

CornNet: Implementation of Transfer Learning for Disease Classification in Corn Plants Based on Web Application

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Abstract

This study addresses the classification of corn leaf diseases caused by infections such as Blight, Common Rust, and Grey Leaf Spot, which significantly affect corn production. Early and accurate classification is crucial for effective disease management and yield improvement. To solve this problem, this research implements Transfer Learning and Explainable AI (XAI) to classify corn leaf disease images and integrates the solution into a web-based system. The contribution of this research lies in combining modern deep learning models with XAI to enhance transparency in plant disease classification systems, specifically through the integration of these models into a web-based platform and a comprehensive performance comparison across different optimizers to evaluate robustness and efficiency. Five pre-trained deep learning architectures—ResNet101, VGG16, EfficientNetB1, DenseNet201, and InceptionV3—are utilized as Transfer Learning models. Grad-CAM (Gradient-weighted Class Activation Mapping) is used to visualize the most influential regions in disease image classification. The dataset used is “Corn or Maize Leaf Disease,” containing 4,188 images across four classes: Blight, Common Rust, Grey Leaf Spot, and Healthy. The results demonstrate that Transfer Learning and Explainable AI can be effectively applied to corn leaf disease classification and web deployment. Among the models, EfficientNetB1 achieved the highest accuracy of 95%, along with clear Grad-CAM visualizations that enhance interpretability. This study contributes to the development of intelligent agricultural systems and supports decision-making in crop disease management using transparent AI solutions.

Keywords— Transfer Learning, Explainable AI, Grad-CAM, Corn Leaf Disease Classification, EfficientNetB1

1. INTRODUCTION

Maize is the third most widely cultivated food crop in the world and the second in Indonesia. It is commonly used as animal feed [1], as well as processed into corn rice for human consumption [2]. However, according to data from the Food and Agriculture Organization (FAO), maize production experienced a decline of 25% in 2019, reaching 22.59 million tons, followed by a further decrease of 0.38% to 22.5 million tons in 2020 [3]. This decline in productivity is influenced by fluctuating supply and demand factors [4], as well as plant diseases [5]. Efforts to prevent plant pests and diseases have been continuously implemented. Nevertheless, natural factors such as weather, temperature, and humidity contribute significantly to the proliferation of plant diseases [3]. Common diseases affecting maize include *Common Rust* [6], *Gray Leaf Spot* [7], dan *Blight* [8]. Identifying these diseases based on leaf symptoms is often difficult due to limited knowledge [9]. Over time, the advancement of *Artificial Intelligence* (AI) [10], particularly in the fields of *Deep Learning* [11] and *Machine Learning* [12], has significantly contributed to

disease detection in crops such as maize, coffee, apples, and tomatoes [13][14][15]. These technologies help improve the accuracy of plant disease classification based on image data. One of the most widely used deep learning algorithms for image analysis is the Convolutional Neural Network (CNN). However, developing CNN models requires large datasets and substantial training time. To address these challenges, transfer learning has emerged as a viable solution in CNN model development. Transfer learning utilizes pre-trained CNN architectures—models trained on existing datasets—which can be fine-tuned for new classification tasks. By leveraging knowledge from previously trained models, transfer learning facilitates the development of new models with high classification accuracy [16]. Several CNN architectures commonly employed in transfer learning to optimize accuracy and efficiency in image classification include *EfficientNet* [17], *ResNet* [18], *Inception* [19], *VGG* [20], dan *DenseNet* [21]. Although transfer learning models can achieve high accuracy in image classification tasks, a significant challenge remains: the lack of interpretability in understanding how the model makes its decisions. Therefore, Explainable Artificial Intelligence (XAI) technologies have been introduced to provide model interpretability [22]. XAI enables deep learning models to produce human-understandable explanations, thereby increasing user trust and comprehension of model predictions. In the context of plant disease classification, one of the most commonly used XAI techniques is Gradient-weighted Class Activation Mapping (Grad-CAM) [23].

According to a study conducted by Kusumastuti et al. [24], *EfficientNet-B1*, *EfficientNet-B2*, and *EfficientNet-B3* were employed as baseline models. The results demonstrated that the *EfficientNet* architectures yielded promising outcomes, achieving a training accuracy of 97.88%. In another study by Putra et al. [25], maize leaf disease classification was performed using the Corn Leaf Infected Dataset from Kaggle, which was split into training and testing sets at an 80:20 ratio. The training process utilized the *ResNet-50* model along with three different optimizers: Adam, Nadam, and SGD. The highest accuracy was achieved by the combination of *ResNet-50* with the Adam optimizer, reaching 98.4%, followed by Nadam with 98.3%, and SGD with 98%. Further research by Sheila et al. [26] applied the *Inception V3* model for detecting diseases in rice plants. They used the Rice Leaf Disease Dataset, also divided into 80% training and 20% testing. The implementation of *Inception V3* resulted in a testing accuracy of 93.75% with a loss value of 0.3076. Another study by Akhyari et al. [27] focused on classifying diseases in maize leaves using the *VGG-16* model as the base architecture. The model achieved a high accuracy of up to 98%. Related research was also conducted by Entuni and Zulcaffle [7], whose study aimed to identify maize leaf diseases such as Blight, Grey Spot, and Rust. They employed *DenseNet 201* as the CNN base model, which, when compared to other models, achieved a final accuracy of 95.11%.

This study aims to compare and evaluate classification models for maize leaf diseases based on image data using various transfer learning architectures, including *EfficientNet*, *ResNet*, *Inception*, *VGG*, and *DenseNet*. The objective is to identify the most effective model and implement it within a web-based application. Ultimately, this research is expected to contribute significantly to the agricultural sector by enabling fast, accurate, and efficient classification of maize diseases.

2. RESEARCH METHODS

In Figure 1, this research begins with a literature review to gather relevant information on classifying corn leaf diseases using Transfer Learning and Explainable AI (XAI). Image data of diseased corn leaves is collected from Kaggle and undergoes preprocessing, including image resizing. In the modeling phase, CNN architectures such as *EfficientNet*, *ResNet*, *Inception*, *VGG*, and *DenseNet* are employed and trained using transfer learning techniques to classify the images into four categories: common rust, gray leaf spot, blight, and healthy. Model interpretation is conducted using Grad-CAM as the XAI method to generate heatmap visualizations highlighting the most influential areas in decision-making. Performance evaluation is carried out using a confusion matrix to assess accuracy, precision, recall, and F1-score. The best-performing model is then integrated into a web application (deployment), followed by a testing phase to ensure the system functions properly and with minimal errors.

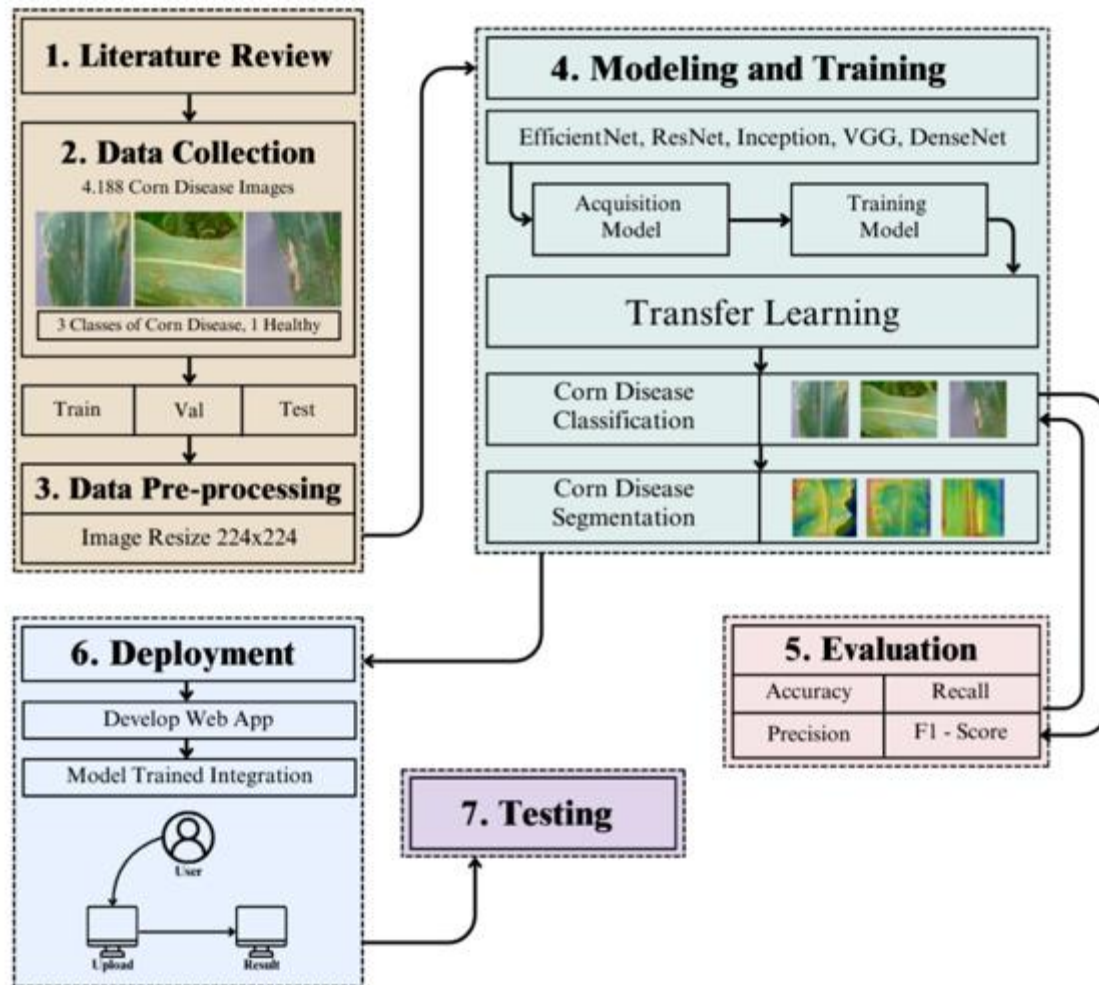


Figure 1. Research Design Framework

2.1. Data Collection

The dataset used in this research is the *Corn or Maize Leaf Disease* dataset, which consists of a total of 4,188 images divided into four classes: three classes of diseased leaf images (Blight, Common Rust, and Grey Leaf Spot) and one class of healthy leaf images (Healthy). Figure 2 shows the total images in the dataset. The dataset is split into three subsets: 81% for training data, 9.5% for validation data, and 9.5% for testing data. The training set contains a total of 3,392 images from all classes, the validation set consists of 398 images, and the testing set also includes 398 images.

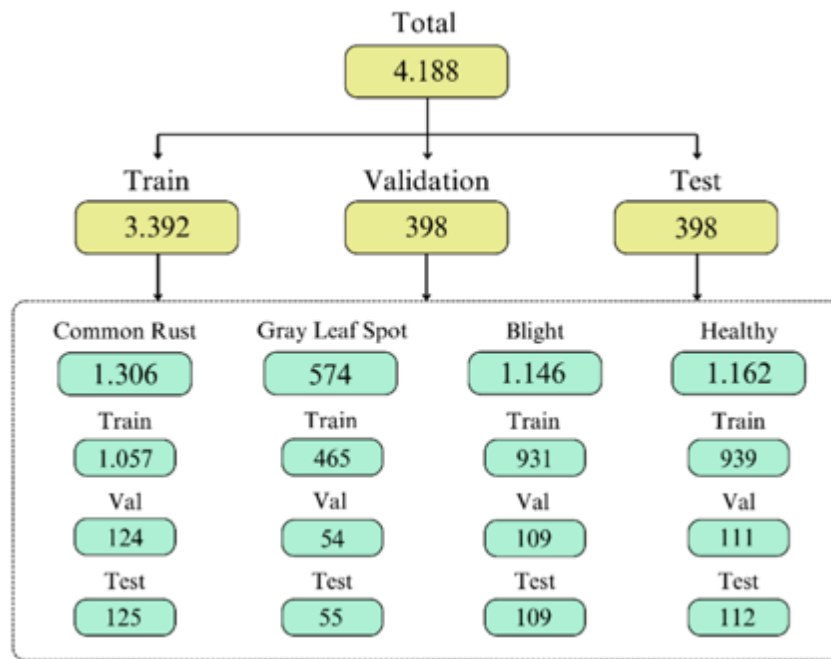


Figure 2. Total Images in Dataset

2.2. Data Pre-processing

In this stage, the researcher performs image resizing to 224x224 pixels to ensure better model performance. This size is considered small enough to speed up data training while being large enough to retain the necessary visual details.

2.3. Modeling and Training

The next stage is Modeling and Training. Initially, model layers are adjusted by adding components such as global average pooling, batch normalization, dense layers, dropout, an output layer, and softmax. To conduct model experiments, Transfer Learning techniques are applied using several model architectures, including ResNet, VGG, EfficientNet, DenseNet, and Inception. From these five architectures, the researcher selects different model types, then compares and acquires the five best-performing variants from each architecture.

Table 1. Selected Architecture Type

Architecture	Type
ResNet	50, 101
VGG	16, 19
EfficientNet	B0, B1, B3, B5
DenseNet	121, 201
Inception	V3

During the model training process, the researcher conducted experiments using three different optimizer scenarios: the first scenario used Adamax, the second used SGD, and the third

used RMSprop. All scenarios used the same parameters, such as a batch size of 32, 100 epochs, and a learning rate of 0.001. The batch size was used to observe the effect on model adjustment speed and memory usage, epochs were set to ensure the model learned all patterns in the training dataset, and the learning rate was applied to achieve a stable and efficient model.

Table 2. Scenario Parameter

Scenario	Optimizer	Batch Size	Epoch	Learning Rate	Loss Function
1	Adamax	32	100	0.001	Categorical Crossentropy
2	SGD	32	100	0.001	Categorical Crossentropy
3	RMSprop	32	100	0.001	Categorical Crossentropy

2.4. Evaluation

At this stage, the researcher performed a performance evaluation using a confusion matrix to calculate the accuracy, recall, precision, and F1-Score. The formulas are as follows.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

$$Precision = \frac{TP}{FP+TP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1-Score = \frac{2 \times Recall \times Precision}{Recall+Precision} \quad (4)$$

2.5. Deployment

At this stage, the researcher will develop a simple web application for classifying diseases in corn plants. This web application is designed to accept image inputs of corn leaves from users. The system will then process the image and display the results in the form of probability percentages and the classification of the image into one of the disease classes: common rust, gray leaf spot, blight, or healthy.

3. RESULT AND DISCUSSION

3.1. Comparative analysis of the best transfer learning model in three different scenarios

Table 3. Top 5 models from each scenario

Model	Optimizer	Loss Function	Accuracy	Scenario
ResNet101	RMSprop	Categorical	93%	3
VGG16	RMSprop	Categorical	92%	3
EfficientNetB1	Adamax	Categorical	95%	1
DenseNet201	Adamax	Categorical	93%	1

InceptionV3	Adamax	Categorical	79%	1
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After conducting experiments with three different scenarios, five best-performing models were identified from each selected architecture, namely: ResNet101 (Scenario 3), VGG16 (Scenario 3), EfficientNetB1 (Scenario 1), DenseNet201 (Scenario 1), and InceptionV3 (Scenario 1). Table 3 evaluates the performance of these models. EfficientNetB1, optimized with the Adamax optimizer, achieved the highest classification accuracy at 95%. This is followed by ResNet101 from Scenario 3 with an accuracy of 93%, although it shows signs of overfitting. DenseNet201 from Scenario 1 also achieved 93% accuracy and demonstrated solid performance, comparable to EfficientNetB1. VGG16 from Scenario 3 attained an accuracy of 92%, but exhibited a greater tendency toward overfitting compared to ResNet101. Lastly, InceptionV3 from Scenario 1 showed the lowest accuracy at 79%. Although it did not show indications of overfitting, the model struggled to capture patterns effectively, which likely contributed to its lower accuracy.

3.2. Performance Comparison Across Scenarios

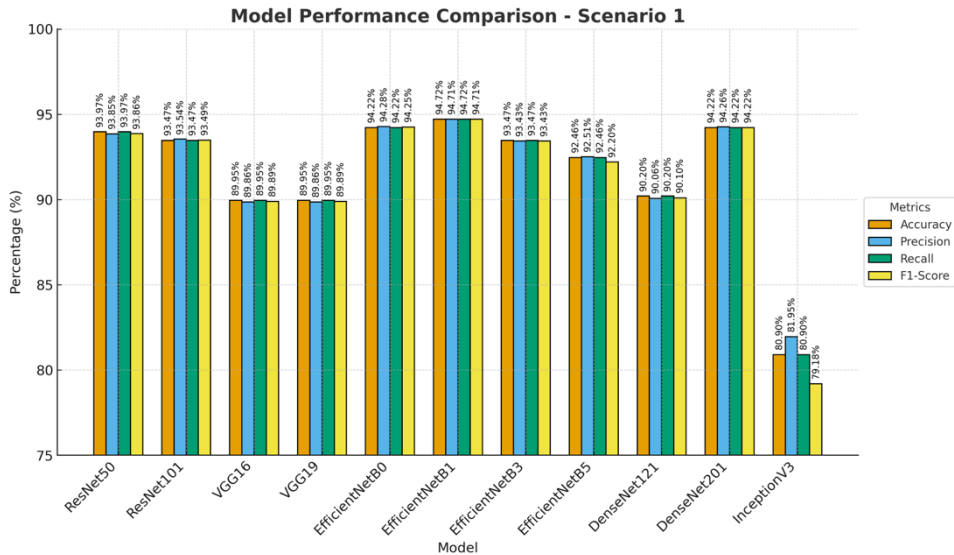


Figure 3. Comparative performance of eleven transfer learning architectures in scenario 1

Figures 3–5 present the comparative performance of eleven transfer learning architectures: ResNet50, ResNet101, VGG16, VGG19, EfficientNetB0–B5, DenseNet121, DenseNet201, and InceptionV3, evaluated under three experimental scenarios. Each figure reports the Accuracy, Precision, Recall, and F1-score for each model to assess their robustness and consistency across different configurations. In Scenario 1 (Figure 3), EfficientNetB1 achieved the highest performance across all metrics, with an accuracy of 94.72%, precision of 94.71%, recall of 94.72%, and an F1-score of 94.71%. Other models, such as EfficientNetB0 and DenseNet201, also demonstrated strong results above 94%, while InceptionV3 lagged significantly with less than 82% accuracy. These findings indicate that the EfficientNet architectures, particularly B1, provide an optimal balance of feature extraction and classification performance. In Scenario 2 (Figure 4), the overall trend remained consistent, with EfficientNetB1 maintaining competitive performance (92.46% accuracy) alongside DenseNet201 (92.96% accuracy). Minor fluctuations in precision and F1-score across models suggest the influence of training parameters such as optimizer selection and batch configuration. Despite these variations, EfficientNet models continued to outperform VGG and ResNet families in terms of stability and generalization. In Scenario 3 (Figure 5), performance slightly improved for most architectures, reflecting the effect of refined parameter tuning and data augmentation strategies. EfficientNetB1 once again achieved superior

results (94.47% accuracy, 94.37% precision, 94.47% recall, 94.37% F1-score), followed closely by VGG16 and DenseNet201. Meanwhile, InceptionV3 consistently produced the lowest scores across all scenarios, confirming its lower suitability for the current dataset and classification objective. Overall, the three scenarios collectively demonstrate that EfficientNetB1 consistently outperformed the other models in both accuracy and consistency across evaluation metrics, making it the most effective architecture for corn leaf disease classification in this study.

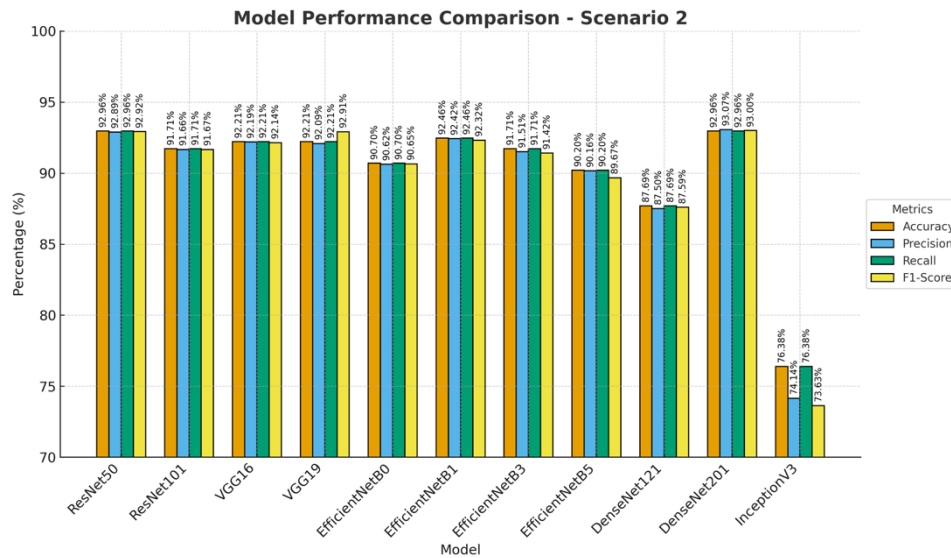


Figure 4. Comparative performance of eleven transfer learning architectures in scenario 2

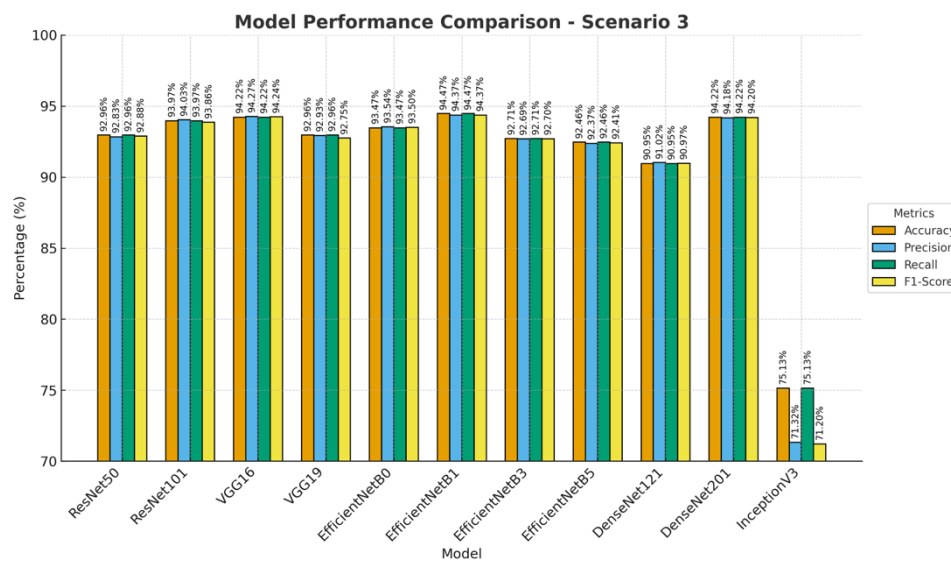


Figure 5. Comparative performance of eleven transfer learning architectures in scenario 3

3.3. ResNet101 Model Evaluation



Figure 6. ResNet101 Loss and Accuracy Graph

Figure 6 presents the experimental results of the ResNet101 model using the RMSprop optimizer in Scenario 3, which demonstrates good performance but indicates signs of overfitting. The training loss decreases significantly up to epoch 7 (the best epoch), indicating strong learning capability from the training data. However, the validation loss begins to increase after epoch 20. Meanwhile, the accuracy graph shows a significant gap between training and validation accuracy, with the best epoch at epoch 65, further reinforcing the indication of overfitting.

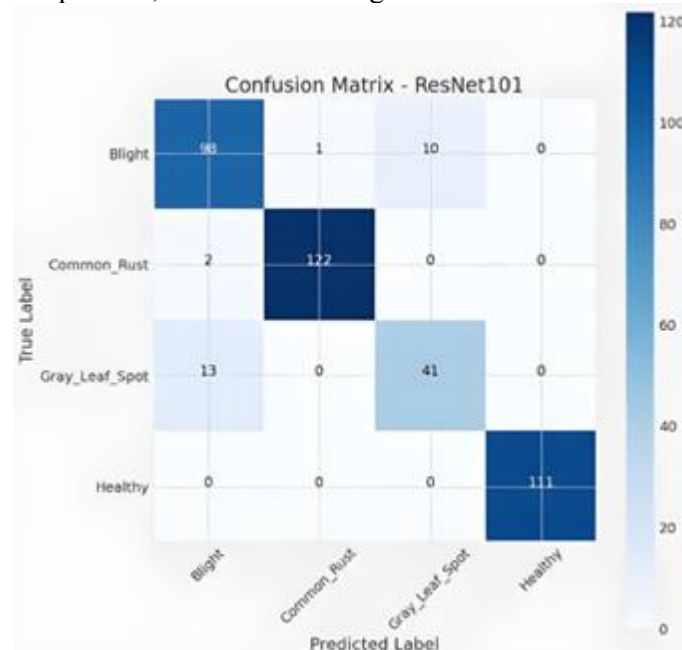


Figure 7. ResNet101 Confusion Matrix

Based on Figure 7, the confusion matrix shows that the model performs well in most classes. For the blight class, the model correctly predicted 98 instances, with 1 misclassified as common rust and 10 as gray leaf spot. In the common rust class, 122 instances were correctly classified, while 2 were misclassified as blight. The gray leaf spot class had 41 correct predictions, but 13 were misclassified as blight, indicating this class as the weakest in terms of accuracy. Lastly, the model achieved perfect prediction in the healthy class with 111 correct instances. Overall, the model demonstrates high accuracy, except for the gray leaf spot class, which showed notable misclassification errors.

3.4. VGG16 Model Evaluation



Figure 8. VGG16 Lost and Accuracy Graph

Figure 8 presents the VGG16 model using the RMSprop optimizer in Scenario 3 shows good training performance, with the best epoch at epoch 38. However, the validation curves indicate signs of overfitting, particularly in the loss graph, where the best epoch appears at epoch 4.

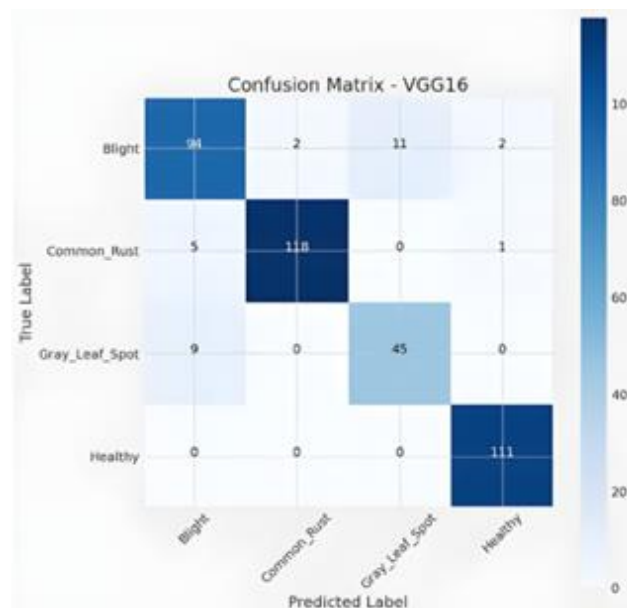


Figure 9. VGG16 Confusion Matrix

Based on Figure 9, the VGG16 model's confusion matrix shows fairly good performance. In the blight class, the model correctly predicted 94 instances, with 11 misclassified as gray leaf spot, with 2 each as common rust and healthy. For common rust, there were 118 correct predictions, with 5 misclassified as blight and 1 as healthy. The gray leaf spot class had 45 correct predictions and 9 misclassified as blight. The healthy class achieved perfect performance, with 111 correct predictions and no misclassifications. Overall, while gray leaf spot improved compared to the previous model, blight still had notable errors, whereas common rust and healthy were classified very accurately.

3.5. EfficientNetB1 Model Evaluation

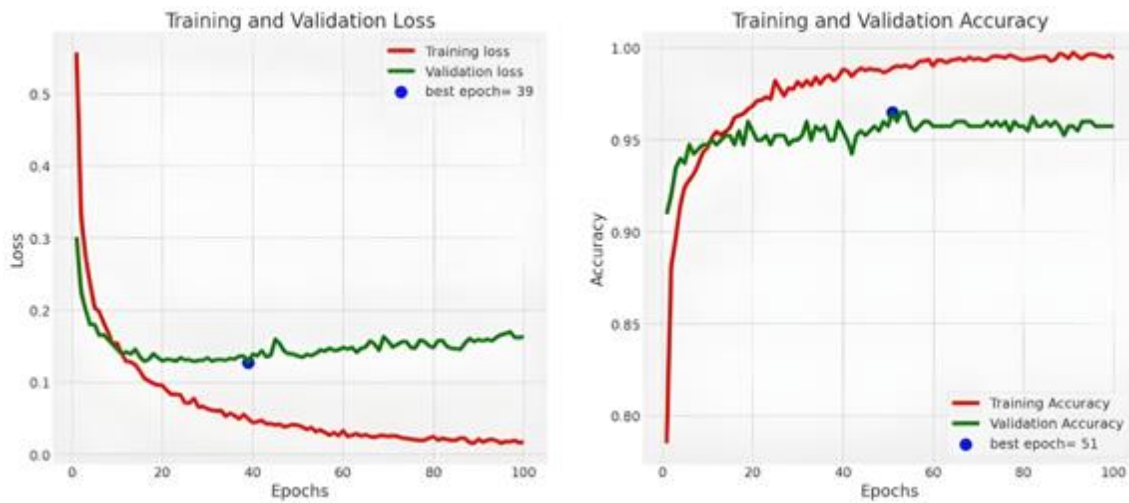


Figure 10. EfficientNetB1 Loss and Accuracy Graph

Figure 10 shows that the EfficientNetB1 model with the Adamax optimizer performs better than the previous two models. The training and validation loss/accuracy graphs show good results, though there is still a gap between them. The best epoch for training and validation loss is at epoch 39, while for training and validation accuracy, it occurs at epoch 51.

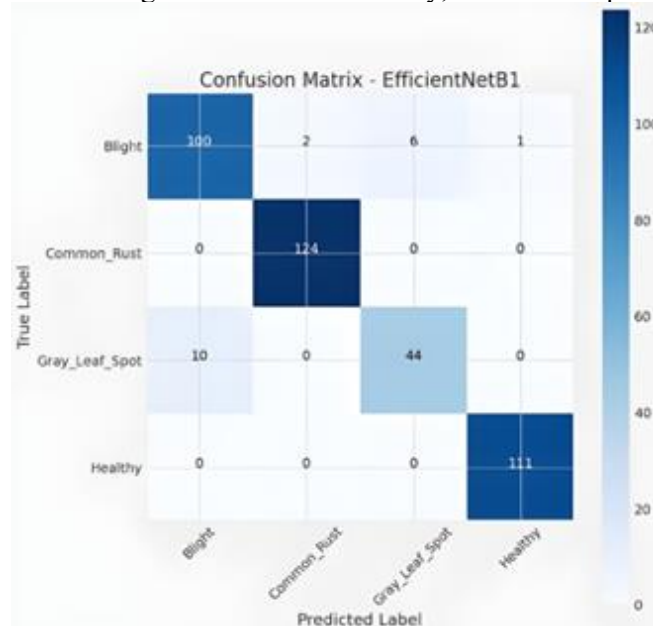


Figure 11. EfficientNetB1 Confusion Matrix

Based on Figure 11, the confusion matrix for the model shows excellent performance. In the blight class, the model correctly predicted 100 instances, with 2 errors on common rust, 6 on gray leaf spot, and 1 on healthy. For the common rust class, the model predicted 124 instances correctly. In the gray leaf spot class, the model correctly predicted 44 instances, with 10 misclassifications on blight. For the healthy class, the model predicted all instances correctly. Although gray leaf spot had 10 misclassifications, the model overall performed excellently, particularly in common rust and healthy, which were perfectly predicted.

3.6. DenseNet201 Model Evaluation

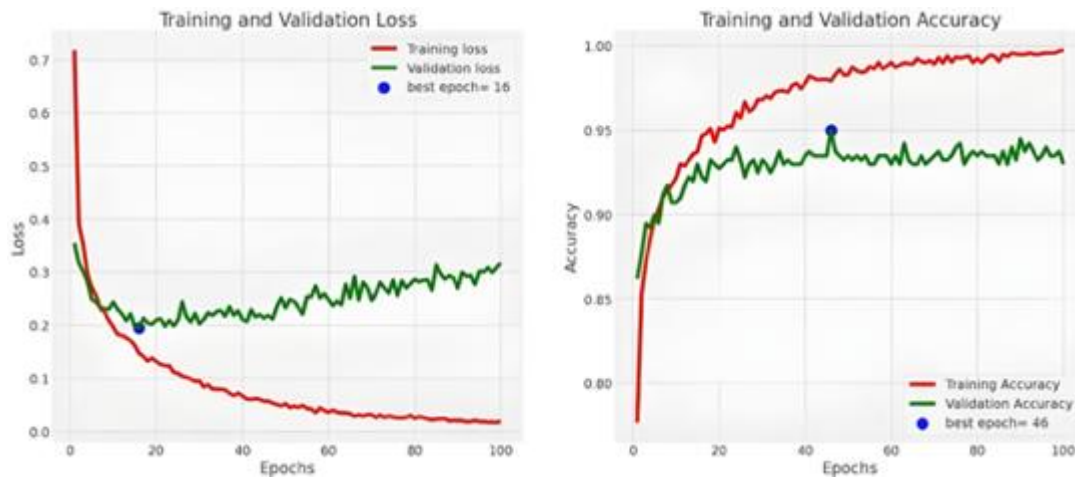


Figure 12. DenseNet201 Loss and Accuracy Graph

Figure 12 presents the DenseNet201 model with the Adamax optimizer in scenario one, showing a significant decrease in training loss, followed by a decline in validation loss until around epoch 16, after which it stabilizes with slight fluctuations. In the right graph, although there is a gap between training and validation accuracy, both graphs remain fairly aligned and do not show significant overfitting. The best epoch occurred at epoch 46.

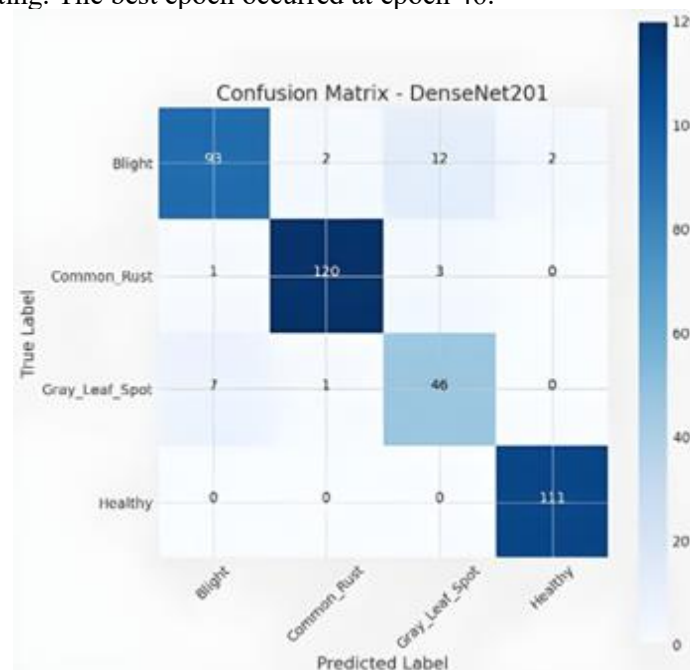


Figure 13. DenseNet201 Confusion Matrix

Based on Figure 13, the model performs reasonably well in predictions, although the blight class shows 12 misclassifications on gray leaf spot, 2 on common rust, and 2 on healthy. The model correctly predicted 93 instances in the blight class. For the common rust class, the model predicted 120 instances correctly, with 1 misclassification on blight and 3 on gray leaf spot. In the gray leaf spot class, the model predicted 46 instances correctly, with 7 misclassifications on blight and 1 on common rust. In the healthy class, the model predicted all instances correctly.

3.7. InceptionV3 Model Evaluation

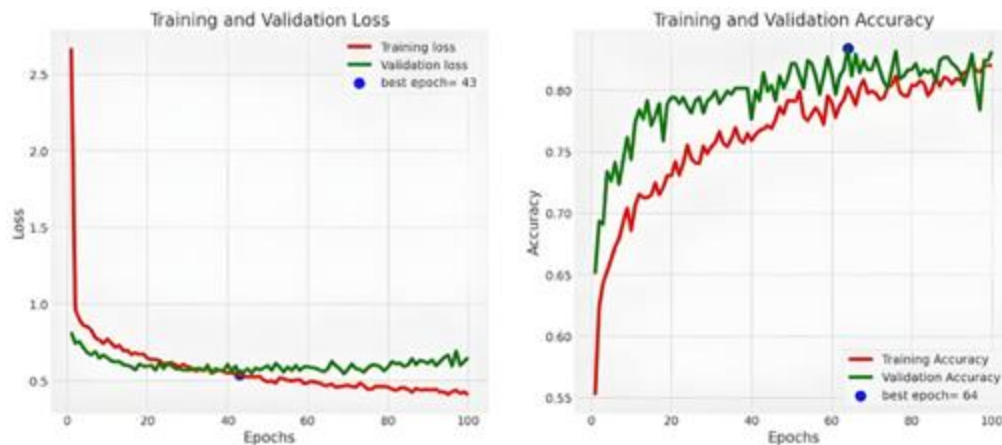


Figure 14. InceptionV3 Loss and Accuracy Graph

Figure 14 presents the InceptionV3 model with the Adamax optimizer has the lowest accuracy compared to the other four models, achieving the best accuracy of around 80% in the first scenario. The graph shows that the training and validation loss decrease consistently, indicating that the model can maintain generalization without overfitting, particularly after epoch 43. However, the accuracy graph shows a large gap between training and validation accuracy, with the training accuracy only reaching around 80% at the best epoch of 64, indicating that the model is still weak at capturing patterns and can be considered to be underfitting.



Figure 15. InceptionV3 Confusion Matrix

Based on Figure 15, the model correctly predicted 92 instances in the blight class, with 12 misclassifications on gray leaf spot, 1 on common rust, and 4 on healthy. In the common rust class, the model predicted 113 instances correctly, with 6 misclassifications on blight, 3 on gray leaf spot, and 2 on healthy. In the gray leaf spot class, the model predicted only 18 instances correctly, with 34 misclassifications on blight, and 1 on both common rust and healthy. In the healthy class, the model predicted 93 instances correctly, with 18 misclassifications on blight. The model performs well in predicting blight, common rust, and healthy, but struggles with gray leaf spot, which has a large number of misclassifications. This is consistent with the relatively low training accuracy.

3.8. Grad-CAM Visualization of Feature Activation in Corn Disease Images

The Grad-CAM visualization in Figure 16 provides a clear interpretability analysis of the model's prediction for corn leaf disease classification. The uploaded image on the left shows a corn leaf infected with Common Rust, while the corresponding Grad-CAM heatmap on the right highlights the specific regions of the leaf that contributed most to the model's decision. The yellow colored activation areas indicate where the EfficientNetB1 model focused its attention when identifying disease patterns. In this figure, the Grad-CAM output demonstrates that the model Efficientnet B1 effectively localized the rust lesions scattered across the upper region of the leaf surface, which are characteristic of Common Rust infection. This strong spatial alignment between the highlighted regions and the actual disease spots confirms that the model is not only achieving high predictive accuracy (100% confidence in this case) but is also making decisions based on relevant visual features rather than background noise.

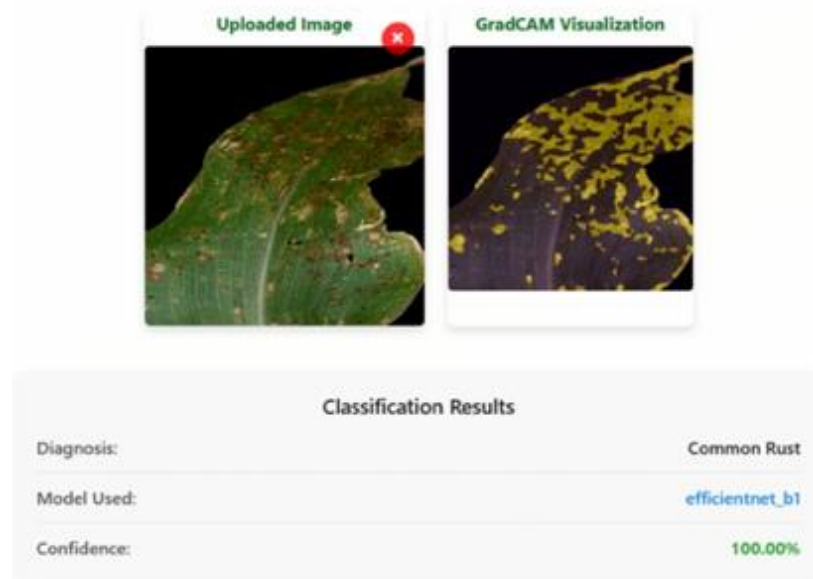


Figure 16. Grad-CAM Visualization of Feature Activation

4. CONCLUSION

In conclusion, this research demonstrates that the integration of Transfer Learning and Explainable AI provides an effective approach for classifying corn plant diseases and can be successfully implemented within a web-based system. The study found that the EfficientNetB1 architecture was the best-performing model, achieving a classification accuracy of 95%, outperforming other models such as ResNet101, VGG16, DenseNet201, and InceptionV3. The strong performance of EfficientNetB1 is attributed to the combination of parameters used, namely the Adamax optimizer, a learning rate of 0.001, a batch size of 32, and the use of categorical cross-entropy as the model's loss function. Overall, this study found that applying the EfficientNetB1 transfer learning model offers the best potential solution for classifying corn leaf disease images, including blight, common rust, gray leaf spot, and healthy categories. Future research could explore the use of larger, multi-regional datasets to improve model generalizability and investigate real-time deployment through mobile devices to enhance accessibility for farmers and agricultural practitioners.

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