Peeled And Raw Arecanut Segregation and Sorting Using Machine Learning Techniques

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***Abstract*—This paper presents an automated arecanut segregation and sorting system using machine learning and image processing techniques. Traditional manual grading methods are time-consuming and prone to human error. The proposed system captures arecanut images using a camera and classifies them into Good, Medium, and Bad categories using machine learning algorithms such as Random Forest, Support Vector Machine (SVM), and Decision Tree. Image preprocessing and feature extraction are performed using OpenCV to improve classification accuracy. The classified output is integrated with Arduino-based hardware and servo motors for automated sorting. Experimental results show that the Random Forest model achieved the highest accuracy of 92.86%, demonstrating reliable and efficient performance. The system reduces manual effort, improves consistency, and provides a cost-effective solution for smart agricultural automation.**

***Index Terms*—Machine Learning, Arecanut Classification, Random Forest, SVM, Image Processing, Arduino, Automation.**

I. INTRODUCTION

The "Peeled and Raw Arecanut Segregation and Sorting using Machine Learning Techniques" project is developed to automate the traditional Arecanut grading process, which is usually done manually based on color, size, and texture. Manual sorting is time-consuming, inconsistent, and prone to human error, making it inefficient for large-scale production. To address this, the project uses Image Processing and Machine Learning techniques to classify Arecanuts accurately and quickly.

With the development of technology, machine learning and image processing techniques are being widely used in agricultural applications to improve efficiency and accuracy. These technologies help computers identify and classify objects based on their visual features such as color, texture, and shape. By using automated systems, the sorting process can become faster, more reliable, and less dependent on manual labor.

The main aim of this project is to develop a system for peeled and raw arecanut segregation and sorting using machine learning techniques. The system captures images of arecanuts through a camera and processes them using image processing methods. Important features are extracted from the images, and a machine learning model is trained to classify the arecanuts into peeled and raw categories.

The proposed system helps in reducing human effort and increasing sorting accuracy. It can also save time and improve productivity in arecanut processing industries.

II. BACKGROUND AND RELATED WORK

Several researchers have explored the use of image processing and machine learning techniques for agricultural product grading and classification. Prasad et al. [1] developed a computer vision-based grading system for arecanuts using image preprocessing and morphological operations, demonstrating that controlled lighting and feature extraction significantly improve classification accuracy. Shetty and Rao [2] proposed a deep learning framework for arecanut quality classification using convolutional neural networks, where transfer learning models such as VGG16 and ResNet achieved high classification performance under controlled conditions.

Verma and Singh [3] introduced a machine learning-based agricultural nut sorting system using Random Forest and clustering algorithms, showing that automated classification provides better consistency compared to manual grading methods. Naik and Kumar [4] focused on texture and colour feature extraction techniques using Gray-Level Co-occurrence Matrix (GLCM) and histogram analysis for raw arecanut classification. Their work highlighted the importance of combining multiple visual features for reliable classification performance.

Velalla et al. [5] proposed a CNN-based arecanut dataset and classification framework for automated grading under varying environmental conditions. Their research emphasized the importance of dataset diversity, preprocessing, and feature optimization for improving model robustness. Inspired by these existing works, the proposed system integrates image processing, machine learning algorithms, and Arduino-based hardware automation to develop a real-time arecanut segregation and sorting system capable of efficient and accurate classification.

III. METHODOLOGY

The proposed arecanut segregation and sorting system combines image processing, machine learning, and hardware automation to classify peeled and raw arecanuts into Good, Medium, and Bad categories. Images are captured using a USB camera under controlled lighting conditions to ensure consistent image quality. The captured images are then processed using OpenCV techniques such as resizing, noise removal, colour correction, and contrast enhancement to improve feature visibility and classification accuracy.

After preprocessing, important visual features such as colour, texture, and shape are extracted from the processed images. These extracted features are converted into numerical representations suitable for machine learning algorithms. Three machine learning models Random Forest, Support Vector Machine (SVM), and Decision Tree were trained and tested using labelled arecanut datasets consisting of Good, Medium, and Bad quality samples. Among the three models, Random Forest provided the highest classification accuracy due to its robustness and reduced overfitting characteristics.

The trained models were evaluated using confusion matrices, classification reports, and accuracy comparison metrics. Visualization libraries such as Matplotlib were used to generate performance graphs for analysing the effectiveness of the models. The comparison results showed that Random Forest achieved the best overall classification performance compared to SVM and Decision Tree algorithms.

The classification output was integrated with an Arduino Nano-based hardware setup for automated sorting operations. The USB camera continuously captures arecanut images, while the Arduino Nano controls servo motors responsible for directing arecanuts into their respective categories. An LCD display was also incorporated to display classification results in real time. The complete workflow of image acquisition, preprocessing, classification, and automated segregation is illustrated in Fig. 1.

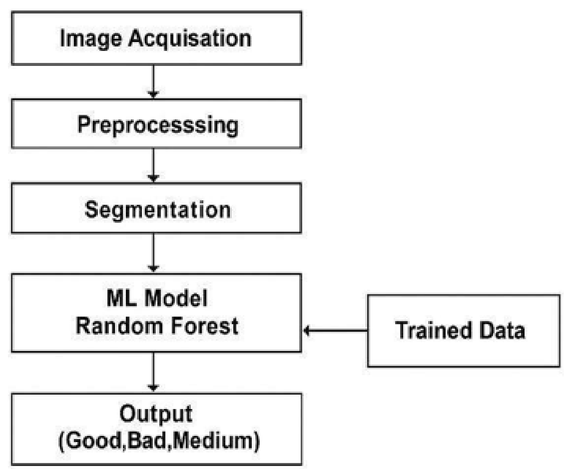

Figure 1. Methodology of the proposed arecanut segregation system.

IV. HARDWARE AND SOFTWARE REQUIREMENTS

A. Hardware Requirements

The hardware setup of the proposed system consists of an Arduino Nano microcontroller, USB camera, servo motors, LCD display, laptop, and external power supply. The USB camera captures real-time images of peeled and raw arecanuts for classification, while the Arduino Nano controls the automated sorting mechanism using servo motors. The LCD display provides real-time output of the predicted category. The complete hardware configuration enables synchronized image acquisition, processing, and automated segregation operations.

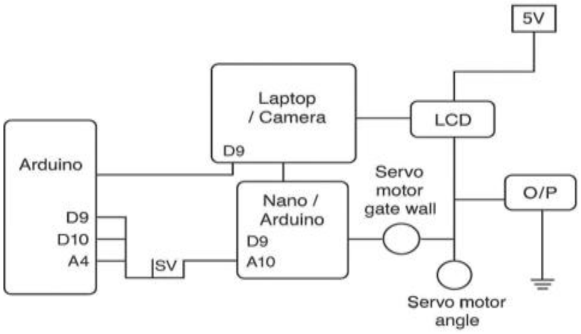

Figure 2. Block diagram of the automated arecanut segregation system.

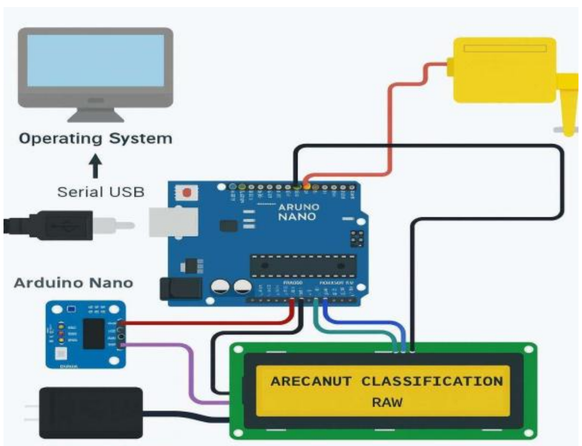

Figure 3. Circuit diagram of the hardware implementation.

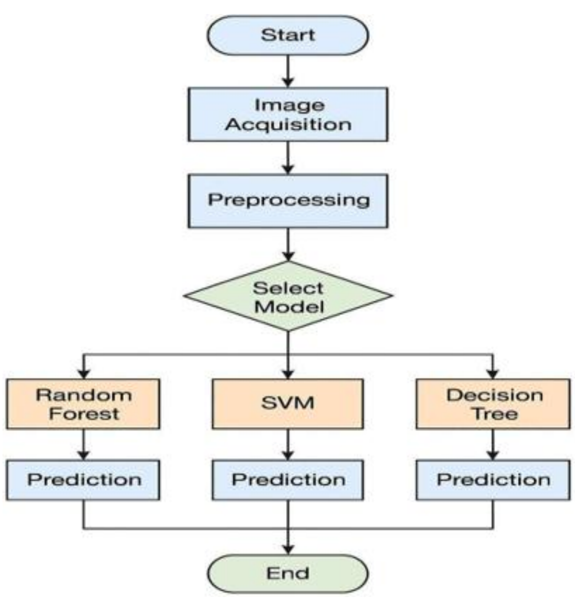

Figure 4. Flow chart of the arecanut classification process.

Table I summarizes the hardware components used in the developed prototype.

S. No	Components	Specifications	Connections (From-To)	Role in Project
01	Arduino Nano	ATmega328P, 5V logic, USB powered	USB → Laptop Digital PWM pins → Servo motors Digital pins → LCD display	Acts as the main microcontroller to control servo motors and display output
02	Web Camera	USB camera, HD resolution	USB → Laptop	Captures real-time images of arecanuts for ML-based classification
03	Laptop / PC	Intel/AMD processor, Python support	Webcam → Laptop (USB) Arduino Nano → Laptop (USB)	Runs image processing and ML algorithms (Random Forest, SVM, Decision Tree)
04	Servo Motor 1	5V DC, 45° rotation	Signal → Arduino Nano PWM pin VCC → 5V supply GND → GND	Controls sorting of peeled arecanuts
05	Servo Motor 2	5V DC, 180° rotation	Signal → Arduino Nano PWM pin VCC → 5V supply GND → GND	Controls sorting of raw arecanuts

B. Software Requirements

The software implementation was carried out using Python and various machine learning libraries in Google Colab. OpenCV was used for image preprocessing operations such as resizing, filtering, colour correction, and feature extraction.

Scikit-learn libraries were used for training and testing the Random Forest, SVM, and Decision Tree models. Arduino IDE was used for programming the Arduino Nano microcontroller, while Gradio was used to develop a user-friendly interface for displaying classification results in real time.

Table II summarizes the software tools used for system implementation.

S. No	Software Used	Purpose / Usage	Features / Specification
01	Python	Used for implementing image processing and machine learning algorithms	Supports OpenCV, NumPy, Pandas, Scikit-learn; easy integration with hardware
02	Arduino IDE	Used for programming the Arduino Nano	C/C++ support, serial communication, easy code upload
03	OpenCV	Used for image acquisition and preprocessing	Image resizing, filtering, color and texture feature extraction
04	Scikit-learn	Used to train and test ML models	Supports Random Forest, SVM, Decision Tree algorithms

V. RESULTS AND DISCUSSION

A. Random Forest Model

The Random Forest model achieved the highest classification accuracy among the three machine learning algorithms. The confusion matrix and classification report demonstrated reliable classification performance for Good, Medium, and Bad arecanut categories. The model achieved an overall accuracy of approximately 92.86%, indicating strong robustness and reduced overfitting characteristics.

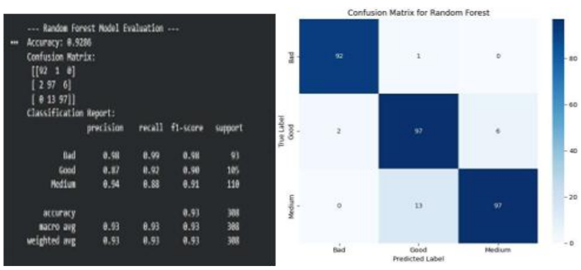

Figure 5. Random Forest confusion matrix and classification results.

B. Support Vector Machine (SVM) Model

The SVM model achieved an overall accuracy of 89.61%. The model correctly classified most samples but showed slight confusion between visually similar categories such as Good and Medium arecanuts. Despite minor misclassifications, the SVM model demonstrated stable and reliable classification performance. The confusion matrix indicates that the model was able to distinguish Bad arecanuts with comparatively higher precision than Medium-class samples. The classification report further shows balanced precision and recalls values, indicating consistent prediction capability across different categories. Overall, the SVM algorithm provided efficient classification performance with good generalization ability for arecanut quality assessment.

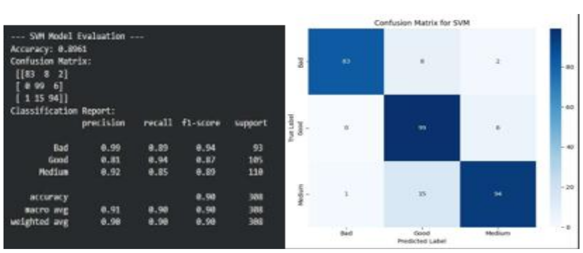

Figure 6. SVM confusion matrix and classification results.

C. Decision Tree Model

The Decision Tree model achieved an accuracy of 87.34%. The model provided faster predictions with lower computational complexity but showed higher sensitivity to visual similarities between categories. The classification results indicate that Decision Tree performance was comparatively lower than Random Forest and SVM models.

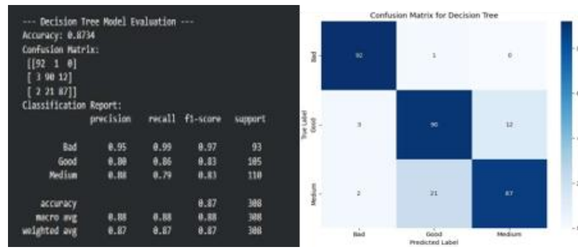

Figure 7. Decision Tree confusion matrix and classification results.

D. Model Accuracy Comparison

Fig. 8 illustrates the comparison of classification accuracies obtained using Random Forest, SVM, and Decision Tree algorithms. Among the three models, Random Forest achieved the best overall performance due to its ensemble learning capability and reduced overfitting behaviour.

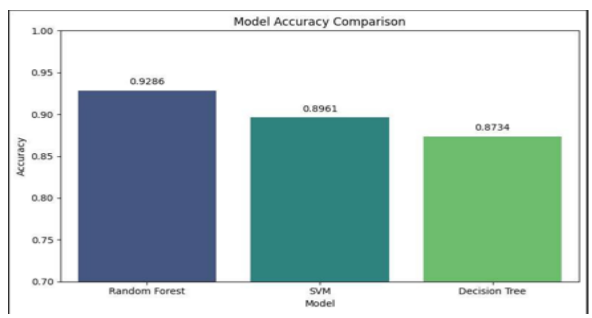

Figure 8. Accuracy comparison of Random Forest, SVM, and Decision Tree models.

E. Hardware Results

The developed hardware prototype successfully demonstrated automated real-time sorting operations. The USB camera continuously captured arecanut images, and the trained machine learning model accurately classified them into Good, Medium, and Bad categories. Based on the prediction result, servo motors automatically redirected the arecanuts into their respective sections. The LCD display showed the classification output in real time. The system achieved reliable performance while significantly reducing manual effort and improving sorting consistency.

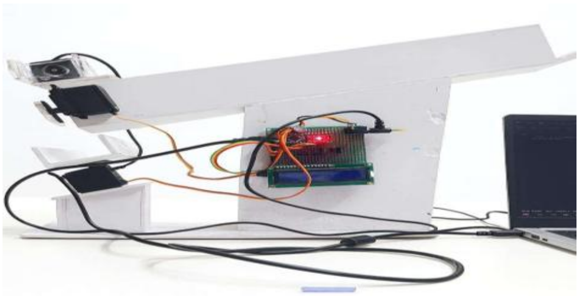

Figure 9. Hardware setup of the automated arecanut segregation system.

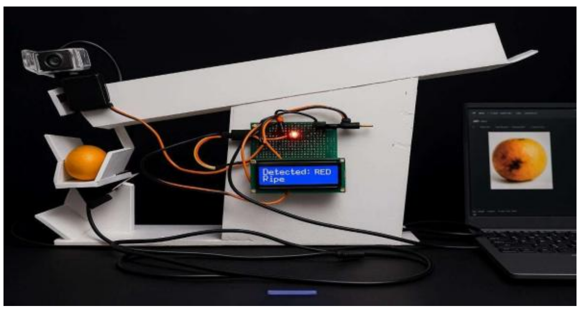

Figure 10. Classification result for ripe arecanut.

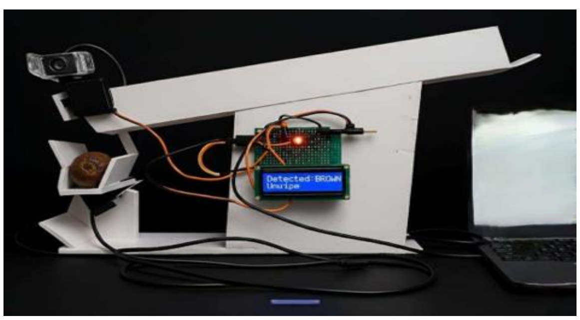

Figure 11. Classification result for unripe arecanut.

VI. CONCLUSION

This paper presented an automated arecanut segregation and sorting system using image processing and machine learning techniques. The proposed system successfully classified peeled and raw arecanuts into Good, Medium, and Bad categories using Random Forest, Support Vector Machine (SVM), and Decision Tree algorithms. Experimental results demonstrated that the Random Forest model achieved the highest accuracy of 92.86%, providing reliable and efficient classification performance. The integration of machine learning models with Arduino Nano-based hardware enabled automated real-time sorting operations. The developed system reduces manual labour, improves consistency, and supports intelligent agricultural automation. Future work may include deep learning-based classification, IoT integration, cloud monitoring, and deployment on embedded AI platforms for large-scale industrial applications.

REFERENCES

[1] Kumar, R. Patil, and S. Shetty, “Machine Learning-Based Classification of Field and Raw Arecanut for Automated Grading,” in *Proceedings of the IEEE International Conference on Intelligent Agriculture Systems*, 2023.

[2] M. Fernandes and P. Rao, “Image Processing Techniques for Arecanut Segregation Using Convolutional Neural Networks,” *Journal of Agricultural Automation*, vol. 18, no. 2, pp. 89–97, 2022.

[3] S. Nayak, K. Bhat, and L. Acharya, “Real-Time Arecanut Sorting Using Deep Learning and Edge Devices,” in *Proceedings of the IEEE International Conference on Smart Farming Technologies*, 2022.

[4] T. Joshi and N. Hegde, “Texture and Color Feature Extraction for Arecanut Classification Using Machine Learning Models,” *IEEE Transactions on Instrumentation and Measurement*, vol. 70, no. 8, pp. 1–8, 2021.

[5] P. Ramesh, S. Kulkarni, and H. Prasad, “Design of an Automated Arecanut Segregation System Using Computer Vision,” in *Proceedings of the IEEE Conference on Automation in Agriculture*, 2021.

[6] J. Thomas, V. Shenoy, and D. Gonsalves, “Low-Cost Arecanut Grading Using Machine Learning on Embedded Platforms,” *Journal of Smart Agricultural Devices*, vol. 9, no. 3, pp. 112–120, 2021.

[7] Pawar and G. Patange, “YOLO-Based Detection and Segregation of Raw and Mature Arecanuts for Industrial Automation,” in *Proceedings of the IEEE International Conference on Computer Vision in Agriculture*, 2020.