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Comparative Analysis of VGG-16, ResNet50 and EfficientNet-B1 with Optimization Techniques for Crop Disease Detection

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ABSTRACT

This paper investigates the application of convolutional neural networks (CNNs) to enhance the identification of leaf diseases in Malaysian agriculture, specifically focusing on tomato and potato crops. The study utilized pre-trained models VGG16, ResNet50 and EfficientNet-B1, employing transfer learning methods. The PlantVillage dataset, known for its comprehensive collection of annotated images of healthy and diseased plants, forms the basis for training and assessing these models. The research aimed to develop a reliable AI system for accurate and efficient disease identification, contributing to sustainable agricultural practices and food security in Malaysia.

1. Introduction

The agricultural sector is a crucial component of Malaysia's economy, contributing significantly to the nation's GDP and food security. However, the sector faces persistent challenges due to crop diseases, which lead to substantial yield losses and economic setbacks for farmers [5]. Traditional methods of crop disease detection, which rely on manual inspection, are time-consuming, labour-intensive and often inaccurate [8]. Recent advancements in artificial intelligence (AI), particularly in the field of deep learning, offer promising solutions to these challenges. Convolutional neural networks (CNNs) have shown remarkable success in various image recognition tasks, including medical diagnostics, autonomous driving and more recently, agricultural applications [6]. This study explores the application of CNN models—VGG16, ResNet50 and EfficientNet-B1—for the detection and classification of crop diseases in tomato and potato plants. Leveraging the PlantVillage dataset, which provides a comprehensive collection of annotated images of healthy and diseased plants, this research employs transfer learning and data augmentation techniques to enhance model performance.

The primary objective is to develop an accurate and efficient disease detection system that can support local farmers, reduce dependency on imports and promote sustainable agricultural practices

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in Malaysia [4,9]. By integrating these advanced AI techniques into agricultural practices, this research aims to contribute to the technological advancement of the sector and ensure food security and economic stability in Malaysia.

2. Literature Review

The detection of crop diseases has been a significant concern in agricultural research, with various methodologies being explored to improve accuracy and efficiency. Traditional methods, relying heavily on manual inspection and expert knowledge, have proven inadequate due to their time-consuming nature and susceptibility to human error [8]. As a result, there has been a shift towards utilizing advanced technologies such as machine learning and deep learning for automated disease detection. Studies have demonstrated the effectiveness of these technologies in identifying and classifying diseases in plants [5]. Machine learning techniques, including support vector machines (SVM) and K-nearest neighbour (KNN), have been widely used for classification tasks in agriculture and other fields [7]. However, these methods often require extensive feature extraction and are less effective with large-scale datasets [4]. In contrast, deep learning models, particularly CNNs, have emerged as powerful tools for image-based disease detection due to their ability to automatically extract relevant features and handle large datasets [1].

CNNs have revolutionized the field of image recognition and have been successfully applied in various domains, including medical imaging, autonomous vehicles and more recently, agricultural applications [2,10]. CNNs consist of multiple layers that automatically and adaptively learn spatial hierarchies of features from input images, making them particularly suited for tasks involving image classification and object detection. Several CNN architectures have been proposed and utilized in agricultural research, such as VGG16, ResNet50 and EfficientNet-B1. VGG16, developed by Simonyan *et al.,* [11] employs a deep architecture with small convolutional filters, demonstrating excellent performance in various image classification tasks. ResNet50, introduced by He *et al.,* [2], addresses the degradation problem in deep networks by incorporating residual learning, enabling the training of much deeper networks without performance degradation. EfficientNet-B1, proposed by Tan *et al.,* [3], optimizes both the depth and width of the network while maintaining computational efficiency, achieving state-of-the-art results with fewer parameters. This research leverages these advanced CNN models, employing transfer learning techniques to adapt pre-trained networks to the specific task of crop disease detection using the PlantVillage dataset. By systematically evaluating and comparing the performance of VGG16, ResNet50 and EfficientNet-B1, this study aims to identify the most effective model for accurately and efficiently detecting diseases in tomato and potato plants, thereby contributing to the development of reliable AI-based disease detection systems in agriculture.

3. Methodology

This research adopts a quantitative methodology to comprehensively analyse and compare the performance of various CNN models for crop disease detection. The study is structured into distinct phases, ensuring a systematic progression from problem identification to model implementation and evaluation [4]. Initially, the specific problem of crop disease detection is identified and the requirements for the study are established. This involves setting clear objectives and determining evaluation criteria for the models' performance. The PlantVillage dataset, known for its extensive collection of annotated images of both healthy and diseased plant leaves, is utilized for data collection [12]. Pre-processing steps such as resizing, normalization and data augmentation are applied to ensure data quality and diversity [13].

The core phase involves the implementation of three CNN architectures: VGG16, ResNet50 and EfficientNet-B1. Transfer learning techniques are employed to adapt these pre-trained models to the specific task of crop disease detection, enhancing their predictive accuracy and computational efficiency [3]. Various optimization techniques, including hyperparameter tuning and learning rate adjustments, are applied to improve the models' performance [2]. The models are trained using the PlantVillage dataset, with a portion reserved for validation to ensure comprehensive evaluation.

Model evaluation is conducted using performance metrics such as accuracy, precision, recall and F1-score, along with statistical analysis to validate the results [1]. Visualization tools, such as confusion matrices, are employed to illustrate the models' classification performance. Finally, a web-based system is developed to facilitate real-time disease detection, allowing users to upload images and receive immediate classification results. This system, built using HTML, Flask and Python, provides a user-friendly interface and operational efficiency. This comprehensive methodology ensures a thorough and systematic approach to achieving the study's objectives, contributing to the advancement of AI-based disease detection systems in agriculture.

4. Research Design and Implementations

This section delves into the practical aspects of the study, outlining the comprehensive approach taken to design and implement the research. The focus is on the utilization of advanced CNN architectures to detect and classify crop diseases in tomato and potato plants. The study employs VGG16, ResNet50 and EfficientNet-B1 models, leveraging transfer learning techniques to optimize their performance for the specific task at hand. This phase of the research involves several critical steps, including data collection, pre-processing, model development and optimization. Each step is meticulously planned and executed to ensure the reliability and accuracy of the models.

The data collection phase utilizes the PlantVillage dataset, renowned for its extensive repository of annotated images of healthy and diseased plant leaves [12]. This dataset forms the foundation for training and evaluating the CNN models. Preprocessing steps, including resizing, normalization and data augmentation, are applied to enhance the quality and variability of the training data [13]. The implementation of the CNN models involves fine-tuning the pre-trained networks using transfer learning, which adapts the models to the specific characteristics of the dataset and the target task [14].

Optimization techniques such as hyperparameter tuning and learning rate adjustments are employed to refine the models' performance [2]. The training phase involves feeding the pre-processed images into the CNN models and iteratively updating the network weights through backpropagation. The performance of the models is evaluated using metrics such as accuracy, precision, recall and F1-score, complemented by statistical analysis to ensure the robustness of the results [1]. Finally, a web application is developed to facilitate real-time testing of the models on custom data. This application, built using HTML, Flask and Python, provides a user-friendly interface for uploading images and receiving disease classification results, thereby enhancing the practical applicability of the research findings [15]. This comprehensive design and implementation strategy ensures a thorough evaluation of the CNN models and their potential for real-world agricultural applications.

Transfer learning involves reusing a pre-trained model on a new but related task. It is particularly beneficial when there is a scarcity of labelled data in the target domain. The process typically include the following steps as in Eq. (1).

In Eq. (1), θ represents the model parameters that need to be optimized. The function $f(x_i;\theta)$ denotes the model's prediction for the input data x_i, given the parameters θ. The term $\mathcal{L}$ is the loss function, which quantifies the difference between the predicted output and the actual label y_i. The goal is to find the parameter values θ^* that minimize the total loss over all N training samples [14].

$$\theta^* = \arg\min_\theta \sum_{i=1}^{N} \mathcal{L}(f(x_i;\theta), y_i) \quad (1)$$

Figure 1 shows the dataset is divided into three distinct segments for training, testing and validation purposes. The training set constitutes the largest portion, comprising 80% of the entire dataset, which ensures that the model has a substantial amount of data to learn from. Both the testing and validation set each account for 10% of the dataset, providing a balanced approach for evaluating the model's performance and fine-tuning the hyperparameters respectively. This allocation strategy is crucial for achieving a reliable and generalized model, as it allows for thorough training while simultaneously preserving sufficient data for unbiased testing and validation.

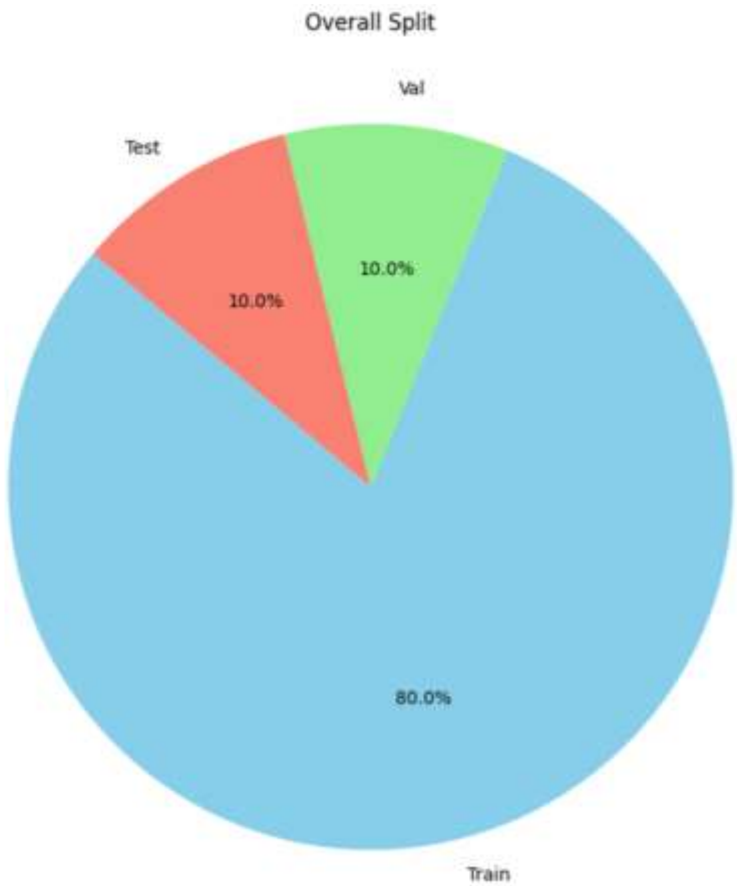

Fig. 1. Dataset split for train, test and validation

As shown in Figure 2, the images depict samples of tomato leaves affected by Septoria leaf spot, a common fungal disease. The symptoms are characterized by circular spots with grey centres and dark borders, which are clearly visible in the provided samples.

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Fig. 2. Tomato disease example: tomato septoria leaf spot sample

As shown in Figure 3, the images illustrate healthy tomato leaf samples. These leaves exhibit no signs of disease or distress, demonstrating a uniform green colour and smooth texture, serving as a baseline for comparison against diseased samples.

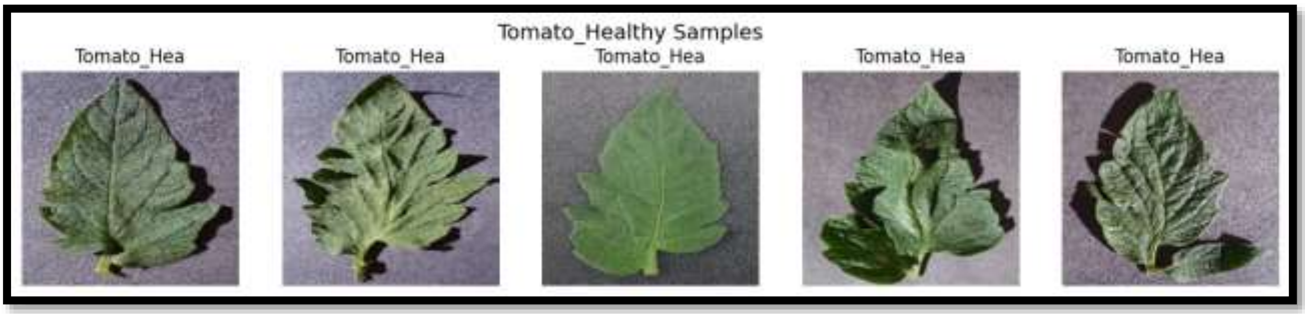

Fig. 3. Tomato healthy example: tomato healthy sample

Figure 4 shows the potato leaves exhibiting early blight symptoms, caused by the fungus Alternaria solani. The affected leaves show irregular brown spots with concentric rings, which are distinctive features of early blight.

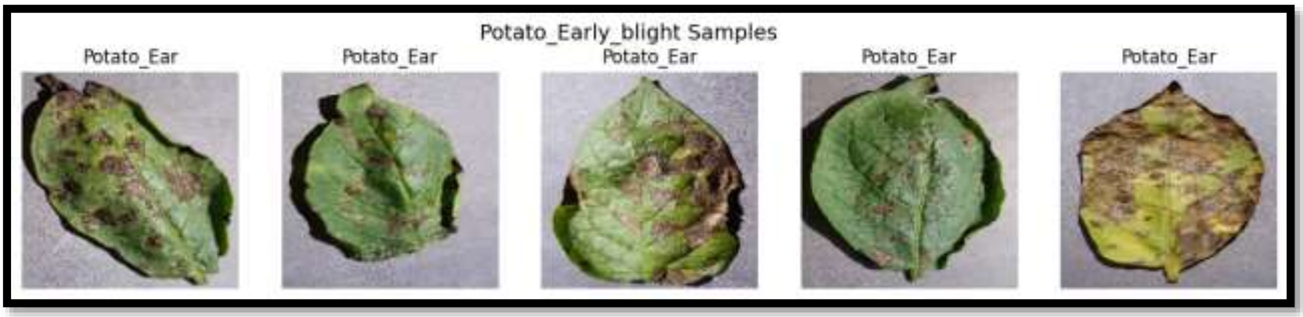

Fig. 4. Potato disease example: potato early blight samples

As shown in Figure 5, the images present healthy potato leaf samples. These leaves are free from any disease symptoms, displaying a consistent green hue and intact structure, which contrasts with the diseased samples shown in the previous figure.

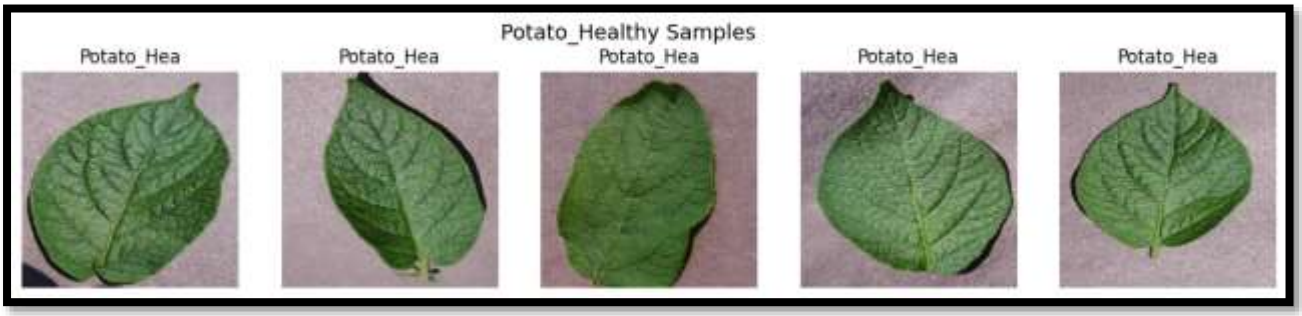

Fig. 5. Potato disease example: potato early blight samples

5. Results

The evaluation of the CNN models—VGG16, ResNet50 and EfficientNet-B1—was conducted using the PlantVillage dataset, which provided a comprehensive benchmark for assessing the models' performance in detecting and classifying crop diseases. The results were analysed using various metrics, including accuracy, precision, recall and F1-score. Statistical methods such as ANOVA and t-tests were employed to validate the findings and ensure their reliability.

Table 1 presented the overall model results where EfficientNet-B1 outperformed the other models with the highest accuracy and F1-score, followed by ResNet50 and VGG16. The results indicate that EfficientNet-B1 is the most effective model for crop disease detection in this study.

Table 1
Overall model results

Model	Accuracy	F1 Score
ResNet50	0.979693	0.979968
VGG16	0.992865	0.992853
EfficientNet-B1	0.994512	0.994516

As shown in Table 2, EfficientNet-B1 achieved the best performance in classifying diseases for both tomato and potato crops. This demonstrates its versatility and robustness across different types of plant diseases.

Table 2
Best model for specific crops class

Class	Best Model
Potato Early Blight	VGG16
Potato Healthy	ResNet50
Potato Late Blight	EfficientNet-B1
Tomato Bacterial Spot	EfficientNet-B1
Tomato Early Blight	EfficientNet-B1
Tomato Healthy	VGG16
Tomato Late Blight	EfficientNet-B1
Tomato Leaf Mold	VGG16
Tomato Septoria Leaf Spot	VGG16
Tomato Target Spot	VGG16
Tomato Yellow Leaf Curl Virus	ResNet50
Tomato Mosaic Virus	VGG16
Tomato Two-Spotted Spider Mites	ResNet50

The VGG16 model exhibited steady improvement in both loss and accuracy metrics during training as shown in Figure 6, but it lagged behind ResNet50 and EfficientNet-B1 in overall performance.

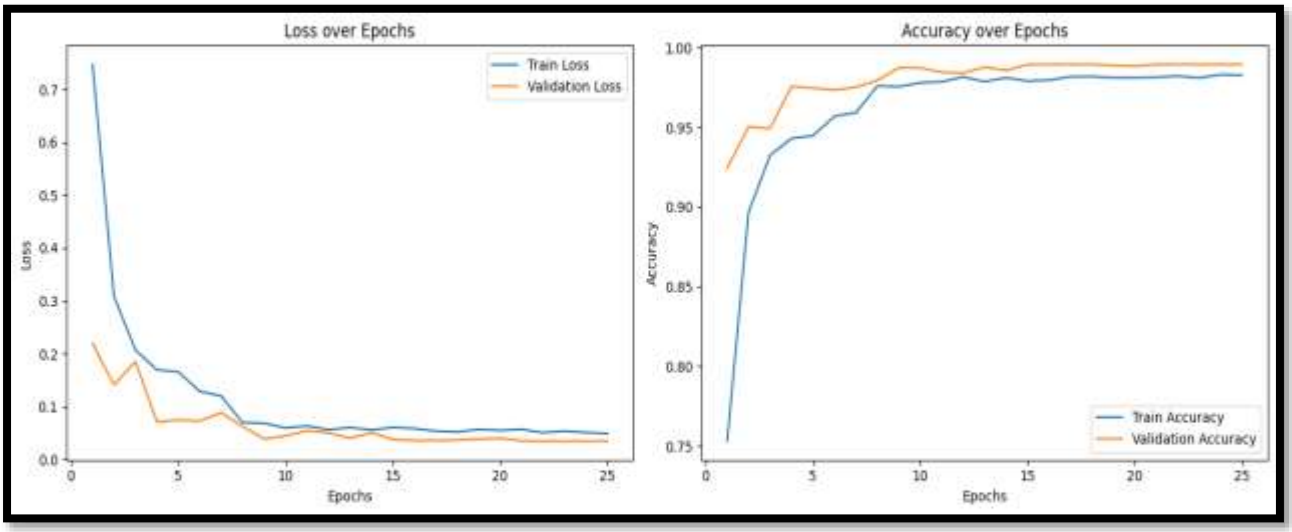

Fig. 6. VGG16 loss and accuracy statistic results

While in Figure 7, ResNet50 showed significant improvements in loss and accuracy, outperforming VGG16 and approaching the performance of EfficientNet-B1.

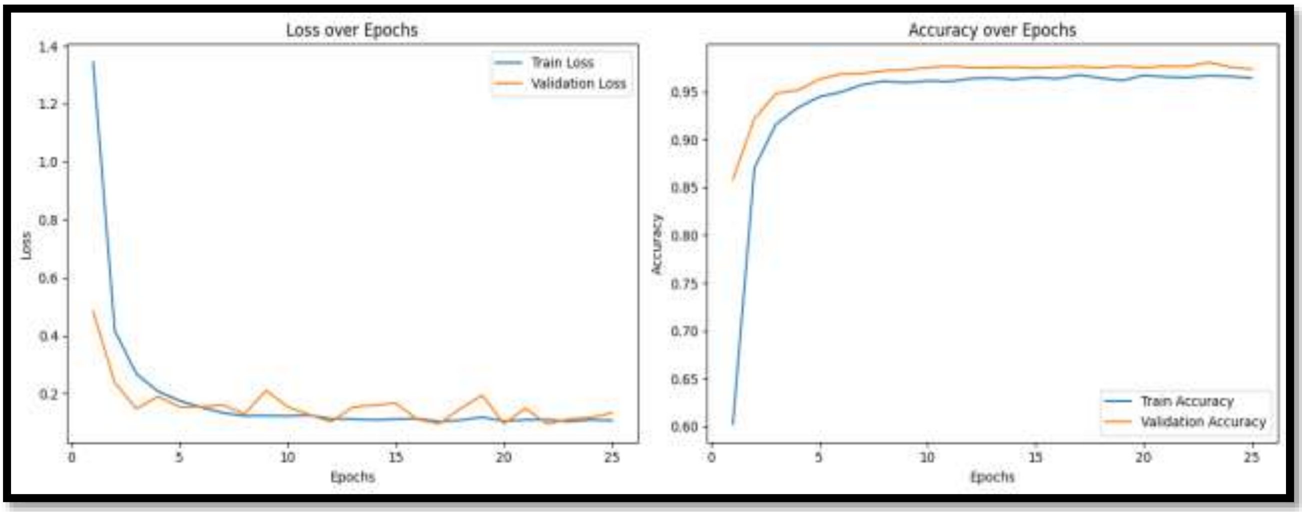

Fig. 7. RestNet50 loss and accuracy statistic results

As shown in Figure 8, EfficientNet-B1 demonstrated superior performance with the lowest loss and highest accuracy among the three models, highlighting its efficiency and effectiveness in crop disease detection.

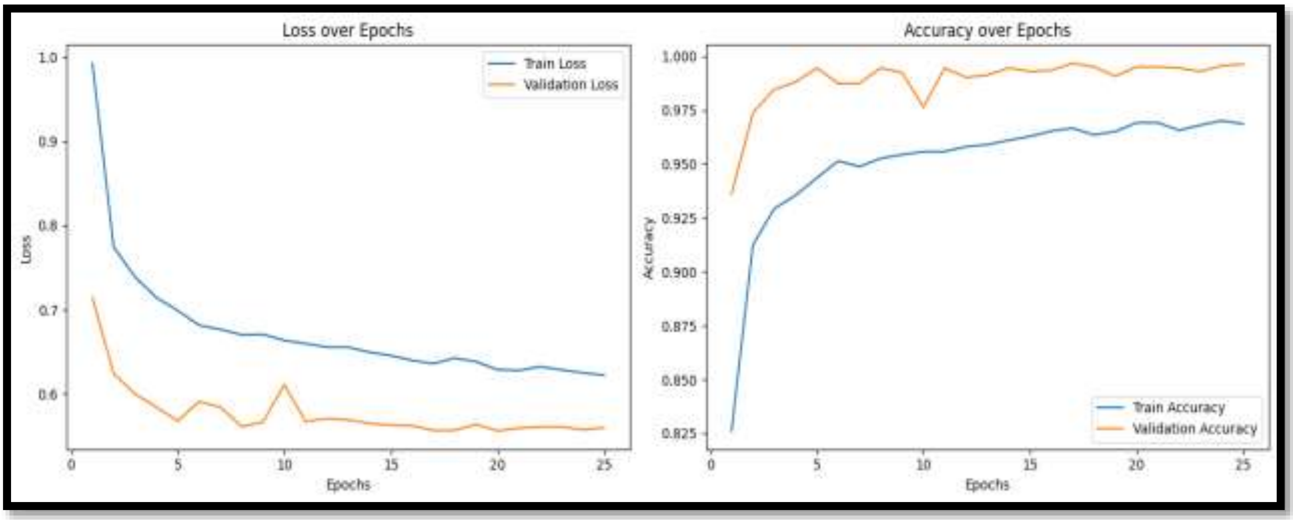

Fig. 8. EfficientNet-B1 loss and accuracy statistic results

Table 3 shows the ANOVA results that indicate a statistically significant difference in the performance metrics (accuracy and F1-score) among the three models, confirming the superior performance of EfficientNet-B1.

Table 3
ANOVA results

Metric	F-statistic	p-value
Accuracy	509.2918	2.0082
F1-score	5627.3151	1.5127

As shown in Table 4, the t-test results for accuracy reveal that EfficientNet-B1's performance is statistically significantly better than that of VGG16 and ResNet50, supporting the findings from the overall model results.

Table 4
T-test accuracy results

Comparison	t-statistic	p-value
VGG-16 vs. ResNet50	21.19894	2.92738
VGG-16 vs. EfficientNet-B1	-10.71201	0.00043
ResNet50 vs. EfficientNet-B1	-24.45500	1.65903

Table 5 shows the t-test results where EfficientNet-B1 outperforms the other models in terms of F1-score, with statistically significant differences in F1-scores compared to VGG16 and ResNet50.

Table 5
T-test results for F1-score

Comparison	t-statistic	p-value
VGG-16 vs. ResNet50	71.05976	2.35008
VGG-16 vs. EfficientNet-B1	-18.3455	5.19369
ResNet50 vs. EfficientNet-B1	-89.4337	9.37097

6. Conclusion

This study successfully demonstrates the application of convolutional neural network (CNN) models—VGG16, ResNet50 and EfficientNet-B1—in detecting and classifying crop diseases in tomato and potato plants using the PlantVillage dataset. By leveraging transfer learning and various optimization techniques, the research enhances the accuracy and efficiency of these models, providing a robust solution for real-time disease detection in agriculture. The findings reveal that EfficientNet-B1 outperforms the other models in terms of accuracy and F1-score, making it the most effective model for this task. The development of a web application further underscores the practical implications of this research, offering a user-friendly tool for farmers and agricultural experts to promptly identify and manage crop diseases.

The integration of advanced AI techniques into agricultural practices not only addresses the critical challenge of crop disease detection but also contributes to the broader goal of promoting sustainable agriculture and ensuring food security in Malaysia. This research highlights the potential of CNN models to transform agricultural diagnostics, providing insights that can guide future innovations in this field. The results underscore the importance of continued research and development in AI-based agricultural technologies, advocating for the expansion of datasets and the exploration of additional optimization strategies to further improve model performance.

Future work should focus on integrating these models with other agricultural data sources to develop more comprehensive decision-support systems. Additionally, investigating the application of emerging deep learning architectures, such as capsule networks and vision transformers, could provide further enhancements in disease detection capabilities. Overall, this study lays a solid foundation for the adoption of AI in agriculture, paving the way for more resilient and efficient crop management practices.

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