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Explainable Deep Learning for Multi-Class Plant Disease Classification Using ResNet and EfficientNet with Grad-CAM Analysis

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ABSTRACT

Plant diseases can reduce crop quality and productivity, making early detection an important aspect of modern agriculture. Recent advances in deep learning, particularly Convolutional Neural Networks (CNN), have shown promising performance in image-based plant disease classification. This study proposes an explainable deep learning approach for multi-class plant disease classification using ResNet50 and EfficientNetB0 combined with Grad-CAM visualization. The experiments were conducted using the PlantVillage dataset consisting of 15 classes of healthy and diseased plant leaves.The research process included image preprocessing, data augmentation, transfer learning, model training, performance evaluation, and explainability analysis. The dataset was divided into training and validation sets with a ratio of 80:20. Model performance was evaluated using accuracy, loss, confusion matrix, precision, recall, and f1-score metrics. Experimental results showed that ResNet50 achieved the best performance with an accuracy of 92% and a validation loss of 0.19, outperforming EfficientNetB0 which obtained 76% accuracy and 0.82 validation loss. The classification report demonstrated that ResNet50 provided more stable and consistent predictions across most disease classes. Furthermore, Grad-CAM visualization successfully highlighted disease-relevant regions such as lesions, discoloration, and damaged leaf areas, improving the interpretability of the CNN model. The findings indicate that the combination of ResNet50 and Grad-CAM is effective for plant disease classification and provides better explainability for deep learning-based agricultural applications.

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I. INTRODUCTION

Agriculture is one of the important sectors that plays a role in maintaining food security and supporting economic growth. In practice, agricultural productivity often experiences various obstacles, one of which is disease attacks on plants. Plant diseases can cause a decrease in the quality and quantity of crops so that it has a direct impact on farmers' income and the stability of food production. Therefore, the process of identifying plant diseases needs to be carried out as early as possible so that treatment can be carried out quickly and appropriately. So far, the identification of plant diseases is generally still carried out manually through visual observation of the condition of the leaves. This method is indeed quite commonly used, but it has some drawbacks. The degree of accuracy of identification is highly dependent on the observer's experience, while symptoms between diseases often have visual similarities. In addition, the direct inspection process takes a relatively long time, especially on agricultural land with a large area. This condition shows that conventional methods still have limitations in supporting the needs of modern agriculture that demands a fast, consistent, and efficient identification process.

The development of artificial intelligence technology, especially in the field of computer vision, opens up new opportunities in the development of automatic plant disease detection systems. One of the widely used approaches is deep learning based on Convolutional Neural Network (CNN). This method is able to learn visual patterns in the image automatically without the need for manual feature extraction. This ability makes CNN widely applied to various image classification researches [1], including the detection of plant diseases based on leaf imagery. Several previous studies have shown that the CNN model is able to produce high classification performance on plant disease datasets, especially by utilizing the PlantVillage dataset which has a large number of images and consists of various types of plant diseases. However, most studies still focus on improving accuracy values without providing an explanation of the model's decision-making process. In fact, deep learning models are often considered black-boxes because the results of the predictions produced are difficult for users to understand. In the context of agriculture, model interpretation is important because users need to know which parts of the leaf are considered to have an effect on the classification results. To overcome these problems, the Explainable Artificial Intelligence (XAI) approach has begun to be widely applied to deep learning systems. One of the methods that is quite popular is Gradient-weighted Class Activation Mapping (Grad-CAM). This method can visualize the areas of imagery that the model focuses on when classifying. With this visualization, users can see if the model is actually detecting disease areas on the leaves or is actually taking advantage of other irrelevant parts. In addition to increasing model transparency, this approach can also help increase user confidence in the developed system.

On the other hand, the selection of CNN architecture varies in detecting objects such as character detail objects [2]-[3] It is also an important factor in determining the performance of classifications with several approaches such as edge detection [4]-[5]. In Deep Learning, the ResNet architecture is known to have a good ability to handle deep networks through residual learning mechanisms, while EfficientNet offers more optimal parameter and computational efficiency while maintaining high classification performance. Both architectures are widely used in various image classification studies, but their performance in multi-class classification of plant diseases is still interesting to be analyzed further, especially in terms of model accuracy and interpretability.

Based on this background, this study proposes an explainable deep learning approach for the multi-class classification of plant diseases using the ResNet and EfficientNet architectures combined with the Grad-CAM method. This study aims to compare the performance of the two models in classifying plant diseases while providing visualization of the image areas that affect the prediction results. Thus, the developed system is not only able to produce classifications with good performance, but also has a higher level of interpretability so that it is easier to understand and trust by users.

The development of artificial intelligence technology has encouraged the emergence of various automated approaches in the detection of plant diseases based on digital imagery. One of the most widely used approaches is deep learning based on Convolutional Neural Network (CNN) because it is able to perform automatic feature extraction and produce high classification performance on various types of plant images [6]-[7]. CNN It is considered more effective than traditional machine learning methods because it is able to learn complex visual patterns without the need for manual feature extraction processes [8].

Recent research shows that modern CNN architectures continue to evolve to improve classification accuracy while reducing the computational complexity of models. Zhao et al. developed a plant disease classification model based on a combination of Inception and residual structure with an attention mechanism and obtained better performance than some conventional CNN models such as ResNet50 and InceptionV3 [6]. The study showed that the integration of residual learning and attention modules was able to improve the model's ability to recognize disease patterns in plant leaves.

In addition, various recent review studies also show that CNN is still the dominant approach in the classification of plant diseases. Pacal et al. explain that most modern research utilizes transfer learning and pretrained CNN models to improve classification performance on plant disease datasets [7]. Meanwhile, Salka et al. emphasized that the research trends for 2022–2025 are starting to focus on lightweight architecture, explainable AI, and the ability to generalize models on real field conditions [8].

The ResNet architecture is still one of the most widely used models in the classification of plant diseases because it has the ability to overcome vanishing gradient through the concept of residual learning [9]-[10]. The use of ResNet in the classification of plant diseases has been shown to be able to produce stable classification performance on multi-class datasets Mishra et al. compared ResNet and EfficientNet in the classification of potato and mango plant diseases, and showed that both models are capable of providing high accuracy performance with different computational characteristics. On the other hand, EfficientNet is starting to be widely used because it offers more optimal parameter efficiency and performance than conventional CNN. EfficientNet uses a compound scaling method that allows for increased performance without increasing the complexity of the model to be too great. Research by Ali et al. shows that EfficientNet-B0 is capable of producing the classification of apple leaf diseases with high accuracy and faster inference time [11]. Another study by Nnamdi et al. also developed a lightweight MobileNet-based architecture for the multi-class classification of plant diseases with a focus on computational efficiency and implementation on resource-constrained devices [12].

In addition to improving classification performance, recent research is starting to highlight the importance of deep learning model interpretability. The CNN model is often considered a black-box model because the decision-making process is difficult for users to understand. In the context of agriculture, model interpretation is important so that users can understand the model's reasons for identifying certain diseases in plant leaves. Therefore, the concept of Explainable Artificial Intelligence (XAI) is starting to be widely applied in modern plant disease classification research.

One of the most widely used explainability methods is Gradient-weighted Class Activation Mapping (Grad-CAM). This method is able to visualize the areas of the image that the model is concerned with during the classification process. Recent research suggests that Grad-CAM integration can help improve model transparency as well as ensure that the model actually studies disease areas on plant leaves, not just image background patterns [13]. Research by Sobuj et al. shows that the use of Grad-CAM on pretrained CNN can help model focus analysis of rice leaf disease areas while improving the interpretability of classification results [14].

Recent research has also begun to combine explainable AI with attention mechanisms to improve the quality of model interpretation. Mahapatra et al. developed attention-enhanced CNN for the classification of plant diseases and showed that the integration of attention mechanisms and Grad-CAM visualizations was able to improve the model's focus on disease areas more accurately. In addition, Singh et al. developed interpretable attention-guided CNN with CBAM and Grad-CAM++ approaches to improve model transparency on plant disease detection [15]-[16].

On the other hand, several studies have also begun to explore hybrid architecture approaches to improve the performance of multi-class classification of plant diseases. SAM et al. developed a combination of Conditional GAN and Vision Transformer to improve the performance of plant disease classification on unbalanced datasets [17]. The study shows that the combination of modern augmentation and transformer-based architecture is able to improve the generalization ability of the model. Although previous studies have shown high classification performance, most studies still focus on improving accuracy without conducting an in-depth analysis of model interpretability. In addition, studies that specifically compare the performance of ResNet and EfficientNet in multi-class classification of plant diseases with the support of Grad-CAM visualization are still relatively limited. Therefore, this study proposes an explainable deep learning approach by comparing the performance of the two architectures and integrating Grad-CAM to improve the transparency and interpretability of plant disease classification results [18]-[20]. The contributions of this study are threefold. First, this work provides a comprehensive comparative evaluation of ResNet50 and EfficientNetB0 for multi-class plant disease classification using the PlantVillage dataset under identical experimental settings. Second, the study incorporates Grad-CAM to enhance the interpretability of CNN-based predictions by highlighting disease-relevant regions in leaf images. Third, the findings offer practical insights into the trade-off between classification performance and explainability, which is essential for developing transparent decision-support systems in smart agriculture.

II. METHODOLOGY

This research began with the process of collecting datasets using the PlantVillage dataset which contains images of leaves of healthy plants and leaves infected with various types of diseases. The dataset was chosen because it has a fairly complete variety of disease classes and is widely used in deep learning-based plant disease classification research. After the dataset is obtained, the image preprocessing stage is carried out to adjust the data to the needs of the CNN model. The entire image was converted to a size of 224×224 pixels to match the ResNet50 and EfficientNetB0 architectures. In addition, pixel values are normalized to help the model training process become more stable. At this stage, data augmentation such as rotation, flip, zoom, and shifting is also applied to increase data variation so that the model is able to generalize better.

To ensure a fair evaluation of model generalization, the dataset was divided into training (70%), validation (15%), and testing (15%) subsets. The training set was used for model learning, the validation set was employed for hyperparameter monitoring and early stopping, while the independent testing set was reserved exclusively for final performance evaluation.

This study uses two Convolutional Neural Network architectures, namely ResNet50 and EfficientNetB0. Both models utilize pretrained weights from ImageNet so that the learning process becomes more effective through a transfer learning approach. At the end of the model, a fully connected layer was added to adjust the number of classes in the plant disease dataset.

Next, the model training process was carried out using the Adam optimizer and the loss categorical crossentropy function. During the training process, fine tuning was applied to improve the model's ability to recognize disease patterns in plant leaves. The training was conducted using Google Colaboratory GPUs to make the computing process run faster and more efficiently.

After the model is completed, performance evaluation is carried out using several test metrics such as accuracy, loss, confusion matrix, and classification report which includes precision, recall, and f1-score. This evaluation stage aims to determine the model's ability to classify each class of plant diseases.

In the final stage, a performance comparison between ResNet50 and EfficientNetB0 was carried out based on the results of the evaluation obtained. The analysis is carried out to determine the model with the best performance while understanding the characteristics of each architecture in the plant disease classification process. The details are shown in the

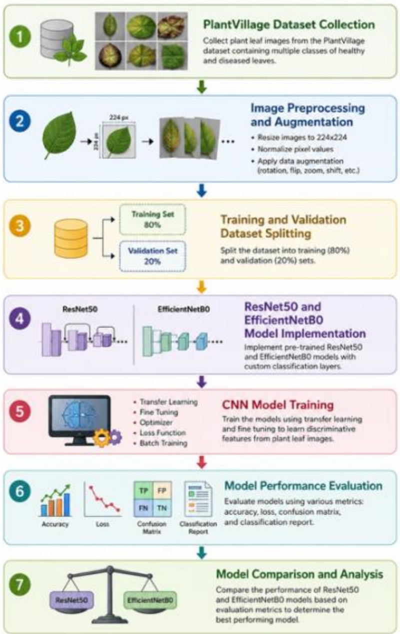

Fig. 1. Research Stage

III. RESULT AND DISCUSSION

A. Dataset Description

This study uses the PlantVillage open dataset obtained from open sources and contains a collection of images of leaves of healthy plants and leaves infected with various types of diseases. This dataset is widely used in computer vision and deep learning research because it has good image quality and a fairly complete variety of disease classes. The dataset consists of several types of crops such as: tomatoes, potatoes, pepper bells, apples, grapes, corn, and other crops. Each class in the dataset represents the condition of certain leaves, both healthy leaves and leaves infected with certain diseases such as bacterial spots, early blight, late blight, leaf mold, and others. All images in the dataset have an RGB format with a relatively clean background, making it easier to extract features using the CNN model. In this study, the image was resized to 224×224 pixels to match the input of the ResNet50 and EfficientNetB0 models. The dataset is then divided into 80% training data and 20% validation data. The division is carried out to ensure that the model can be evaluated using data that was not used during the training process. The following are some examples of images from the dataset used

Fig. 2. Sample Image 1

Fig. 3. Sample Image 2

The distribution of data used in this study is shown in Table I.

TABLE I. DISTRIBUTION OF DATASET

Class	Total Images
Pepper bell bacterial spot	997
Pepper bell healty	1478
Potato early blight	1000
Potato late blight	1000
Potato healthy	152
Tomato bacterial spot	2127
Tomato early blight	1000
Tomato late blight	1909
Tomato leaf mold	952
Tomato septoria leaf spot	1771
Tomato spider mites	1676
Tomato target spot	1404
Tomato yellow leaf curl	3209
Tomato mosaic virus	373
Tomato healthy	1591

B. Model Training Results

In this study, the training process was carried out using two Convolutional Neural Network architectures, namely ResNet50 and EfficientNetB0. Both models were trained using the PlantVillage dataset with an image size of 224×224 pixels and applied transfer learning and data augmentation techniques. The training process is carried out using Google Colaboratory with NVIDIA T4 GPU accelerators to speed up computing. The training parameters used included the Adam optimizer, batch size 32, and categorical crossentropy as a loss function.

C. ResNet50 Performance

Based on the results of the training, the ResNet50 model showed excellent performance in the plant disease classification process. The model managed to achieve a high level of accuracy with a fairly good loss value. The following are the results of the performance of ResNet50 on Table II.

TABLE II. RESNET50 RESULT

Category	Result
Accuracy	92%
Precision Average	93%
Recall Average	92%
F1-Score Average	93%

The test results showed that ResNet50 obtained an accuracy of 92% with a loss value of around 0.22. These values show that the model is able to effectively study the visual patterns of leaf disease and produce stable predictions. The residual connection architecture in ResNet50 helps the model retain important information during the training process so that the feature extraction process becomes more optimal.

D. EfficientNetB0 Performance

The EfficientNetB0 model was also able to classify plant diseases quite well, but its performance was still below ResNet50 in this experiment. The results of the evaluation showed that EfficientNetB0 obtained an accuracy of around 76% with a loss value of around 0.78. The following are the results of EfficientNetB0 on Table III.

TABLE III. EFFICIENTNETB0

Category	Result
Accuracy	76%
Precision Average	79%
Recall Average	76%
F1-Score Average	76%

Although this model is known to be more efficient in the use of parameters, the results of experiments show that EfficientNetB0 has not been able to achieve optimal performance on the PlantVillage dataset. One of the reasons is that the fine tuning process is still limited so that the model is not fully able to learn the visual characteristics of each class of plant diseases.

E. Model Comparison

The comparison of the results of the evaluation of the two models is shown in Fig. 4 and Fig. 5.

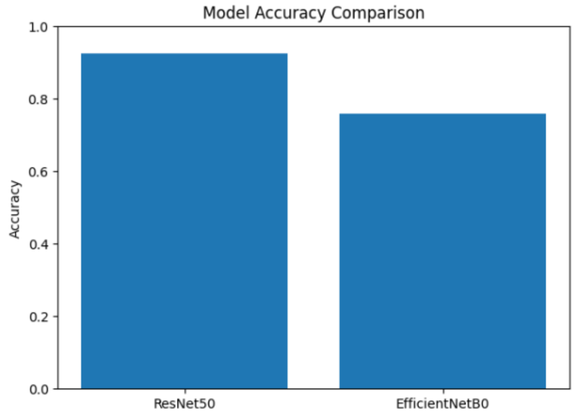

Fig. 4. Accuracy Comparison

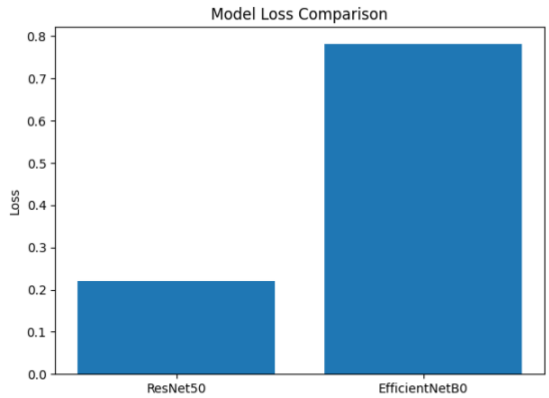

Fig. 5. Loss Comparison

Based on these results, ResNet50 provides better performance than EfficientNetB0 in terms of accuracy and loss. This shows that the ResNet50 architecture is more suitable for the plant disease classification process in the PlantVillage dataset. In addition to having higher accuracy, the lower loss value of ResNet50 indicates that the model produces more stable and consistent predictions than EfficientNetB0. Next are the results of the comparison of training and validation accuracy in Fig. 6.

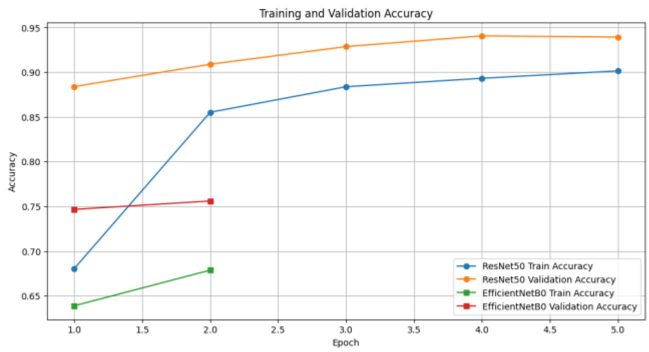

Fig. 6. Training and Validation Accuracy

Based on the training graph and validation accuracy, it can be seen that the ResNet50 model shows better and more stable performance than the EfficientNetB0 during the training process. In the ResNet50 model, the training accuracy increased significantly from about 68% in the first epoch to about 90% in the fifth epoch. Validation accuracy has also experienced a consistent improvement to reach around 94%.

This pattern shows that the model is able to learn important features of plant leaf imagery well and has a fairly high generalization ability to validate data. In addition, the gap between training accuracy and validation accuracy on the ResNet50 is relatively small, indicating that the model does not experience significant overfitting. The stability of the curve also indicates that the training process is going well and that the model has successfully achieved convergent conditions. Meanwhile, EfficientNetB0 shows lower performance than ResNet50. Training accuracy only increased from around 64% to around 68%, while validation accuracy was in the range of 74% to 75%. The increase in accuracy in EfficientNetB0 appears to be slower and tends to stagnate after the second epoch. These results show that EfficientNetB0 has not been able to optimally study the visual characteristics of plant diseases in this experiment. One of the possible causes is the limited number of epochs and the fine tuning process that has not been maximized. Overall, the graph shows that ResNet50 has better learning capabilities than EfficientNetB0 in the PlantVillage dataset. The ResNet50 model not only results in higher accuracy, but also shows better training stability during the training process. Hasil selanjutnya adalah perbangingan training dan validation loss pada Fig. 7.

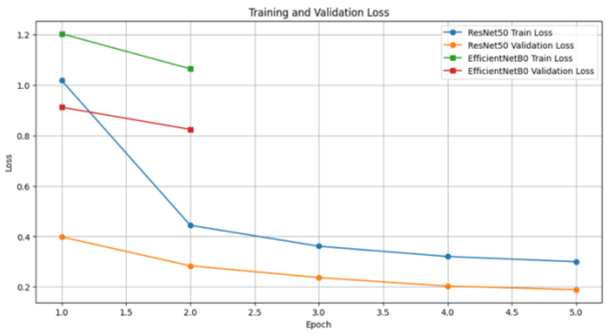

Fig. 7. Training and Validation Loss

Based on the training and validation loss graphs, it can be seen that both models experienced a decrease in losses during the training process. The decrease in loss shows that the model is increasingly able to study the patterns and characteristics of plant diseases in the PlantVillage dataset. In the ResNet50 model, training losses have decreased significantly from around 1.02 in the first epoch to around 0.30 in the fifth epoch. Validation loss also continues to decrease until it reaches around 0.19. A steady decrease in loss indicates that the model learning process is running well and the model is able to optimize parameters effectively. In addition, the distance between training loss and validation loss in ResNet50 is relatively small, indicating that the model has good generalization capabilities to validation data. There is no drastic increase in validation loss, so the indication of overfitting is still relatively low. Meanwhile, EfficientNetB0 also showed a decrease in loss, but its value was still higher than ResNet50. Training loss only decreased from around 1.20 to 1.06, while validation loss decreased from around 0.91 to 0.82. The relatively slow decline in loss shows that the model has not been able to optimally study plant disease features. The difference in loss values between the two models showed that ResNet50 had a more stable and more effective learning process than EfficientNetB0 in this experiment. This is in line with the previous accuracy results where ResNet50 produced higher classification performance. Overall, the loss graph shows that ResNet50 has better convergence capabilities than EfficientNetB0. The ResNet50 model is able to achieve lower loss values resulting in more accurate and consistent predictions in the plant disease classification process.

F. *Confusion Matrix and Classification Report Analysis*

Confusion matrix analysis was carried out to see the model's ability to classify each class of plant diseases. Based on the test results, most of the classes were successfully recognized by the ResNet50 model. Nevertheless, some classes of diseases with similar visual characteristics still suffer from misclassification. Prediction errors generally occur in classes that have almost similar patterns of patching and discoloration of the leaves. However, overall the model is still able to maintain high classification performance in most classes of plant diseases.

The results of the classification report show that the ResNet50 model has higher precision, recall, and f1-score values than the EfficientNetB0 in most classes. A high precision value indicates that the model is able to reduce positive prediction errors, while a high recall value indicates the model's ability to better recognize disease samples. The combination of precision and recall results in a good f1-score so that the model can be said to have a fairly stable classification performance.

G. *Explainability Analysis Using Grad-CAM*

To improve the interpretability of the model, this study applied the Gradient-weighted Class Activation Mapping (Grad-CAM) method. This technique is used to visualize the areas of the image that the model focuses on during the classification process. The visualization results showed that the model was able to focus attention on areas of the leaves that have disease characteristics such as spotting, discoloration, and damage to leaf tissue. In healthy leaf imagery, the model's attention tends to be scattered on the general structure of the leaf and the overall green color pattern. Meanwhile, in images of disease-infected leaves, the Grad-CAM heatmap showed a stronger focus on lesion areas and parts of the leaf that underwent visual changes. These results show that the model not only performs classification based on the general shape of the image, but also takes advantage of important visual features directly related to the characteristics of plant diseases. The result of Grad-CAM show on Fig. 8. and Fig. 9.

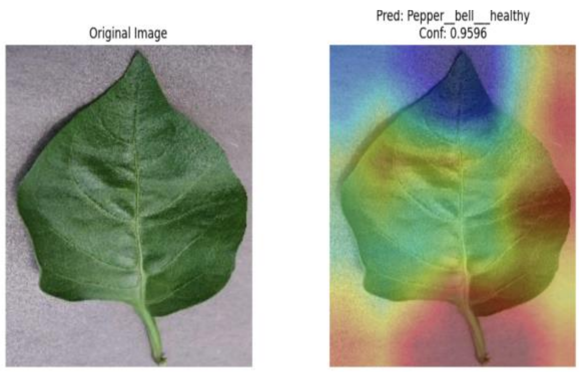

Fig. 8. Grad-CAM Result 1

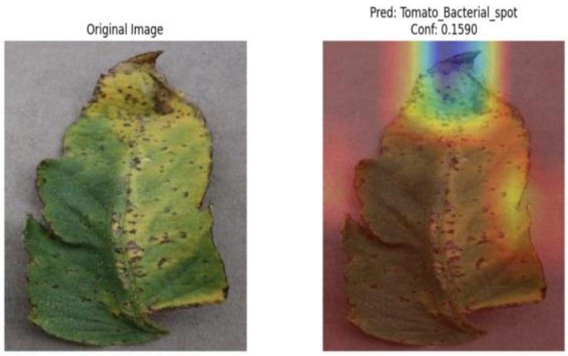

Fig. 9. Grad-CAM Result 2

Grad-CAM visualization is used to see the areas of imagery that the model focuses on during the plant disease classification process. The resulting heatmap shows the part of the leaf that is considered to be the most influential in the model's decision-making. In the first image, the model managed to classify the leaves as Pepper Bell Healthy with a confidence of 95.96%. The heatmap shows the model's attention is spread over almost the entire leaf surface, especially in the area of texture and green color patterns of the leaves. There is no strong focus on specific areas of spotting or damage, suggesting that the model recognizes healthy leaf characteristics based on color consistency and general leaf structure. Meanwhile, in the second image, the model predicts the class of Tomato Bacterial Spot. The Grad-CAM heatmap shows that the model's attention is more focused on areas of black spots and discoloration on the leaf surface. The red and yellow areas indicate the parts that the model considers most important in the classification process. This suggests that the model is able to recognize visual symptoms of the disease such as lesions, spotting, and leaf tissue damage. The results of the visualization show that the CNN model does not only classify based on the general shape of the image or background, but actually utilizes the visual characteristics of plant diseases as a basis for decision-making. Thus, the application of Grad-CAM helps to improve the interpretability of deep learning models so that the classification process becomes more transparent and easy to understand. Grad-CAM analysis revealed distinct attention patterns across healthy and diseased leaves. For healthy samples, the model considered global leaf morphology and color consistency. In contrast, diseased samples exhibited concentrated activations around lesion regions, discoloration patterns, and damaged tissues. These findings suggest that the model relies on biologically meaningful features rather than background information, thereby increasing confidence in its predictions.

H. Explainability Analysis Using Grad-CAM

The results showed that ResNet50 provided the best performance in the classification of plant diseases compared to EfficientNetB0. Although EfficientNet is known as an efficient model, in this study ResNet50 was able to produce higher accuracy and lower losses. The better performance of ResNet50 is thought to be influenced by the use of residual connections that are able to retain important feature information during the training process. In addition, the PlantVillage dataset has a relatively simple image background so that ResNet50 can perform feature extraction more optimally. The implementation of Grad-CAM also provides additional interpretability to the CNN model used. The heatmap visualization helps to show that the model is actually paying attention to the disease area on the leaves of the plant, rather than simply taking advantage of the background imagery. Overall, the combination of ResNet50 and Grad-CAM is able to produce a plant disease classification system that has good performance and is easier to interpret.

IV. CONCLUSION

This study proposed an explainable deep learning approach for multi-class plant disease classification using ResNet50 and EfficientNetB0 models combined with Grad-CAM visualization. The experiments were conducted using the PlantVillage dataset consisting of 15 classes of healthy and diseased plant leaf images. The experimental results demonstrated that ResNet50 achieved better performance compared to EfficientNetB0. ResNet50 obtained an accuracy of 92% with lower validation loss, while EfficientNetB0 achieved 76% accuracy. The results indicate that the residual learning architecture in ResNet50 was more effective in extracting visual features from plant disease images. The evaluation results using confusion matrix and classification report also showed that ResNet50 produced more stable predictions across most disease classes. Several classes with distinctive visual characteristics achieved very high precision, recall, and f1-score values, while classes with visually similar symptoms still presented classification challenges. In addition, the implementation of Grad-CAM successfully visualized the important regions used by the model during the classification process. The heatmap results indicated that the CNN model focused on disease-relevant areas such as lesions, discoloration, and damaged leaf tissues rather than background information. This finding improves the interpretability and transparency of deep learning models in agricultural applications. Overall, the combination of ResNet50 and Grad-CAM proved effective for plant disease classification and has strong potential for supporting intelligent agricultural monitoring systems. Future work may focus on using real-world field datasets, lightweight architectures for mobile deployment, and advanced explainable AI techniques to further improve model performance and practical implementation.

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