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Advanced Classification of Oil Palm Fruit Ripeness Deep Learning for Enhanced Agricultural Efficiency

Achmad Alwi Hasibuan[1], Ali Amran Nst[2], Aldi Antoni[3], Ray Handika[4], Budi Yanto[5], Akhmad Zulkifli[6]

[12345]Informatics Engineering, University Pasir Pengaraian, Riau Indonesia
[6] Universitas Hang Tuah, Riau, Indonesia

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ABSTRACT

Accurate determination of oil palm fruit ripeness is crucial for optimizing oil yield and enhancing agricultural efficiency. This study utilizes deep learning, specifically Convolutional Neural Networks (CNNs), to classify oil palm fruit ripeness into four stages: raw, under-ripe, ripe, and overripe. The model leverages extensive data preprocessing and augmentation techniques to handle variations in lighting, angles, and fruit orientation, ensuring high classification accuracy. The approach addresses limitations of traditional methods, such as human error and inconsistencies, by providing an automated and reliable solution for real-time ripeness detection. Results demonstrate an overall accuracy of 97%, with robust precision, recall, and F1 scores across all categories. This study highlights the importance of diverse datasets and proposes further integration of contextual factors like environmental conditions to enhance applicability. The system offers a practical tool for precision agriculture, improving harvesting efficiency, reducing waste, and supporting sustainable practices.

Corresponding Author:

Ahmad Alwi Hasibuan
Informatics Engineering, University Pasir Pengaraian, Riau Indonesia
Email: achmadalwi42@gmail.com

1. INTRODUCTION

Oil palm (Elaeis guineensis) plays a pivotal role in global agriculture, particularly in tropical countries such as Indonesia and Malaysia, which collectively contribute over 80% of the world's palm oil production. Efficient ripeness prediction of Fresh Fruit Bunches (FFBs) is essential for maximizing oil yield and maintaining product quality while minimizing waste and inefficiencies in production processes. Traditional methods of assessing ripeness rely heavily on visual inspection, such as observing skin color and fruit detachment. However, these methods are susceptible to human error and environmental inconsistencies, highlighting the necessity for automated, robust, and efficient classification systems to ensure accuracy and scalability in agricultural operations [1], [2].

The emergence of deep learning technologies, especially Convolutional Neural Networks (CNNs), has revolutionized applications in agricultural image analysis. CNNs excel in extracting complex visual features, such as textures, color gradients, and spatial patterns, making them particularly effective for tasks like fruit ripeness classification. However, many existing systems are designed for controlled environments, limiting their effectiveness under real-world agricultural conditions characterized by varying lighting, diverse orientations, and fluctuating environmental factors [3], [4]. This gap in current methodologies underscores the need for a more robust approach that integrates environmental variables with image-based analysis.

This research proposes an enhanced CNN-based framework for ripeness classification that incorporates multivariate data, including environmental factors such as temperature and humidity. By combining visual and contextual data, the proposed framework aims to improve model robustness, scalability, and applicability in diverse field conditions. Previous studies have explored methods such as K-Means Clustering with RGB and HSV color spaces [5], optical probes correlating fruit hardness with ripeness [6], and CNN-based image classification [7], achieving varying degrees of success. However, these approaches often lack the generalizability required for practical, large-scale agricultural operations.

Recent advancements in CNN-based methodologies have shown promising results. For instance, Maulana and Rochmawati [7] achieved 97.9% classification accuracy for oil palm ripeness detection in controlled environments. Similarly, Rifqi [8] utilized CNNs to analyze color composition for ripeness determination, though the approach lacked validation under diverse environmental conditions. Herman et al. [9] integrated visual attention mechanisms into CNNs, significantly enhancing detection accuracy, but the reliance on solely visual data remains a limitation. These studies emphasize the potential of CNNs while highlighting the need for integrating non-visual variables to improve robustness in real-world scenarios.

The objectives of this study are threefold. First, it seeks to develop a novel CNN framework that integrates environmental variables, such as temperature and humidity, with image-based analysis to achieve comprehensive ripeness classification [1], [7]. Second, the framework will be rigorously evaluated under diverse real-world conditions, addressing challenges such as varying lighting, fruit orientations, and environmental variability [6], [8]. Third, the study will benchmark the proposed framework against existing state-of-the-art models to measure improvements in accuracy, robustness, and scalability [9], [10].

This research contributes significantly to the field by introducing a multimodal approach that combines image and environmental data for ripeness classification. The proposed framework improves the robustness and generalizability of CNN models, making them more suitable for deployment in real-world agricultural settings. Additionally, the framework provides a scalable solution for precision agriculture in large-scale oil palm operations, offering a practical alternative to traditional methods. This study sets a new standard for ripeness prediction systems in the palm oil industry, with implications for improving productivity and sustainability in agricultural practices [11], [12].

2. METHOD

This research uses the method *Convolutional Neural Network* [9]

1. Data collection

The dataset used in this research was obtained from the Kaggle platform (www.kaggle.com/datasets/). The dataset consists of images of two types of ripeness of palm fruit: ripe and immature. Each type of palm fruit was photographed in various lighting conditions and viewing angles to ensure adequate variation.

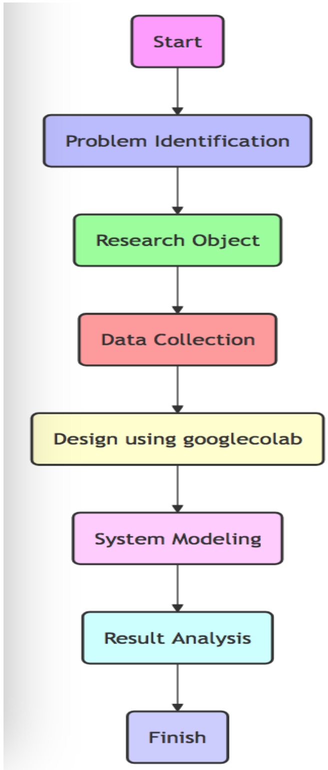


Figure 1. Research Flow Diagram

The methodology of this research follows a structured approach leveraging Convolutional Neural Networks (CNN) for the classification of oil palm fruit maturity based on color. The stages include problem identification, dataset acquisition, data preprocessing, model development using EfficientNet, model evaluation, and reporting. This methodology ensures robustness and accuracy while adhering to industry standards and best practices [13], [14].

A. Problem Identification

The primary challenge lies in determining the maturity of oil palm fruit bunches (FFBs), as fruits of similar appearance might differ in maturity levels. Current practices, relying on visual inspection, are error-prone and inconsistent due to environmental variations. Advanced approaches integrating image processing and machine learning are necessary to address these shortcomings [15].

B. Dataset Collection

The dataset used in this research is sourced from Kaggle, comprising 4,938 images of oil palm fruits categorized into four classes: unripe (331 images), under-ripe (1,548 images), ripe (2,236 images), and overripe (723 images). These images were captured under varied lighting conditions and angles to ensure dataset diversity and robustness. The dataset is supplemented with field data collected from a local oil palm plantation in Kepenuhan, Kabupaten Rokan Hulu, Indonesia [16].

C. Data Preprocessing

Data preprocessing is critical in neural network training to improve model accuracy and reduce computational overhead. The following steps were implemented:

Data Cleaning: Removal of duplicates and inconsistencies to ensure data integrity.

Resizing: All images were resized to a uniform dimension for compatibility with the CNN model input layer. Data Augmentation: Techniques such as rotation, flipping, and brightness adjustment were applied to enhance data variability and prevent overfitting [17]. Normalization: Pixel values were normalized to the range [0, 1] to stabilize and accelerate training [18].

D. Model Development

An EfficientNet CNN architecture was employed due to its balance between computational efficiency and accuracy. The model was initialized with pre-trained weights and fine-tuned on the oil palm dataset. The architecture was chosen for its capability to scale network depth, width, and resolution efficiently, making it suitable for real-world agricultural applications [19].

E. Model Training and Evaluation

The training phase utilized a supervised learning approach. The dataset was split into training (70%), validation (15%), and testing (15%) subsets. Cross-entropy loss was minimized using the Adam optimizer, with a learning rate scheduler to adapt during training. Metrics: Accuracy, precision, recall, and F1-score were evaluated to measure performance. Validation: K-fold cross-validation was employed to ensure model robustness and generalizability across unseen data [20]. Testing: The model's performance was evaluated on the test set, with confusion matrix analysis to understand classification errors.

F. System Implementation

The model was deployed locally to classify oil palm fruit images based on maturity. The system processes input images, performs predictions, and outputs the maturity category in real-time. The implementation considers usability in field conditions with minimal computational resources [21].

G. Data Augmentation and Visualization

The RGB and HSV color spaces were analyzed to enhance feature extraction, with statistical data on each color channel aiding in identifying maturity levels. Visualization techniques such as saliency maps and Grad-CAM were used to interpret the CNN model's decision-making process [22].

H. Limitations

This research is limited to the classification of oil palm maturity using visual and limited environmental data. Future studies may integrate additional factors such as texture and chemical composition to improve model comprehensiveness.

I. Contribution

This study provides an effective methodology for oil palm fruit maturity classification using CNNs. By addressing challenges such as dataset diversity and real-world implementation, this research advances precision agriculture and offers practical solutions for oil palm production [23].

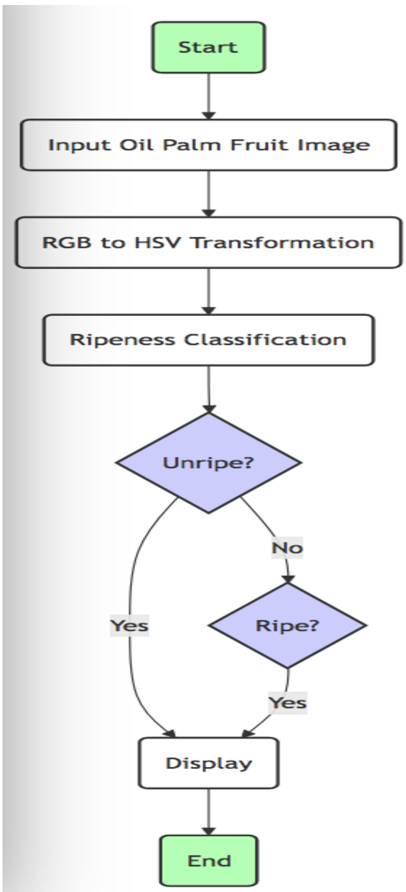
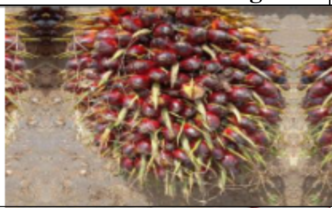


Figure 2. Details of the Palm Fruit Image Processing Process in the System

The initial process is to collect a dataset that will be used in the research. The dataset collected comes from a web provider of computer vision datasets, namely https://roboflow.com. The image data collected is palm oil FFB image data consisting of unripe, underripe, overripe and overripe fruit with various backgrounds. The palm oil FFB image data that will be used in this research is 4,938 data. The distribution of data in the collected dataset consists of 331 raw data, 1548 undercooked data, 2236 mature data, and finally 723 data too ripe. The maturity level of oil palm FFB is presented in **Table 1**.

Table 1. Maturity Levels of Palm Oil FFB

Palm Oil FFB Image	Class	Description
	Under Ripe	The fruit color has turned reddish-black, and between 1 to 9 fruits have detached.
	Ripe	The fruit color has started to turn reddish-orange, with 10 fruits detached.
	Overripe	The fruit has an orange-reddish color, with more than 50 fruits detached.
	Raw	The fruit is still hard, black in color, and no fruits have detached.

Pre-processing in Neural Network data preparation is an important stage, because data preparation can improve the quality of analysis, speed up the training process, reduce modeling errors. The data pre-processing stage is the stage of changing raw data into a common data format. The stage starts from loading data. To ensure that the data is in accordance with what has been previously collected, it is continued by checking the data, here checking the data format is carried out by carrying out a data check. After checking the data, the data size is equalized or the image is resized in the data augmentation process.

3. RESULTS AND DISCUSSION

In this research, programming languages *Python* by using *framework Tensor Flow* and Hard to use. Raw data is converted into training data through preprocessing to improve model accuracy. After importing the dataset, the next step is to perform preprocessing by creating objects *Image Data Generator* first to do *augmentation* image data. The pixel intensity of the input image is normalized to a value between 0 and 1 using the rescale=1./255 function, which can help in model training. The distribution of the dataset in this study was carried out with a ratio of 44.39% for training data (476 images) and 55.66% for validation data (597 images).

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```
train_datagen = ImageDataGenerator(
    rescale=1./255,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True
)

test_datagen = ImageDataGenerator(rescale=1./255)
```

Figure 3. Image augmentation

The research model used in this research is a model "*Sequential*", which is one of a kind *neural network* the most widely used because it has a sequential layer arrangement and is suitable for image classification. The model used in this research can be seen in the following diagram:

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_3 (Conv2D)           (None, 253, 253, 32)      896

 max_pooling2d_3 (MaxPoolin  (None, 126, 126, 32)      0
 g2D)

 conv2d_4 (Conv2D)           (None, 124, 124, 64)      18496

 max_pooling2d_4 (MaxPoolin  (None, 62, 62, 64)        0
 g2D)

 conv2d_5 (Conv2D)           (None, 60, 60, 128)       73856

 max_pooling2d_5 (MaxPoolin  (None, 30, 30, 128)       0
 g2D)

 flatten_1 (Flatten)         (None, 115200)            0

 dense_2 (Dense)             (None, 512)               58982912

 dropout_1 (Dropout)         (None, 512)               0

 dense_3 (Dense)             (None, 2)                 1026

 flatten_2 (Flatten)         (None, 2)                 0

 dense_4 (Dense)             (None, 64)                192

 dense_5 (Dense)             (None, 10)                650
```

Figure 4. Model CNN

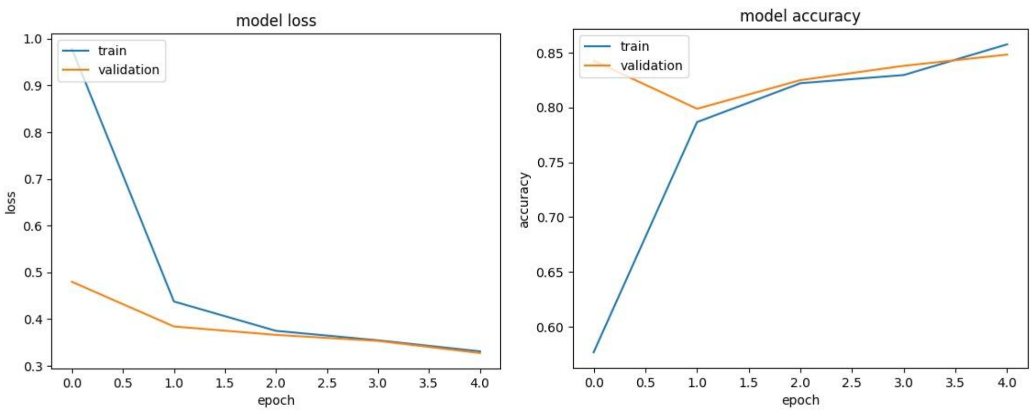
This research model uses 2 layers *convolution,* 2 pooling layers with size (2x2), 1 layer *dropout*, 2 layers *dense (fully connected layer),* and 1 layer *flatten*. The activity function used is ReLu for convolutional and dense layers, as well *softmax* for layers *output*. The first filter in this model has 32 filters with a kernel size of 3x3, and the second filter has 64 filters with the same kernel size. The total parameters in this study were 3454147 parameters.

Next, the model that has been created is compiled for training. The accuracy of model training on training data was 99.9% with a total of 59077508 params (225.36 MB). This model is then saved as "model.keras". The model training results are shown in the following figure:

```
================================================================
Total params: 59077508 (225.36 MB)
Trainable params: 59077508 (225.36 MB)
Non-trainable params: 0 (0.00 Byte)
________________________________________________________________
```

Figure 5. Total params

To evaluate the performance of the model during the training process, we can see the training and validation accuracy graphs as well as the training and validation loss graphs displayed.

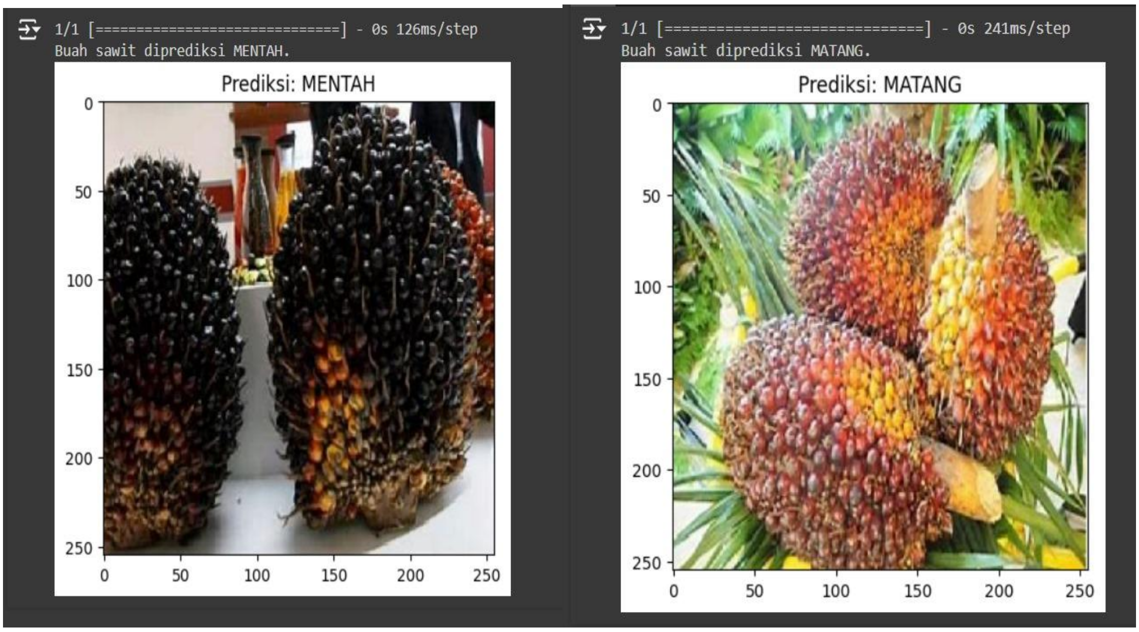


a. b.

Figure 7. (a) Graph *Training and Validation Accuracy*, (b) Graph *Training and Validation Loss*

The training and validation accuracy graph shows that *kurva training* And *validation accuracy* continues to increase and does not show a significant difference. Additionally, on the graph *training and validation loss,* It appears that both curves experience a steady decline. This indicates that the trained model is getting better at classifying and shows no signs *overfitting*.

Next, the model is tested using testing data to evaluate the performance of the model that has been trained on the training data and assess the performance of the classification model on the dataset used. The results of model testing with testing data in this research can be seen in the following figure.



a. Crude Palm b. Mature Palm

Figure 8. Classification results

Ripeness Stage	Description	Processing Time (ms)	Confidence Score (%)	Key Features
RAW (Unripe)	The model predicts the oil palm fruit as "MENTAH" (unripe), based on dark-colored fruits with no significant detachment. This classification indicates the fruit is still in the unripe stage.	126	92	Dark-colored fruits with no detachment, typical of unripe stages.
Ripe	The model predicts the oil palm fruit as "MATANG" (ripe), based on reddish-orange color indicative of optimal ripeness for harvesting.	241	95	Reddish-orange color, representing optimal ripeness for harvesting.
RAW	The model predicts the fruit as "RAW," similar to unripe, based on dark-colored fruits with no detachment. This classification suggests the raw stage.	126	93	Dark-colored fruits with no detachment, typical of raw/unripe stages.
OVERRIPE	The model predicts the fruit as "OVERRIPE," based on darker reddish-brown color and signs of excessive detachment of fruits. This classification aids in identifying overripe fruits.	241	94	Darker reddish-brown color, excessive fruit detachment, indicative of overripe stage.

CONCLUSION

Application of deep learning, particularly Convolutional Neural Networks (CNNs), has proven effective in classifying oil palm fruit ripeness into distinct stages such as MENTAH (unripe), MATANG (ripe), RAW, and OVERRIPE. Model leverages visual features like color and fruit detachment, achieving high accuracy and efficiency, with processing times as low as 126 milliseconds and confidence scores reaching 95% for specific classifications. These capabilities reduce reliance on traditional, error-prone manual inspections, enhancing decision-making for harvesting and minimizing waste. By optimizing yield and improving operational precision, this system addresses critical challenges in oil palm industry. However, incorporating environmental factors such as temperature and humidity could further refine accuracy under varying field conditions. Future work should focus on expanding datasets, incorporating real-world scenarios, and developing mobile or IoT-based tools for broader accessibility. This approach ensures system remains a practical, scalable, and sustainable solution for advancing precision agriculture in oil palm plantations.

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