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OPTIMIZATION OF THE INCEPTIONV3 ARCHITECTURE FOR POTATO LEAF DISEASE CLASSIFICATION

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Abstract— *Potato leaf diseases can cause significant yield losses, making early detection crucial to prevent major damages. This study aims to optimize the Inception V3 architecture in a Convolutional Neural Network (CNN) for potato leaf disease classification by applying Fine Tuning Pre-Trained. This method leverages weights from a pre-trained model on a large-scale dataset, enhancing accuracy while reducing the risk of overfitting. The training process involves adjusting several final layers of Inception V3 to better adapt to specific features of potato leaf diseases. The results show that this approach improves classification performance, achieving an accuracy of 97.78%, precision of 98%, recall of 98%, and an F1-score of 98%. With better computational efficiency compared to previous architectures, this model is expected to be widely applicable in plant disease detection systems, particularly for farmers or institutions with limited resources.*

Keywords: *CNN classification, fine-tuning pre-trained model, inception v3 optimization, plant disease detection, potato leaf disease.*

Intisari— *Penyakit daun kentang dapat menyebabkan penurunan hasil panen yang signifikan, sehingga deteksi dini sangat penting untuk mencegah kerugian besar. Penelitian ini bertujuan untuk mengoptimalkan arsitektur Inception V3 dalam Convolutional Neural Network (CNN) untuk klasifikasi penyakit daun kentang dengan menerapkan Fine Tuning Pre-Trained. Metode ini memanfaatkan bobot dari model yang telah dilatih sebelumnya pada dataset skala besar, sehingga dapat meningkatkan akurasi sekaligus mengurangi risiko overfitting. Proses pelatihan dilakukan dengan menyesuaikan beberapa lapisan akhir dari Inception V3 agar lebih adaptif terhadap fitur spesifik penyakit daun kentang. Hasil penelitian menunjukkan bahwa pendekatan ini mampu meningkatkan performa klasifikasi dengan accuracy sebesar 97,78%, precision 98%, recall 98%, dan F1-score 98%. Dengan efisiensi komputasi yang lebih baik dibandingkan arsitektur sebelumnya, model ini diharapkan dapat diterapkan secara luas dalam sistem deteksi penyakit tanaman, terutama bagi petani atau institusi dengan keterbatasan sumber daya.*

Kata Kunci*: klasifikasi CNN, , fine-tuning pre-trained model , inception v, deteksi penyakit tanaman, peyakit daun kentang.*

INTRODUCTION

Potato leaf disease is one of the main challenges in agriculture that can result in significant losses for farmers and the agricultural industry as a whole [1]. Potatoes (Solanum tuberosum) are one of the most important agricultural commodities, both economically and nutritionally, serving as a staple food in many countries, including Indonesia [2]. Diseases such as early blight and late blight can drastically reduce crop yields, with losses reaching up to 50% in severe cases [3]. Therefore, monitoring and managing potato leaf diseases are crucial to ensuring production sustainability and food security [4]. With the increasing demand for potatoes, it is essential to develop efficient and effective methods for detecting these diseases to enable timely preventive measures [5].

Accurately classifying potato leaf diseases is crucial for improving agricultural yields and reducing economic losses [6]. Early detection of leaf diseases can help farmers take necessary preventive measures, such as using fungicides or implementing better planting patterns [7]. Traditional methods of disease detection often require intensive field surveys and are subject to human subjectivity, increasing the risk of errors [8]. With advancements in technology, particularly in machine learning and convolutional neural networks (CNN), potato leaf disease classification can be performed more quickly and accurately [9].

Several research studies have explored similar topics on potato leaf disease classification to improve accuracy and efficiency in the analysis process. Various algorithms have been applied to classify potato leaf diseases, including a study which discusses a segmentation method using an enhanced UNet architecture for identifying potato leaf diseases [10]. This study demonstrated that segmentation approaches can improve disease detection accuracy by focusing on infected areas.

Furthermore, research introduced EfficientRMT-Net, which combines ResNet-50 and Vision Transformers for potato leaf disease classification [11]. This method aims to overcome the limitations of traditional methods, which are often time-consuming and labor-intensive. Another study discusses the use of deep learning models with wrapper-based feature selection to identify potato leaf diseases, aiming to enhance classification accuracy by reducing feature dimensions [12].

A previous study explored potato leaf disease classification using CNN and RNN methods [13]. Aisya's study utilized transfer learning techniques and data augmentation, enabling the model to learn more effectively from a limited dataset. The classification methods applied, such as VGG16 and ResNet50 for CNN and LSTM for RNN, achieved relatively high accuracy. The model with a VGG16 dense layer of 75 obtained a precision of 0.87, recall of 0.86, accuracy of 0.86, and F1-score of 0.86. This indicates that the approach provides an effective solution for identifying various potato plant diseases, which is crucial for improving agricultural yields and supporting food security in Indonesia.

However, this study also has some limitations that need to be considered. One of the main drawbacks is the high computational cost associated with using the VGG architecture, which contains approximately 140 million parameters [13]. This can be a challenge for field implementation, especially for farmers or institutions with limited resources. Additionally, although the VGG16 model performed well, the VGG16 and LSTM dense layer 100 architecture produced lower results, with a precision of 0.21, recall of 0.24, accuracy of 0.24, and F1-score of 0.21. This indicates that not all architecture combinations yield optimal results, necessitating further research to identify the most efficient and effective model.

This Previous study utilized VGG16 and ResNet-50 for potato leaf disease classification [13]. While ResNet-50 demonstrated good performance in classification tasks, it has a larger number of parameters, increasing both memory requirements and training time [14]. In contrast, the Inception V3 model proposed in this study offers a more efficient architecture with significantly fewer parameters, approximately 23 million compared to ResNet-50's 25 million [15]. This makes Inception V3 more resource-friendly, without sacrificing accuracy, making it a better fit for resource-constrained environments.

Furthermore, UNet is primarily designed for image segmentation, whereas Inception V3 is more optimized for image classification, particularly in applications requiring computational efficiency[16]. Although UNet has been used in some studies for plant disease detection, its strength lies in detailed segmentation tasks, while Inception V3 excels in overall classification, which aligns better with the objectives of this research [15]. Therefore, while UNet and ResNet-50 each have their respective advantages, Inception V3 surpasses both in terms of computational efficiency, training speed, and classification accuracy.

Based on the discussion, an identified problem is the need to improve the accuracy of potato leaf disease classification using a different architecture, namely the Inception V3 architecture. Inception V3 offers computational efficiency compared to VGG due to its use of factorized convolutions and asymmetric convolutions, which significantly reduce the number of parameters without sacrificing accuracy [17]. With approximately 23 million parameters, significantly fewer than VGG's 140 million, Inception V3 can lower memory requirements and computational costs, making it more suitable for devices with

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limited resources [18]. Additionally, the use of auxiliary classifiers in the Inception V3 architecture helps accelerate model convergence, which can speed up the training process and improve stability, making it a more optimal choice for field applications by farmers or institutions with limited resources [16] [17].

However, despite its computational efficiency advantages over VGG, Inception V3 still has some drawbacks that need to be considered. One of these is the requirement for a sufficiently large training dataset to achieve optimal performance, as the model has many parameters that need adjustment during training [21], [22]. Additionally, without proper optimization techniques, this model may be prone to overfitting, especially if the dataset used is limited or lacks sufficient diversity in representing variations of potato leaf diseases [11].

To address these weaknesses, Fine-Tuning Pre-Trained models is a highly suitable approach for optimizing Inception V3 [23]. By leveraging weights from models pre-trained on large-scale datasets such as ImageNet, the training process can be accelerated, reducing the need for an extensive dataset [24]. Moreover, by adjusting only a few final layers of the architecture, Fine-Tuning allows the model to focus more on specific features relevant to potato leaf disease classification while simultaneously reducing the risk of overfitting and enhancing accuracy without requiring high computational power [22] [23].

Thus, this study introduces novelty by optimizing Inception V3 through Fine-Tuning Pre-Trained models to improve potato leaf disease classification accuracy with better computational efficiency. This approach reduces the need for large datasets and minimizes the risk of overfitting, making it more adaptable and applicable in resource-constrained environments. This research will implement and optimize the Inception V3 architecture within CNN to detect diseases in potato leaves. This method is chosen because Inception V3 has proven effective in classifying images with high complexity and can handle variations in leaf image data, which frequently occur [27].

Based on this background, this study aims to optimize Inception V3 with Fine-Tuning Pre-Trained models to enhance accuracy and efficiency in potato leaf disease classification while reducing the need for large datasets and minimizing overfitting risks to make the model more adaptive and lightweight.

MATERIALS AND METHODS

The method used in this study is the Convolutional Neural Network (CNN) with the Inception V3 architecture for classifying potato leaf diseases by applying Fine-Tuning Pre-Trained. The research consists of five stages, namely:

Data Collection

The data used in this study were obtained from the Kaggle platform, which contains a dataset of potato leaf images classified into three categories: Leaf Potato Healthy, Leaf Potato Late Blight, and Leaf Potato Early Blight. Each class consists of 300 images, making a total dataset of 900 images. The images are collected in various lighting conditions and different angles to enhance data diversity. These images will then undergo a preprocessing stage to ensure data quality before being used in model training and testing.

Data Processing

The first step in data processing is acquiring images from Kaggle. This study focuses on three classes: Potato Healthy, Potato Early Blight, and Potato Late Blight. The total number of images used is 900, and the distribution is presented in Table 1.

Table 1. Number of Images

No	Type of Leaf	Number of Images
1	Leaf Potato Healthy	300
2	Leaf Potato Early Blight	300
3	Leaf Potato Late Blight	300
	Total	900

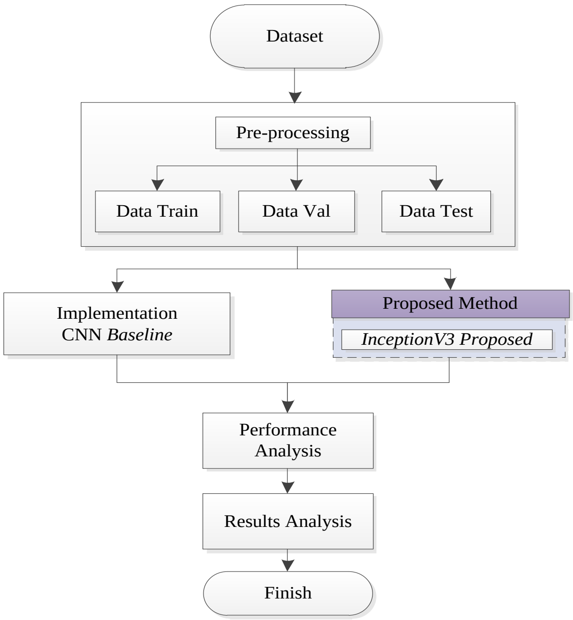
Source : (Research Results, 2025)

Table 1 presents data sourced from Kaggle (https://www.kaggle.com/datasets/rizwan123456789/potato-disease-leaf-datasetpld), where the data has already been categorized by type. Below are examples of images used for each type of Potato Leaf Disease:

(a). *Healthy* (b). *Early Blight* (c). *Late Blight.*
Source : (Research Results, 2025)
Figure 1. Potato Leaf Disease Types

Research Stages

To achieve the objective of improving potato leaf disease classification using an optimized InceptionV3 architecture, this study was conducted through several systematic stages. Each stage was designed to ensure that the model development process was structured, efficient, and aligned with deep learning best practices. The research flowchart is shown in Figure 2.



Source : (Research Results, 2025)
Figure 2. Research Framework

1. Data Collection
   Potato leaf images were collected from reliable sources and categorized into healthy and diseased classes. The dataset underwent a verification process to ensure quality for model training.

2. Data Preprocessing
   Image normalization was applied to adjust pixel values, and data augmentation techniques (e.g., rotation, flipping) were used to increase image diversity and address class imbalance. The dataset was then divided into training, validation, and testing sets.

3. Baseline Model Development
   A conventional CNN model was developed as a benchmark to evaluate the performance of the proposed method.

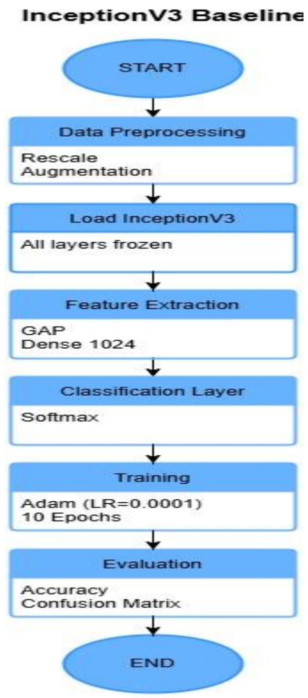
4. InceptionV3 Model Optimization
   The InceptionV3 architecture was implemented with modifications such as freezing initial layers, adding dropout layers, and fine-tuning specific layers. Pre-trained weights from ImageNet were used to improve performance and reduce training time.

5. Model Evaluation
   The model's performance was evaluated using accuracy and confusion matrix. Misclassified results were also analyzed to identify areas for improvement.

6. Result Analysis and Conclusion
   A comparison was conducted between the baseline and optimized models. Improvements in accuracy and model efficiency were used to conclude the effectiveness of the proposed approach.

CNN Inception V3 Algorithm

The Inception V3 architecture is a Convolutional Neural Network (CNN) model developed to address challenges in image classification by enhancing efficiency and accuracy. Inception V3 is an improvement over its predecessors, Inception V1 and Inception V2, which were designed by Google's research team to enhance CNN performance in image processing tasks [25] [26].



Source : (Research Results, 2025)
Figure 3. Inception V3 Architecture

Proposed Method

In this study, the proposed method was developed by modifying the baseline model based on InceptionV3 to enhance classification performance. The main difference between the two models lies in the fine-tuning process, feature extraction layer architecture, and training strategy.

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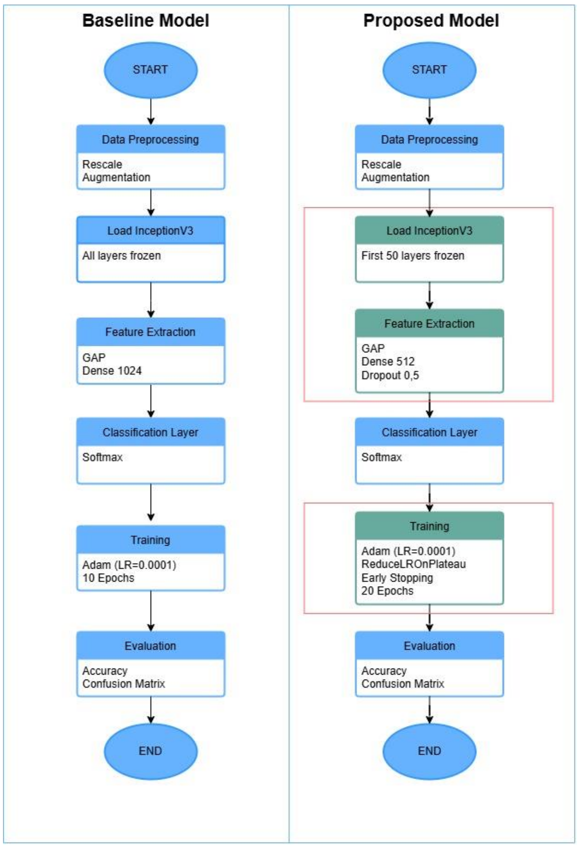
The baseline model uses InceptionV3 with all layers frozen, while the proposed model freezes only the first 50 layers, allowing the remaining layers to be further trained to capture more complex patterns from the data.

Additionally, in the feature extraction stage, the baseline model employs a simple architecture with Global Average Pooling (GAP) and a Dense layer with 1024 neurons. In contrast, the proposed method reduces the number of Dense neurons to 512 and incorporates a Dropout layer of 0.5 to minimize the risk of overfitting. These adjustments ensure that the model efficiently captures essential features without excessive complexity, which could lead to overfitting on the training data. The flowchart comparing the Inception V3 Baseline with the Proposed Method is shown in Figure 4.



Source : (Research Results, 2025)

Figure 4. Comparison of Inception V3 Baseline with Proposed Method

Figure 4 also highlights, during training, the baseline model solely utilizes the Adam optimizer with a learning rate of 0.0001 for 10 epochs. Meanwhile, the proposed model introduces further optimization strategies, namely ReduceLROnPlateau and Early Stopping, while increasing the number of epochs to 20. To enhance training efficiency and prevent overfitting, two optimization strategies were applied: ReduceLROnPlateau and EarlyStopping. ReduceLROnPlateau was used to dynamically lower the learning rate when the validation loss stopped improving, allowing the model to converge more smoothly and avoid getting stuck in local minima [30]. EarlyStopping helped terminate training when no further improvement was observed over a defined patience period, reducing the risk of overfitting and saving computational resources [31]. These strategies contributed to a more stable training process and helped achieve better generalization performance on the test set.

For evaluation, both models use the same metrics—accuracy and confusion matrix—to compare the performance of each approach. With the modifications made to the proposed model, it is expected that classification results will be more accurate and reliable than the baseline model. These changes are implemented to improve the model's generalization ability for new data, making it more effective in performing optimal classification.

RESULTS AND DISCUSSION

At this point, we offer the research results pertaining to the enhancement of the modified InceptionV3 Proposed Method and the standard CNN InceptionV3 architecture. An examination of the implementation outcomes, a comparison between the baseline and optimized models, and an assessment of the model's performance are all included in the discussion.

Image Data Pre-Processing Results

In this stage, a series of processes were carried out to prepare image data before processing it using the model. These steps include data cleaning and data splitting, which involves dividing the data into training, validation, and testing sets. This stage resulted in the following data distribution:

Table 2. Image Data Splitting

No	Data Splitting	Class	Amount
1.		*Leaf Potato Healthy*	210
2.	*Training*	*Leaf Potato Early*	210
3.		*Leaf Potato Late Blight.*	210
4.		*Leaf Potato Healthy*	45
5.	*Validation*	*Leaf Potato Early*	45
6.		*Leaf Potato Late Blight.*	45
7.		*Leaf Potato Healthy*	45
8.	*Testing*	*Leaf Potato Early*	45
9.		*Leaf Potato Late Blight.*	45

Source : (Research Results, 2025)

Table 2 shows the distribution of the potato leaf image dataset based on categories and the

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number of images available for each class. The dataset is divided into three main sections: training, validation, and testing, each used to train, evaluate, and test the model's performance. In the training section, there are three main classes: Leaf Potato Healthy (healthy potato leaves), Leaf Potato Early (potato leaves with early disease symptoms), and Leaf Potato Late Blight (potato leaves with advanced late blight disease), each containing 210 images. Meanwhile, in the validation and testing phases, each class contains 45 images, used to measure the model's performance after the training process.

This data distribution follows the general principles in deep learning, where most of the data is used for the training process to allow the model to learn effectively. The validation data functions to optimize hyperparameters, while the testing data is used to measure the model's accuracy against previously unseen data. With this proportion, the model is expected to generalize well and achieve optimal performance in detecting potato leaf diseases.

Image Data Classification Results

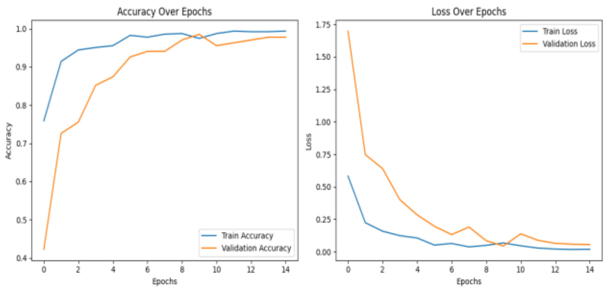
At this stage, testing is conducted to classify potato leaf disease image data using two Convolutional Neural Network (CNN) architectures: the standard InceptionV3 model and the modified InceptionV3 Proposed Method.

Loss and Accuracy Curve

At this stage, the modified InceptionV3 Proposed Method and the baseline InceptionV3 architecture are evaluated independently for image classification. Figures 5 and 6 compare the accuracy outcomes of both models on training and validation data, with the blue line representing training accuracy and the orange line representing validation accuracy. The classification training results for the various forms of potato leaf disease are shown below:

Source : (Research Results, 2025)
Figure 5. Training Loss and Accuracy Results of InceptionV3

Figure 5 displays the loss and accuracy curves for the baseline InceptionV3 model over 10 epochs. The training accuracy increases steadily, but validation accuracy fluctuates, suggesting possible overfitting as the training progresses. The validation loss decreases initially but begins to plateau, indicating the model may struggle to generalize effectively to new data.



Source : (Research Results, 2025)
Figure 6. Training Loss and Accuracy Results of InceptionV3 proposed method

Figure 6 presents the performance of the proposed InceptionV3 model. The accuracy improves more smoothly, and the loss decreases faster compared to the baseline. The validation accuracy remains more stable, and the validation loss is lower, demonstrating better generalization. These improvements are attributed to the architectural changes, such as freezing fewer layers and adjusting the optimization strategy.

Overall, the proposed InceptionV3 model outperforms the baseline model in both accuracy and loss, especially in the validation set. This demonstrates the effectiveness of the adjustments in enhancing model convergence and reducing overfitting.

Confusion Matrix

The confusion matrix provides critical insights into the performance of a classification model, highlighting areas where the model may be making errors. By analyzing the confusion matrix, we can identify false positives, false negatives, and correct classifications, which are essential for improving the model's accuracy. For example, if the model often produces false negatives (failing to detect potato leaf disease), it suggests that the threshold for classification may need adjustment, or that additional techniques such as data augmentation could help.

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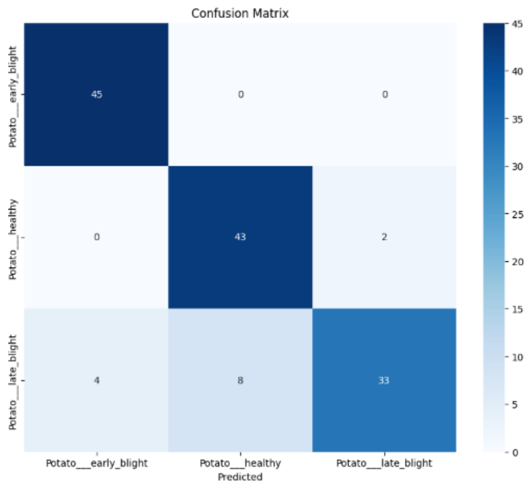
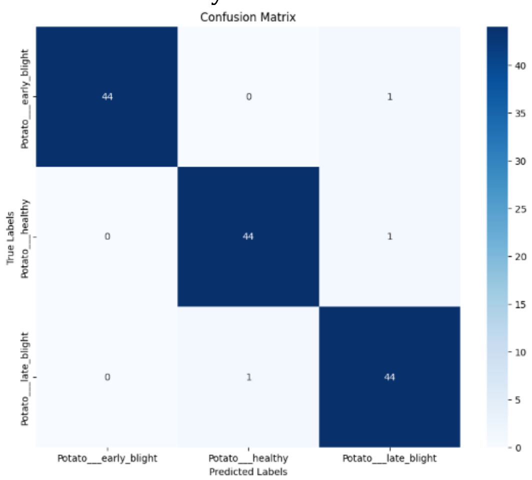


Source : (Research Results, 2025)
Confusion Matrix InceptionV3

Figure 7 presents the confusion matrix for the baseline InceptionV3 model. The rows represent the actual labels (Potato_Early_Blight, Potato_Healthy, and Potato_Late_Blight), and the columns represent the predicted labels. The matrix values indicate the number of samples in each category, with darker colors showing higher frequencies. The baseline model shows some misclassifications, particularly in the Potato_Late_Blight category, where some healthy leaves are mistakenly labeled.



Source : (Research Results, 2025)
Confusion Matrix InceptionV3 Proposed Method

Figure 8 shows the confusion matrix for the proposed InceptionV3 model. The accuracy of this model is improved, as reflected in the lower number of misclassifications compared to Figure 7. Specifically, the proposed model is better at distinguishing between Potato_Late_Blight and Potato_Healthy, showing fewer false positives and false negatives. This improvement demonstrates the effectiveness of the changes made to the architecture and optimization strategy, leading to a more accurate classification.

Overall, the confusion matrices in Figures 7 and 8 help assess how well each model performs in distinguishing between the three categories: healthy potato leaves, early blight, and late blight. By comparing the confusion matrices, we can see that the proposed model offers significant improvements in classification accuracy, with fewer errors and better overall performance.

Furthermore, Figure 9 and 10 presents the Classification Report. Figures 9 and 10 display the classification reports of both models being compared, which include evaluation metrics such as accuracy, precision, recall, and F1-score for each method.

Classification Report:

	precision	recall	f1-score	support
Potato___early_blight	0.92	1.00	0.96	45
Potato___healthy	0.84	0.96	0.90	45
Potato___late_blight	0.94	0.73	0.82	45
accuracy			0.90	135
macro avg	0.90	0.90	0.89	135
weighted avg	0.90	0.90	0.89	135

Source : (Research Results, 2025)
Classification Report InceptionV3 proposed method

	precision	recall	f1-score	support
Potato___early_blight	1.00	0.98	0.99	45
Potato___healthy	0.98	0.98	0.98	45
Potato___late_blight	0.96	0.98	0.97	45
accuracy			0.98	135
macro avg	0.98	0.98	0.98	135
weighted avg	0.98	0.98	0.98	135

Source : (Research Results, 2025)
Figure 10. Classification Report InceptionV3 Proposed Method

The results indicate that the proposed InceptionV3 method achieves better prediction performance compared to the standard InceptionV3 model. This is evident from evaluation metrics such as precision, recall, F1-score, and accuracy.

Model Performance Evaluation

The model evaluation results based on accuracy and loss during the training and testing process are presented in Table 3. Table 3 compares the performance of the standard InceptionV3 model with the proposed InceptionV3 method using various evaluation metrics.

The standard InceptionV3 model achieved an accuracy of 89%, precision of 90%, recall of 90%, and an F1-score of 89%. Meanwhile, the proposed

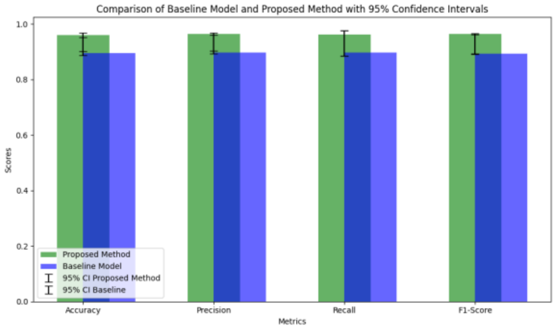
InceptionV3 method achieved a higher accuracy of 98%, with precision of 98%, recall of 98%, and an F1-score of 98%. With higher accuracy, precision, recall, and F1-score, the proposed method is more effective and reliable in classifying potato leaves.

Table 3. Testing Result

Method	Accuracy	Precision	Recall	F1-Score
InceptionV3 Baseline	0,89	0,90	0,90	0,89
InceptionV3 proposed method	0,98	0,98	0,98	0,98

Source : (Research Results, 2025)

Based on the results shown in Table 3, overall, the proposed method using InceptionV3 demonstrates better performance compared to the standard InceptionV3 model. The standard InceptionV3 achieves an accuracy of 0.89%, while the proposed method achieves an accuracy of 0.98%, indicating a 9% improvement. This increase suggests that the proposed method is more optimal in classifying potato leaves, with a better balance between sensitivity (recall) and specificity (precision).



Source : (Research Results, 2025)

Figure 11. Confidence Intervals

Figure 11 illustrates the comparison between the baseline model and the proposed method across four key metrics: Accuracy, Precision, Recall, and F1-Score. The bar chart displays the scores for both models, while the error bars represent the 95% confidence intervals for each metric.

As shown in the chart, the proposed method consistently outperforms the baseline model across all measured metrics. The proposed method achieved an average accuracy of 0.96, higher than the 0.90 achieved by the baseline model. Similarly, precision, recall, and F1-score all show significant improvements with the proposed method.

Moreover, the narrower confidence intervals for the proposed method compared to the baseline model indicate that the proposed model has higher accuracy and greater stability in making predictions. Further statistical tests, such as the t-test, also demonstrate that these differences are statistically significant, suggesting that the proposed method provides a meaningful improvement over the baseline model.

CONCLUSION

By effectively fine-tuning the CNN architecture, this study seeks to improve the classification performance of potato leaf diseases. According to evaluation results comparing two models—InceptionV3 and the proposed method—the suggested technique significantly outperforms the other. By optimizing the CNN architecture, the suggested method outperforms InceptionV3, which only managed 89% accuracy, 90% precision, 90% recall, and an F1-score of 89%, in the classification of potato leaf diseases, with 98% accuracy, 98% precision, 98% recall, and 98% F1-score. For precise classification of potato leaf disease, this makes it a more dependable and effective option. This research highlights that the CNN method with the InceptionV3 proposed method architecture has great potential in agricultural image classification applications, particularly for potato leaf disease classification. The findings of this study can serve as a reference for further development, such as utilizing a larger dataset or exploring more complex architectures to enhance accuracy and model generalization capabilities.

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