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Development of a Robotic Arm Using a Convolutional Neural Network for Areca Nut Sorting

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ABSTRACT

Manual post-harvest sorting of areca nuts is time-consuming and may result in inconsistent classification. To address this limitation, this study developed an automated sorting system that integrates a Convolutional Neural Network (CNN) with a robotic arm to classify and transfer areca nuts into the juice and split categories. The system comprises webcam-based image acquisition, image processing and classification using Python and the MobileNetV3 architecture, and a microcontroller-based control system for a 4 degree of freedom (4 DOF) robotic arm. The CNN model was trained to classify three categories: juice areca nut, split areca nut, and surrounding objects. Based on the reported confusion matrix, the model correctly classified 188 of 189 validation images, achieving an accuracy of 99.47%. The image processing evaluation also reported accuracy values of 99.07% for color, 91.65% for shape, and 94.62% for dimensional measurement. Integrated system testing was conducted on 30 areca nuts, comprising 15 juice type and 15 split type nuts. All 30 objects were successfully transferred to their designated bins, resulting in a sorting success rate of 100% under the tested conditions. The reported CNN inference time was 0.032 s, while the average robotic arm movement time was 15 s per cycle, yielding an estimated total sorting time of 15.032 s per object. These findings demonstrate the feasibility of integrating CNN based image classification with robotic manipulation for automated areca nut sorting. Further testing involving more diverse samples and operating conditions is required to assess the system's generalizability and operational reliability.

INTRODUCTION

The agricultural sector is one of the important sectors of the economy because it produces various economically valuable commodities, including areca nuts (Areca catechu L.). At the post-harvest stage, sorting is required to classify the fruit based on specific characteristics and quality attributes. The visual characteristics of areca nuts can be utilized as a basis for digital classification to support the development of automated sorting systems (Ganapathi et al. (2025) However, manual sorting still has limitations in terms of time efficiency, consistency, and subjectivity in visual assessment. Therefore, an automated approach is needed to identify the visual characteristics of objects more consistently and efficiently.

Advances in image processing and computer vision have enabled characteristics such as object color, shape, and size to be extracted as classification information (Dijaya & Setiawan, 2023; Fansyuri, 2022). HSV color space based segmentation can also be used to identify object regions based on color characteristics (Oni et al., 2021), while webcams can be utilized as image acquisition sensors for real time image capture (Ad et al., 2022). The development of deep learning, particularly Convolutional Neural Networks (CNNs), has further enabled automatic learning of image features. The application of various CNN architectures has demonstrated their capability for image classification, while Python and OpenCV can support image acquisition and processing in computer vision-based systems (Muriagista & Kurniadi, 2025; Hidayah et al., 2024).

Successful visual classification needs to be accompanied by a physical mechanism for transferring objects according to the prediction results. A robotic arm can function as a manipulator for picking and placing objects at designated locations. Previous studies have shown that 4 DOF robotic arms can be integrated with classification systems to perform object transfer, while forward and inverse kinematics are used to determine the relationship between object positions and the manipulator's motion configuration (Rendyansyah et al. (2025); Widyacandra et al., 2022; Afif et al., 2025; Chelinia & Putri, 2025). The integration of computer vision and robotic arms enables the identification and sorting processes to be performed automatically.

Color sorting research based on image processing has demonstrated the use of visual information as a basis for controlling sorting processes (Chairi & Mukhaiyar, 2023), while computer vision-based sorting systems have been

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developed to integrate object recognition with sorting mechanisms (Fitriati et al., 2024). Research on the digital classification of areca nuts has also been conducted as a basis for developing sorting technologies (Ganapathi et al. (2025). However, there remains an opportunity to further develop the integration of CNNs with a 4 DOF robotic arm to simultaneously classify and transfer areca nuts based on visual categories automatically.

LITERATURE REVIEW

Automation of sorting processes has evolved through the integration of perception, decision-making, and actuation systems. A robotic arm serves as a manipulator for performing pick-and-place operations, while successful sorting depends on the system's ability to identify objects and determine their destination locations. Almaliki et al. (2026). demonstrated that the integration of mechanical, electronic, microcontroller, and software components can be used to develop an object transfer system. Rendyansyah et al. (2025) developed a 4 DOF robotic arm integrated with an RGB sensor for object classification and transfer based on color. This approach demonstrates the integration of vision and robotics; however, it remains limited to relatively simple visual characteristics. Furthermore, Widyacandra et al. (2022), Afif et al. (2025), and Chelinia and Putri (2025) demonstrated the importance of forward and inverse kinematics in determining the robot's motion configuration toward target positions. These developments indicate that an automated sorting system requires the integration of visual perception and motion control.

Image processing enables visual information from objects to be used as a basis for classification and decision-making. Dijaya and Setiawan (2023) discussed image processing stages for obtaining visual information, while Fansyuri (2022) utilized color and shape features for fruit classification. A color based approach was also applied by Chairi and Mukhaiyar (2023) using the HSV color space for a sorting system. Although these methods can be effective under certain conditions, their dependence on illumination conditions and threshold parameters represents a limitation when object and environmental characteristics vary. This indicates the need for methods capable of learning object visual representations in a more adaptive manner.

Convolutional Neural Networks (CNNs) enable image feature extraction and classification to be performed automatically through hierarchical learning. CNN based approaches have been applied to various image classification problems, including the use of ResNet50 by Muriagista and Kurniadi (2025). Other studies have also demonstrated the growing application of deep learning and computer vision for object recognition (Debnath et al. (2022).; Ad et al., 2022; Hidayah et al., 2024; Fitriati et al., 2024; Yulianto et al., 2024). Compared with manually engineered features, CNNs have a greater capacity to learn variations in object appearance. However, their implementation in robotic systems requires consideration not only of classification accuracy but also of inference time and the ability to integrate with the control system in real time.

Previous studies indicate that vision systems and robotic arms have been developed both independently and in integrated configurations. Rendyansyah et al. (2025) demonstrated the use of color information to determine robotic actions, whereas studies on kinematics have focused on determining the position and movement of manipulators (Widyacandra et al., 2022; Afif et al., 2025). In contrast, image-based sorting studies have primarily emphasized object identification (Chairi & Mukhaiyar, 2023; Fitriati et al., 2024). Integrating a CNN with a robotic arm enables visual classification results to be directly used as a basis for motion decision-making. Thus, the system can connect perception, classification, and action within a unified automation sequence.

Based on previous studies, two main research trends can be identified. First, research on robotic arms has primarily focused on pick-and-place mechanisms, control, and kinematics. Second, image processing research has focused on object identification using color and shape features or learning-based methods. Research on the digital classification of areca nuts has also demonstrated the potential of visual characteristics as a basis for sorting (Ganapathi et al. (2025). However, research integrating CNNs with a 4 DOF robotic arm to automatically classify and sort areca nuts remains limited.

This research gap provides the basis for developing a system that integrates a webcam camera, a CNN based on the MobileNetV3 architecture, and a 4 DOF robotic arm. The CNN is used to classify areca nuts based on their visual characteristics into the juice and split categories, while the classification results are used to control the robotic arm to perform pick and place operations. Through this approach, the study aims to connect image classification capabilities with the physical actions of a robotic arm within an automated sorting system. The proposed approach places the study at the intersection of computer vision, deep learning, and robotics, with a primary focus on integrating visual classification and the automated sorting mechanism for areca nuts.

METHOD

This section presents the implementation of the proposed system to address inefficiencies in the manual sorting process. The proposed solution is an automated sorting system that integrates visual pattern recognition with the mechanical movement of a robotic arm. In terms of hardware architecture, the system utilizes a webcam camera as the primary sensor to capture images of areca nuts in real time, a computer as the CNN processing unit, and a microcontroller to control four servo motors mounted on a four degree of freedom (4 DOF) robotic arm. Conceptually, the developed system follows the workflow illustrated in Figure 1.

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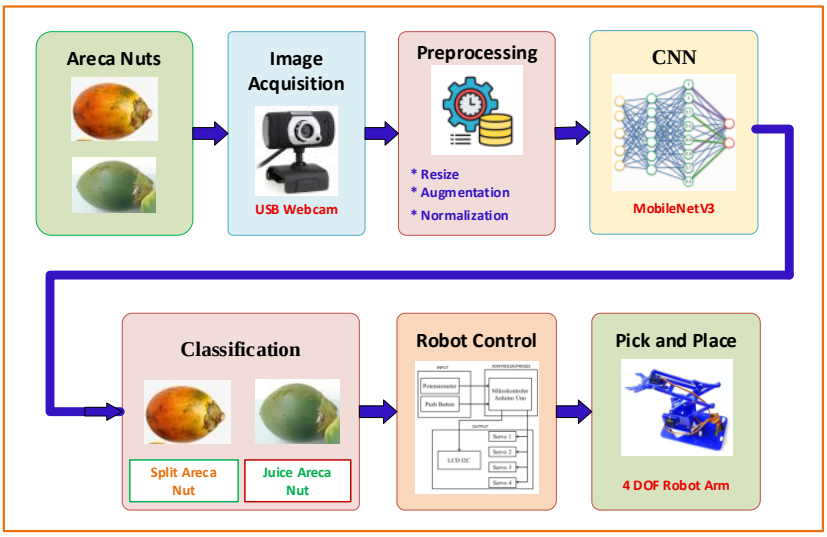


Figure 1. Workflow of the Areca Nut Sorting Robotic Arm System

Fig. 1 illustrates the automated areca nut sorting process, from image acquisition using a webcam and image preprocessing to classification using the MobileNetV3 CNN into two categories: juice and split areca nuts. The classification results are then transmitted to a microcontroller, which controls the 4-DOF robotic arm to pick and place each nut into the appropriate container.

The mechanical design of the robotic arm is shown in Figure 2. The robotic arm is mounted on a baseplate with dimensions of 66 × 51 cm. The robotic arm is constructed using 3 mm thick acrylic material, with an extended reach of up to 23 cm and an operational height of up to 20 cm. The camera is positioned on a tripod at a viewing distance of approximately 20 cm directly above the object detection area.

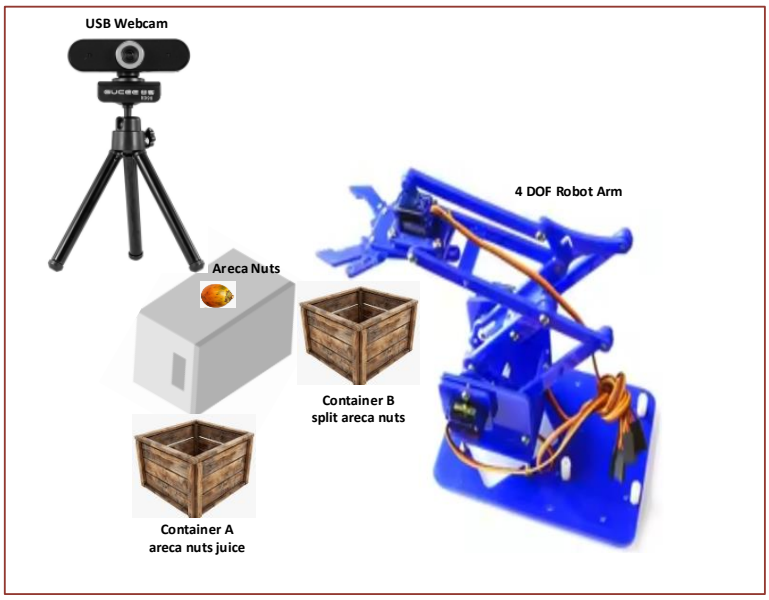


Figure 2. Design of the Areca Nut Sorting Robotic Arm

For the software design, the system begins with webcam initialization and the development of the classification model. The captured areca nut images are then processed using a CNN with the MobileNetV3 architecture. The model is designed to distinguish between the juice and split areca nut categories while evaluating the object's color, shape, and size characteristics. When an object is identified with a valid prediction probability, the classification result is converted into a signal and transmitted via USB serial communication to the microcontroller. The Arduino Uno then executes a sequence of robotic movements, including moving toward the object position, closing the gripper, transferring the object to container A (juice areca nuts) or container B (split areca nuts), opening the gripper, and returning to the initial position. The software instructions and decision making process are illustrated in detail in the flowchart shown in Figure 3.

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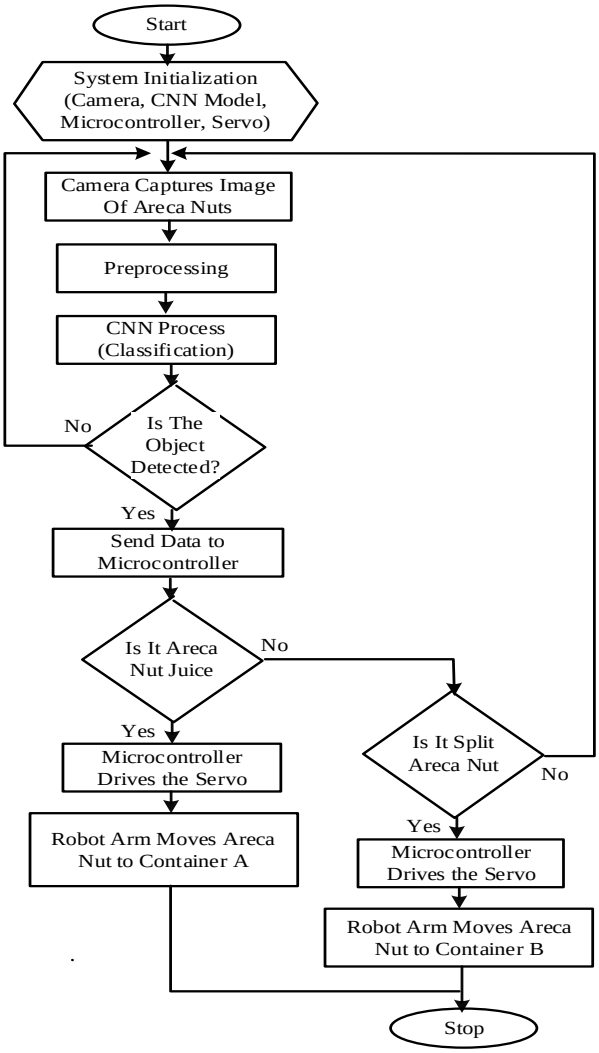


Figure 3. System Flowchart

Fig. 3 illustrates the operational sequence of the areca nut sorting system, beginning with device initialization and image acquisition using a webcam, followed by image preprocessing and classification using the MobileNetV3 CNN. The classification results determine whether each nut belongs to the juice or split category and guide the 4-DOF robotic arm to place it in the corresponding container.

The dataset used to train the artificial intelligence model consisted of 941 images, comprising 752 training images and 189 validation images. To reduce the potential for false-positive detections of surrounding objects with color tones similar to those of areca nuts, the model was trained using three classes: split areca nuts (343 images), juice areca nuts (368 images), and surrounding objects (230 images). Before the training stage, data preprocessing was performed, including pixel dimension adjustment, data augmentation through random flipping and rotation to increase feature diversity, and normalization of RGB color-channel tensors. The physical scale conversion was calibrated using a reference coin, resulting in a calibration factor of 0.088 cm per pixel. The training parameters were set to a batch size of 32, 15 epochs, and a learning rate of 0.001. A thresholding mechanism was implemented in the program code so that the actuator was allowed to operate only when the CNN prediction probability exceeded 90%.

The testing methodology for the proposed solution was divided into four main stages to evaluate system reliability. These stages included evaluating CNN model accuracy using a confusion matrix, testing real-time classification through direct camera image capture, evaluating the accuracy of the robotic arm's pick-and-place positions, and evaluating the overall integrated system performance by measuring the sorting success rate and total processing time.

RESULT

The areca nut sorting automation system was evaluated through CNN classification performance assessment, visual feature extraction testing, robotic arm mechanical testing, and integrated system performance evaluation. During

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the CNN classification evaluation, the dataset consisted of 941 images, divided into 752 training images and 189 validation images. The MobileNetV3 model was trained to classify three categories: split areca nut, juice areca nut, and surrounding objects. Based on the reported confusion matrix, the model correctly classified 69 images of split areca nuts, 74 images of juice areca nuts, and 45 out of 46 images classified as non areca nut. Thus, 188 out of 189 images were correctly classified, yielding a calculated accuracy of 99.47%. One non areca nut image was misclassified as a split areca nut. These results indicate high classification performance on the evaluated samples, although a classification error remained. The confusion matrix for the trained model is presented in Figure 4.

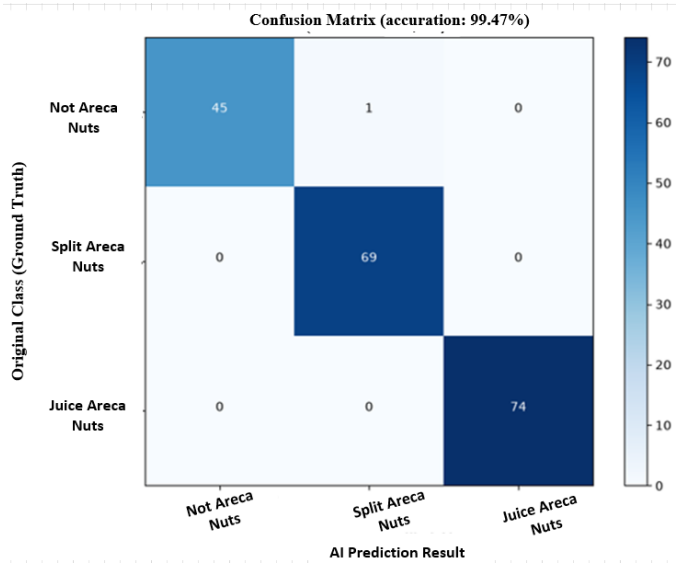


Figure 4. Confusion Matrix of the MobileNetV3 Model

The visual feature evaluation yielded reported accuracy values of 99.07% for color, 91.65% for shape, and 94.62% for dimensional measurement. These values should be interpreted according to the respective metrics and measurement procedures. In particular, dimensional measurements require validation against reference measurements to establish agreement between image-based measurements and the actual physical dimensions of the objects. A summary of the visual feature evaluation results is presented in Table 1.

Table 1. Summary of Image Processing Accuracy

Parameter	Accuracy
CNN Classification	99,47%
Color	99,07%
Shape	91,65%
Size	94,62%

During real time classification testing, the computer-based program successfully detected areca nuts within the webcam's field of view and displayed the prediction confidence in real time, as shown in Fig. 5. The camera distance was maintained at approximately 20 cm to ensure a consistent scale for converting pixel measurements into centimeters.

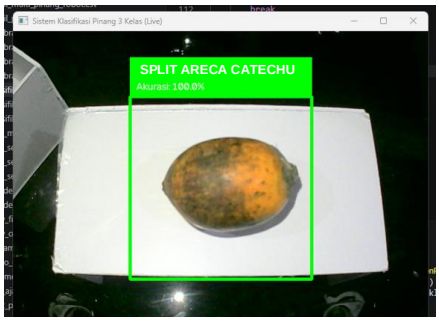


Figure 5. Real-Time Classification Results for Areca Nuts

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Mechanical testing of the robotic arm included 30 gripper trials, with a reported gripping success rate of 100%. The coordinate tests yielded positional errors of 0 cm at the Home position, 1.118 cm at Bin A, and 0.50 cm at Bin B. The average positional error across these three target points was approximately 0.54 cm. These results indicate that the robot was able to reach the programmed target positions with measurable deviations under the tested configuration. The coordinate test results are summarized in Table 2.

Table 2. Sorting Coordinates from the Robotic Arm to the Classification Containers

Target	Target Coordinates	Actual Coordinates	Error
Home	(20, 0, 11)	(20, 0, 11)	0 cm
Container A – Juice Areca Nuts	(20, 14.5, 11.5)	(21, 14.5, 11)	1,12 cm
Container B – Split Areca Nut	(20, -14.5, 12.5)	(20.5, -14.5, 12.5)	0,50 cm

The integrated system was tested using 30 objects, consisting of 15 juice areca nuts and 15 split areca nuts. All objects were reported to have been successfully transferred to their designated bins, resulting in a sorting success rate of 100% under the tested conditions. The reported CNN inference time was 0.032 seconds, while the average mechanical movement time of the robotic arm was 15 seconds per cycle. Assuming that the two processes occurred sequentially without overlap, the estimated total sorting time was 15.032 seconds per object, as summarized in Table 3.

Table 3. Average Execution Time for the Sorting Process

Parameter	Average Time
CNN Processing	0,032 s
Robotic Arm Mechanical Movement	15 s
Total Sorting Time	15,032 s

DISCUSSION

The evaluation results indicate that the CNN model based on the MobileNetV3 architecture achieved high classification performance on the dataset used in this study. The inclusion of the surrounding objects class may help the model distinguish areca nuts from other objects with similar colors or visual characteristics. However, the occurrence of one misclassification in the non areca nut class indicates that the risk of false positive predictions has not been completely eliminated.

The accuracy calculated from the confusion matrix was 99.47%. Therefore, this value should be reported consistently throughout the results, discussion, tables, and conclusion sections unless another validated evaluation result is available. In addition, the sample size and characteristics of the dataset should be considered when interpreting the model's performance under different operating conditions.

The visual feature evaluation yielded reported accuracy values of 99.07% for color, 91.65% for shape, and 94.62% for size. These differences indicate that image processing performance may vary depending on the visual characteristic being measured. Nevertheless, interpreting these values requires clarification of the measurement methods, sample sizes, and definitions of accuracy. For dimensional measurement, variations in the natural shape of the fruit, camera angle, camera distance, and optical distortion may affect the measurement results.

In the mechanical subsystem, a gripping success rate of 100% across 30 trials indicates that the gripper performed successfully under the tested conditions. The addition of foam padding may help increase friction between the gripper and the surface of the fruit. Meanwhile, the average positional error of 0.54 cm was calculated from three test points. This value describes the deviations observed at those points but is insufficient to establish the robot's repeatability and positional accuracy throughout its entire workspace.

The integrated system achieved a sorting success rate of 100% across the 30 tested objects. This result demonstrates that the integration of the camera, CNN classification model, and robotic arm was able to perform the sorting process under the tested scenario. However, this conclusion is limited by the number and types of objects evaluated, as the integrated system testing did not include the Surrounding Objects class used during model training.

The reported CNN inference time of 0.032 seconds was substantially shorter than the robotic arm's mechanical movement time of 15 seconds. Therefore, based on the reported measurements, mechanical movement constituted the largest component of the total sorting cycle. Optimizing the robot's motion trajectory, adjusting actuator speed, and implementing an automatic feeding system could be considered to reduce cycle time. The effectiveness of these improvements must be demonstrated through further testing.

CONCLUSION

This study developed a prototype automated areca nut sorting system that integrates a MobileNetV3-based Convolutional Neural Network (CNN) with a 4 degree of freedom (4 DOF) robotic arm. Based on the reported confusion matrix, the model correctly classified 188 out of 189 images, achieving an accuracy of 99.47%. This value was recalculated from the number of correct predictions and the total number of samples reported in the document.

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The image processing evaluation reported accuracy values of 99.07% for color, 91.65% for shape, and 94.62% for dimensional measurement. In the mechanical subsystem, the gripping success rate reached 100% across 30 trials, while the average positional error across the three tested target points was approximately 0.54 cm.

Integrated system testing involving 30 objects, comprising 15 juice areca nuts and 15 split areca nuts, achieved a sorting success rate of 100% under the tested conditions. The estimated total sorting time was 15.032 seconds per object, assuming that CNN inference and mechanical movement occurred sequentially.

Overall, the findings demonstrate the potential of combining CNN based classification with a robotic arm to support automated areca nut sorting. However, further testing is required to evaluate system performance under varying environmental conditions, increase the number and diversity of test samples, include the surrounding objects class in integrated sorting tests, and assess the robot's positional accuracy and repeatability through repeated trials. Future development may include mechanical motion optimization and the integration of an automated feeding system to improve operational efficiency.

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