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Improved Deep Learning Models for Plants Diseases Detection for Smart Farming

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Abstract: Traditional farming methods consume time and effort, which affects productivity. Intelligent farming seeks to enhance decision-making and agricultural of crops through the integration and data analysis abilities of the Internet of Things. Plant diseases result in significant financial losses in the farming sector. Accurately detecting of diseases is crucial for ensuring the long-term sustainability of agriculture. Deep learning, has recently garnered significant attention for plant and weed detection, disease diagnosis, and pest classification in agricultural industries.
In this paper, the most previous studies have been discussed focusing on a several plant species and a specific type of disease. PlantVillage dataset utilized for the DL models. The dataset includes 14 types of plants images with 39 different classes of plant diseases. We propose an enhanced deep learning models (EfficientNetB2, Xception, ResNet50) by adding a custom classification layer, which significantly improved the model's accuracy and classification performance. The improved models achieved accuracy as: (EfficientNetB2 is 97.70% , ResNet50 is 97.86% and Xception is 98.97%). The primary objective of this study is to empower farmers to identify plant diseases in early stage of disease without consulting experts..

Keywords: Artificial Intelligence, Computer Vision, Deep Learning Models, Image Detection, Plant Disease Classification.

1. Introduction

The agriculture industry is crucial due to the expected worldwide population rise. The Food and Agriculture Organization predicts a 2 billion rise in world population by 2050 [1]. Thus, food demand rises. The agriculture industry is experiencing the 4th revolution in industry, amalgamating innovative technologies with conventional agricultural practices. Smart agriculture is essential for modernizing the farming industry with creative solutions[2]. Smart agriculture modern on exact geographical and temporal resolution by employing modern information technology to acquire, alter, and analyze data from many sources. The goal is to improve crop production management and inform agricultural decision-making [3]. To ensure high-quality plant-based products, they must be protected from pathogens[4]. Food security is threatened by plant diseases that harm agricultural crops during growth. Many plant diseases generate significant economic losses in the agriculture business globally. Immediate growth retardation may harm yields[5][6]. Artificial intelligence-based technologies can build faster and more accurate plant disease detection tools[7]. Object Detection is computer vision technique used to detect object and identify its localization [8]. Abnormality detection identifies unusual patterns in datasets due to its feature. This method has many applications, such as detecting financial fraud, network intrusions, disease indicators in medical diagnostics, and smart agricultural systems [9]. Recently, Deep Learning, particularly CNN[10], has gained popularity in agriculture for plant and weed identification, disease diagnosis, and pest categorization. One benefit of the CNN-based approach is its ability to automatically extract relevant characteristics from datasets[11]. Typically, deep learning models require several parameters. This leads to significant processing costs for deep learning models.

The implementation will be difficult. A smart agricultural embedded system must minimize computational complexity and memory utilization while retaining high accuracy. The rest of this paper include: Section 2: gives an evaluation of existing studies. Section 3: demonstrate the proposed models implementation. Section 4: Shows the proposed system's experimental results, describes these results and compares them with previous works. Section 5: Covers the conclusions and prospective research recommendations.

2. Related literature study

Geetharamani et al. (2019) presented a deep CNN (DCNN) system for detecting of plant disease based on the PlantVillage dataset, which includes 39 leaf classifications and background pictures. To improve model performance, data augmentation was used. After extensive simulation, the suggested model outperformed standard machine learning approaches with 96.46% classification accuracy [12].

A ResNet101-based deep learning approach by Prabhakar et al. (2020) identified tomato plant illness. Disease classification by fold scope microscope, while severity evaluation uses ResNet101. Images of weakly, moderately, and severely damaged tomato leaves and healthy leaves from PlantVillage are used for model training. Among pre-trained models, ResNet101 had the highest accuracy of 94.65 in estimating tomato leaf early blight severity[13].

Jasim et al. (2020) suggested a CNN-based on the disease on plant leaf for classification and detection system. Used PlantVillage photos to focus on potatoes, peppers, and tomatoes. The suggested system has 98.29% training accuracy and 98.029% testing accuracy across the dataset[14].

Falaschetti et al. (2022) recommended utilising the OpenMV Cam Plus, a cost-effective, energy-efficient platform, to construct a CNN-based detector for real-time plant disease categorization. CNNs are trained using ESCA and PlantVillage datasets. CNN-based image detectors had 98.10% ESCA and 95.24% PlantVillage accuracy [15].

In 2023, Jasrotia et al. introduced a customized CNN system for maize detecting plant disease. Preprocessing is used in this model. Image conversion from RGB to HSV with contrast limiting adaptive histogram equalization. The models are evaluated against CNN and SVM approaches with no pre-processing. PlantVillage maize crop dataset was used for tests. The model's accuracy was 96.76%[16].

Shafik et al. (2024) presented Initial fusion (AE) and dominate polling quintet plant disease detection models. To enhance plant disease diagnosis and categorization, these models were combined with 9 pre-trained DL models and fine-tuned by extraction of deep feature. 15 categories from the widely used PlantVillage dataset were studied. In last phase, a (LR) classifier measure CNN model combinations. AE and LVE had 96.74% and 97.79% accuracy, respectively[17].

3. Plantvillage Dataset Description

The PlantVillage dataset is an extensive collection of plant images designed for diagnosing agricultural diseases. The PlantVillage project offers the dataset openly[18]. The dataset contains 55448 images, including 39 classes of 14 plants, including healthy, infected leaves images, and background images. The plant categories classes within PlantVillage includes: cherry, potato, apple, raspberry, soybean, squash, blueberry, strawberry corn, grape, orange, tomato, peach and pepper. The plant diseases classes defined as : Tomato yellow leaf curl virus, powdery mildew, bacterial spot, spider mites, early blight, mosaic virus, septoria leaf spot, cedar apple rust, two-spotted spider mites, apple scab, target spot, common rust, late blight, and leaf curl.

Figure 1: Samples images from PlantVillage dataset.

4. The Proposed Models

The models presented in this study consist of two main stages. The first stage is data preprocessing, this aims to effectively prepare the input data to optimize the performance of DL algorithms. The second stage involves improving the EfficientNetB2, ResNet50 and Xception.

4.1preprocessing phase

Preprocessing plays a crucial role in preparing image data for DL modeling. Preparing and transforming raw data is essential for effective model training. This phase includes two steps:

a. **Image resizing step**: resizing the images in the dataset. Plant images dimension were resized from (256×256) to (180×180) thus, reduce the runtime.

b. **Image Enhancement step**: The quality of the input data can significantly impact the model's accuracy. This step included to make the input plant image supported with more Sharpening, to ensuring that the images used in the system are clear and contains much more detailed to obtain more reliable and accurate results. Based on our experiment the best contrast and sharpening on input image when the enhanced a parameter value = 3.

Five image augmentation techniques were applied:

a) Rotation with a range of (15) degrees to provide variations in the orientation of objects within the image.

b) Shear with a range of (0.2) to skew the image along a specified axis introducing new perspectives and shapes.

c) Zoom with a range of (0.2) to simulate different scales and perspectives of the objects in the image.

d) Horizontal and vertical flip to create mirror image; this enables the model to acquire consistent attributes irrespective of the object's position.

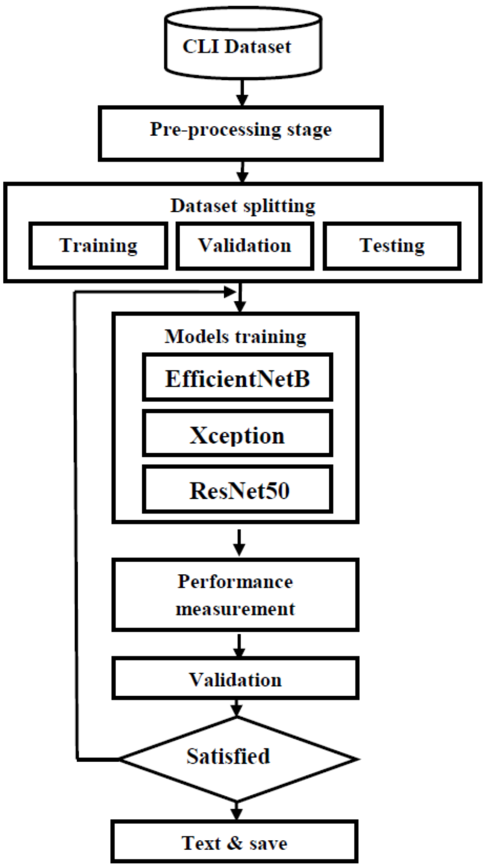


Figure 2: The proposed model flowchart.

4.2. The dataset Splitting

In this step the dataset categorized for three subsets:

a) The training set is the largest set in the dataset (80%) and is used to train presented models and modify the weights by observing and learning the correct output.

b) The validation set (10%). This component is employed to evaluate the model by modifying the hyperparameters. This data has an indirect impact on the models as it is seeing by the models but not utilized for learning purposes.

c) The testing set (10%) is an independent component of the dataset that is utilized to provide an unbiased and accurate evaluation of the models after the complete training process is complete

4.3. The proposed models

The use of pre-processing steps and diverse integrated methods with deep learning to enhance detection efficiency [19]. In our research paper, we employs there deep learning models for improvement (EfficientNetB2, Xception, ResNet50), where we focusing on the final classification layer to obtain more accuracy , in each model the final classification layer was removed for further investigate to consolidating by utilizing the models for feature extraction only, leveraging their learned features from the ImageNet dataset. A custom classification layer was added, allowing more accurate and context-specific predictions. This modification capitalizes on the robust feature extraction capabilities of the models while ensuring that the final classification is optimized for the dataset, thus enhancing overall models performance. The modified classification layer includes the bellow stage:

a) applied batch normalization, which improve the performance, stability and accelerates training by normalizing each layer's inputs; batch normalization allows higher learning rates, which speeds up the training process.

b) Incorporate two dense layers, each containing 64 and 256 neurons. These dense layers include different regularization techniques to prevent overfitting. The first technique includes use of the kernel_regularizer, with L2 regularization strength of 0.013, penalizes large weights, the activity_regularizer and bias_regularizer, with L1 regularization strength of 0. 006.

c) c) Linear activation functions are advantageous just for estimating linear hypothesis functions. Nonlinear activation functions are often utilized because to the often nonlinear connection between input and output in complicated issues.

d) The ReLU function is basically employed in dense layers because it enhances learning speed and efficiency.

e) a dropout layer is added, featuring a seed value of 123 and a rate of 0.35, defined as a technique for regularizing deep learning models. With this technique, randomly chosen neurons can be disregarded while training. This causes the contribution of these neurons to be momentarily suppressed during forward propagation, prevents overfitting by speeding up models training.

f) The final dense layer is output layer comprises 39 units, corresponding to the many kinds of diseases of plant in which the models needs to classify.

g) Softmax is utilized in the last layer to categorize the output, generating a probability distribution across the classes. This enables us to interpret the models output as each class's probability.

A general overview of the models is presented in Figure (3). A hyperparameters in the proposed model presented in Table (1).

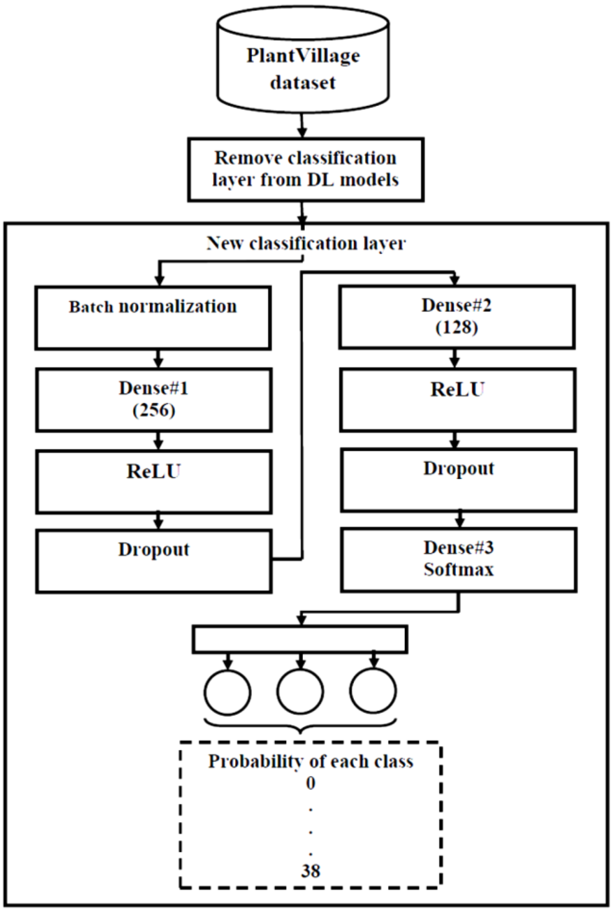


Figure 3: Structure Diagram of the proposed DL Model.

Table 1: The Proposed DL models Hyperparameters of.

Models	Hyperparameters
Proposed DL models	Activation function ReLU Training epochs 60 Mini batch sizes 32 Dropout value 0.35 Learning rate 0.001 Optimization Adam Momentum = 0.99 L1_Regularization = 0.006 L2_Regularization = 0.013

5. Experimental Results

5.1. Software and hardware framework

The studies are conducted in an environment equipped with the following hardware: Central Processing Unit (CPU): Intel(R) Core(TM) i5- 11400H @ 2.70GHz 2.69 GHz, and a RAM capacity of 16.0 GB. The operating system is Windows 11, specifically the 64-bit version. The code was implemented in Python 3.8 programming language within the PyCharm environment. The library and programming environments utilized in the project included Tensor Flow, Scikit-learn, Keras, Pandas, OpenCV2, Matplotlib, Pickle, and NumPy. The proposed models applied using 55,448 plant images, divided for 44,358 for training and validation and testing get 55, 45 images.

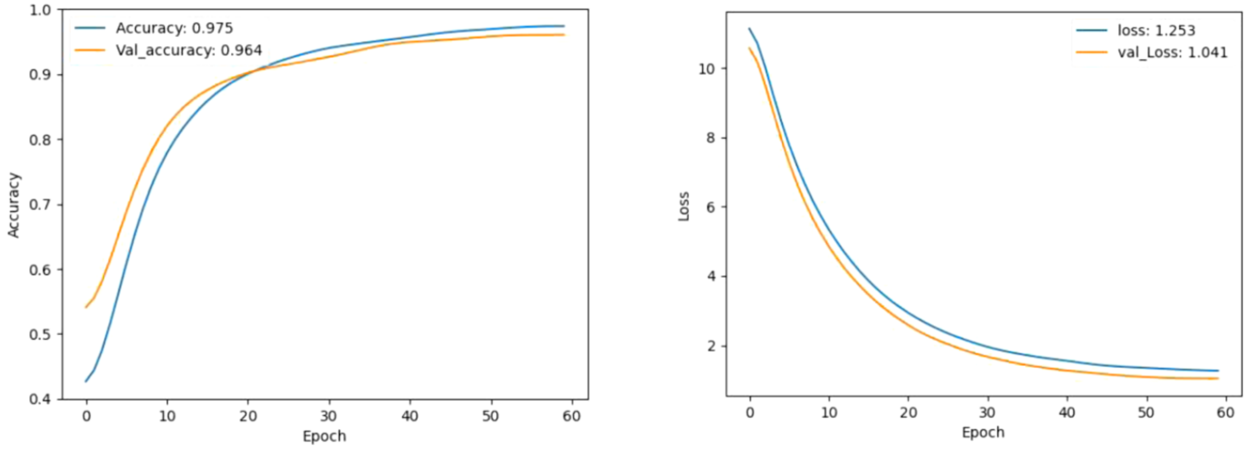
Table 2: Dataset descriptions used in Proposed Models.

Class Name	Total Images	Train (80%)	Validation (10%)	Test (10%)
Apple scab	630	509	67	54
Apple Black rot	621	493	62	66
Apple Cedar apple rust	275	230	23	22
Apple healthy	1645	1311	162	172
Background without leaves	1143	901	131	111
Blueberry healthy	1502	1213	139	150
Cherry Powdery mildew	1052	848	104	100
Cherry healthy	854	662	92	100
Corn Cercospora leaf spot	513	416	50	47
Corn Common rust	1192	955	112	125
Corn Northern Leaf Blight	985	797	95	93
Corn healthy	1162	926	111	125
Grape Black rot	1180	933	108	139
Grape Black Measles	1383	1102	153	128
Grape Leaf blight	1076	882	86	108
Grape healthy	423	343	40	40
Orange Haunglongbing	5507	4383	591	533
Peach Bacterial spot	2297	1857	249	191
Peach healthy	360	288	32	40
Pepper bell Bacterial spot	997	811	91	95
Pepper bell healthy	1478	1179	143	156
Potato Early blight	1000	793	103	104
Potato Late blight	1000	814	87	99
Potato healthy	152	125	12	15
Raspberry healthy	371	296	37	38
Soybean healthy	5090	4060	530	500
Squash Powdery mildew	1835	1474	183	178
Strawberry Leaf scorch	1109	872	112	125
Strawberry healthy	456	364	48	44
Tomato Bacterial spot	2127	1694	214	219
Tomato Early blight	1000	808	89	103
Tomato Late blight	1909	1493	200	216
Tomato Leaf Mold	952	764	83	105
Tomato Septoria leaf spot	1771	1447	165	159
Tomato spider mite	1676	1362	167	147
Tomato Target Spot	1404	1120	128	156
Tomato Yellow	5357	4242	565	550
Tomato mosaic virus	373	294	43	36
Tomato healthy	1591	1297	138	156
Total	**55,448**	**44,358**	**5,545**	**5,545**

A set of experiments conducted to train the models, the best result was obtained when The final classification layer was removed, and two dense layers were added, each containing 64 neurons and 256 neurons, following a normalization process. Both of these layers include L1 and L2 regularization. Then, a dropout layer was added. The output layer comprises 39 units of dense layer. Softmax is utilized in the last layer to categorize the output.

5.2. Efficientnetb2 model result

The EfficientNetB2 model demonstrated outstanding performance; the model also achieved a loss function of 1.25% in the training and a loss function of 1.05% in the validation. The accuracy of the EfficientNetB2 was 97.70%. It exhibited precision (98.54%) and recall (98.07%) across all disease categories, and an overall F1- score of 98.07%. The model's efficacy was also assessed by calculating the confusion matrix as show in Figure 5. Figures 4 (a) show the training accuracy and (b) show loss function, both training and validation losses consistently decreased over the 60 epochs.



(a) (b)

Figure 4: EfficientNetB2 Model (a) Accuracy of Training and Validation, (b) Loss Function.

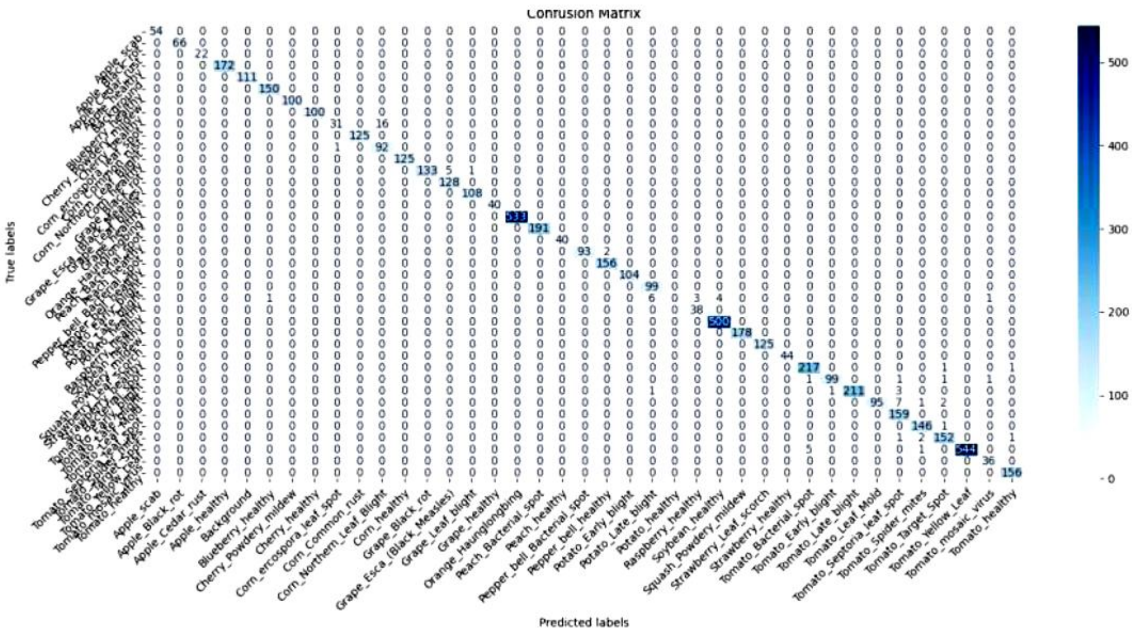
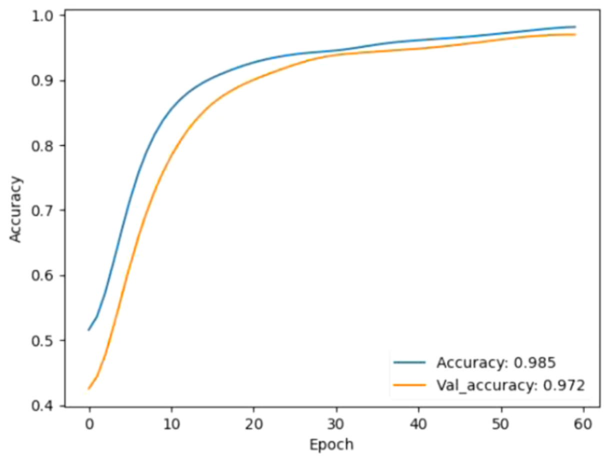


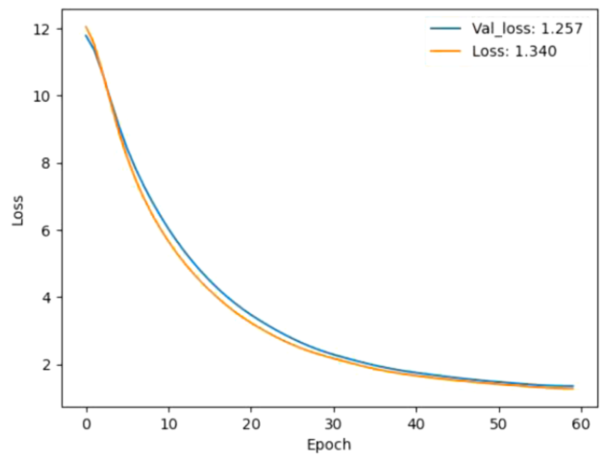
Figure 5: EfficientNetB2 Model Confusion Matrix.

5.3. Xception Model Result

Accuracy of training is 97.23 and validation is 98.97. The loss function is 1.35% in the training and 1.26% in the validation. The model's precision is 98.50% and recall is 90%, for the training. As for validation, it has reached precision 97.48 % and recall 97.74 %. Figures 6 (a) show the training accuracy and Figures (b) show loss function for training and validation.



(a)



(b)

Figure 6: Xception Model (a) Accuracy of Training and Validation, (b) Loss Function.

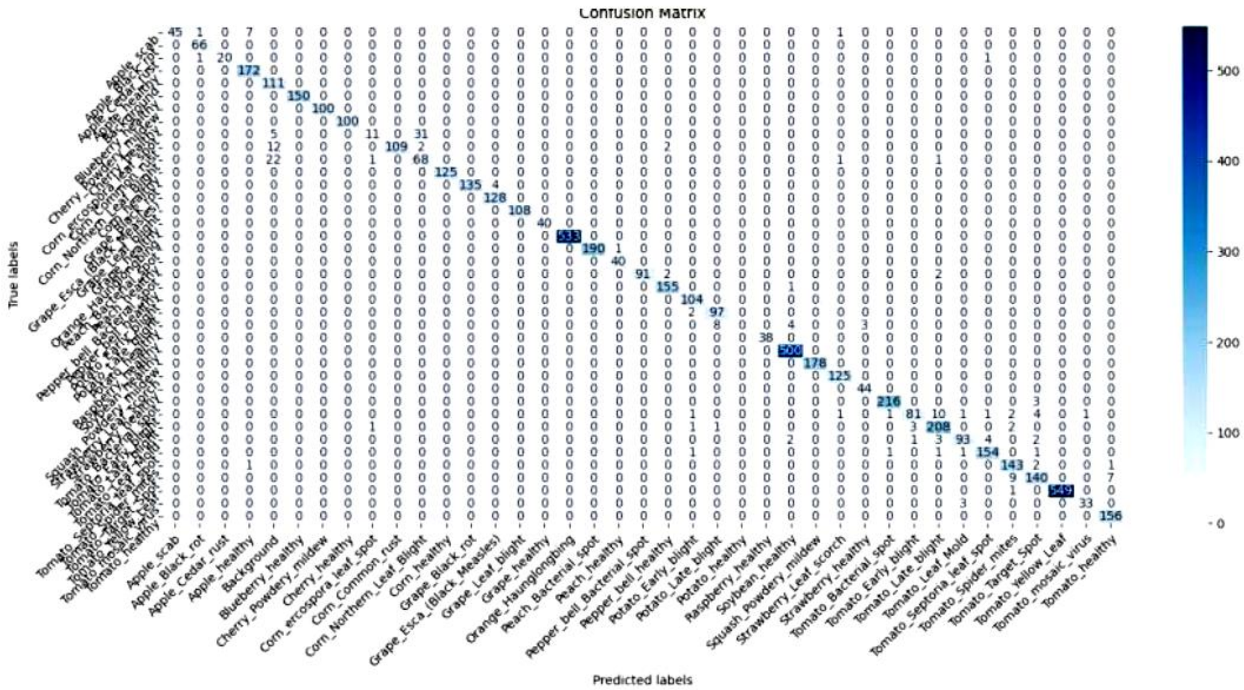
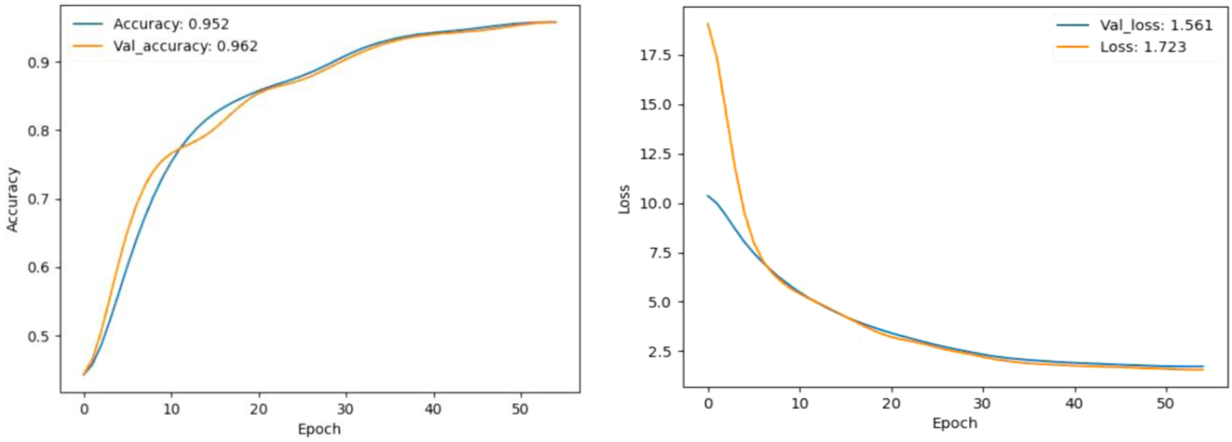


Figure 7: Xception Model Confusion Matrix.

5.4. Result of resnet50 model

The Accuracy of training is 96.17% and validation is 97.86%. The loss function is 1.72% in the training and 1.56% in the validation. The model's precision and recall are 97.86% and 84.52%, respectively for the training. As for validation, it has reached precision and recall 97.12%, 93.72%, respectively. Figures 8 (a) show the training accuracy and (b) show loss function for training and validation.



(a) (b)

Figure 8: ResNet50 Model (a) Accuracy of Training and Validation, (b) Loss Function.

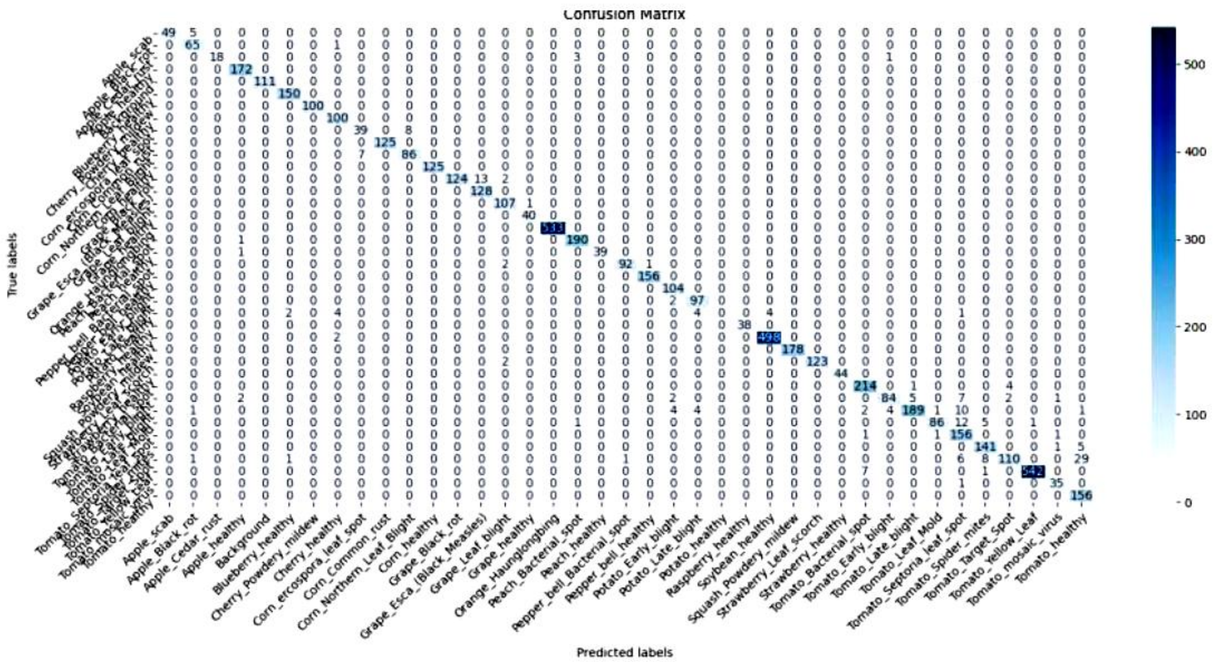


Figure 9: ResNet50 Model Confusion Matrix.

Table 3: Comparison of the Proposed models.

Model	Accuracy	Precision	Recall	F1-Score
EfficientNetB2	97.70	98.54	98.07	98.07
ResNet50	97.86	97.12	93.72	95.36
Xception	98.97	97.48	97.74	97.61

Table 4: Comparison with the Related Work

Ref. No.	Year	Technique	Dataset Used	Accuracy	No. of Classes
[10]	2019	DCNN	PlantVillage	96.46%	39
[11]	2020	ResNet101	PlantVillage	94.6%	4

[12]	2020	CNN	PlantVillage	98.029%	15
[13]	2022	CNN	PlantVillage	95.24%	38
[14]	2023	CNN	PlantVillage (Maize crop)	96.76%	4
[15]	2024	PDDNet-AE, PDDNet-LVE	PlantVillage	96.74% - 97.79%	15
Proposed models	2025	EfficientNetB2	PlantVillage	97.70%	39
	2025	ResNet50	PlantVillage	97.86%	39
	2025	Xception	PlantVillage	98.97%.	39

6. Conclusion

Plant diseases represent major problems that concerns food security and cause significant economic losses. Detecting diseases using traditional methods is ineffective in time and effort, especially in large agricultural areas. This paper develops effective methods for the timely diagnosis of plant diseases to avoid plant losses. Three types of CNN were applied for plant diseases detection and classificatin, EfficientNetB2, Xception, and ResNet50 models. These models were trained, validated and tested on PlantVillage dataset. preprocessing phase is crucial for implementing the proposed system. At this stage, the original image of the plant leaves undergo several operations, including the sharpening technique to highlight the edges of the images, which facilitates the extraction of features. The augmentation represent a powerful method for improving the training of the proposed models, reducing overfitting and increasing accuracy.CNN models achieved a high accuracy as EfficientNetB2 is 97.70% , ResNet50 is 97.86% and Xception is 98.97%. Future work may include enhancing the efficiency and robustness and Expanding disease detection to cover plant components beyond leaves, such as flowers, fruits, and stems.

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