have achieved good results for detecting diseases in specific regions, they may not work well for other regions, where environmental factors, leaf shapes, and varieties may differ. Therefore, there is a need to develop models that can accurately detect potato diseases in different regions.

III. MODELING AND ANALYSIS

To develop and evaluate our proposed model for potato blight detection, we used the publicly available PlantVillage dataset that contained images of various potato leaf conditions including late blight, early blight, and healthy leaves. Each image in the dataset had a resolution of 256 × 256 pixels. We categorized the images into three classes and assigned them indices of 0, 1, and 2 for healthy, early blight, and late blight leaves, respectively. However, we found that the number of healthy potato leaf images in the dataset was significantly lower than the number of images for the other two classes. The distribution of the total number of images in each category of the dataset is presented

Class	Count
Late blight	1000
Early blight	1000
Healthy leaves	1000
Total	3000

Table 1. Number of images in each class of PlantVillage dataset.

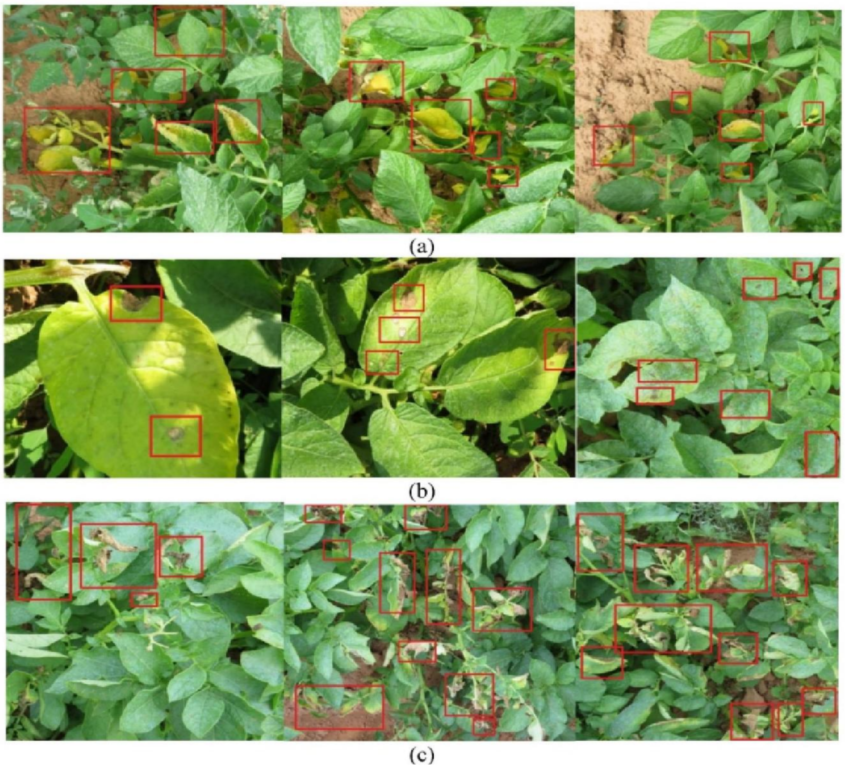

Figure 1. Sample images for identification of early blight disease stages on potato leaves; (a) yellow color leaves at the initial stage of the disease, (b) concentric brown circles in the leaves at mid-stage, and (c) senescence of leaves at the laststage of the disease.

The images used in this study were captured in 2018 using a digital camera positioned 140 cm above the soil surface. The pictures were taken between 9:00 a.m. and 4:00 p.m. under natural sunlight. To prepare the dataset for analysis, the images were resized to 1280 × 720 pixels using a custom-built Python program. This resolution was chosen to allow for real-time applications of the model and to test the feasibility of integrating the CNN model with hardware, such as a smart variable rate sprayer using real-time video feed from a webcam.The different disease stages of potato leaves were

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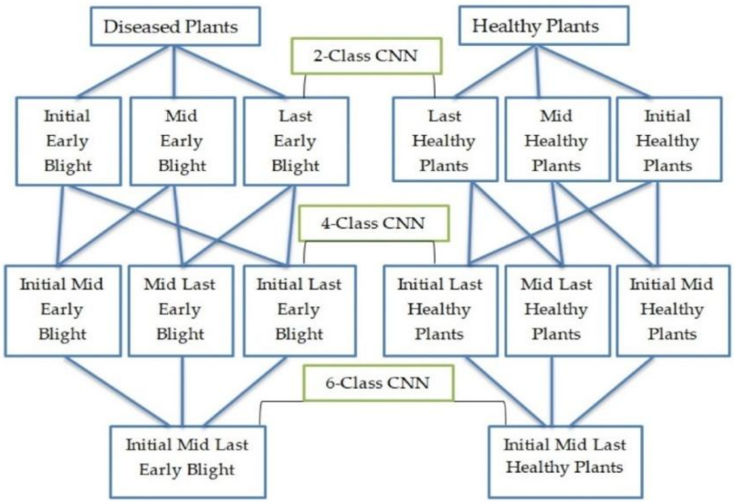
identified by collecting images throughout the growing season from June to October 2018. The collected images were then categorized according to their disease stage and used to train different CNNs. A dataset of 532 images was set aside for testing and evaluating statistical measures after training the CNNs. The remaining images were used for training (70%) and validation (30%) of the CNNs. The precision, recall, and FScore were used to evaluate the accuracy of the CNNs in identifying the early blight disease stages

IV. RESULTS AND DISCUSSION

The proposed model for detecting blight on potato leaves involved the use of a customized convolutional neural network (CNN). The process of classifying potato blight involved several steps including data balancing, augmentation, splitting, training, vali-dation, and testing. The data was first shuffled, resized and distributed into batches. To address the issue of unbalanced data, the number of healthy potato leaf images were increased through data pre-processing. The data was then split into training, testing, and validation data, and the training data was augmented using various para-meters and normalized between 0 and 1. The testing and validation data were also normalized between 0 and 1. The model was trained on the training and validation data, and its performance was evaluated using the testing data. The dataset was shuffled to ensure randomness in selection of training and testing data.



The proposed CNN model consisted of two blocks, with each block containing a pair of convolution layers followed by a pooling layer. The number of blocks can vary based on the dataset and application. The pooling layers were intentionally reduced compared to the convolutional layers to avoid information loss. The ReLU activation function was used to reduce linearity and vanishing gradient problems by restricting all negative values in the feature maps and only allowing positive values. Overall, the proposed model showed promising results in accurately detecting blight on potato leaves.

The proposed PDDCNN model was evaluated through two sets of experiments. The first set involved applying four different groups of data augmentation techniques to the training set of the PLD dataset. The second experiment involved training the model without any data augmentation. The experiments all used the Adam optimizer, categorical-cross-entropy loss function, 32 batch size, 100 epochs, and the default learning rate. To estimate the classification accuracy of the model visually, a confusion matrix was used. The confusion matrix is a valuable machine learning method that calculates precision, recall, accuracy, and the AUC-ROC curve. It displays correct predictions diagonally and incorrect predictions off-diagonally. The PDDCNN model exhibited higher classification accuracy of the corresponding class in a dark color, and misclassified samples were represented in a lighter color.

Figure (**a**) Accuracies graph with data augmentation. (**b**) Accuracies graph without data augmentation.

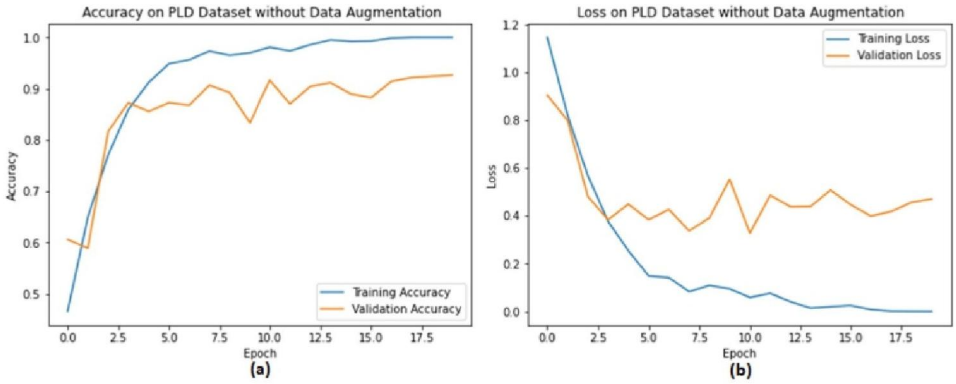


Figure (**a**) Accuracy graph without data augmentation. (**b**) Loss graph without data augmentation.

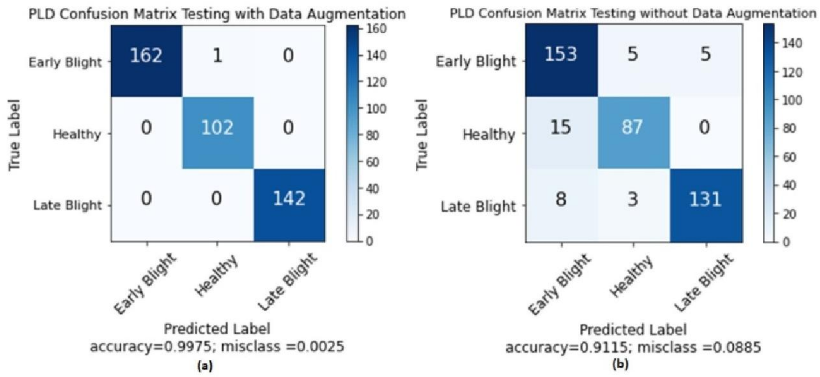


Figure (**a**) The confusion matrix with augmentation. (**b**) The confusion matrix without augmentation

Classification Accuracy

Classification accuracy is calculated by the number of correct predictions divided by the total number of accurate predictions.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}$$

Precision

precision describes the inconsistency you find when using the same instrument

$$Precision = \frac{TP}{(TP + FP)}$$

Recall

The recall is another critical metric, characterized as the division of input samples from a class accurately anticipated by the model.

$$Recall = \frac{TP}{(TP + FN)}$$

F1 Score

One well-known metric that combines precision and recall is called the F1-score, which is defined as:

$$F1Score = \frac{2 * Precision * Recall}{(Precision + Recall)}$$

Classes	TP	FP	TN	FN	Accuracy	Precession	Recall	F1-Score
Early blight	103	3	185	0	0.99	1.0	0.97	0.98
Late blight	107	0	181	3	0.99	0.97	1.0	0.99
Healthy	78	0	210	0	1.0	1.0	1.0	1.0

Table: Performance analysis of the proposed model with testing data.

Folds	k = 1			k = 2			k = 3			k = 4			k = 5		
Class	0	1	2	0	1	2	0	1	2	0	1	2	0	1	2
Precision	0.9765	0.9595	0.9172	1.0000	0.9268	0.9394	0.9854	0.9550	1.0000	0.9663	0.9770	0.9852	0.9531	0.9515	1.0000
Recall	0.9674	0.9071	1.0000	0.9282	0.9596	1.0000	0.9621	0.9845	0.9920	0.9829	0.9636	0.9852	0.9632	0.9561	0.9778
F1-Score	0.9720	0.9326	0.9568	0.9628	0.9429	0.9688	0.9736	0.9695	0.9960	0.9745	0.9703	0.9852	0.9581	0.9538	0.9888

Table: The Performance matrices of Accuracy, Precision, Recall, and F1-Score using k-fold cross validation method (k = 5)

Dataset	Mean	Standard Deviation
Training	0.9682	0.0084
Validation	0.9628	0.0075
Testing	0.9656	0.0093

Table: Average mean and standard deviation for training, testing, and validation dataset using k-fold cross validation k = 5

V. CONCLUSION

In this study, we aimed to enhance the performance of the CNN model while reducing the number of trainable parameters, computation time, and information loss. To achieve this, we customised the CNN model architecture by intentionally reducing the number of pooling layers. This was done to minimise the loss of important features. The proposed architecture consisted of two blocks, each containing a pair of convolution layers followed by a pooling layer. We tested the proposed model using potato blight images obtained from the PlantVillage dataset. The model's performance was compared to other similar studies using similar datasets, and our proposed model outperformed them with an overall accuracy of 99%. In the future, it would be beneficial to evaluate the performance of the proposed model using a dataset with real-time potato blight images, rather than pre-processed and segmented images. Additionally, the trainable parameters of the architecture could be further reduced without affecting the model's performance or increasing its likelihood of overfitting.

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