Automated harvest machine for precision farming

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Abstract— This article proposes a review and a system design that integrates machine learning and an automated machine for automatic areca nut classification and harvesting. Analyzing images through machine learning, the system classifies nuts as ripe, unripe, or rotten based on characteristics such as color, texture, and shape. The hardware system enables selective picking of mature nuts, through an IoT based automated machine. Replacing conventional practices, this approach enhances productivity in areca nut collection. This article presents an overall review of the available system and a system under deployment.

Keywords— Areca Nut Classification, Machine Learning, Image Processing, Raspberry Pi, Agricultural Automation, Ripeness Detection, Precision Agriculture

1. Introduction

Areca nut, commonly known as betel nut, is an essential agricultural product widely cultivated in South India, especially in states like Karnataka, Kerala, and Tamil Nadu. It is a significant cash crop for local farmers, used in various cultural, medicinal, and economic contexts. The areca nut cultivation requires considerable labour, as the nuts grow at the top of tall palm trees, often in difficult-to-reach areas. The manual process of harvesting is labour-intensive, time-consuming, and poses safety risks for workers.

The traditional method of plucking areca nuts involves climbing the tree manually or using makeshift tools, both of which are inefficient and dangerous. Workers are exposed to the risk of falls and other injuries, leading to accidents and health-related issues. Moreover, the harvesting process is often inaccurate, with unripe or damaged nuts being harvested, affecting the quality and yield of the crop.

To address these challenges, there is a growing need for automation in the harvesting process. Automation can not only ensure the safe and efficient harvesting of areca nuts but also help in accurately identifying the maturity of the nuts. This reduces labour costs, minimizes wastage, and increases overall productivity.

This work aims to solve these problems by introducing a system that automates the classification and harvesting of areca nuts. Integrating machine learning and hardware components, the system accurately classifies the nuts based on their maturity and selectively harvests the ripe nuts, ensuring higher yields and safer working conditions for farmers. This solution offers a promising step towards modernizing agriculture in South India, making the cultivation of areca nuts more efficient, sustainable, and profitable.

Fig.1. Areca nut

2. Literature Reviews

To develop a robust system for detecting diseases and classifying the ripeness of areca nuts, key aspects from research were identified. A large, diverse dataset is essential for training and generalization. Using images of husk-removed areca nuts ensures accuracy in detecting diseases and maturity [1,10]. Effective segmentation techniques like k-means clustering, and feature extraction methods such as HSV for color and GLCM for texture, form a solid base for classification [1, 5, 12].

For machine learning models, CNNs outperform traditional classifiers like Decision Trees and SVMs, while KNN performs well with smaller datasets [7, 9, 13, 16]. Hyperparameter tuning, data augmentation, and iterative retraining can further improve accuracy, with metrics like precision, recall, and F-measures for evaluation [4, 5, 6].

In disease detection, integrating image processing techniques like Gabor Wavelets and LBP with CNNs yields strong results for identifying diseases such as Mahali and Stem Bleeding. Preprocessing, like resizing and normalizing images, enhances efficiency. For maturity classification, identifying areca nuts as raw, ripe, or old based on texture and color helps in harvesting and valuation [8, 9, 11, 15].

A hybrid approach combining image processing and deep learning improves accuracy and ensures real-time capabilities for agricultural use. User-friendly interfaces and preventive recommendations further increase the system's value [6, 4]. Community-centric solutions, like local farmer training, maximize impact. Future steps include developing mobile applications, expanding datasets, and validating the system in real-world conditions [2, 7, 9].

Advanced technologies like pneumatic systems and Raspberry Pi enable robust climbing and remote operation. Hexagonal mechanisms powered by DC motors ensure energy-efficient climbing, with durable, lightweight materials like GI pipes for safety and adaptability. [16,20].

Motorized rope-pulley systems and conical rollers provide effective grip and stability for diverse tree sizes, ensuring versatile and damage-free climbing. Rotating cutters and automated arms with IR sensors ensure precise harvesting. Adjustable cutters enhance functionality for varying nut sizes. [19, 17, 21].

Arduino and Raspberry Pi-based systems enable remote operations. Bluetooth and wireless controls offer scalability, with AI integration paving the way for intelligent automation.

Sensor-based nut detection and AI-driven selective harvesting boost precision and efficiency. [18, 22] Lightweight, eco-friendly materials improve scalability and sustainability. round level operations enhance safety, while solar-powered designs reduce costs and environmental impact, aligning with user-friendly and sustainable goals. [23, 24, 25].

3. Research Objectives

- *Develop a Machine Learning Model*: Design and implement a machine learning model to classify areca nuts based on ripeness and quality using images and features like color, texture, and density to identify stages of maturity (ripe, unripe, or rotten).
- *Integrate Software and Hardware*: Seamlessly integrate the machine learning model with hardware components (tree-climbing mechanism and nut-cutting tool) to automate nut detection and plucking based on classification results.
- *Improve Accuracy and Quality:* Enhance the model's classification accuracy by exploring different techniques and optimizing parameters to ensure only ripe areca nuts are harvested.
- *Minimize Resource Usage*: Optimize the system's efficiency by making the model lightweight and suitable for embedded devices, like Raspberry Pi, with minimal power and processing requirements.
- *Ensure Operational Safety*: Implement safety measures for both the machine and users, including emergency stops, secure hardware designs, and precise nut-plucking targeting to prevent harm.

4. Proposed Methodology

The methodology outlines the step-by-step approach adopted to develop the automated system for classifying and harvesting areca nuts. This involves a combination of machine learning, image processing techniques, and hardware integration. The following stages were implemented:

A. Image capturing

The Raspberry Pi with its Camera Module offers a simple and efficient solution for image capturing. The camera is securely positioned to focus on the areca nuts, and Python scripts using the pi camera library automate the process by setting resolution and capture intervals. Proper lighting is maintained to enhance image quality and minimize background distractions. The captured images are stored systematically on the Raspberry Pi or an external device, ensuring a clear and organized dataset for preprocessing and classification.

B. Image preprocessing

Image preprocessing is a critical step to refine and prepare areca nut images for analysis, focusing on enhancing clarity, isolating regions of interest, and standardizing input for the model.

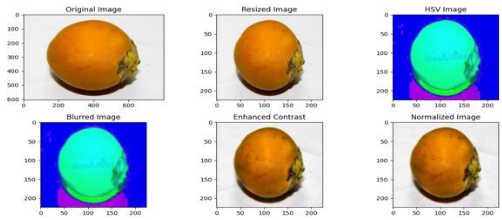

Fig.2. Stages in Image preprocessing

The preprocessing pipeline involves the following steps:

- Image Resizing: Images are resized to a fixed standard dimension, such as 224 x 224 or 256 x256 pixels, depending on the level of detail required. This ensures consistency in image dimensions and optimizes input for the machine learning model.
- Color Space Conversion: RGB images are converted to the HSV color space to focus on color information while minimizing the impact of lighting variations. HSV separates color from intensity, making the images more robust to changes in light and shade.
- Noise Reduction: To remove unwanted noise that could obscure important texture details, Gaussian Blur is applied. This smooths the image, enhancing edges and boundaries for better feature extraction.
- Contrast Enhancement: Uneven lighting conditions can reduce contrast, making it challenging to distinguish the nut from the background. Contrast Limited Adaptive Histogram Equalization (CLAHE) is used to enhance image contrast, improving the visibility of texture and colour details.
- Pixel Normalization: Pixel values, originally in the range of 0-255, are normalized to a range of 0-1. This standardization ensures consistency across images and prevents the model from being biased by varying pixel intensities. By implementing this preprocessing pipeline, captured images are cleaned, refined, and standardized, facilitating robust feature extraction and improving the overall accuracy of the analysis.

C. Image Segmentation

Image segmentation is essential for isolating the areca nut from its background, streamlining the process for analysis and classification. The process begins with color thresholding, where a specific range of color values corresponding to the nut is selected to differentiate it from the background. A binary mask is then created, assigning white (1) to pixels that match the nut's color and black (0) to all other pixels. This mask is applied to the original image using bitwise AND operations, retaining only the segmented nut region while eliminating the background. To further refine the segmentation, Canny Edge Detection is used to highlight and define clear, continuous boundaries around the nut. This approach effectively isolates the areca nut, providing a clean and noise-free region of interest for subsequent feature extraction and classification.

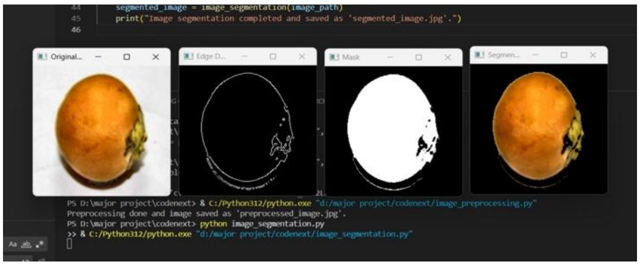

Fig.3. Process of Image segmentation

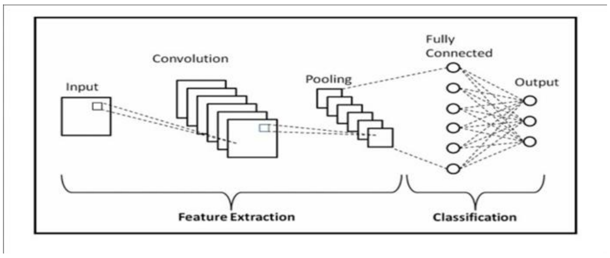

Fig.4. CNN Architecture

Convolutional Neural Networks (CNNs) are highly effective for image classification tasks due to their ability to automatically extract and learn hierarchical features from images. The process begins by feeding the pre-processed and segmented image into the CNN model.

- Input Layer: The pre-processed image is introduced as input to the CNN for further processing.
- Feature Extraction: The CNN utilizes 3-5 convolutional layers to extract relevant features such as edges, textures, and patterns that are critical for identifying the ripeness and health of the areca nut.
- Pooling Layers: To reduce the spatial dimensions and computational complexity, 2-3 max-pooling layers are applied. These layers retain essential features while discarding redundant information, enhancing efficiency.
- Flatten Layer: The pooled feature maps are flattened into a one-dimensional vector, preparing the data for the fully connected layers.
- Fully Connected Layers: The flattened vector is passed through 1-2 dense layers where the network learns complex patterns and relationships for classification.
- SoftMax Activation: The final output layer employs a SoftMax activation function to categorize the input image into predefined classes: ripe, unripe, rotten, or diseased.

The CNN model is trained on a labeled dataset through iterative optimization of weights using backpropagation. The trained model is then evaluated on test data to assess its accuracy and robustness.

CNNs are particularly suited for this project due to their ability to learn hierarchical patterns from images, making them ideal for accurately classifying areca nuts based on ripeness and health.

D. Integration of Software with Hardware

Option 1: Local Processing with Cloud Storage

In this approach, the Raspberry Pi captures images in real time, processes them locally using a pre-trained model, and makes decisions (e.g., plucking ripe nuts) without relying on external services. The images and classification results are then uploaded to the cloud for storage and later analysis. This method ensures reduced latency, as all critical decisions are made locally, and the system can function offline if the internet is unavailable. Additionally, the cloud serves as a backup for data, enabling post-analysis and the possibility of retraining a better model with real-world data. This approach is ideal for scenarios prioritizing independence from cloud processing while maintaining centralized data storage for insights.

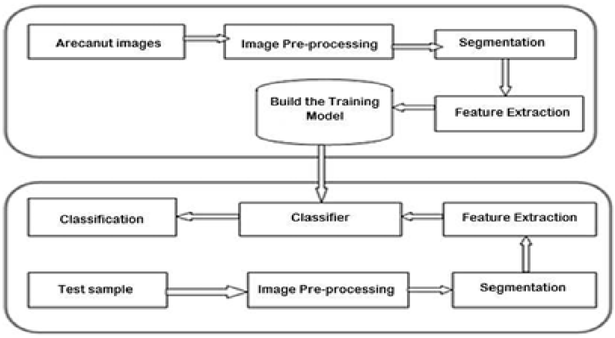

Fig 5: Processed areca nut classification system [1]

Option 2: Cloud-Based Classification

In this setup, Raspberry Pi captures images and sends them to a cloud platform for processing and classification using a powerful, pre-deployed model. The classification results (e.g., "ripe," "rotten") are sent back to the Raspberry Pi, which then performs the necessary actions, such as activating a motor to pluck the nut. This method offloads all computationally intensive tasks to the cloud, reducing the burden on the Raspberry Pi and enabling centralized model updates. It is scalable for managing multiple devices and ensures high accuracy through robust cloud-based resources. However, it requires constant internet connectivity, and latency depends on the network speed.

Option 3: Hybrid Approach

The hybrid approach combines local and cloud processing to balance efficiency and accuracy. The Raspberry Pi performs initial classification using a lightweight model, making quick decisions locally for straightforward cases. Images and results are sent to the cloud for storage, and in cases where local confidence is low (e.g., borderline results), the cloud reclassifies the image using a more accurate, resource-intensive model. The final decision is then sent back to the Raspberry Pi for execution. This approach ensures reliability through local inference, leverages the cloud for ambiguous cases, and reduces overall cloud usage costs. It is a cost- effective and scalable solution for ensuring high performance and accuracy with offline capabilities.

5. Hardware System

The systematic approach to designing and integrating hardware components for agricultural automation systems. Emphasis is placed on robust, cost-effective solutions tailored to improve productivity, address labor shortages, and ensure operational safety. Each methodology follows a structured framework from component selection to system integration and testing.

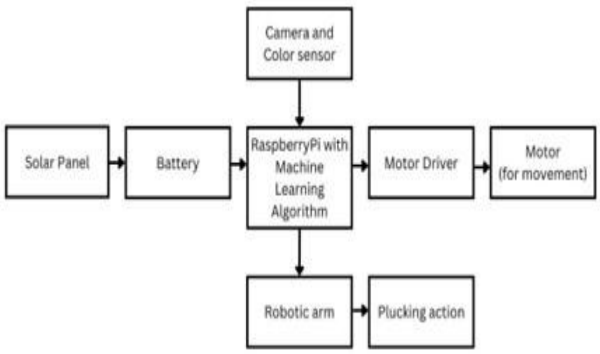

Fig.6. Block diagram

The block diagram represents a solar-powered automated harvesting bot designed to efficiently pluck fruits with minimal human intervention.

Solar Panel: The solar panel serves as the primary power source for the bot, ensuring eco-friendly and sustainable energy use. It converts sunlight into electricity, which is stored in the connected battery for uninterrupted operation.

Battery: The battery stores energy generated by the solar panel and supplies it to various components, ensuring the bot functions reliably even during low sunlight conditions.

Camera and Color Sensor: These components are responsible for detecting ripe fruits. The camera captures live images or video, while the color sensor identifies the ripeness of fruits based on predefined color thresholds. These inputs are critical for decision-making by the processing unit.

Raspberry Pi with Machine Learning Algorithm: The Raspberry Pi acts as the central processing unit, executing machine learning algorithms to analyse inputs from the camera and color sensor. It determines which fruits are ready for harvesting and controls the bot's actions accordingly.

Motor Driver: The motor driver interfaces between the Raspberry Pi and the motors, converting low- power signals from the Raspberry Pi into appropriate current and voltage levels to drive the motors.

Motor for Movement: This motor enables the bot's mobility, allowing it to navigate through the farm and position itself for fruit harvesting. It is guided by commands from the Raspberry Pi.

Robotic Arm: The robotic arm is designed to reach the fruit and perform the plucking action. It operates with high precision and is controlled by the Raspberry Pi, ensuring accurate and efficient harvesting.

Plucking Action: This is the final mechanical action of the system, where the robotic arm uses a gripper or cutter to detach the fruit from the tree without causing damage to either the fruit or the plant.

6. Overview of Basic Components Required

1. Servo Motor for Robotic Arm: A servo motor is an electromechanical device used to achieve precise control of angular or linear position, velocity, and acceleration in robotic arms. These motors are integral to robotic systems due to their ability to handle tasks requiring high precision. The servo motor used in this system has a torque of more than 20 kg·cm at 6V, an operating voltage range of 4.8V to 7.4V, and uses Pulse Width Modulation (PWM) as its control signal.

2. Camera: The camera module plays a crucial role in visual processing and object detection within the robotic system. This component enhances the robot's ability to perceive its environment and interact with objects effectively. The camera has a minimum resolution of 1080p HD, supports frame rates greater than 30 frames per second, and interfaces with the system using USB or MIPI CSI-2.

3. Color Sensor: The color sensor is designed to detect and identify the colors of objects based on the RGB color space. This functionality enables the system to classify objects accurately, which is essential for tasks requiring color differentiation. The sensor operates within a detection range of 400 nm to 700 nm, covering the visible light spectrum, and uses an I2C interface for communication.

4. Solar Panel: A solar panel ensures sustainable and efficient energy generation for the robotic system. By harnessing solar energy, the system can operate in an environmentally friendly manner while reducing reliance on external power sources. The solar panel provides an output voltage of 24V, delivers power between 50W and 100W, and achieves an efficiency of greater than 20%.

5. 24V LiPo Battery (10000mAh): The 24V lithium polymer (LiPo) battery serves as a reliable and high-capacity energy storage solution for the robotic system. With a voltage rating of 24V and a capacity of 10000mAh, the battery ensures prolonged operation. It features a discharge rate of up to 20C, making it suitable for high-performance robotic applications.

6. Hard Nylon Wheels with Rubber Grip: The wheels used in this system are built for durability and provide excellent mobility and traction for the robot. Each wheel has a diameter of 6 inches and features a hard nylon core with a rubberized exterior. These wheels can support a load of up to 20 kg per wheel, ensuring stability during operation.

7. Motor Driver: The motor driver is responsible for controlling the power supplied to the motors, enabling precise motion control. It operates at a voltage of 24V and supports a continuous current of 10A. The motor driver interfaces with the system through PWM or analog input, ensuring compatibility with various motor configurations.

8. Motor: The primary motor provides the mechanical power necessary for the robot's motion. This DC motor operates at a voltage of 24V and delivers power ranging from 250W to 500W. It is optimized for high-performance applications and plays a critical role in the robot's mobility and functionality.

9. Buck-Boost Converter: The buck-boost converter adjusts the voltage from the battery to match the requirements of different system components. It supports an input voltage range of 6V to 36V and provides an adjustable output voltage between 3V and 24V. With an efficiency of over 90%, it ensures minimal energy loss during voltage conversion.

10. Relay Module: The relay module enables high-power switching in the robotic system, allowing it to handle circuits with higher voltages and currents. It features a trigger voltage of 3.3V or 5V and a load capacity of 10A at 250V AC or 30V DC. This module ensures safe and efficient power management for various components.

11. *Raspberry Pi 5:* The Raspberry Pi 5 is a powerful single-board computer designed for versatile applications, including Cortex-A76 processor, running at 2.4 GHz, and up to 8GB of LPDDR4X RAM. With dual 4K HDMI output, Gigabit Ethernet, PCIe support, and multiple GPIO pins, it provides robust connectivity and expandability. It supports USB 3.0, onboard Wi-Fi 6, and Bluetooth 5.2 for seamless communication. Raspberry Pi 5 is ideal for high-performance computing tasks, AI applications, and multimedia processing, ensuring efficient and reliable operation in various systems. Previously developed prototypes are depicted in Fig. 7 and Fig. 8 respectively. These images are obtained from articles [21] and [26] respectively.

To advance precision farming in areca nut harvesting, the proposed system integrates cutting-edge technologies and tools to design a highly efficient and adaptable harvesting system. Table I highlights these proposed innovations, comparing them with existing approaches from the literature and emphasizes their potential to bridge current gaps and enhance productivity.

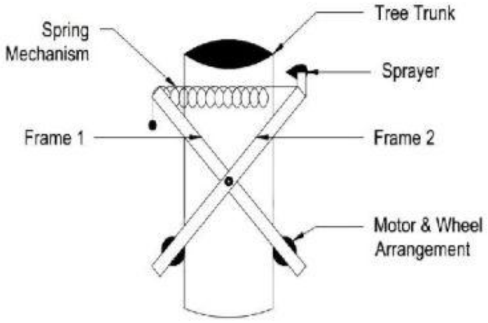

Fig.7. Prototype 1 [21]

Fig.8.Prototype 2 [26]

TABLE I: Comparison of Proposed Technologies for Precision Areca Nut Harvesting with Existing Systems

Aspect	Proposed Technologies/ Tools	Existing Approaches in Literature	Advantages of Proposed System
Nut Detection	Advanced AI models (e.g., YOLO, Faster R-CNN) for nut detection using drones or fixed cameras	Basic image processing techniques with limited accuracy[1,2]	High detection accuracy, real-time processing capabilities
Classification	Deep learning models (CNNs) trained on large datasets with	Traditional machine learning models like	Improved precision in classifying

	cloud-based support	SVM or k-NN[2,7,15]	ripe, unripe, or rotten nuts
Harvesting Mechanism	Robotic arms with adaptive grippers, integrated with IoT for remote operation	Manual or semi-automated tools [16]	Faster, selective harvesting; reduced manual effort
Navigation	GPS and LiDAR-based navigation for drones or ground robots	Simple GPS or manual navigation	Precision in locating and accessing nuts
Energy Efficiency	Solar-powered harvesting robots with battery backup	Electricity or fuel-driven systems	Sustainable and cost-effective in the long term
System Integration	IoT-enabled systems for real-time monitoring and data analysis	Standalone systems without real-time integration	Centralized control, scalability, and actionable insights
User Interface	Mobile application for farmers to control and monitor the system	Limited or no user-friendly interfaces [19 -21]	Enhanced usability and adoption among farmers
Field Adaptability	Weather-resistant materials and adaptable designs for different terrains	Limited adaptability to environmental conditions[16]	Higher operational efficiency across varied farm conditions

7. Conclusion

This work proposes to integrate machine learning and automation to revolutionize areca nut harvesting. Using image processing and machine learning models, the system efficiently classifies ripe nuts. The selective harvest of the nuts through the proposed prototype are under development. This system is precisely developed to reduce labor costs, minimize wastage, and offer a scalable, sustainable solution for modern agriculture. With potential for advancements like predictive analytics, disease control, and multi-crop utility, this system will be a promising innovation for the future of farming, addressing both economic and environmental challenges.

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