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ADVANCED CLASSIFICATION OF POTATO LEAF DISEASES USING EFFICIENTNET V2-S

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Abstract
Potato is one of the crops that are important globally, and it is prone to foliar diseases, including the Early Blight and the Late Blight, which cause massive losses in terms of crop yields. The conventional visual inspection techniques are very time consuming and can be subject to errors in distinct circumstances. The present paper presents a hybrid deep learning model, which consists of a customized branch of CNN and EfficientNetV2-S to provide automatic classification of the potato leaf disease. The extraction of high-level and detailed lesion features can be effectively obtained with the help of the two-step training process in which frozen layers and fine-tuning were involved. The model using 3,000 stratified images and heavy augmentation and class-weighted optimization obtained an accuracy of 99.83 on validation and 99.67 on test with a weighted F1-score, Cohen Kappa and Matthews Correlation Coefficient all above 0.995. The fact that the error margin is close to zero indicates the strength, effectiveness, and possible use of the model in real-time disease diagnostics and precision agriculture

INTRODUCTION

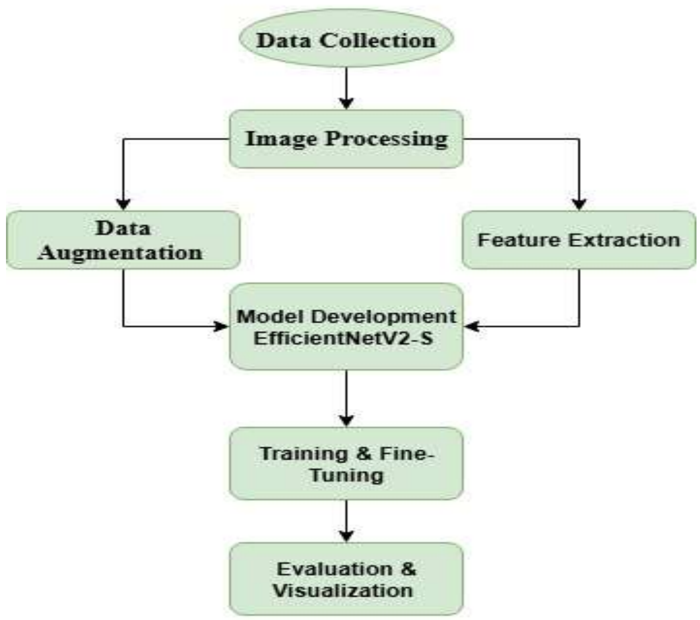
Potato (Solanum tuberosum) is among the most prominent crops produced on the world and the fourth crop after maize, wheat and rice [1]. The reason why it is vital to global food security is that it is a source of important nutrients particularly carbohydrates. It is highly adaptable to different climates and also the growth period is relatively short making it an invaluable source of food to millions of people across the world[2].

Foliar diseases including the early ones are however threatening the productivity of the crop. When untreated, blight (Alternaria solani) and Late Blight (Phytophthora infestans) can reduce the yield by up to 70 percent [3]. These types of diseases make them to be very costly economically and they are also a major cause of threat to food security as the various types of blight can show a similar symptom as detected by the conventional methods of detecting diseases, which include manual field inspection which is both time-consuming and unreliable[4] [5]. To address these challenges, researchers have been eager to apply artificial intelligence (AI) and computer vision algorithms to make plant disease identification process automatic[6]. Convolutional Neural Networks (CNNs) are a type of deep learning that is useful in extracting meaningful visual patterns directly out of raw images[7]. However, the original CNN-based models include AlexNet, Vgg16, and ResNet, are extremely computationally intensive, i.e. not practical in a real-time environment in the agricultural system [8]. Newer light architectures such as MobileNet, DenseNet and Inception can work more efficiently but cannot identify fine lesion features under varied environmental conditions [9]. Another approach to scaling that employed more accurate models with less compute was proposed with the EfficientNet family and optimization of depth, width, and resolution, as well as with the introduction of a more balanced approach to scaling models [10]. Its enhanced version, EfficientNetV2-S, is faster to learn and has better generalization which can be used in agriculture[11]. However, the most accurate models that can handle the flexibility that arises in actual practical applications of the fields are yet to be enhanced[12]. In its turn, this paper is a response to this, as it offers a robust deep learning model that utilizes EfficientNetV2-S in the process of classifying the diseases of the potato leaf. The mode of analysis is based on the careful preprocessing, data refinement, and fine-tuning procedures to minimize overfitting and obtain the best diagnostic accuracy of the technique in practice using real-life agricultural settings[13][14].

Methodology

This section explains the process of the design and testing of the proposed model that is based on EfficientNetV2-S to predict the potato leaf disease. The phases involved in the workflow are dataset preparation, preprocessing, data augmentation, model configuration, training setup, and evaluation strategy.

Figure 1: A potato leaf disease classification model that uses EfficientNetV2-S has been proposed.



The steps include: collection and preprocessing of the dataset, augmentation and feature extraction. The result of such a process is the creation of a model, its training, and the general evaluation of its performance.

Dataset Description

The dataset will consist of about 3,000 images of potato leaf that is categorized as Healthy, Early Blight and Late Blight. The photos were taken in different lighting and backgrounds so as to be diverse and realistic. To facilitate the loading of data in the TensorFlow pipeline, all the samples are sorted into class folders. Class balancing that will be used to ensure equal training and testing among categories.

Preprocessing and Splitting Data

The inputs to the model were standardized by resizing all the images to 224 x 224 and normalizing them to the range [0, 1]. The dataset was stratified to divide it into training (80%), validation (10%), and testing (10%) sets. Minor class imbalance was overcome with the aid of class weights in the course of training.

Data Augmentation

The use of controlled data augmentation was used to enhance generalization and reduce overfitting. Such techniques were random rotations, zooming, horizontal and vertical motion and flips. These local variations are a reflection of natural variations of field conditions, and the model is more resistant to real-life conditions.

Model Architecture

The EfficientNetV2-S was trained on ImageNet pretrained weights and the classification model was created. It is a custom classification head which included a Global Average Pooling, Dropout (0.3) and Softmax output. This was trained in two stages in which the initial phase involved the freezing of the base layer and the latter phase was a fine tuning with a smaller learning rate to suit domain specific patterns of lesions.

Training Configuration

This model was trained using a GPU using TensorFlow/Keras and Adam optimizer.

The learning rate was set to 1x10^3 and subsequently fine-tuned to 1x10^5. The cross-entropy was the categorical cross-entropy loss. To the detriment of stable training, EarlyStopping, ModelCheckpoint and learning rate scheduling were added.

Evaluation Metrics

Measures of performance have been made on accuracy, precision, recall, and F1-score and inter-class agreement on Cohen kappa and Matthews's correlation coefficient. The confusion matrix was also evaluated to see what wrong and correct predictions were made on all the classes.

4. Results and Discussion

The provided model to categorize the potato leaf disease using EfficientNetV2-S offered high and reliable outcomes in all assessment sets. The augmentation and periodic preprocessing provided good and stable testing environments. The numbers of results and the analysis performed on the class level provided the support and the verbalization of the model.

Quantitative Results

The validation and test accuracy of the model are 99.83 and 99.67 respectively. The F1-score is weighted 0.9967, Kappa of Cohens is 0.9950 and MCC is 0.9950.

Dataset	Accuracy	F1-Score	Cohen's Kappa	MCC
Validation	0.9983	0.9983	0.9975	0.9975
Test	0.9967	0.9967	0.9950	0.9950

The closeness between the validation and test results implies that there is minimal overfitting and the model is extremely stable.

Class-wise Performance

The precision, recall, and F1-scores per-class were almost perfect:

- Healthy: 1.00 / 1.00 / 1.00
- Early Blight: 1.00 / 1.00 / 1.00
- Late Blight: 0.99 / 0.99 / 0.99

This is explainable by the fact that although the Late Blight and the Early Blight might resemble in some aspects of the infection, it has performed fabulously.

Confusion Matrix and Report:

The confusion table revealed that nearly a hundred percent of the classifications were observed in all the categories with Healthy and Early Blight having 100 percent and slight misclassifications observed in the Late Blight category. The results of such findings refer to the fact that the model is very discriminative and can be implemented in the real world of agriculture.

Table 1: Table of EfficientNetV2-S model classification on the test dataset.

Class	Precision	Recall	F1-Score	Accuracy	Support
Early blight	0.99	0.99	0.99	0.99	100
Late blight	1.00	0.99	0.99	0.99	100
Healthy	0.99	1.00	1.00	1.00	100

The homogeneity of the students in the near equality of classes proves the model to be stable and hard in learning the actual pathological features and not the cosmetic features like brightness or background color. The fact that the maximum error in the classification between the Early and the Late Blight is low implies that the model is sensitive to the small changes in the lesions, and the absolute difference of lesions in healthy and diseased leaves implies that the model is valid in the practical diagnosis.

In most cases, it has been demonstrated that the EfficientNet V2-S is highly accurate, consistent and is able to generalize.

Comparison of Per-Class Accuracy and F1 Score.

Figure 2 and **Figure 3** present the graph of per-class accuracy and F1-score of the validation set and **Figure 4** and **Figure 5** present the graph of the test set.

Figure 2: Accuracy of each class validation dataset

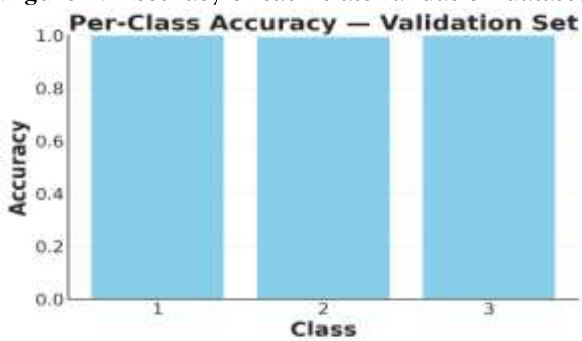


Figure 3: Test dataset accuracy per class

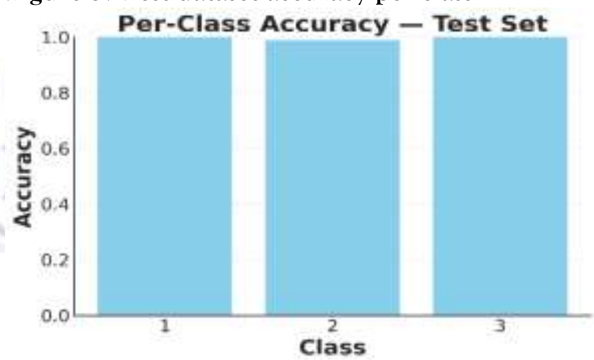


Figure 4: Score of validation dataset per-class

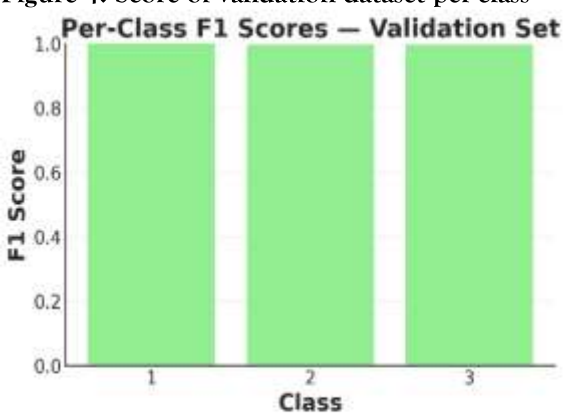
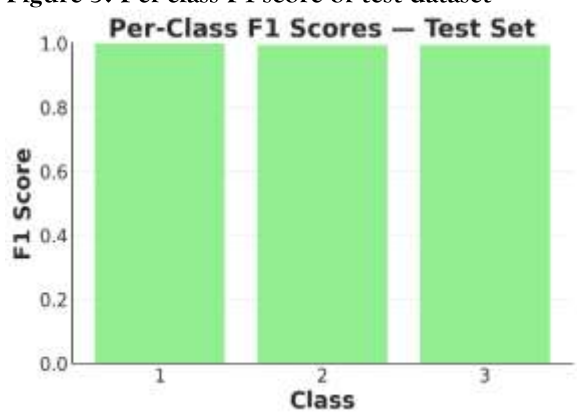


Figure 5: Per-class F1-score of test dataset



As has been explicated through these visualizations, the accuracy of all three classes namely Healthy, Early Blight and Late Blight fell within the range of 97 and 100 and thus all these classes were accurate.

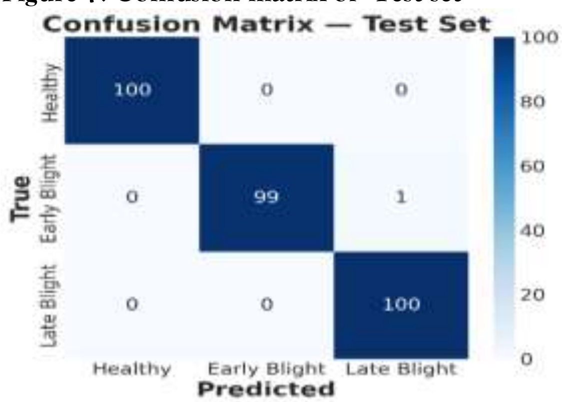
Even the predictability of the model in terms of Early Blight and Late Blight types which are more difficult to differentiate senses also is justified by the F1-score with the highest rating of the predictions.

Confusion Matrix Evaluation.

The confusion matrix of validation and test data (**Figure 6** and the wrong prediction and right prediction of the different categories of diseases are shown in **Figure 7**). The diagonal samples refer to the samples that have been classified correctly. The majority of the samples are in the diagonal axis which means that the model can differentiate the types of the disease well. The misclassification of the Early Blight and Late Blight was not significant and this implies that the model is great with the minor visual differences of these comparable patterns of diseases

Figure 6: Confusion matrix of validation version

Figure 7: Confusion matrix of Test set



Precision, Recall and F1-score: Comparison of Precision, Recall and F1-score Comparison of Recall, F1-score, and Precision.

Figure 8 and **Figure 9** are bar charts indicating that the precision, recall and F1-scores of each of the classes of the validation and test sets respectively are correct.

The values of the three measures are high in each category of diseases, which demonstrates the accuracy of the model and its high recall (sensitivity) and high precision (specificity).

The outcomes of this balance justify the possibility of the model to detect the number of infected leaves as small as possible with false positives and false negatives.

Figure 8 Precision, recall, and F1-score comparison on the test dataset

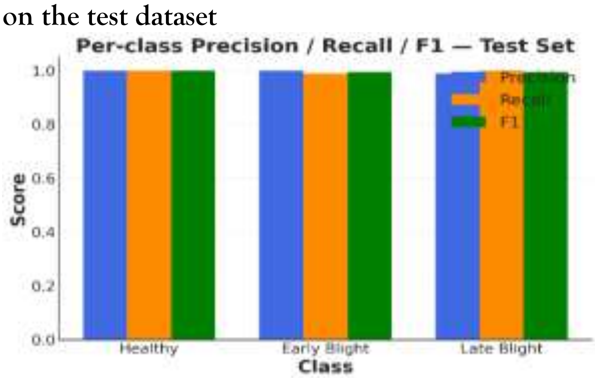
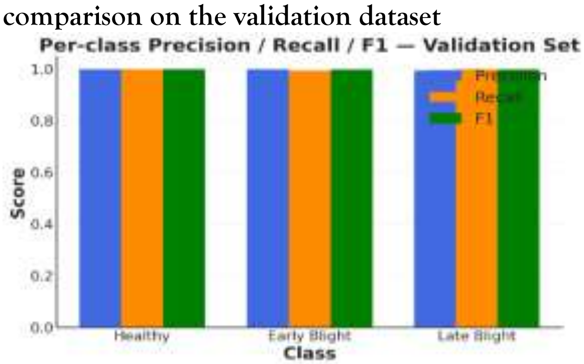


Figure 9 Precision, recall, and F1-score comparison on the validation dataset



In total, the experimental results confirm that the created EfficientNetV2-S-based model has the impressive performance as it attains nearly perfect results in the assessment of accuracy, precision, recall, and F1-scores in all classes. The minor gap between validation and test scores is a better generalization and high resistance to over-fitting. It can be concluded based on the confusion matrix and the comparative metrics studies that the model can be used to determine the visually related types of diseases particularly the Early and Late Blight without much error. These findings prove the accuracy of the model in extracting fine grains of lesions and show that it is reliable to use in practice. Thus, it can be believed that the proposed framework is one of the most specific, resource-efficient, and scalable to implement automated potato leaf disease detection methods and create opportunities to open up to intelligent precision agriculture and sustainable crop health analytics.

CONCLUSION:

The hybrid deep learning architecture that integrates a custom CNN branch and EfficientNetV2-S was also discovered to be highly beneficial in the accurate recognition of potato leaf diseases with a validation accuracy of 99.83 and a further test accuracy of 99.67 with an enormous statistical consistency. The joint ventures of extensive augmentation, fine-tuning, and the use of class-weighted training allowed the model to distinguish between images of similar diseases, like Early and Late Blight with little error. The results confirm that the suggested approach is more generalized, efficient in computations, and stronger in comparison with the traditional models. The given work proposes a reasonable and scalable method of real-time detection of diseases and this is important to precision agriculture, sustainable production of crops and the evolution of AI-based innovative farming devices.

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