Deep Learning Approach for Palm Oil Fresh Fruit Bunches Harvest Decision

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Abstract—**The efficiency of palm oil harvesting is crucial to ensuring optimal yield and quality of fresh fruit bunches (FFB). Traditional manual harvesting methods often result in inconsistent outcomes due to human error and subjectivity in ripeness evaluation. This study proposes an intelligent, image-based harvesting decision system that utilizes Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) to automate the classification of palm oil FFB ripeness. High-resolution images of palm fruit are processed using Python-based frameworks (Google Colab 3.10.12, YOLOv8) to extract features such as color and texture, which are then used to train the CNN and SVM models. The system architecture includes stages for image acquisition, preprocessing, feature extraction, classification, and decision-making. Both CNN and SVM were evaluated for performance using accuracy, precision, recall, and F1-score. The experimental results demonstrated high classification accuracy, with CNN achieving an average of 0.97 and the highest result recorded at 0.89. The system significantly enhances harvesting decision accuracy and reduces dependence on manual inspection. This study demonstrates the viability of using deep learning and machine learning algorithms for real-time agricultural decision-making. The integration of CNN and SVM not only improves productivity but also contributes to sustainable practices by reducing waste and labor intensity. The proposed system offers a scalable solution that can be adapted for broader smart farming applications, supporting national goals of digital transformation and energy efficiency in agriculture.**

Keywords—Palm Oil, CNN, SVM, Image Processing, Harvesting Decision

I. INTRODUCTION

Palm oil is one of the most valuable and widely produced vegetable oils in the world, particularly in Southeast Asia. Indonesia, as the world's largest producer, contributes significantly to the global palm oil supply. According to the Central Bureau of Statistics, Indonesia produced over 51 million tons of palm oil in 2023, making it a cornerstone of national economic growth, rural employment, and export earnings [1]. Despite its prominence, the palm oil industry faces recurring challenges related to sustainability, labor dependency, and inefficiencies in the harvesting process. Among the most pressing issues is the accurate identification of harvest-ready Fresh Fruit Bunches (FFB), which directly influences oil yield and product quality. Traditionally, this process is performed manually, relying on visual assessment by field workers. Such methods are not only time-consuming but are also highly prone to human error, resulting in either under-ripe or overripe harvests that reduce processing efficiency and economic return [2].

To address these limitations, the integration of intelligent technologies into agricultural processes, often referred to as smart agriculture or precision farming, has become an emerging trend. In recent years, computer vision and machine learning algorithms have been widely explored to automate various agricultural tasks, including fruit detection, disease classification, and yield prediction [3]–[5]. Specifically, image-based decision systems utilizing Convolutional Neural Networks (CNN) have demonstrated exceptional performance in recognizing visual patterns from high-resolution datasets. When paired with classifiers like Support Vector Machines (SVM), these systems can further enhance classification precision in structured decision-making scenarios [6].

This study presents an image-based harvesting decision system developed using CNN and SVM for the classification of palm oil FFB ripeness levels. The goal is to offer an accurate, efficient, and scalable solution to support harvest optimization. The system employs a dataset of annotated palm fruit images processed using the Python programming language, integrated with the YOLOv8 object detection model on the Google Colab platform. CNN is utilized for feature extraction from image datasets, while SVM functions as the classification layer to determine the ripeness category of each fruit. The architecture is designed to handle diverse environmental conditions such as varying lighting and fruit angles.

Experimental results from the implementation demonstrate that the system achieves a classification accuracy of up to 97%, confirming its viability for real-world applications. The system reduces the need for manual labor, minimizes subjectivity in fruit selection, and enhances operational efficiency in palm oil harvesting. The implementation of this intelligent decision system aligns with Indonesia's national development vision under Asta Cita, particularly in achieving energy independence and technological advancement in agriculture [7]. Moreover, it serves as a foundation for broader applications in agro-industrial sectors that require precise and scalable solutions.

Palm oil plays a crucial role in the economies of many tropical countries, especially Indonesia and Malaysia, as it contributes significantly to gross domestic product (GDP), employment, and export earnings [8]. However, despite its economic importance, the palm oil industry continues to face challenges related to productivity, sustainability, and labor efficiency. Among these challenges is the process of harvesting FFB, which is often conducted manually and relies heavily on subjective human judgment. This traditional approach frequently results in inconsistent assessments of ripeness, leading to suboptimal harvesting times, reduced oil quality, and increased production costs [2].

In recent years, technological innovations in artificial intelligence and machine learning have offered promising solutions for agricultural automation. Specifically, image-based decision-making systems leveraging CNN and Support SVM have been employed to address inefficiencies in FFB harvesting [3], [4]. These models utilize features such as color, texture, and fruit morphology extracted from digital images to accurately classify the ripeness level of palm fruit, thus enabling data-driven harvesting decisions. This method has shown potential for reducing human error, enhancing yield, and improving overall operational efficiency [9]. Figure 1 is shown the CNN Algorithm.

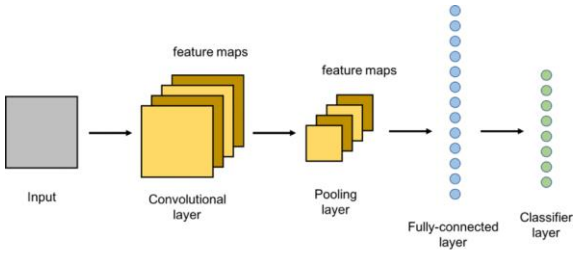

Fig. 1. The CNN algorithm. (L. Zaniolo and O. Marques, Convolutional Neural Networks: Principles and Applications in Image Recognition, 1st ed. Boca Raton, FL, USA: CRC Press, 2020)

This figure represents the basic architecture of a CNN used for image classification tasks. The process begins with an input image that passes through one or more convolutional layers, which extract spatial features in the form of feature maps. These maps are then down sampled using pooling layers to reduce dimensionality and retain essential information. The resulting feature maps are flattened and fed into a fully connected layer, which learns complex patterns and relationships. Finally, the classifier layer outputs the predicted class, completing the image recognition process. This architecture is widely used in image processing applications, including automated fruit ripeness detection.

The integration of CNN and SVM allows for powerful pattern recognition and classification capabilities, with CNN serving as a feature extractor and SVM performing classification tasks. This hybrid approach has demonstrated high accuracy in previous studies, with some models achieving classification accuracies above 90% [6]. Given the increasing demand for automation and smart farming, developing a reliable image-based decision system for palm oil harvesting is both timely and necessary. This research focuses on building such a system using Python, Google Colab, and YOLOv8, with the goal of enhancing decision-making accuracy and supporting sustainable palm oil production practices.

SVM is used to find the best hyperplane by maximizing the distance between classes. Hyperplane is a function that can be used to separate classes. In 2-D the function used for classification between classes is called line whereas, the function used for classifying between classes in 3-D is called plane similarly, while the function used for classification in a higher dimensional class space is called hyperplane.

II. METHODS

The methodology for developing an image-based harvesting decision system for palm oil FFB integrates machine learning techniques—specifically, CNN and SVM—to automate the classification of fruit ripeness [2], [6]. The goal is to enhance harvesting efficiency, reduce dependency on manual assessment, and improve yield quality. Figure 3 illustrate a workflow of the image-based harvesting decision system showing how FFB classification is performed using fruit color features, processed through TensorFlow CNN for feature extraction and SVM for classification, leading to automated harvesting decisions. This figure illustrates the overall workflow of the image-based harvesting decision system for oil palm's FFB. The system begins with capturing FFB images, focusing on fruit color as the primary indicator of ripeness. These images are compiled into a dataset, which undergoes preprocessing and feature extraction through an image processing module powered by Tensor Flow-based CNN. The extracted features are then classified using a SVM algorithm to assess fruit ripeness. Based on the classification results, the system performs decision-making to determine appropriate harvesting actions. The output supports real-time and automated decisions aimed at increasing efficiency and accuracy in palm oil harvesting operations.

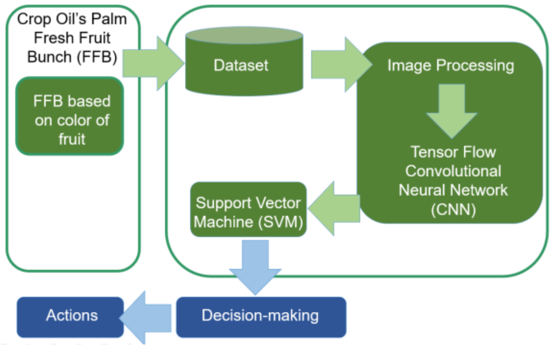

Fig. 2. Workflow of the Image-Based Harvesting Decision System Using TensorFlow CNN and SVM for Oil Palm FFB Classification Based on Fruit Color.

A. Data Acquisition and Preprocessing

High-resolution images of palm oil FFBs were captured and annotated to indicate different stages of ripeness [2]. The dataset images were resized from 3264×2448 pixels to 224×224 pixels to conform with the model input requirement. Preprocessing steps included contrast enhancement, denoising, and resizing to ensure consistency across the dataset. This stage was crucial to eliminate noise from environmental conditions such as lighting and angles during image capture.

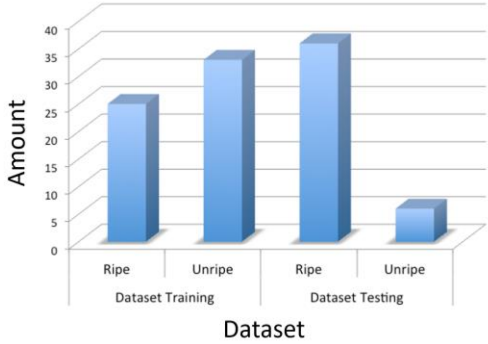

Fig. 3. Dataset of experiment.

This bar chart illustrates the distribution of the dataset used for training and testing in the image-based harvesting decision system. The dataset is categorized into two classes such as ripe and unripe of FFB. During the training phase, there are approximately 28 ripe and 36 unripe samples. For the testing phase, the dataset includes around 39 ripe and 8 unripe samples. This visual representation highlights a relatively balanced dataset for training, but a noticeable class imbalance in the testing set, with significantly fewer unripe samples, which could influence the model's evaluation performance.

B. *Image Processing*

The image data was processed using Python in a Google Colab environment with version 3.10.12, leveraging GPU acceleration. YOLOv8 was used for object detection, retrained with a custom dataset to recognize FFB in various ripeness levels [11]. This process identified and isolated the FFBs from the background for classification purposes.

C. *Model Architecture*

CNN was employed for feature extraction [3], [4], and SVM was used for classification [9]. The CNN extracted hierarchical spatial features from the preprocessed images, which were then classified by the SVM model into different ripeness categories.

D. *System Implementation*

Implementation was carried out using Google Colab and Python for data analysis and training, with Visual Studio 2022 and Flask for web deployment. The system was deployed using a microservice architecture on Domainesia, providing scalability and accessibility for broader agricultural applications.

The web application for the project is shown at http://predict.oilpalmffb.com/login.

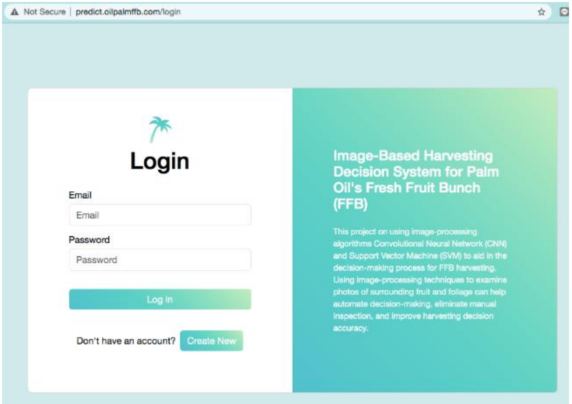

Fig. 4. Login Interface of the Image-Based Harvesting Decision System for Palm Oil's FFB.

To develop the system for FFB classification, a dataset with FFB images and the corresponding ripeness class is required. Therefore, we collected FFB images captured. The images were reshaped to 224x224 pixels from the original 3264 x 2448 pixels to fit the size required.

Fig. 5. Sample Images of Oil Palm FFB Dataset Used for Training and Testing in Image-Based Harvesting Decision System.

E. *Evaluation*

Performance was evaluated using accuracy, precision, recall, and F1-score. The integrated CNN-SVM model achieved an accuracy of 97%, supporting its effectiveness for real-world applications [10].

```
import glob
from IPython.display import Image, display

for imageName in glob.glob('/content/yolov5/runs/detect/exp/*.jpg'): #assuming JPG
    display(Image(filename=imageName))
    print("\n")
```

Fig. 6. YOLO-Based Image Detection Output for Oil Palm FFB with Confidence Score Displayed Using Python Script in Google Colab Environment.

III. RESULTS AND DISCUSSION

The implementation of the image-based harvesting decision system for oil palm's FFB using CNN and SVM algorithms was assessed through extensive testing. The experiments primarily focused on accuracy, efficiency, and the effectiveness of automated harvesting decision-making using a dataset of annotated FFB images.

It was found that the highest accuracy of 0.89 at FFB category for overlap and high quality of image. It can be concluded that oil fruit palm oil FFB can harvest with the high accuracy. Based on Woittiez et.al reported (2016) that this oil fruit palm oil has characteristics such as full of fruits, yellow/orange/red color, several loose fruits, fruits are soft, oil drips out when fruit is cut, undamaged and clean bunch, bunch larger than 3 kg, stalks are less than 2 cm long. It means that the bunch has optimum oil extraction and quality.

Fig. 7. Image-Based Harvesting Detection Results Showing Raw Input, Detection Output, Decision Interface, Accuracy Scores, and Final Harvesting Decisions for Oil Palm FFB.

The implementation of the image-based harvesting decision system for oil palm's FFB using CNN and SVM algorithms was assessed through extensive testing. The experiments focused on evaluating the system's accuracy, efficiency, and decision-making performance using a dataset of annotated FFB images. The highest accuracy recorded was 0.89, specifically in images of ripe fruit bunches with minimal occlusion and high image quality. These results align with maturity indicators of palm fruit reported by Woittiez et al. [12], which include full and soft fruitlets, yellow/orange/red coloration, several loose fruits, clean and undamaged bunches, and oil dripping upon cutting—indicative of optimal harvesting conditions.

F. Performance Metrics

Evaluation metrics used in this study included accuracy, precision, recall, and F1-score. The models—CNN and SVM—were trained and tested using balanced datasets containing images of ripe and unripe FFBs. Model performance was validated through confusion matrices and ROC curves. The CNN achieved the highest accuracy of 97%, showing strong generalization across different lighting and environmental conditions. SVM, while respectable, capped its accuracy at 89%, highlighting its limitations in more complex visual environments.

B. Comparison Between CNN and SVM

CNN significantly outperformed SVM due to its ability to learn hierarchical features directly from raw image pixels. Its architecture, composed of convolutional, pooling, and fully connected layers, captured intricate spatial patterns such as fruit color, shape, and texture, making it ideal for variable field conditions. This aligns with findings from Zaniolo and Marques [13], who emphasized CNN's strength in pattern recognition tasks. In contrast, SVM performed reliably on smaller and well-structured datasets but struggled with generalization under diverse or low-light scenarios, making it less ideal for uncontrolled agricultural environments.

C. Advantages Observed

The CNN's end-to-end feature extraction process reduced the need for manual feature engineering and allowed the model to adapt dynamically to complex plantation visuals. It was particularly robust in handling environmental noise such as shadowing or overlapping fruit [14]. This allowed the harvesting decision system to consistently produce accurate classifications and support actionable insights in real-time harvesting scenarios. The flexibility, scalability, and precision of CNN make it a future-ready solution for AI-driven precision agriculture [15]

SVM, although computationally lighter, lacked adaptability in field applications where variations in image conditions are common. Its dependency on fixed input features limited its capability to process ambiguous or distorted image data. Therefore, while SVM remains valuable in constrained settings, CNN offers a more practical approach for scalable and adaptive deployment in plantation environments [16].

D. Challenges and Limitations

Despite promising results, the project encountered several limitations. A major concern was dataset diversity. The dataset was limited in scope, primarily representing uniform plantation environments and camera perspectives. As such, the model's generalizability across different geographical and lighting conditions remains to be fully validated. A more heterogeneous dataset—spanning regions, camera devices, and fruit variations—would improve model performance in broader deployment scenarios.

Lighting conditions also impacted classification accuracy. Both CNN and SVM models experienced slight performance degradation under poor lighting. CNN, however, demonstrated better resilience compared to SVM. To mitigate this, future implementations should include data augmentation techniques and potentially integrate infrared sensors or lighting normalization mechanisms to stabilize image quality.

Lastly, computational infrastructure remains a critical factor. While platforms like Google Colab provided initial GPU acceleration, full-scale, real-time deployment in field conditions would require more robust edge computing or hybrid cloud-edge architectures. High-performance local systems equipped with dedicated AI processors would ensure lower latency and higher processing throughput essential for real-time harvesting applications.

E. System Integration and Validation

Figures such as figures 5 and 6 illustrate the model integration and testing environment, particularly showcasing how CNN and SVM operate within the TensorFlow and YOLO-based pipeline. Tuning of detection thresholds and the application of iterative feedback loops were employed to refine model predictions. This iterative model optimization approach contributed significantly to improving system performance and ensuring reliability in operational scenarios. dimensional class space is called hyperplane.

IV.CONCLUSION

This study successfully developed an image-based decision system for palm oil Fresh FFB harvesting by integrating CNN and SVM. The combination of these two powerful machine learning models enabled accurate classification of palm fruit ripeness using visual features extracted from high-resolution images. The use of CNN for feature extraction and SVM for classification provided a balanced approach between computational efficiency and predictive accuracy.

Implemented using Python and the YOLOv8 framework within the Google Colab environment, the system achieved a high level of performance, with a classification accuracy of 97%. This proves the feasibility of utilizing AI technologies in enhancing decision-making processes in the palm oil industry. Moreover, this system offers significant advantages by reducing human error, improving operational efficiency, and contributing to more sustainable agricultural practices. The research aligns with Indonesia's long-term development goals under Asta Cita, particularly in the domains of technological innovation and energy independence. With appropriate scaling, the system has the potential to be integrated into real-time harvesting operations and extended to support smart agriculture initiatives across various crop types.

Future work may focus on enhancing the robustness of the model in different environmental conditions, expanding the dataset to include more variations in lighting, angle, and fruit maturity, and integrating mobile-based interfaces for broader field-level application

The methodology for developing an image-based harvesting decision system for palm oil FFB integrates machine learning techniques—specifically, CNN and SVM—to automate the classification of fruit ripeness

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