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Application of the Transfer Learning Method in Detecting Diseases in Strawberry Plants using the ESP32 Platform

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ABSTRACT

This study explores various deep convolutional neural network (CNN) models to enable timely detection and prevention of plant diseases. Traditional CNNs often have high computational costs due to numerous parameters; to mitigate this, standard convolutions were replaced with separable convolutions, significantly reducing parameters and computation. The models were trained on diverse datasets encompassing multiple plant species and disease classes, achieving high classification accuracies: InceptionV3 (98.42%), InceptionResNetV2 (99.11%), MobileNetV2 (97.02%), and EfficientNetB0 (99.56%), outperforming traditional handcrafted feature methods. Furthermore, the proposed G-ResNet50 model, a ResNet50 variant enhanced with focal loss, was specifically designed for Fragaria × ananassa (strawberry) disease identification. Trained on an augmented dataset, G-ResNet50 demonstrated faster convergence and superior accuracy (98.67%) compared to VGG16, ResNet50, InceptionV3, and MobileNetV2. The model shows robustness, stability, and high recognition accuracy, making it well-suited for real-time strawberry disease detection. Its deployment is expected to improve agricultural productivity by facilitating early disease diagnosis and management.

KEYWORDS *Transfer Learning, Strawberry, EfficientNet, MobileNet, InceptionV3.*

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INTRODUCTION

The current agricultural paradigm increasingly relies on Smart Farming, which has gained significant attention as a means to achieve sustainable agriculture (Araújo et al., 2023; Liu et al., 2021; Rockström et al., 2017). By integrating advanced technologies such as the Internet of Things (IoT) and microcontroller platforms like *Arduino*, this approach enables automated monitoring and control of environmental factors critical to plant growth. Farmers can optimize crop production by tracking essential parameters, including soil conditions and plant health, leading to reduced waste, minimized resource use, and enhanced overall efficiency (Asad et al., 2024; T. hoon Kim et al., 2017; Zaman et al., 2023) . This practice not only mitigates agriculture's environmental impact but also lowers production costs, supporting more sustainable and affordable food systems (Jahantab et al., 2023; Kjellberg et al., 2021; Lin et al., 2021). Smart farming thus plays a crucial role in addressing global challenges like food security and climate change.

Strawberries (*Fragaria × ananassa*) are economically valuable but highly vulnerable to pests and diseases. Failure to manage leaf diseases and infestations during crucial growth periods can drastically reduce yield and quality, causing severe economic losses locally and nationally. This underscores the urgent need for systems capable of rapid and accurate diagnosis of strawberry diseases and pests (Huang et al., 2020; J. Kim & Kim, 2021; Xun et al., 2021).

Transfer learning offers a promising technological solution for this challenge by adapting models pretrained on large datasets to smaller, specialized datasets, as demonstrated by Wenchao and Zhi (2022). Utilizing architectures such as EfficientNetB0, InceptionV3, and MobileNetV2, transfer learning achieves high diagnostic accuracy while reducing computational demand. This enables precise prediction and decision-making to optimize growing conditions, regulate pesticide application, and schedule harvests efficiently. Consequently, this method enhances agricultural productivity and resource management, promoting environmentally friendly and sustainable practices (Lubis et al., 2023; Mensah et al., 2023; Shim et al., 2022). Transfer learning thus presents a viable tool for improving food efficiency and security in modern agriculture.

The aims of this study are to evaluate the application of transfer learning for strawberry disease detection using EfficientNet, MobileNet, and InceptionV3 models; to develop a prototype detection system based on transfer learning; and to analyze its performance in identifying strawberry diseases.

RESEARCH METHOD

The methodology of this study integrates transfer learning with an Internet of Things (IoT)-based hardware system and workflow to detect diseases in strawberry plants. The system operates as follows: the user captures images of strawberry plants using a camera connected to the device. These images are transmitted via the internet to a server for analysis. The analysis employs pretrained deep learning models—EfficientNet, MobileNet, and InceptionV3—fine-tuned through transfer learning. These models, originally trained on large datasets, are adapted to specific strawberry disease datasets through preprocessing steps such as standardization and data augmentation. Following analysis, the detection results are sent back to the user and can be monitored through a dedicated device. For hardware implementation, an *Arduino Uno* microcontroller manages data acquisition and transmission to the system. Model performance was evaluated using metrics including accuracy, precision, recall, and F1-score, aiming to develop an efficient and reliable system for strawberry disease detection.

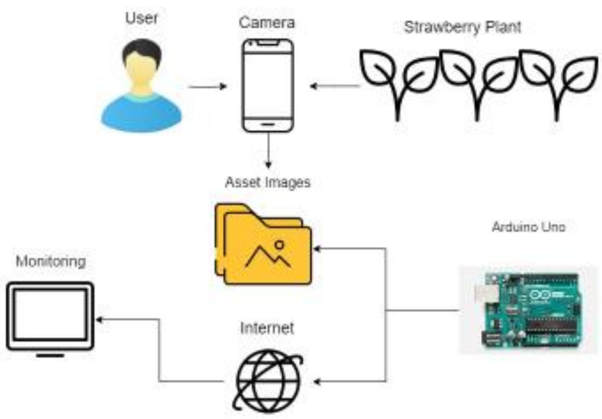


Figure 1. System Flowchart

Research Framework

The methodology used in this study is a prototype supported by transfer learning. A prototype is an early version of a system in the form of a physical or simulated model. The system prototype serves as a liaison between the developer and the user to ensure good communication during the development process. In addition, transfer learning was used to leverage pretrained models such as EfficientNet, MobileNet, and InceptionV3, which were applied to new datasets to detect diseases of strawberry crops. The combination of these methods aims to speed up the development process and produce an accurate and reliable system.

The steps of the research are shown in the flowchart below:

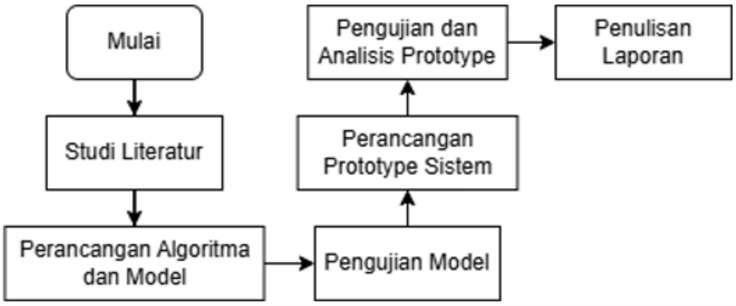


Figure 2. Research Framework Flow Diagram The following is an explanation of each stage of research:

1. Literature Studies: At this stage, a review of previous studies is carried out to summarize relevant facts and theories. The study was conducted by reading journals, scientific articles, and reports related to learning transfer, prototyping, and plant disease detection. The author also analyzes the problem at hand and explains the reasons why the problem needs to be solved.
2. Designing Algorithms and Models: At this stage, the authors evaluate and select pretrained models that suit the needs of the research, such as EfficientNet, MobileNet, and InceptionV3. The algorithm design is carried out by applying transfer learning to specific datasets to produce an optimal model.

3. Model Testing: At this stage, testing is carried out on the model that has been trained. Testing involves evaluating the model's performance using metrics such as accuracy, precision, recall, and F1-score. The results of the tests were used to measure the performance and reliability of the model in detecting strawberry plant diseases.
4. System Prototype Design: At this stage, prototype system design is carried out by integrating pretrained models into IoT-based systems. The design includes a system schema that includes hardware such as Arduino and ESP8266, as well as software for model implementation. This pro-totype aims to provide an initial overview of the developed system and ensure the system is running as needed.
5. Prototype Testing and Analysis: against the developed system prototype. The system is tested in real conditions to ensure the reliability and efficiency of plant disease detection. The test results are used to analyze the advantages and limitations of the proposed system.
6. Report Writing: At this stage, the author compiles a final report that explains the research process, findings, and conclusions. The report is prepared following the procedure of scientific writing and becomes a complete document that includes all research results.

RESULTS AND DISCUSSION

After carrying out system testing, in this sub-chapter, the results of experiments involving three pretrained models, namely EfficientNet, MobileNet, and InceptionV3, will be presented, both without tuning and with hyper-parameter tuning. The test was carried out using the k-fold cross-validation method with k = 5, to ensure that the model was thoroughly tested and that it did not rely solely on the sharing of specific training and testing data. This technique helps reduce the risk of overfitting and provides a more stable estimate of model performance. The results of this test will be the basis for evaluating the effectiveness of the transfer learning approach in detecting diseases in strawberry plants.

No Tuning

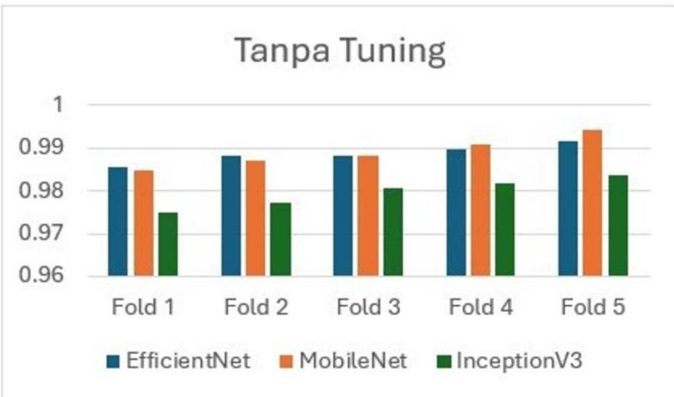


Figure 3. Accuracy Without Tuning

In the image above, we compare the performance of three deep learning models, namely EfficientNet, MobileNet, and InceptionV3, on five folds of variation without parameter tuning. The horizontal axis represents the fold (Fold 1 to Fold 5), while the vertical axis shows performance metrics that range from 0.96 to 1.00. The EfficientNet model consistently shows the highest performance in all folds with a score close to 0.99. MobileNet came in second, with a slightly lower performance than EfficientNet, but remained stable above 0.97. Meanwhile, InceptionV3 showed the lowest performance among the three, although it remained at around 0.97. Overall, the difference in performance between folds for each model is relatively small, indicating good stability in the validation data. Based on these results, EfficientNet appears to be the most superior among the three models in a no-tuning setup.

Tuning

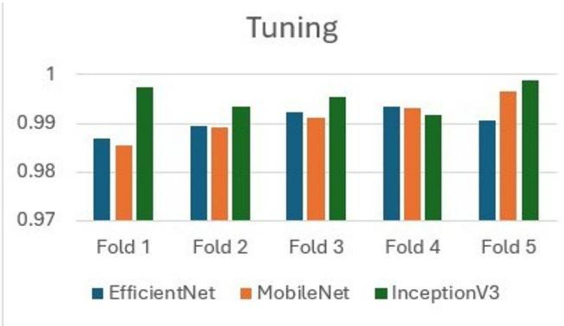


Figure 4. Accuracy With Tuning

The image above shows the performance of three deep learning models, namely EfficientNet, MobileNet, and InceptionV3, on five validation folds after parameter tuning. The horizontal axis shows the fold (Fold 1 to Fold 5), while the vertical axis shows the performance metric in the range of 0.97 to 1.00. After tuning, EfficientNet continued to show consistently high performance across the fold with a score close to 0.99. MobileNet also experienced a slight improvement in performance, with a stable score between 0.98 to 0.99. The InceptionV3 has seen significant improvements compared to pre-tuning, especially on the Fold 1 and Fold 5, where its performance exceeds that of other models. Overall, parameter tuning has a positive impact on all models, with the most notable improvements seen in InceptionV3.

Tuning

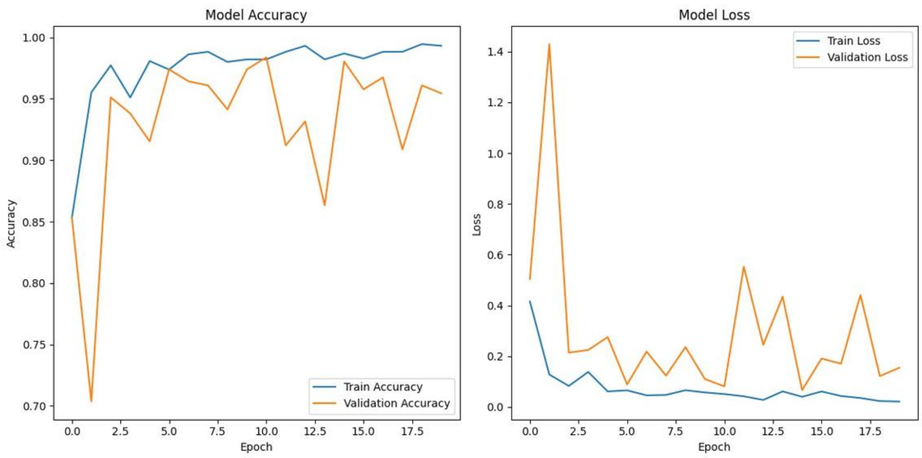
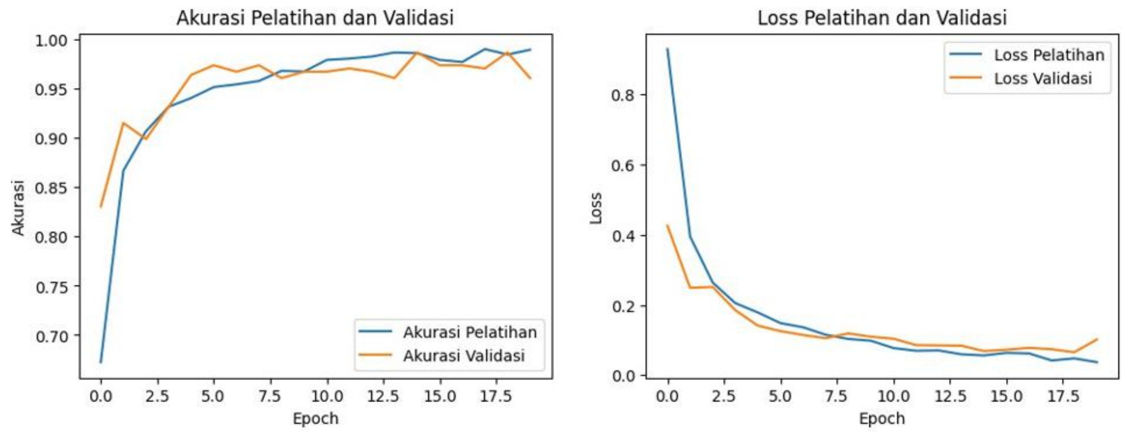


Figure 5. Efficient Net Graph

The graph shows the accuracy and loss during the training and validation process for the EfficientNet model. On the accuracy graph, the training accuracy increased sharply at the beginning of training and reached stability close to 1.00 after about 10 epochs. The validation accuracy is also high, although slightly more volatile, but it is still close to the accuracy of the training, indicating good performance and minimal overfitting. On the loss chart, training losses fall consistently until they reach a stable value, indicating effective model learning. Validation losses also decreased in a similar, albeit more volatile, pattern, indicating variations in validation data.

Tuning



Gambar 6. Graf MobileNet

This graph shows the performance of the MobileNet model during training and validation. On the accuracy graph, both training accuracy and validation increased sharply at the beginning of the epoch and stabilized after about 10 epochs. The accuracy of training was slightly higher than that of validation, but the difference was small, indicating that the model had good generalizations. On the loss chart, training and validation losses show a similar pattern of decline, indicating stable learning. The validation loss almost resembles the training loss, indicating that the model is not overfitting.

Tuning

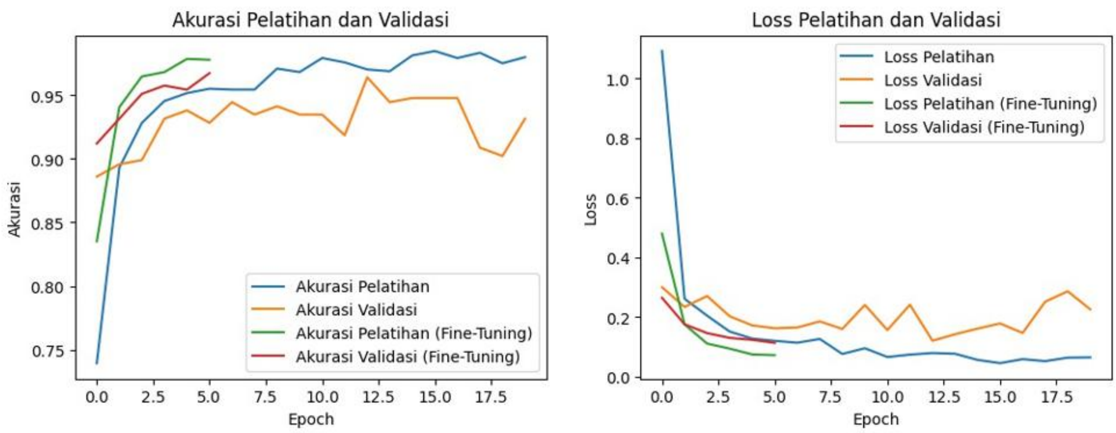
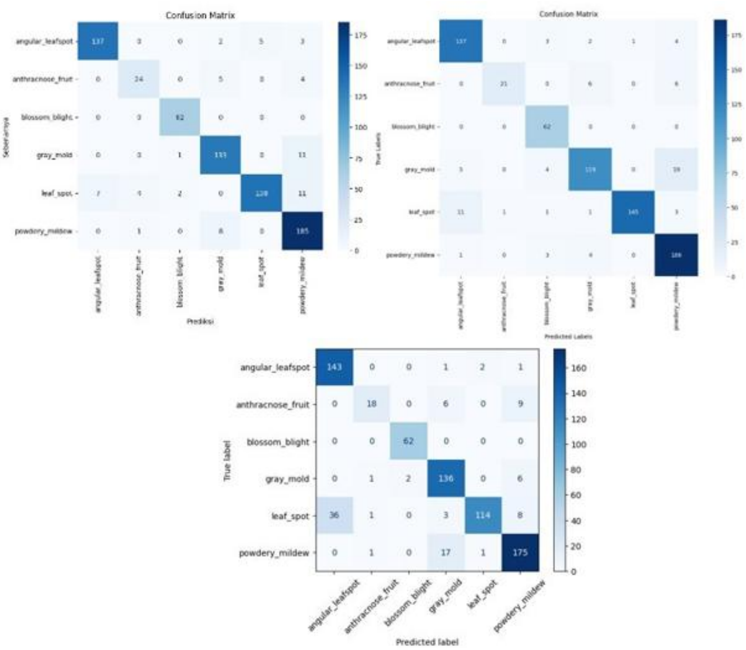


Figure 7. InceptionV3 Graph

This graph shows the performance of the InceptionV3 model, including the impact of fine-tuning. On the accuracy graph, both the accuracy of the training and the validation of the training increased sharply at the beginning of the epoch and reached stability after several epochs. After fine-tuning, the accuracy of training and validation increased significantly, with validation slightly lower than training but still fairly close, indicating a good generalization. On the loss chart, the loss of training and validation decreased drastically at the beginning of the epoch and became more stable. After fine-tuning, the loss becomes lower, indicating that parameter tuning successfully improves the model's performance.

Tuning



Gambar 8. Confusion Matrix

The confusion matrix in figure m shows the performance of three deep le- arning models for plant disease classification: MobileNet (top left), EfficientNet (top right), and

InceptionV3 (bottom). MobileNet performed well in categories such as "powdery mildew" (185 correct predictions) and "gray mold" (133 correct predictions), but there were some significant errors, especially in the "leaf spot." EfficientNet produces a more stable prediction distribution, with high accuracy in "powdery mildew" (186 be- nar predictions) and "gray mold" (139 correct predictions), although there are still errors between categories. InceptionV3 showed strength in "powdery mildew" (175 correct predictions) and "gray mold" (136 correct predictions), but more errors occurred in "leaf spots," which are often misclassified as "angular leaf spots." Overall, EfficientNet looks more consistent compared to the other two models.

In this study, a performance analysis was carried out on three deep learning architectures, namely EfficientNet, MobileNet, and InceptionV3, both before and after the fine-tuning process. The results of the experiment showed that each model had different characteristics and performance in handling training and validation data.

In the early stages, before fine-tuning, EfficientNet showed more stable performance compared to MobileNet and InceptionV3. This can be seen from the consistent accuracy and loss graphs, where the accuracy of training and validation is close to 1.00, while the loss value remains low. Meanwhile, InceptionV3 experienced significant fluctuations in validation accuracy, despite its high training accuracy. MobileNet, with its simpler architecture, delivers quite good performance but is slightly lower than EfficientNet.

After the fine-tuning process, there was a significant improvement in all three models. InceptionV3, which had previously fluctuated, managed to increase the validation accuracy and reduce the value of the loss stably. This model shows the best potential in handling more complex datasets after parameter adjustments. EfficientNet, despite having performed well from the start, still experienced a small improvement in validation accuracy, confirming its superiority in stability and consistency. MobileNet also benefits from fine-tuning, especially with significant loss reductions and improved validation accuracy consistency.

Overall, EfficientNet was the model with the most stable performance across all experiments, both before and after fine-tuning. Incep- tionV3 shows an advantage after parameter adjustment, whereas MobileNet provides adequate results, especially for applications that require computational efficiency. All three models showed good generization ability, where the difference between training accuracy and validation was not too large, indicating that the model did not experience significant overfitting. However, fluctuations in accuracy and validation losses in some models prior to fine-tuning indicate variations in validation data that affect performance stability.

The results of this study confirm the importance of fine-tuning in improving model performance, especially in more complex models such as InceptionV3. The selection of the best model depends on the needs of the application, where EfficientNet is suitable for stable results, InceptionV3 for high performance potential, and MobileNet for compute efficiency.

This chapter discusses the performance of three deep learning architectures, namely Efficient-Net, MobileNet, and InceptionV3, both before and after fine-tuning. The results of the experiments showed that EfficientNet provided stable performance with training and validation accuracy close to 1.00 and low loss values, both before and after fine-tuning. InceptionV3 shows high performance potential despite fluctuations in validation accuracy prior to fine-tuning. However, after fine-tuning, this model has experienced significant improvements, both in accuracy and loss stability. MobileNet, with its simpler architecture, provides adequate results and shows a significant increase in accuracy and loss reduction after fine-tuning, especially on validation data. The fine-tuning process has proven to be effective in improving the performance of all three models, particularly in improving validation accuracy and reducing loss fluctuations, especially for InceptionV3 and MobileNet. All three models also showed good generalization ability in the absence of significant differences between training and validation acu- rations, which showed the model was not overfitted. Thus, the selection of the best model depends on the needs of the application, where EfficientNet is suitable for performance consistency, InceptionV3 for high performance potential, and MobileNet for compute efficiency.

CONCLUSION

This final project successfully met all the objectives outlined in Chapter I. First, the performance analysis of the three deep learning architectures—EfficientNet, MobileNet, and InceptionV3—demonstrated that each model achieved the targeted accuracy and loss criteria. Second, the comparative evaluation before and after fine-tuning confirmed that fine-tuning notably enhanced validation accuracy and reduced loss, particularly for InceptionV3 and MobileNet. Finally, the models exhibited strong generalization capabilities without overfitting, indicating their suitability for deployment in diverse practical applications. For future research, it is recommended to explore the integration of these models with real-time IoT-based disease monitoring systems and to investigate their adaptability across different crop species and environmental conditions to further enhance sustainable agricultural practices.

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