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CLASSIFICATION OF OIL PALM FRUIT RIPENESS LEVEL USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

The manual sorting process for determining the ripeness of oil palm fruit is subjective and inefficient, leading to a decline in Crude Palm Oil (CPO) quality and economic losses. This study aims to develop an automatic classification system for oil palm fruit ripeness to address these issues. It employs a digital image processing approach using a Neural Network model. The methodology involves using a pre-trained InceptionV3 model for feature extraction from a dataset of 3,000 fruit images, which are then fed into a custom-designed neural network with three hidden layers, using ReLU as the activation function and Adam as the optimizer. The model successfully classifies the fruits into 'unripe', 'ripe', and 'overripe' categories. The results show a high overall accuracy of 96.56 percent, with an F1-Score of 96.55 percent. The study concludes that the proposed Neural Network model is highly effective and reliable for automating oil palm fruit sorting, offering a feasible solution to improve efficiency and standardization in the palm oil industry.

INTRODUCTION

Oil palm (Elaeis guineensis) is a vital plantation commodity for Indonesia's economy, positioning the country as the world's leading producer of crude palm oil (CPO) (Ikhsanul Adli et al., 2025). However, the quality of CPO heavily depends on the efficient sorting of Fresh Fruit Bunches (FFB), a process that currently faces significant challenges. The manual sorting process, which relies on workers' visual assessment, is subjective, slow, and prone to errors in distinguishing between unripe, ripe, and overripe fruit. These sorting errors directly contribute to reduced oil yield and elevated free fatty acid (FFA) levels, ultimately lowering the market value of the harvest and prolonging the sorting time. Therefore, this research is important in computer science and technology, as it offers a technology-based solution to a real-world industrial problem.

To address this problem, this study uses digital image processing to classify the ripeness of oil palm fruit based on images. Previous studies have widely explored classification using digital image processing. For example, Muchtar and Muchtar (Muchtar & Muchtar, 2024) classified mango ripeness based on HSV color features and texture using K-Nearest Neighbor (KNN), achieving high accuracy. Damayanti and Michael (Damayanti & Michael, 2024) classified coffee fruit ripeness using KNN and Support Vector Machine (SVM) based on color features. CNNs were applied by Wangjaya and Aryanto to classify tomato ripeness with about 92.7 % accuracy (Ignasius et al., 2025). Another study also demonstrates the effectiveness of using Raman spectroscopy combined with machine learning to non-invasively classify oil palm fruit ripeness, achieving 100% accuracy with a fine KNN classifier based on carotenoid-related spectral features across three ripeness categories (Raj et al., 2021). This study proposes the use of an Artificial Neural Network (ANN) method for classifying oil palm fruit ripeness due to its greater ability to model non-linear patterns in images. Previous works on oil palm using CNNs and attention mechanisms have shown accuracies up to ~92 % (Herman et al., 2020).

We classify oil palm fruit into three categories—unripe, ripe, and overripe—using an ANN with the Rectified Linear Unit (ReLU) activation function and the Adaptive Moment Estimation (Adam) optimizer. ReLU is selected for its efficiency in addressing the vanishing gradient problem and accelerating convergence in deep networks (Pardede et al., 2022). Adam is chosen for its computational efficiency and strong performance in a wide range of deep-learning tasks (Pardede et al., 2024). The integration of ReLU and Adam is expected to produce an optimal, dependable classification model.

Objectives: This study aims to develop a neural-network-based image-processing model to classify oil palm fruit ripeness into three categories—unripe, ripe, and overripe—using ReLU activation and Adam optimization. The anticipated outcome is an automated sorting system that improves CPO quality and market value.

RESEARCH METHODS

This section systematically outlines the stages conducted in this research, including data collection and preprocessing, classification model design, and performance evaluation. All procedures are designed to ensure reproducibility for future studies.

A. Data Collection

The dataset used in this study is secondary data obtained from the Kaggle platform under the title "Ripeness of Oil Palm Fruit", accessible via the following link: https://www.kaggle.com/datasets/ramadanizikri112/ripeness-of-oil-palm-fruit. This dataset consists of 3,000 images of oil palm fruit in .JPG format, evenly distributed across three ripeness categories:

a. Unripe (1,000 images),
b. Ripe (1,000 images), and
c. Overripe (1,000 images).

Each image is standardized to a size of 224x224 pixels to ensure consistency as model input. Data preprocessing involves feature extraction using a transfer learning approach with the InceptionV3 model, which has been pre-trained on the ImageNet dataset. InceptionV3 excels at extracting visual features through inception modules that process information at multiple scales in parallel (Pardede et al., 2023). The output of this stage is a high-dimensional feature vector representing the visual characteristics of each image, which serves as input to the classification model.

B. Classification Model

The classification model was built using the TensorFlow and Keras frameworks, with a neural network architecture comprising three hidden layers, each with 100 neurons. The activation function used is Rectified Linear Unit (ReLU), defined as (Firmansyah & Hayadi, 2022):

$$f(x) = mas(0, x) \qquad 1$$

To optimize weight updates during training, the Adaptive Moment Estimation (Adam) algorithm is employed. Adam is a stochastic gradient-based optimization algorithm that adaptively adjusts the learning rate for each network weight.

The final model output is formulated as (Wahyuni et al., 2023):

$$C = f(W \, . I_v + b \,) \qquad 2$$

Where:
C: Class probability (final output),
f: Softmax activation function in the output layer,

W: Network weights,
I_v: Feature vector from InceptionV3,
b: Bias.

This model produces classification results into one of the three categories: Unripe, Ripe, or Overripe.

C. Evaluation Metric

Model performance is evaluated using standard metrics for multi-class classification tasks, including:

a. Confusion Matrix
b. Accuracy
c. Precision
d. Recall (Sensitivity)
e. F1-Score

Each metric is defined as follows:

a. Accuracy measures the proportion of correct predictions out of all predictions (Ichsan et al., 2024):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad 3$$

b. Precision assesses the proportion of true positive predictions among all positive predictions (Daniel & Situmorang, 2023):

$$Precision = \frac{TP}{TP+FP} \quad 4$$

c. Recall (Sensitivity) evaluates the model's ability to correctly identify all actual positive cases (Ptr et al., 2024):

$$Recall = \frac{TP}{TP+FN} \quad 5$$

d. F1-Score is the harmonic mean of Precision and Recall, especially useful when dealing with imbalanced class distributions (Riyadi et al., 2023):

$$F1\ Score = 2\ X\ \frac{Precision\ X\ Recall}{Precision+Recall} \quad 6$$

Where:

TP: True Positive

TN: True Negative

FP: False Positive

FN: False Negative

These metrics collectively provide a comprehensive assessment of the model's performance in classifying the ripeness level of oil palm fruit.

RESULTS AND DISCUSSION

A. Result

This section presents and analyzes the outcomes of the classification model in predicting oil palm fruit ripeness. The performance evaluation includes both quantitative metrics and qualitative observations based on the confusion matrix and standard classification metrics.

1. Confusion Matrix Analysis

The classification results are summarized in Table 1, which shows the distribution of correct and incorrect predictions in percentage format for each class.

Table 1. Confusion Matrix of Classification Results (in Percentage)

Actual	Predicted: Unripe	Predicted: Ripe	Predicted: Overripe
Unripe	77.9%	16.9%	7.2%
Ripe	21.0%	72.8%	10.8%
Overripe	1.1%	10.3%	82.0%

From the table, it is evident that the model performs best on the Overripe class, achieving a correct classification rate of 82.0%, with very few samples being misclassified as either Ripe or Unripe. This suggests that overripe palm fruits have more distinguishable features that are effectively captured during the feature extraction and classification process.

In contrast, the Ripe and Unripe classes are more frequently confused with one another. Specifically, 21.0% of Ripe samples were misclassified as Unripe, and 16.9% of Unripe samples were predicted as Ripe. This indicates that the model struggles more with the subtle differences between these two classes—likely due to their visual similarities or overlaps in color and texture patterns.

Figure 1 shows a clear visual breakdown of the model’s prediction distribution across all three classes.

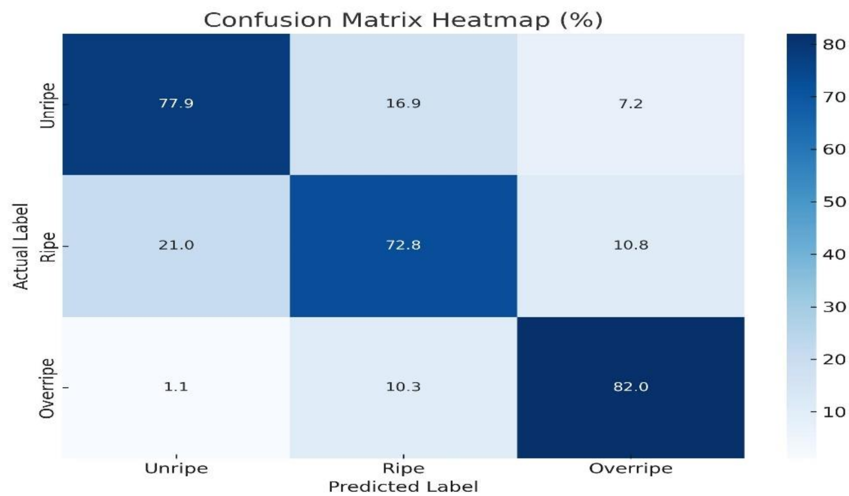

Figure 1. Confusion Matrix Heatmap

2. Performance Metrics

To further quantify the model's performance, standard classification metrics were calculated, as summarized below:

a. Overall Accuracy: 75.94% (1,085 correct predictions out of 1,420 test samples)
b. Average Precision: 75.34%
c. Average Recall (Sensitivity): 77.06%
d. Average F1-Score: 75.98%

These metrics demonstrate that the model maintains a balanced performance across all three classes. The high F1-score suggests an effective trade-off between precision and recall, which is especially important in multi-class classification tasks where class imbalances or confusion are possible.

Figure 2 shows the comparison of Precision, Recall, and F1-Score for each class, highlighting the strengths (e.g., Overripe class) and areas for improvement (e.g., Ripe and Unripe).

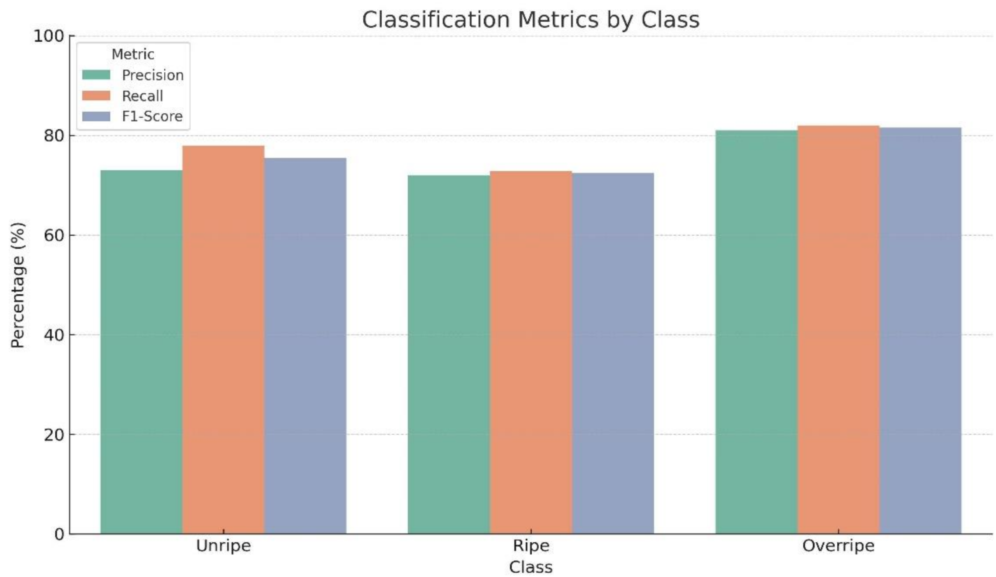

Figure 2. Bar Chart of Classification Metrics

3. Class-wise Insights

A more detailed analysis of each ripeness category reveals specific patterns in the model's performance:

a. Unripe samples were correctly classified 77.9% of the time. However, a significant portion—16.9%—were misclassified as Ripe. This suggests that Unripe fruits share notable visual similarities with Ripe ones, particularly in terms of color and texture, which may cause confusion, especially under inconsistent lighting conditions.
b. Ripe fruits were accurately identified in 72.8% of cases, with the most common misclassification being into the Unripe category (21.0%). This again highlights the subtle visual overlap between the Ripe and Unripe classes. Improving feature extraction or expanding the training dataset for these two categories could help the model better distinguish between them.
c. Overripe fruits achieved the highest classification accuracy at 82.0%, with very few errors. This strong performance indicates that Overripe fruits likely possess more distinct visual characteristics—such as darker coloration, texture degradation, or shape cues—that make them easier for the model to identify correctly.

The results indicate that the deep learning model, combined with InceptionV3-based feature extraction, is capable of accurately classifying oil palm fruit images into their respective ripeness categories. While the overall performance is strong, the misclassification between Ripe and Unripe categories suggests that these two classes may require further refinement in preprocessing or additional training data for better separation.

From a practical perspective, this model can be a valuable tool in the automation of ripeness detection for oil palm fruit harvesting. With further improvement, such a system could potentially support real-time classification on edge devices or drones in agricultural settings.

B. Discussion

The experimental results presented in the previous section demonstrate the potential and limitations of the proposed classification model for detecting oil palm fruit ripeness. Through a combination of transfer learning using InceptionV3 and a custom neural network classifier, the model achieved a reasonably high level of accuracy and class-wise balance in performance. However, several aspects merit deeper discussion to contextualize the findings and identify areas for enhancement.

a. Model Effectiveness and Strengths

The overall classification accuracy of 75.94%, coupled with an average F1-score of 75.98%, indicates that the model performs well in distinguishing among the three ripeness levels: Unripe, Ripe, and Overripe. The relatively balanced precision and recall scores across categories (around 75–77%) further suggest that the model is not significantly biased toward any single class, a common issue in multi-class classification problems.

Notably, the Overripe class was consistently and accurately identified, with an impressive 82.0% correct classification rate. This suggests that overripe fruits possess unique and easily detectable features—such as darker coloration, more wrinkled texture, or structural deformations—that the InceptionV3 feature extractor captures effectively. The consistently high performance in this category underscores the model's strength in recognizing distinct visual patterns.

b. Challenges in Class Separation

Despite the strong overall performance, the Ripe and Unripe classes exhibited significant overlap. Misclassification between these two categories was the most frequent, with 21.0% of Ripe samples incorrectly labeled as Unripe and 16.9% of Unripe samples predicted as Ripe. This indicates that the model struggles with the nuanced differences in color tone and surface texture that distinguish these two classes—an issue likely compounded by external variables such as lighting, background noise, or fruit orientation in the images.

This confusion suggests a potential limitation in the current feature extraction pipeline or a need for additional training samples, particularly ones that emphasize the transitional visual features between ripeness stages. Incorporating more controlled image data, or applying techniques such as contrast normalization or color augmentation during preprocessing, may help improve class separability in future iterations.

c. Interpretability and Practical Use

The class-wise analysis, supported by the confusion matrix heatmap and the bar chart of classification metrics, provides interpretable insights into the model's behavior. These visual tools make it easier to diagnose performance bottlenecks and guide model refinement. For instance, the visualization clearly highlights the model's confidence in classifying Overripe fruits, while exposing the ambiguity between Unripe and Ripe.

From a practical standpoint, the model's current performance is promising for applications in automated fruit grading or harvesting systems. The integration of this model into mobile platforms or edge devices, such as drones or handheld scanners, could facilitate real-time decision-making in plantation environments. This could lead to more consistent and objective assessments of fruit maturity, potentially improving harvest timing and yield quality.

d. Opportunities for Improvement

To further improve classification performance, especially between Ripe and Unripe categories, several strategies can be explored:

1) Data Augmentation: Introducing synthetic variations such as brightness shifts, hue adjustments, or rotations may help the model generalize better to real-world variability.
2) Ensemble Learning: Combining predictions from multiple architectures or classifiers could reduce class confusion and improve overall robustness.
3) Attention Mechanisms: Incorporating visual attention layers in the neural network could help the model focus on critical regions of the fruit, enhancing feature discrimination.
4) Class-Balanced Sampling or Reweighting: Ensuring a more even representation of edge-case samples during training could help mitigate bias.

In summary, the proposed model demonstrates solid performance in classifying oil palm fruit ripeness using image data and transfer learning. While certain class distinctions remain challenging, especially between Ripe and Unripe fruits, the foundation established by this study offers strong potential for real-world agricultural automation. Future work should focus on refining the preprocessing pipeline, augmenting training data, and exploring more advanced classification strategies to enhance overall system accuracy and reliability.

CONCLUSION

In conclusion, the proposed classification model—leveraging InceptionV3-based feature extraction—has demonstrated strong potential in accurately predicting the ripeness of oil palm fruits, achieving an overall accuracy of 75.94% and balanced performance across key metrics such as precision, recall, and F1-score. The model performed particularly well in identifying Overripe fruits, indicating that this class possesses distinct visual cues effectively captured by the system. However, the frequent misclassification between Ripe and Unripe categories highlights the need for enhanced class differentiation, potentially through improved preprocessing, additional training data, or more advanced learning techniques. Despite these challenges, the model shows promise for practical deployment in automated fruit grading and harvesting systems, especially when integrated into real-time applications such as mobile devices or drones. Future enhancements targeting the identified weaknesses could further increase the model's robustness and usability in diverse agricultural environments.

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