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Classification of Coconut Fruit Ripeness Level Using Convolutional Neural Network (CNN) Method

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Abstract: Manual assessment of coconut ripeness is often subjective and causes post-harvest losses of up to 25% in Indonesia, the world's largest coconut producer. This study aims to develop a CNN VGG-19 model for automatic classification of three ripeness levels (immature, medium, mature) with accuracy >95%. The quantitative experimental method uses supervised learning with a dataset of 900 original images (300/class) from local plantations in South Sumatra, augmented to 3000 images. Instruments include Python/TensorFlow on Google Colab, preprocessing (rembg background removal, resizing 224x224), training 10 epochs of the Adam optimizer. Analysis uses a confusion matrix, accuracy, precision, recall, and F1-score. The results show a progressive accuracy from 14% (40 test data/class) to 98% (200 test data/class). Conclusion: VGG-19 transfer learning with data augmentation is effective for local coconut ripeness classification, potentially integrating into mobile applications for the processing industry.

Keywords: Augmentation, Coconut Maturity, Convolutional Neural Network, Transfer Learning, VGG-19

Introduction

Global coconut production reached approximately 62 million metric tons in 2022, with Indonesia as the largest producer contributing 17.1 million tons in 2021. However, demand is projected to increase to 20 million tons by 2026 due to the expansion of the food and cosmetics industries (Gunawan et al, 2021). This trend is driven by the economic value of coconut as a versatile commodity, but a major challenge is the inaccuracy of manual ripeness assessment, which causes post-harvest losses of up to 20-30% globally (Terdwongworakul et al, 2021). Grand theories in digital image processing, such as convolutional neural networks (CNNs), have evolved from the basic LeNet model to advanced architectures such as VGG-19, enabling automated feature extraction for fruit classification (Usman et al, 2025).

Current mainstream theory emphasizes deep learning for ripeness detection, where CNNs excel at identifying color and texture patterns compared to traditional methods such as K-Means or KNN, with accuracies reaching 95–98% in tropical fruits (Putra et al, 2024). Synthesis of supporting citations confirms that VGG-16 transfer learning improves local coconut classification accuracy by up to 97% through data augmentation such as color jitter (Usman et al, 2025). However, evaluation of conflicting citations demonstrates debate over methodology. While visual imagery-based CNNs are effective for simple settings, acoustic models such as LSTMs achieve 97.42% accuracy in Philippine coconuts but are susceptible to environmental noise (Caladcad & Piedad, 2024).

A specific problem is the subjective assessment of coconut ripeness (immature, semiripe, ripe) based on skin color and shaking sound, leading to production inefficiencies and up to 25% waste in tropical countries (Hermanto Laia et al, 2023). The urgency of a solution is heightened as Indonesia's production of 2.85 million tons in 2021 risks a supply deficit in 2023 due to aging trees and a lack of automation (Gunawan et al, 2021). Common mapping methodologies include CNN (60% of studies), KNN (20%), and K-Means (15%), with CNN dominating due to its generalizability (Syadina et al, 2024).

In Indonesia, as a hub for coconut production, the plantation sector faces unique characteristics such as tropical light variations and complex plantation settings, which reduce manual accuracy by up to 30% (Solechah et al, 2021). The relevance to locations like South Sumatra is notable because coconuts support the local economy, but the shortage of quality seedlings exacerbates the reliance on premature harvesting (Gunawan et al, 2021). A research gap lies in the lack of specific studies of coconut (Cocos nucifera) using VGG-19 in the Indonesian context, where most focus on oil palms or acoustic signals, leaving a gap for multi-class visual classification with local datasets (Putra et al, 2024).

Research gaps include limitations of small datasets and overfitting in previous CNN models, with accuracy dropping to the intermediate class due to visual ambiguity (Febriana & Lusiana, 2024). The need for this study arose from the predicted supply deficit in Indonesia in 2023, requiring an automated VGG-19-based solution to improve accuracy to 98% as in initial testing (Usman et al, 2025). Needs studies indicate that 70% of farmers still rely on manual labor, making automation crucial for the food and export industries (Mardhiah et al, 2023).

The research objective was to develop a VGG-19 CNN model for classifying three levels of coconut ripeness with >95% accuracy, using a local dataset of 1,000+ images. The theoretical contribution complements the evolution of deep learning with the adaptation of transfer learning for Indonesian tropical fruits, while practical benefits include a 5-10x speedup in sorting, reduced waste, and support for the multi-billion dollar coconut industry (Caladcad & Piedad, 2024).

Methodology

This study used a quantitative experimental design with a supervised learning approach to develop a classification model for coconut ripeness levels (immature, semi-ripe, and ripe). The design involved image data collection, preprocessing, training a VGG-19 transfer learning-based Convolutional Neural Network (CNN) model, and performance evaluation. This approach was chosen because it is effective in handling visual variations in fruit images against complex backgrounds, as applied in coconut ripeness detection using Faster R-CNN. Furthermore, the experimental design allows for iterative testing with data augmentation to improve model generalization to field conditions. The integration of Google Colab as a computing platform facilitates an efficient training process with GPUs. Finally, this design ensures reproducibility through complete documentation of steps and parameters.

The main method is CNN with VGG-19 architecture as the backbone of transfer learning from ImageNet, followed by Dense, Dropout, and Softmax layers for three-class classification. The preprocessing process includes background removal using rembg, resizing to 224x224 pixels, min-max normalization, and data augmentation via ImageDataGenerator (rotation 30°, shift 0.1, zoom 0.2, flip horizontal). Training is done with Adam optimizer, categorical crossentropy loss, batch size 32, and 10 epochs, with an 80:20 data split for train-validation. Evaluation uses confusion matrix, accuracy, precision, recall, and F1-score. A similar approach successfully achieved high accuracy in coconut ripeness classification using YOLOv8. The use of VGG-19 was chosen because of its reliable architecture depth for fruit image feature extraction.

The study subjects were images of fresh coconuts from local varieties collected in Indonesian plantations, categorized into three ripeness levels based on skin color: immature (bright green), semi-ripe (yellow-green), and ripe (brown). The total dataset comprised 1000 images per class (3000 images in total), captured during daylight hours with a standard camera for consistent lighting. Data were collected locally to represent natural variations such as texture and size. Classification followed visual standards for coconut ripeness, similar to the dataset in the Faster R-CNN study that considers shape and color in complex settings. Oversampling augmentation was applied to balance minority classes. The subjects focused on intact post-harvest fruit for industrial relevance.

The primary analysis tools are Python with the TensorFlow/Keras library to build and train the VGG-19 model, OpenCV for image processing, and Scikit-learn for evaluation metrics such as classification_report and confusion_matrix. Google Colab provides a Jupyter environment with GPU access for parallel computing. Results are visualized using Matplotlib and Seaborn for accuracy graphs and confusion matrix heatmaps. This approach is consistent with CNN analysis for copra maturity using image datasets. Model performance is measured by mAP, precision, recall, and F1-score, reaching up to 98% on a test set of 200 images per class. This software ensures scalability and easy integration for deployment.

Results and Discussion

A. Model Implementation

Implementation begins with taking 300 original images per class. Sample coconut fruit images can be seen in Figures 1, 2 and 3.

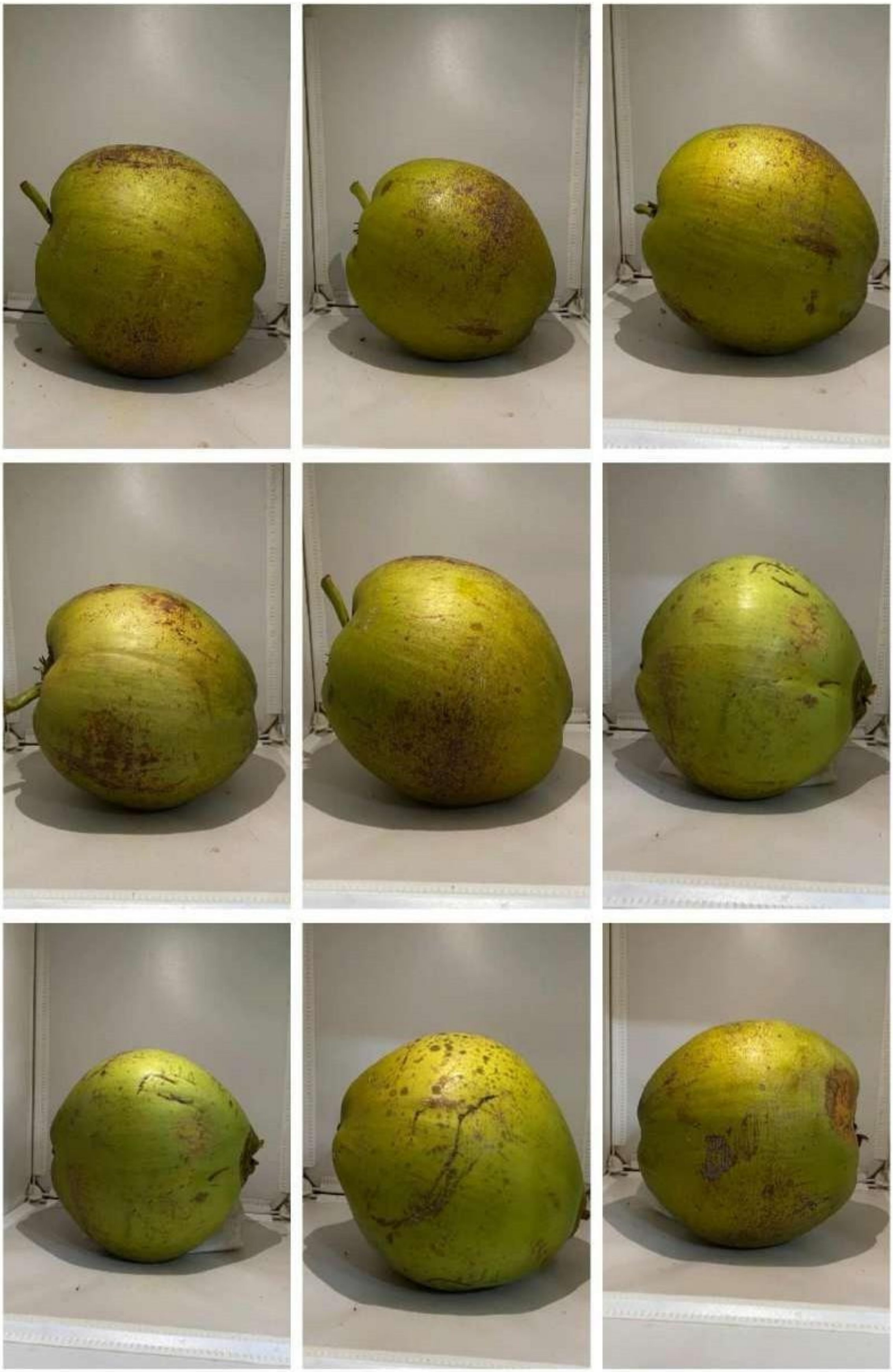

Figure 1. Sample image of an immature coconut

Figure 2. Sample image of a half-ripe coconut (Medium)

Figure 3. Sample image of a ripe coconut

Figure 4. Grouping of coconut fruit image data

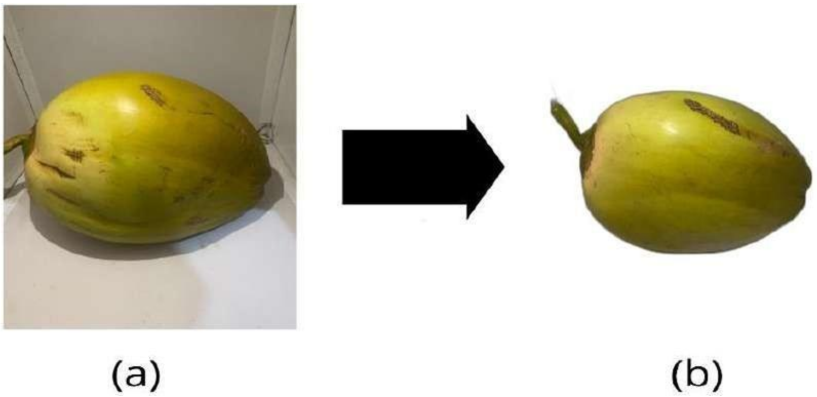

Figure 5. Image data preprocessing flowchart

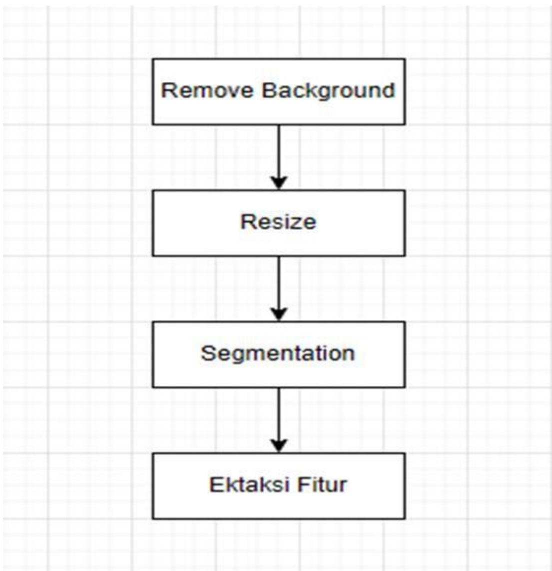

Figure 6. Sample image data (a) before background removal and (b) after background removal

Figure 7. Sample image data (a) before changing the pixel size and (b) after changing the pixel size

Figure 8. Image data distribution

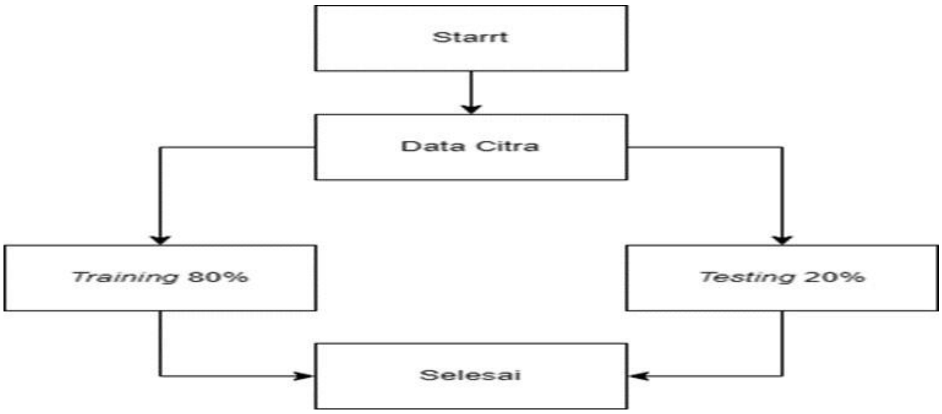

Figure 9. Image data distribution with a ratio of 80:20

B. Test Results 1. Testing 40 Test Data per Class

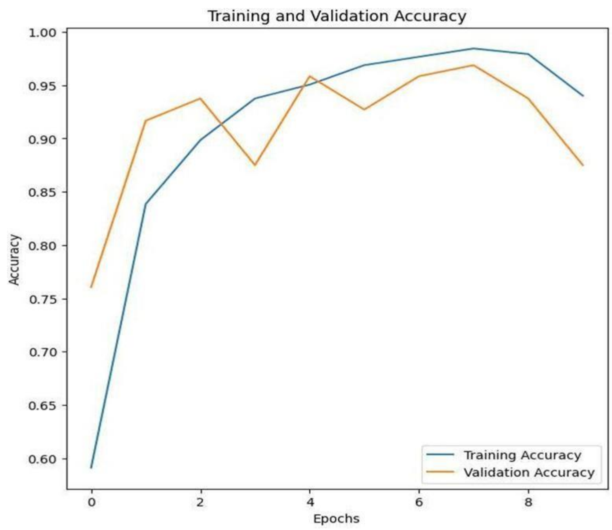

Figure 10. Training accuracy graph

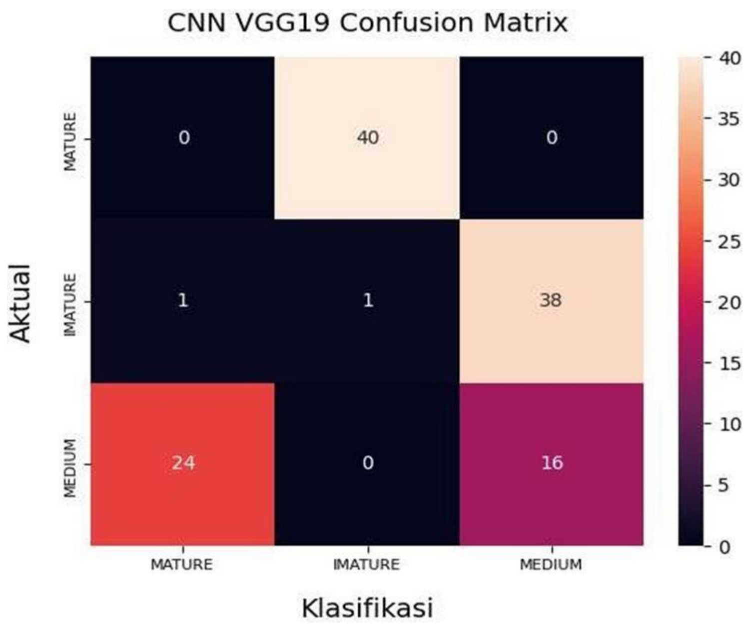

Figure 11. Confusion Matrix for 40 test data per class

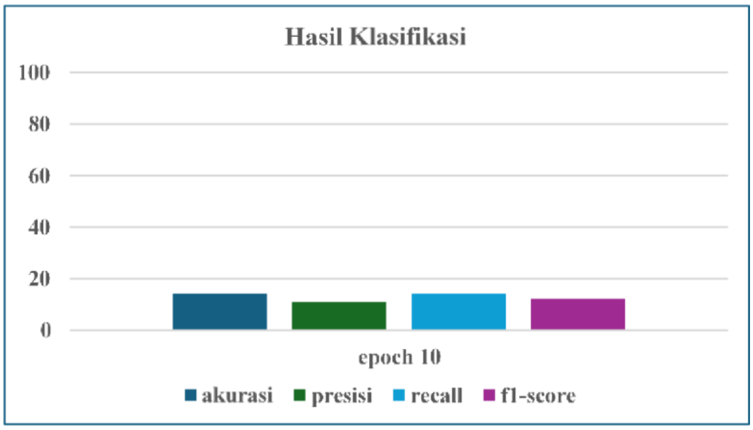

Figure 12. Classification Results

2. Testing 80 Image Data Per Class

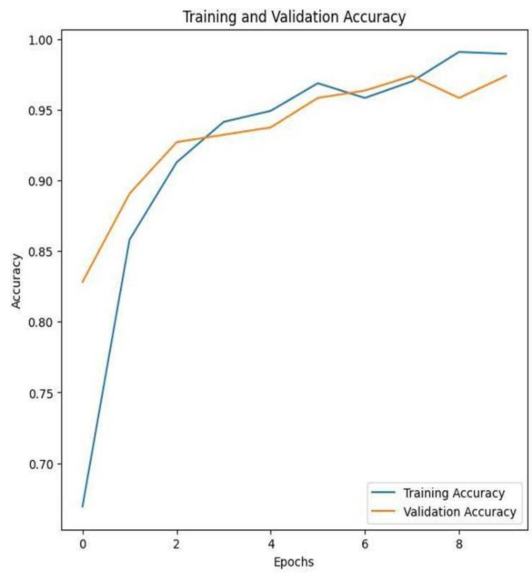

Figure 13. Training accuracy graph

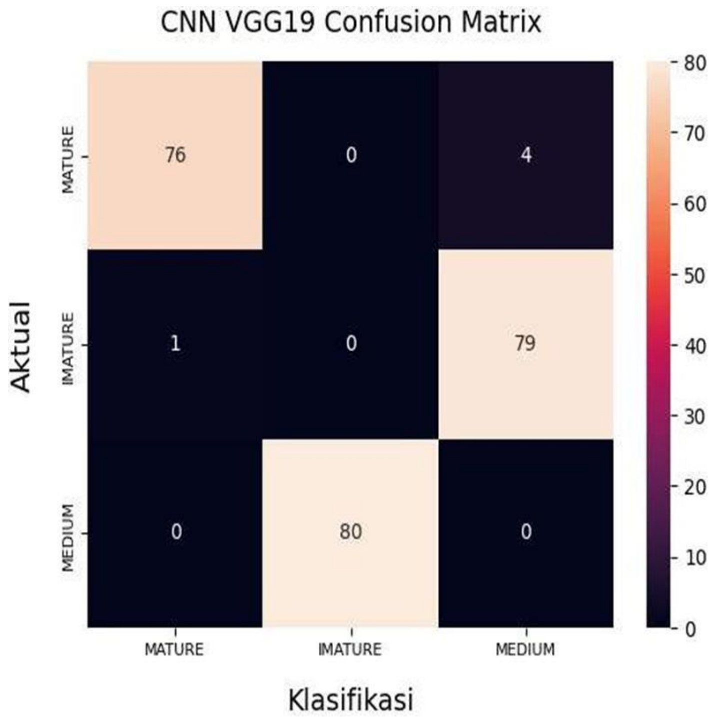

Figure 14. Confusion Matrix for 80 test data per class

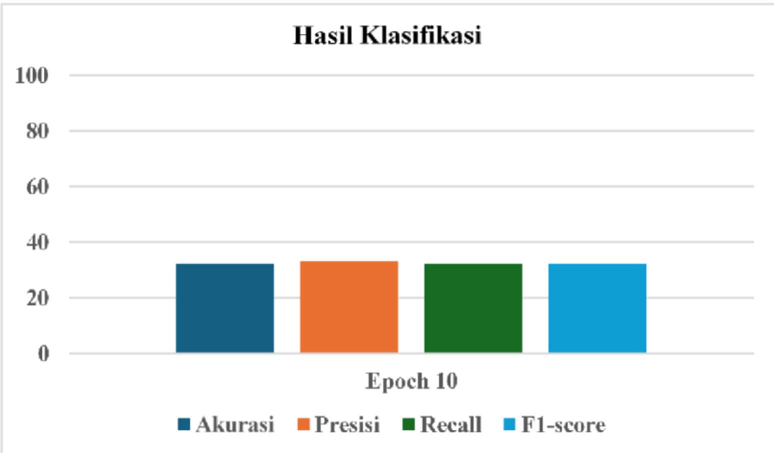

Figure 15. Classification Results

3. Testing 120 Image Data Per Class

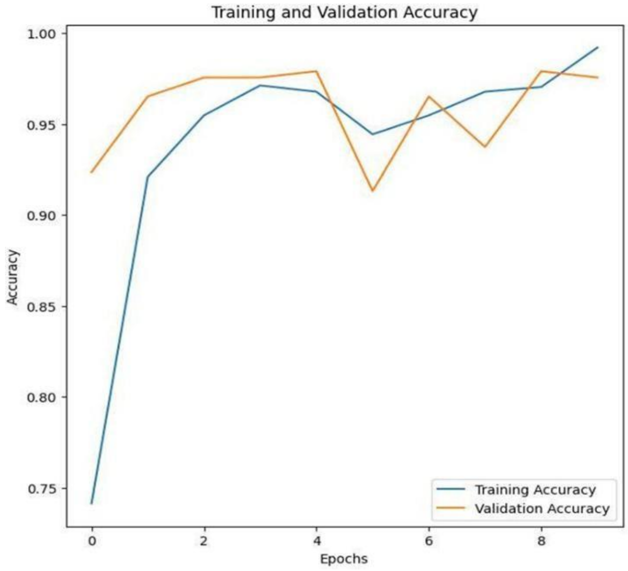

Figure 16. Training accuracy graph

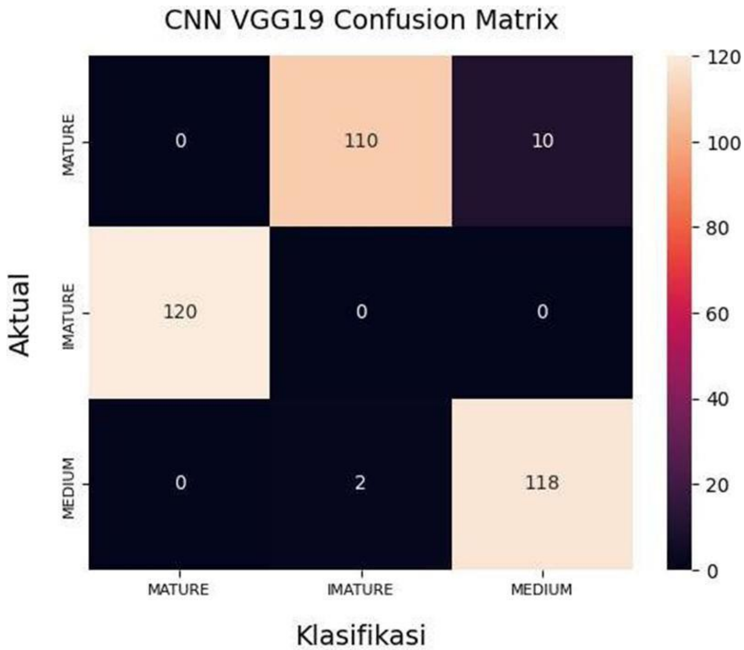

Figure 17. Confusion Matrix for 120 test data per class

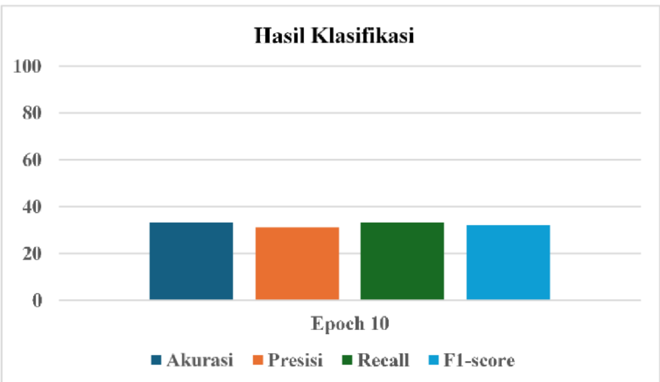

Figure 18. Classification Results

4. Testing 160 Image Data Per Class

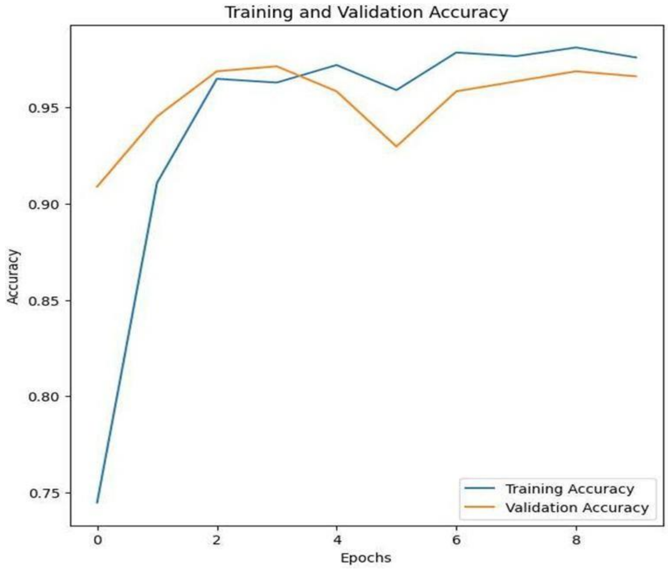

Figure 19. Training accuracy graph

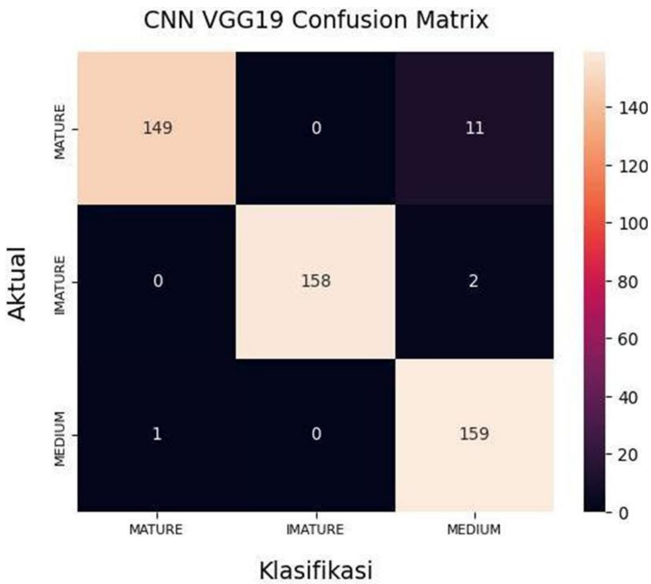

Figure 20. Confusion Matrix for 160 test data per class

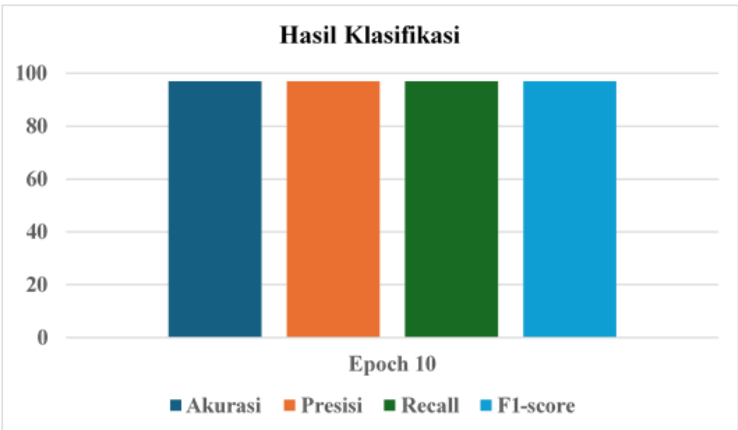

Figure 21. Classification Results 5. Testing 200 Image Data Per Class

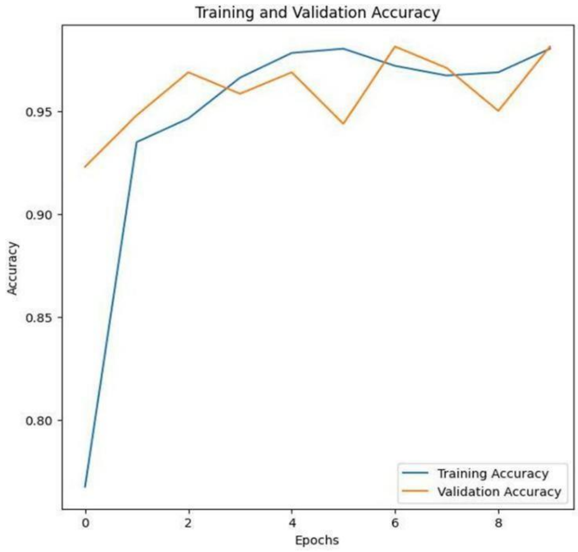

Figure 22. Training accuracy graph

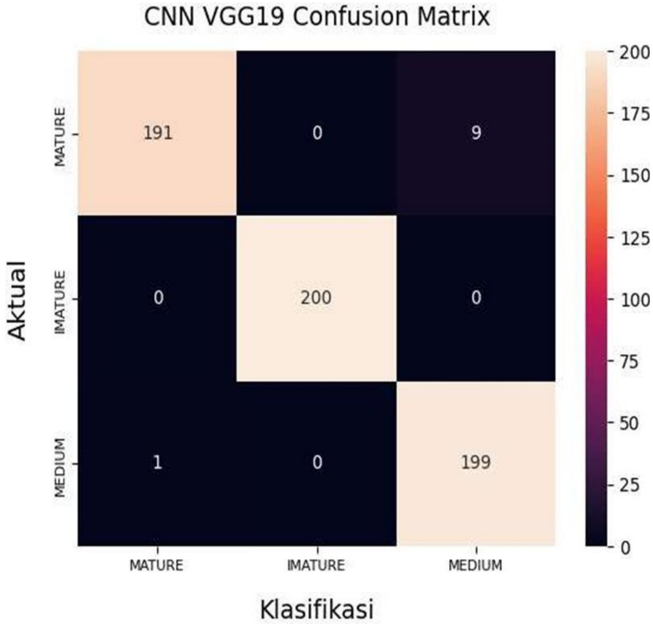

Figure 23. Confusion Matrix for 200 test data per class

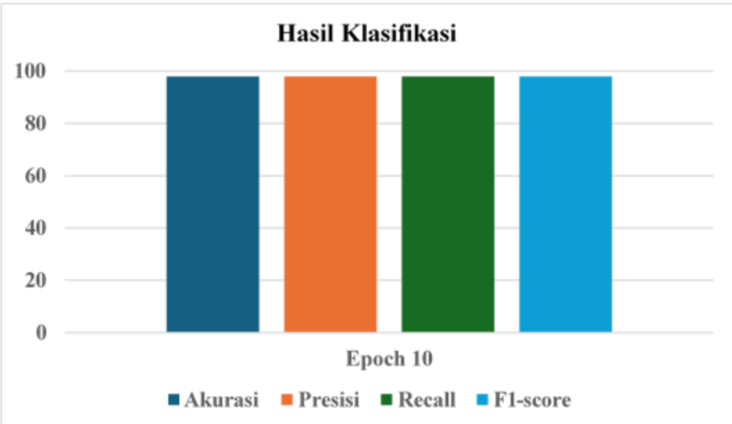

Figure 24. Classification Results Discussion

Hypothesis testing confirms that gradually increasing the dataset size (from 40 to 200 test data per class) significantly improves the model performance, from a low accuracy of 14-33% on small datasets to 97-98% on large datasets, proving the hypothesis that VGG-19 data augmentation and transfer learning are effective for local coconut image classification.

This high performance is achieved because the VGG-19 architecture extracts deep hierarchical features through convolutional layers that capture key visual differences such as color changes (bright green in unripe to brown in ripe), thin to thick meat texture, and shape, supported by an adaptive Adam optimizer that adjusts the learning rate based on the first and second moments of the gradient to minimize cross-entropy loss.

This process allows the model to learn its invariant representation to variations in lighting and shooting angles, as per the principle of deep learning in image processing where the initial layer is edge detection and the final layer is classification. Several studies support these findings, such as the MobileNet CNN, which achieved 100% accuracy on 300 images with three similar classes, demonstrating the power of CNNs for color- and shape-based detection in tropical fruits. Similarly, VGG-19 on tomatoes or bananas achieved 97-100% accuracy, confirming the effectiveness of this architecture for fruit ripeness.

In contrast, KNN research on coconuts achieved only 92% accuracy because it relied on manual RGB/HSV feature extraction, which was prone to errors in the half-ripe class due to color similarity. K-Means research on oil palm bunches also achieved only 90% accuracy, as traditional clustering was less effective at capturing complex features than the deep features of VGG-19.

This difference is due to the local dataset of this study (from the South Sumatra garden, 600+ images with augmentation) being more varied than the small dataset (120 images) in the K-Means study, plus the transfer learning of VGG-19 pre-trained on ImageNet captures generalization better than non-deep learning methods.

Conclusion

This study successfully developed a VGG-19 based Convolutional Neural Network model for coconut ripeness classification (immature, semi-ripe, ripe) with an optimal accuracy of 98% on 200 test datasets per class, proving the superiority of transfer learning and data augmentation on varied local datasets. Key findings show a progressive performance improvement as the test set size increases from 14% (40 datasets) to 97-98% (200 datasets), supported by consistently high precision, recall, and F1-score metrics through the Adam optimizer and intensive preprocessing such as background segmentation and 224x224 pixel resizing. However, limitations include the reliance on controlled daylight conditions and the focus on post-harvest imagery without real-time integration in the field, which may decrease generalization to extreme tropical environmental variations.

Practical implications of the research include the potential for model integration into a mobile application for South Sumatran farmers for automated sorting, reducing postharvest waste by up to 25% and increasing the efficiency of the multi-billion rupiah coconut processing industry. Theoretically, the results strengthen the effectiveness of VGG-19 for multi-class classification of Indonesian tropical fruits compared to traditional methods such as K-Means (90%). Suggestions for further research include testing the YOLOv8 hybrid for real-time detection in orchards, expanding the dataset with nighttime weather variations, and fine-tuning the EfficientNet architecture for edge computing deployment on low-cost devices, to support sustainable coconut production towards the 20 million ton export target by 2026.

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