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Classification Of Palm Oil Fruit Maturity Using CNN And Multiclass SVM In Ara Bungong Village

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ABSTRACT

The determination of the ripeness level of fresh fruit bunches (FFB) of oil palm is still largely performed manually, making it susceptible to subjectivity and classification errors that can affect harvest quality and consistency. This study aims to develop an automated classification system for oil palm fresh fruit bunch ripeness by combining a Convolutional Neural Network (CNN) as a feature extractor and a Multiclass Support Vector Machine (SVM) as the classification algorithm. The dataset consisted of 300 images of oil palm fresh fruit bunches categorized into three classes: unripe, ripe, and overripe. The research stages included image data collection, image preprocessing, feature extraction using CNN, classification using Multiclass SVM, and performance evaluation based on the confusion matrix, accuracy, precision, recall, and F1-score. The CNN was employed to automatically extract representative visual features from the input images, while the Multiclass SVM classified the extracted feature vectors into the corresponding ripeness categories. The experimental results showed that the proposed model achieved an accuracy of 90%, precision of 90%, recall of 90%, and an F1-score of 90% in classifying the ripeness levels of oil palm fresh fruit bunches. These findings indicate that the combination of CNN and Multiclass SVM effectively recognizes the visual characteristics of each ripeness level and provides reliable classification performance. The developed system is expected to serve as an alternative decision-support tool for determining the optimal harvesting time in a more objective, consistent, and efficient manner, thereby supporting productivity improvement and reducing the potential for human error during harvest assessment.

INTRODUCTION

Oil palm is one of the leading plantation commodities in Indonesia and plays a significant role in supporting the national economy (Purnomo et al., 2020). The quality of harvested products is highly influenced by the accuracy of determining the ripeness level of fresh fruit bunches (FFB) (Makky & Soni, 2014). In practice, ripeness assessment is still commonly performed manually by workers based on visual observations of fruit color and the number of detached fruitlets, making the process susceptible to subjectivity and human error (Goh et al., 2025). Errors in determining the ripeness level may result in harvesting the fruit either too early or too late, leading to reduced oil extraction rates, increased free fatty acid (FFA) content, and lower production quality (Prasad et al., 2018). Therefore, an automated, objective, and consistent system for classifying the ripeness level of FFB is required to support a more optimal harvesting process (Adriyansyah et al., 2025).

Recent advances in digital image processing and artificial intelligence have provided promising solutions to address this issue (Archana & Jeevaraj, 2024). Convolutional Neural Networks (CNNs) are capable of automatically extracting visual features from images, while Multiclass Support Vector Machines (SVMs) can effectively perform multiclass classification based on the extracted features (Maqsood et al., 2022). The combination of these two methods is expected to improve the system's ability to distinguish different ripeness levels of oil palm fresh fruit bunches (Lai et al., 2023). This study aims to develop an oil palm fresh fruit bunch ripeness classification system using a CNN as the feature extractor and a Multiclass SVM as the classifier, and to evaluate its performance using accuracy, precision, recall, and F1-score metrics. The results of this study are expected to provide an alternative decision-support tool for determining the optimal harvesting time more accurately and consistently.

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METHOD

The research workflow is illustrated in the following diagram:

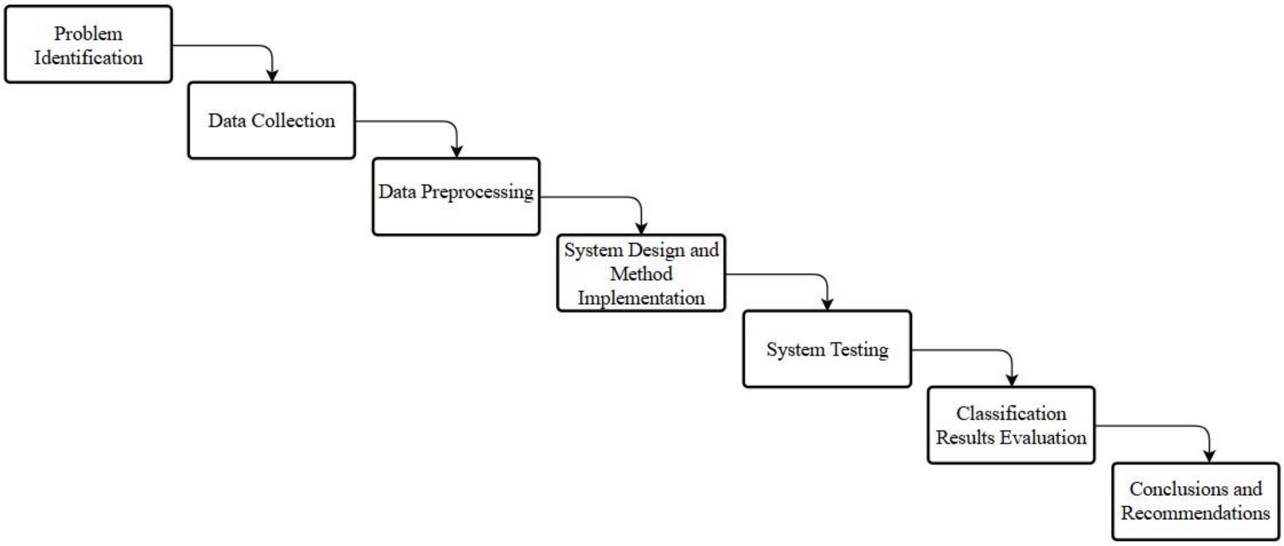

Figure 1. Research Workflow

The research workflow illustrates the systematic stages carried out, starting from problem identification and ending with conclusions and recommendations. The process begins with problem identification to understand the issues being addressed, followed by the collection of relevant data. The collected data then undergo preprocessing to prepare it for further analysis before proceeding to system design and the implementation of the proposed method in accordance with the research objectives (Alonso-Coello et al., 2016).

After the system is developed, it is tested to ensure that it produces the expected outputs. The resulting classification results are then evaluated to determine the performance and accuracy of the proposed method. The final stage involves drawing conclusions and providing recommendations based on the evaluation results, which are expected to serve as a basis for decision-making and future research development.

Problem Identification

The process of determining the ripeness level of oil palm fresh fruit bunches (FFB) in Ara Bungong Village is still carried out manually based on visual observations of fruit color and the number of detached fruitlets. This approach relies heavily on the experience of workers, resulting in classification outcomes that are often inconsistent. Variations in lighting conditions, viewing angles during observation, and worker fatigue may lead to errors in distinguishing between unripe, ripe, and overripe fruit bunches. These conditions have the potential to reduce harvest quality and affect the oil extraction rate.

Based on these issues, an automated classification system is required to identify the ripeness level of oil palm fresh fruit bunches more objectively and accurately. The application of digital image processing technology by combining a Convolutional Neural Network (CNN) as a feature extractor and a Multiclass Support Vector Machine (SVM) as a classifier is expected to reduce errors caused by manual assessment (Bilal et al., 2024). Therefore, the proposed system is expected to assist in identifying fruit bunch ripeness more consistently and support decision-making in determining the optimal harvesting time (Goh et al., 2025).

Data Collection

The data used in this study consisted of images of oil palm fresh fruit bunches (FFB) collected directly from Ara Bungong Village. The dataset comprised 300 images categorized into three ripeness levels: unripe, ripe, and overripe. The images were captured under natural lighting conditions with minimal background interference to ensure that the visual characteristics of the fruit bunches were clearly represented. Each image was then labeled according to its ripeness level to serve as the ground truth for the training and testing processes of the classification model (Zhang et al., 2018).

Data collection was conducted through direct observation at the research site and supported by a literature review to obtain references regarding the ripeness characteristics of oil palm fresh fruit bunches and digital image classification methods. All collected images subsequently underwent a preprocessing stage before feature extraction using a Convolutional Neural Network (CNN) and classification using a Multiclass Support Vector Machine (SVM). The dataset was then divided into 70% training data and 30% testing data to evaluate the model's performance based on accuracy, precision, recall, and F1-score (Obi, 2023).

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Data Preprocessing

Data preprocessing was performed to improve the quality of the images before they were used in the classification process (Dehbozorgi et al., 2024). This stage aims to reduce image noise and produce a standardized dataset that can be processed efficiently by the proposed model (Zamir et al., 2020). Each image was inspected to ensure its quality, followed by resizing to a predetermined resolution so that all images had consistent dimensions (Sun et al., 2023). Subsequently, pixel values were normalized to a specific range to enhance the stability and efficiency of the model training process (Agughasi, 2024).

After the preprocessing stage was completed, all images were labeled according to their ripeness levels: unripe, ripe, and overripe. The processed dataset was then divided into 70% training data and 30% testing data. The training data were used to develop the model, employing a Convolutional Neural Network (CNN) as the feature extractor and a Multiclass Support Vector Machine (SVM) as the classifier, while the testing data were used to evaluate the model's performance based on accuracy, precision, recall, and F1-score.

System Design

The system developed in this study is a web-based application for classifying the ripeness levels of oil palm fresh fruit bunches (FFB) using digital images. The classification process begins with image upload, followed by image preprocessing to standardize image quality and dimensions. A Convolutional Neural Network (CNN) is then employed to extract visual features, which are subsequently classified by a Multiclass Support Vector Machine (SVM) into three categories: unripe, ripe, and overripe. The classification results are displayed through the web interface, while the model performance is evaluated using a confusion matrix, accuracy, precision, recall, and F1-score. The proposed system provides a faster, more objective, and more consistent alternative to conventional manual ripeness assessment.

The system interface is presented in Figure 2:

Figure 2.Classification Website Dashboard

Figure 2 presents the homepage of the web-based oil palm fresh fruit bunch (FFB) ripeness classification application developed in this study. The homepage is designed with a simple, responsive, and user-friendly interface, enabling users to quickly understand the system's functionality. The center of the page displays the application title, a brief description of the Convolutional Neural Network (CNN) and Multiclass Support Vector Machine (SVM) methods employed in the system, and a "Start Classification" button that directs users to the classification page. In addition, a sample image of an oil palm fresh fruit bunch is provided to illustrate the object to be analyzed by the system. The layout and color scheme are intentionally designed to be simple, allowing the presented information to be easily understood while providing a more comfortable user experience.

At the bottom of the homepage, the system provides concise information, including the dataset size of more than 300 images, the three ripeness categories (unripe, ripe, and overripe), and the classification method, which combines a Convolutional Neural Network (CNN) as the feature extractor with a Multiclass Support Vector Machine (SVM) as the classifier. The navigation menu at the top of the page enables users to access the Home, Classification, Training Data, Accuracy, and About pages, allowing all major system functions to be accessed conveniently. The user interface is designed to enhance usability while presenting essential information about the proposed classification system. With this

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design, users can identify the ripeness level of oil palm fresh fruit bunches more quickly, conveniently, and systematically without requiring extensive technical knowledge of the underlying algorithms.

System Testing

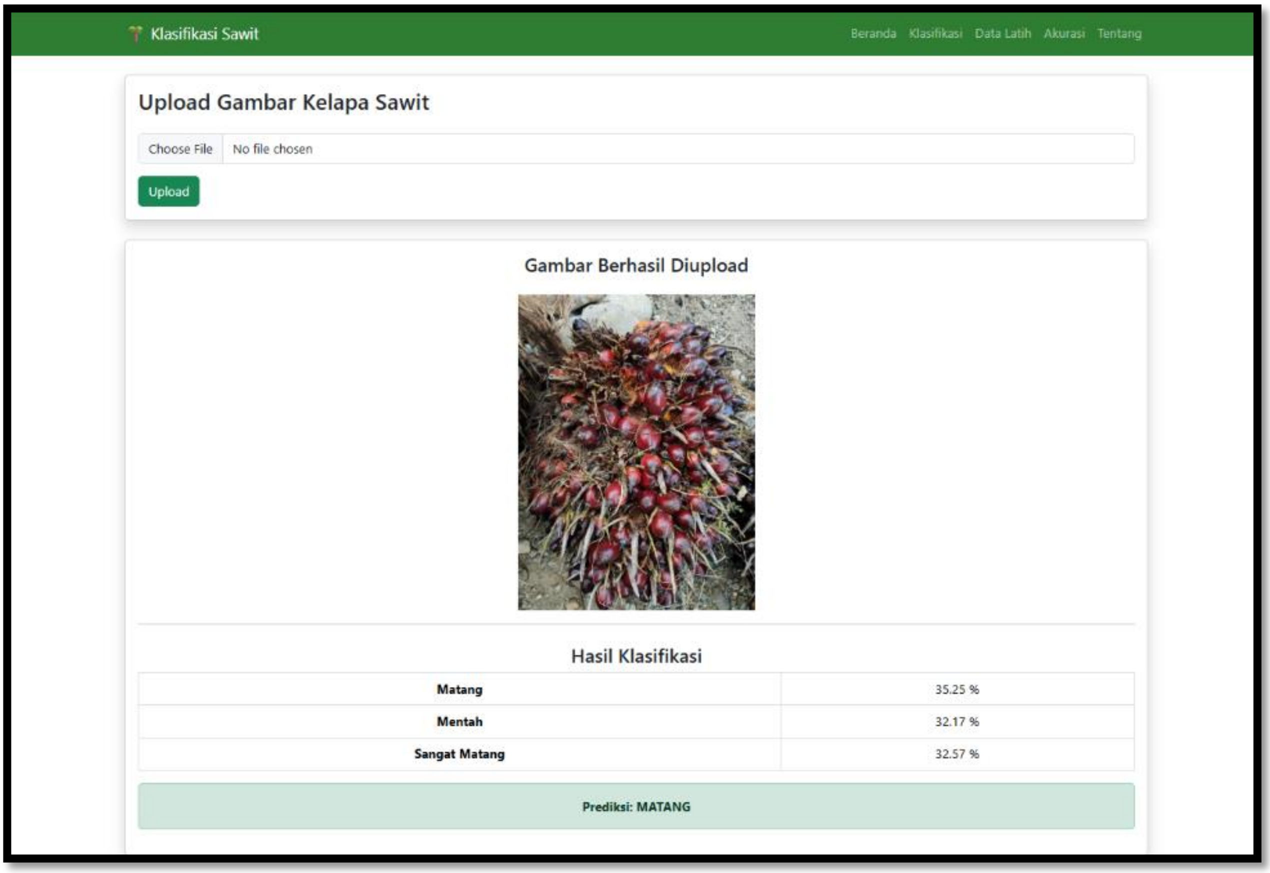

Figure 3 Classification Result

System testing was conducted to evaluate the capability of the developed application in classifying the ripeness levels of oil palm fresh fruit bunches (FFB) based on digital images. During the testing process, users uploaded an image through the system interface, after which the image underwent preprocessing, feature extraction using a Convolutional Neural Network (CNN), and classification using a Multiclass Support Vector Machine (SVM). The classification results were then displayed directly on the web interface, indicating the predicted ripeness level along with the corresponding confidence score. An example of the system testing results is presented in the following figure to illustrate the classification process performed by the application.

Based on the testing results presented in Figure 3, the system successfully received the uploaded image of an oil palm fresh fruit bunch (FFB) and processed it through the preprocessing stage, feature extraction using a Convolutional Neural Network (CNN), and classification using a Multiclass Support Vector Machine (SVM). After the classification process was completed, the system displayed the probability scores for each ripeness category, namely Ripe (35.25%), Unripe (32.17%), and Overripe (32.57%). Based on the highest probability score, the system classified the image as Ripe, and the prediction result was displayed at the bottom of the webpage as the final classification outcome.

The testing results indicate that the system is capable of performing the classification process automatically and providing information regarding the model’s confidence level for each ripeness category. Although the differences in probability scores among the classes are relatively small, the Ripe class obtained the highest score and was therefore selected as the final classification result. This condition suggests that the tested image possesses visual characteristics that are sufficiently similar to those of the other classes, particularly during the transition stage between unripe, ripe, and overripe fruit bunches. Nevertheless, the system was still able to determine the most appropriate class based on the extracted features and the classification process performed. These findings demonstrate that the integration of CNN and Multiclass SVM methods can support the objective identification of oil palm fresh fruit bunch ripeness levels and provide prediction results that can serve as a basis for assisting decision-making in the harvesting process.

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Table 1. Model Evaluation Result

Metode	**CNN & Multiclass SVM**
Accuracy	91.11%
Precision	91.74%
Recall	91.11%
F1-Score	91.24%

Based on the evaluation results, the proposed classification model, which combines a Convolutional Neural Network (CNN) as the feature extractor and a Multiclass Support Vector Machine (SVM) as the classifier, achieved an accuracy of 91.11%, a precision of 91.74%, a recall of 91.11%, and an F1-score of 91.24%. The accuracy value indicates that the majority of oil palm fresh fruit bunch (FFB) images were correctly classified according to their ripeness levels. Meanwhile, the precision of 91.74% demonstrates that the model generated highly accurate predictions, resulting in a relatively low number of incorrect class assignments.

Furthermore, the recall of 91.11% indicates that the model successfully identified most images across all ripeness categories, while the F1-score of 91.24% reflects a good balance between precision and recall. Overall, these evaluation results demonstrate that the combination of CNN and Multiclass SVM provides strong performance in identifying the visual characteristics of oil palm fresh fruit bunches across the three ripeness levels, namely unripe, ripe, and overripe. Therefore, the proposed model is considered sufficiently reliable for implementation as a decision-support system for the automatic determination of oil palm fresh fruit bunch ripeness, thereby improving objectivity and consistency in harvest timing decisions.

RESULT

The proposed web-based system successfully classified the ripeness level of oil palm fresh fruit bunches (FFB) into three categories: unripe, ripe, and overripe. The classification process begins when the user uploads an FFB image through the web interface. The uploaded image is first preprocessed to standardize its dimensions and pixel values before feature extraction is performed using the Convolutional Neural Network (CNN). The extracted feature vectors are subsequently classified by the Multiclass Support Vector Machine (SVM), and the predicted ripeness category is displayed together with the confidence score.

Performance evaluation was conducted using 90 testing images representing 30% of the total dataset, while the remaining 210 images were used for training. The evaluation results demonstrate that the proposed CNN–Multiclass SVM model achieved an accuracy of 91.11%, precision of 91.74%, recall of 91.11%, and F1-score of 91.24%. These results indicate that the developed model provides reliable classification performance across the three ripeness categories.

Although several testing samples produced relatively close probability values among the three classes, the model consistently selected the class with the highest confidence score as the final prediction. This demonstrates that the developed system is capable of automatically identifying oil palm FFB ripeness levels through a practical web-based interface while maintaining stable classification performance.

DISCUSSION

The experimental results demonstrate that the proposed hybrid model combining a Convolutional Neural Network (CNN) and a Multiclass Support Vector Machine (SVM) provides effective performance for classifying the ripeness levels of oil palm fresh fruit bunches. The achieved accuracy of 91.11%, precision of 91.74%, recall of 91.11%, and F1-score of 91.24% indicate that CNN successfully extracted representative visual features, while Multiclass SVM effectively separated the feature vectors into the three ripeness categories. Although several testing samples exhibited similar visual characteristics, particularly between adjacent ripeness stages, resulting in relatively close probability scores, the model consistently identified the most appropriate class based on the learned decision boundaries. These findings are consistent with previous studies reporting that CNN is highly effective for extracting discriminative image features (Archana & Jeevaraj, 2024), while integrating CNN with SVM improves classification performance compared with using conventional classifiers alone (Maqsood et al., 2022; Bilal et al., 2024). Furthermore, the obtained performance supports recent studies on automated oil palm ripeness classification, which emphasize that artificial intelligence can reduce subjectivity and improve the consistency of harvest decision-making (Lai et al., 2023; Goh et al., 2025). Nevertheless, the present study is limited by the relatively small dataset consisting of 300 images collected from a single plantation area, which may affect the model's generalization capability under different environmental conditions. Therefore, future research should consider using larger and more diverse datasets, together with more advanced CNN architectures, to further improve the robustness and practical applicability of the proposed classification system.

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CONCLUSION

This study successfully developed a digital image-based classification system for determining the ripeness levels of oil palm fresh fruit bunches (FFB) by combining a Convolutional Neural Network (CNN) as the feature extractor and a Multiclass Support Vector Machine (SVM) as the classifier. The developed system is capable of automatically identifying three ripeness levels, namely unripe, ripe, and overripe, through a web-based application. Based on the experimental results, the proposed model achieved an accuracy of 91.11%, a precision of 91.74%, a recall of 91.11%, and an F1-score of 91.24%. These results demonstrate that the combination of CNN and Multiclass SVM provides strong performance in classifying the ripeness levels of oil palm fresh fruit bunches, indicating its potential as an objective and efficient decision-support tool for determining the optimal harvesting time.

For future research, it is recommended to use a larger dataset with more diverse image acquisition conditions, including variations in lighting intensity, camera angles, and background settings. In addition, the performance of the proposed system can be further improved by comparing alternative hybrid methods or adopting more advanced CNN architectures to develop a classification model with higher accuracy and better generalization capability under real-world field conditions.

REFERENCES

Agughasi, V. I. (2024). *The superiority of fine-tuning over full-training for the efficient diagnosis of COPD from CXR images*. *Inteligencia Artificial, 27*(74), 62–79.

Adriyansyah, Y. A., Adriyanto, F., & Laksono, P. W. (2025). *Deep learning approach for palm oil fresh fruit bunches harvest decision*. *Journal of Electrical, Electronic, Information, and Communication Technology, 7*(1), 29–33. https://doi.org/10.20961/jeeict.7.1.100897

Alonso-Coello, P., Schünemann, H. J., Moberg, J., Brignardello-Petersen, R., Akl, E. A., Davoli, M., et al. (2016). *GRADE Evidence to Decision (EtD) frameworks: A systematic and transparent approach to making well informed healthcare choices. 1: Introduction*. *BMJ, 353*. https://doi.org/10.1136/bmj.i2016

Archana, R., & Jeevaraj, P. S. (2024). *Deep learning models for digital image processing: A review*. *Artificial Intelligence Review, 57*(1). https://doi.org/10.1007/s10462-023-10638-7

Bilal, A., Imran, A., Baig, T. I., Liu, X., Long, H., Alzahrani, A., & Shafiq, M. (2024). *Improved support vector machine based on CNN-SVD for vision-threatening diabetic retinopathy detection and classification*. *PLOS ONE, 19*(1), e0295951. https://doi.org/10.1371/journal.pone.0295951

Dehbozorgi, P., Ryabchykov, O., & Bocklitz, T. (2024). *A systematic investigation of image pre-processing on image classification*. *IEEE Access, 12*, 64913–64926. https://doi.org/10.1109/ACCESS.2024.3395675

Goh, J. Y., Md Yunos, Y., & Mohamed Ali, M. S. (2025). *Fresh fruit bunch ripeness classification methods: A review*. *Food and Bioprocess Technology, 18*(1), 183–206. https://doi.org/10.1007/s11947-024-03711-7

Lai, J. W., Ramli, H. R., Ismail, L. I., & Wan Hasan, W. Z. (2023). *Oil palm fresh fruit bunch ripeness detection methods: A systematic review*. *Agriculture, 13*(1), 156. https://doi.org/10.3390/agriculture13010156

Makky, M., & Soni, P. (2014). *In situ quality assessment of intact oil palm fresh fruit bunches using rapid portable non-contact and non-destructive approach*. *Journal of Food Engineering, 120*, 248–259. https://doi.org/10.1016/j.jfoodeng.2013.08.012

Maqsood, S., Damaševičius, R., & Maskeliūnas, R. (2022). *Multi-modal brain tumor detection using deep neural network and multiclass SVM*. *Medicina, 58*(8), 1090. https://doi.org/10.3390/medicina58081090

Obi, J. C. (2023). *A comparative study of several classification metrics and their performances on data*. *World Journal of Advanced Engineering Technology and Sciences, 8*(1), 308–314. https://doi.org/10.30574/wjaets.2023.8.1.0058

Prasad, K., Jacob, S., & Siddiqui, M. W. (2018). *Fruit maturity, harvesting, and quality standards*. In *Preharvest Modulation of Postharvest Fruit and Vegetable Quality* (pp. 41–69). Academic Press. https://doi.org/10.1016/B978-0-12-809807-3.00003-0

Purnomo, H., Okarda, B., Dermawan, A., Ilham, Q. P., Pacheco, P., Nurfatriani, F., & Suhendang, E. (2020). *Reconciling oil palm economic development and environmental conservation in Indonesia: A value chain dynamic approach*. *Forest Policy and Economics, 111*, 102089. https://doi.org/10.1016/j.forpol.2020.102089

Sun, S., Alkahtani, M. E., Gaisford, S., Basit, A. W., Elbadawi, M., & Orlu, M. (2023). *Virtually possible: Enhancing quality control of 3D-printed medicines with machine vision trained on photorealistic images*. *Pharmaceutics, 15*(11), 2630. https://doi.org/10.3390/pharmaceutics15112630

Zamir, S. W., Arora, A., Khan, S., Hayat, M., Khan, F. S., Yang, M. H., & Shao, L. (2020). *CycleISP: Real image restoration via improved data synthesis*. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2696–2705. https://doi.org/10.1109/CVPR42600.2020.00276

Zhang, Y., Lian, J., Fan, M., & Zheng, Y. (2018). *Deep indicator for fine-grained classification of banana's ripening stages*. *EURASIP Journal on Image and Video Processing, 2018*(1), 1–10. https://doi.org/10.1186/s13640-018-0358-5