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PICKPERFECT: COCONUT MATURITY DETECTOR AND HARVESTER

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Abstract: **Coconut farming often requires significant labor to determine the right time for harvesting and to pick the coconuts. This paper presents a new AI-based system designed to make this process easier. The system uses computer vision to analyze images of coconuts, assessing their ripeness based on color, texture, and size. A Convolutional Neural Network (CNN) classifies coconuts into different stages of maturity to ensure that only the right coconuts are harvested. The system includes a machine with adjustable arms that can climb trees and pick coconuts at various heights. These arms are manually controlled to guarantee that only mature coconuts are selected. The machine is designed to navigate the tree carefully to avoid damaging it or the coconuts. By combining AI with advanced machinery, this system aims to reduce labor costs, improve harvesting efficiency, and lessen the need for human intervention. It offers a more efficient and sustainable solution for coconut farming, enhancing overall productivity.**

***Index Terms* – Classification, YOLOv5, Detection, Harvesting**

I. INTRODUCTION

Coconut farming typically involves a lot of manual labor, from determining when the coconuts are ripe to physically harvesting them from tall trees. This study introduces an AI-based system designed to streamline this process, using Computer Vision and Deep Learning, specifically a CNN, to analyze images of coconuts and assess their ripeness based on factors like color, texture, and size. The system includes a harvesting machine with adjustable arms that can climb trees and pick coconuts at various heights, allowing operators to focus on selecting only the fully mature coconuts with the help of AI-driven ripeness assessments.

One of the system's major advantages is its ability to reduce human error by providing accurate, data-driven ripeness classifications. This ensures that only ripe coconuts are picked, improving the overall quality of the harvest. Additionally, the machine's flexible design allows it to navigate the tree without causing damage, protecting both the coconuts and the tree itself. Operators can make real-time adjustments to the machine, combining the precision of AI with human control for optimal harvesting efficiency.

Beyond improving accuracy and efficiency, the system also enhances worker safety by minimizing the need for tree climbing, a dangerous and physically demanding task in traditional coconut farming. With the machine handling much of the hard work, the risks to workers are greatly reduced. By automating key parts of the process, the system helps lower labor costs, improve productivity, and create a safer, more sustainable approach to coconut farming.

A. PROBLEM STATEMENT

Coconut farming faces several key challenges that can affect productivity and safety, largely due to the labor-intensive nature of harvesting. Farmers often struggle to determine the right time to harvest coconuts, relying on manual inspection methods that can lead to inconsistent results. This can result in the waste of immature or overripe fruit, affecting the overall quality of the harvest and increasing labor costs, while also putting a strain on workers.

Additionally, climbing tall trees to pick coconuts is a dangerous task, posing significant safety risks to workers. Traditional harvesting methods can also cause damage to both the coconuts and the trees, which affects long term productivity and sustainability.

To tackle these issues, there is a clear need for a modern solution that combines technology with effective harvesting techniques. This project aims to create an AI-based system that uses computer vision and deep learning to accurately assess the ripeness of coconuts and guide a harvesting machine to pick them efficiently. By automating the harvesting process, this system seeks to improve the quality of the harvest, lower labor costs, enhance worker safety, and promote more sustainable practices in coconut farming.

II. LITERATURE SURVEY

The literature review, focuses on how recent advancements in AI and automation are helping to improve agriculture, especially for tasks like checking fruit ripeness, selective harvesting, and crop quality assessment. Researchers have shown that AI can make a big difference in high-value crops by improving the accuracy and efficiency of harvesting, which in turn boosts both productivity and the quality of the yield. In this section, this research on deep learning, computer vision, designed to tackle similar challenges in various types of crops. From these studies, we gain insights into how image analysis techniques, like CNN, can evaluate fruit ripeness by examining factors such as color, texture, and size. Additionally, explore automated harvesting machines designed to operate safely and efficiently, even in challenging environments like tall trees, which is particularly relevant for coconut farming [4].we selected five papers for the survey: [1] A Lightweight Cherry Tomato Maturity Real-Time Detection Algorithm Based on Improved YOLOV5n, [2] CES-YOLOv8: Strawberry Maturity Detection Based on the Improved YOLOv8, [3] On-Tree Coconut Maturity Estimation and Age Prediction Using Machine Vision.

A. Lightweight Cherry Tomato Maturity Real-Time Detection Algorithm Based on Improved YOLOV5n

This system represents a significant advancement in agricultural technology, specifically focusing on the detection of cherry tomatoes in diverse and challenging environments. This enhanced version of the YOLOv5n model, termed the IYOLOv5n network model, is precisely designed to address the unique challenges associated with fruit detection, such as occlusions, varying lighting conditions, and complex backgrounds that can hide the target objects. At the core of this system is the implementation of the K-means++ clustering algorithm, which plays a crucial role in optimizing the selection of anchor boxes. By ensuring that these anchor boxes are closely aligned with the actual size and shape of cherry tomatoes, the model significantly reduces the likelihood of missed detections and enhances the overall accuracy of the detection process. This is particularly important in agricultural settings where timely and precise identification of ripe fruits can directly impact harvest efficiency and crop yield [17].

In addition to the anchor box optimization, the I-YOLOv5n model incorporates a sophisticated Coordinate Attention (CA) mechanism. This innovative feature allows the model to dynamically learn the significance of each channel and allocate attention to specific channels based on the task requirements. By considering both channel and spatial dimensions, the CA module effectively filters out irrelevant information, enabling the model to focus on the most pertinent features for cherry tomato detection. This capability is essential in real-world applications where background noise and distractions can affect the model's performance. The integration of the CA mechanism not only enhances the model's robustness but also improves its ability to accurately recognize semi-occluded cherry tomatoes, which were previously challenging to detect.

B. CES-YOLOv8: Strawberry Maturity Detection Based on the Improved YOLOv8

The paper titled CES-YOLOv8: Strawberry Maturity Detection Based on the Improved YOLOv8 presents a deep learning model optimized for detecting strawberry maturity in real-time, specifically within complex agricultural environments. This research addresses challenges in fruit maturity detection using automated robots, which is a critical task in smart agriculture to enhance harvesting efficiency and reduce labor reliance. Traditional methods often lack accuracy due to environmental dependencies, so the authors propose a new model, CES-YOLOv8, by enhancing the YOLOv8 framework. [12]

C. On-Tree Coconut Maturity Estimation and Age Prediction Using Machine Vision

The paper On-Tree Coconut Maturity Estimation and Age Prediction Using Machine Vision presents a novel approach to coconut farming that leverages machine vision and deep learning to address common challenges in determining the ripeness and age of coconuts on the tree. Traditional coconut harvesting relies on manual inspection and visual judgment, which can be inconsistent, time-consuming, and labor-intensive. These methods often require farmers to physically climb trees to assess maturity, a task that not only risks worker safety but also reduces overall productivity due to its high labor demand [2]. With the increasing demand for precision and efficiency in agriculture, this paper proposes a system that combines a CNN with a mobile application to automate the assessment process. By using images captured through a smartphone, the system can 15 classify coconuts into maturity stages — premature, mature, and potential and estimate their age in real-time. The CNN model is trained on a diverse dataset of coconut images, allowing it to accurately detect subtle features associated with ripeness, such as color, texture, and size.

The proposed system in the paper provides a practical and scalable solution for coconut farmers, allowing them to make data-driven harvesting decisions. This application of machine vision and mobile technology in agriculture highlights a shift toward smarter, safer, and more efficient farming practices. [6] [7]

TABLE I. LITERATURE SURVEY TABLE

PAPER	DESCRIPTION	AUTHOR
A Lightweight Cherry Tomato Maturity Real-Time Detection Algorithm Based on ImprovedYOLOV5n.	Presents a real-time, light weight algorithm for detecting cherry tomato maturity to support automated picking in precision agriculture.	Congyue Wang,Chaofeng Wang, Lele Wang, Jing Wang, JiapengLiao, Yuan
CES-YOLOv8: Strawberry Maturity Detection Based on the Improved YOLOv8.	TheCES-YOLOv8 model enhances accurate strawberry ripeness detection in agriculture.	Yongkuai Chen, Haobin Xu, Pengyan Chang, Yuyan Huang, Fenglin Zhong, Qi Jia, Ling xiao Chen, Huaiqin Zhong and ShuangLiu
On-Tree Coconut Maturity Estimation and Age Prediction Using Machine Vision.	Coconut ripeness detection app using CNN for improved harvesting timing.	Syamraj B S, Sikha Sasidharan, Arya M H, Hari Priya V, Pranav R and Milan Georgy Mathew.

III. METHODOLOGY

The system enables efficient, autonomous harvesting by combining advanced object detection with robotic precision and control. The process begins with a dataset that undergoes augmentation to enhance variability and is then split into training and testing sets.This data is processed by the YOLOv5 architecture, which consists of three main components: the backbone, which extracts image features; the neck, which enhances spatial relationships through upsampling and concatenation; and the head, which performs bounding box regression and object classification. This results in a trained YOLOv5 model capable of detecting objects like fruits and their maturity levels.

Input images are preprocessed and fed into the trained YOLOv5 model. The model analyzes the images to identify objects, classify them, and generate bounding box coordinates along with confidence scores. The output includes harvesting information, a maturity report, and classification results, which are stored in a feature database for further analysis. The system integrates a ground station and a robotic unit for execution. The ground station includes a joystick and switch for manual control, power management to regulate energy, a video monitor for real-time visualization, and a transmitter for communication. The robotic unit consists of a climber and a robotic arm. The climber, equipped with a controller, power drivers, and a high-definition camera, navigates the environment and captures visual data. The robotic arm, controlled by motor drivers, performs the harvesting based on the maturity and position information provided by the YOLOv5 model. Communication between the ground station and robotic unit is facilitated via transducers, transmitters, and receivers, ensuring seamless coordination.

IV. PROPOSED SYSTEM

The proposed system determine the maturity of coconuts directly on the tree. By capturing an image, the system's CNN model analyzes features like color and texture to classify the coconut as premature, mature, and potential. This system helps farmers harvest only ripe coconuts, improving efficiency, safety, and crop quality while reducing manual labor.

A. User Interface and Dataset Collection

The User Interface and Dataset Collection module serves as the foundational component for the coconut maturity detector and harvester, facilitating seamless interaction between users and the system. This module is central to the accurate identification and classification of coconut maturity, crucial for efficient harvesting. Within the image processing segment, coconuts are categorized into three classes of maturity, potential, and premature based on characteristics such as color, texture, and size. These classifications are powered by a deep learning model, YOLOv5, supplemented by additional models to enhance accuracy. The system leverages a custom-built dataset, "pickperfectcoconut-dataset", specifically designed for training and refining the maturity detection model. Users interact with this system through an app interface that provides detailed information on maturity classifications, helping them identify which coconuts are ready for harvest. This stream lined interface empowers users to make informed harvesting decisions, maximizing yield and efficiency.

B. Image Processing and Detection Module

The Image Processing and Detection module not only identifies coconuts ready for harvest but also continuously refines its detection accuracy through deep learning, adapting to varying lighting and environmental conditions. By leveraging multi-angled image capture, the system ensures that even coconuts partially obscured by leaves or branches are effectively analyzed. The use of high-resolution cameras enables detailed recognition of subtle texture and color differences, critical for differentiating between closely ripened stages. Additionally, the YOLOv5 model's high-speed processing capabilities allow for real-time feedback, making it practical for use in dynamic field environments. With regular updates, the module maintains alignment with seasonal variations in coconut maturity, further enhancing the precision and adaptability of the harvesting system.

C. Control System

The Control System Module serves as the operational backbone of the coconut harvesting system, enabling smooth interaction between all functional modules. Anchored by a central control unit, often powered by a microcontroller or embedded system, it interprets data from the Image Processing and Detection Module and precisely directs the harvesting equipment. This module controls high-torque DC motors that regulate the positioning of both the camera and cutter, ensuring precise alignment for each harvest. Furthermore, the control system manages real-time communication between the user and the machinery by relaying signals from a radio frequency controller, allowing users to accurately steer the harvesting process. This seamless integration of control enhances opera tional efficiency and user convenience, empowering operators to execute each task with greater precision and effectiveness.

D. Actuation and harvesting

The Actuation and Harvesting Module is the system's physical execution hub, tasked with carrying out precise, targeted harvesting actions based on commands from the Control System Module. This module houses various actuators, including electric motors, servo mechanisms, and other components, each meticulously calibrated to ensure smooth and accurate movements. These actuators control the machinery's reach, orientation, and cutting force, enabling the system to engage physically with the coconuts in a controlled and reliable manner. The module's primary function is to harvest only the coconuts classified as mature by the detection system, reducing the chances of premature or wasted harvesting. The cutter, powered by high-torque motors, operates with precision to sever each coconut from the tree without damaging the fruit or surrounding foliage. This system's design allows for user- specified harvesting, responding to real-time adjustments to ensure that only desired coconuts are targeted. Altogether, the Actuation and Harvesting Module enhances the system's effectiveness, delivering accurate and efficient harvesting that minimizes labor and maximizes yield.

V. PROPOSED SYSTEM DESIGN

The system integrates YOLOv5-based object detection with robotic components to enable automated harvesting. YOLOv5 processes input data through its backbone, neck, and head modules during training and testing phases to generate object classifications, bounding box coordinates, and confidence scores. The operational phase consists of a ground station and a robotic unit. The ground station features a joystick for control, power management, video monitoring, and a transmitter for communication. The robotic unit includes a climber with a controller, power drivers, and a high-definition camera for mobility and data collection, as well as a robotic arm equipped with motor drivers for precise harvesting. Communication between the ground station and robotic unit is facilitated by transducers, transmitters, and receivers, enabling efficient and autonomous harvesting.

A. Training Phase

- Dataset : Images and labels containing coconut objects are prepared.
- Augmentation : Data augmentation techniques are applied to improve the model's robustness (e.g., flipping, scaling, color jitter).
- Data Splitting : The dataset is divided into training and testing sets.
- YOLOv5 Architecture:

An architecture diagram visually represents the structure and interactions of components within a system, providing a high-level overview of how the system functions. It typically shows the relationships between hardware, software, data flows, and control mechanisms, helping stakeholders understand the system's design and operation. Architecture diagrams can include layers or modules such as input/output flows, processing units, communication networks, and storage components. They serve as a blueprint for development, aiding in system planning, troubleshooting, and ensuring alignment between technical and functional requirements.

The figure 1, architecture diagram, illustrates a complete system that integrates YOLOv5-based object detection with a robotic coconut harvesting platform, consisting of both a ground station and robotic components.

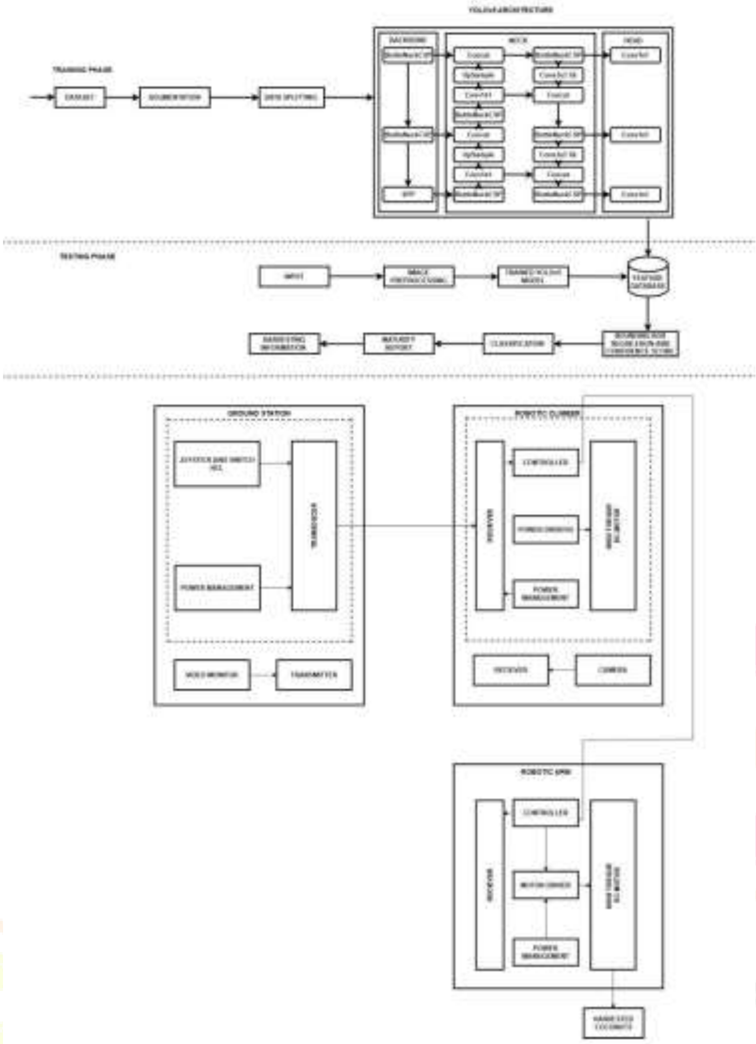

Figure 1. Architecture Diagram

a) Backbone: Extracts feature maps from input images. Uses BottleneckCSP modules to improve computational efficiency. The SPP(Spatial Pyramid Pooling) block is employed to capture features at different scales.

b) Neck: Involves layers like Concat (concatenation) and Upsample to fuse features from different levels. Helps detect objects across multiple scales using the combination of bottleneck blocks and convolution layers.

c) Head: Performs object classification and localization by producing bounding boxes with their corresponding class labels.

B. Testing Phase

• Input: Images from the robotic platform's camera serve as the input for detection during operation.
• Image Preprocessing: The input image is resized and normalized to fit the YOLOv5 model's input format.
• YOLOv5 Model: The trained YOLOv5 model identifies objects (e.g., coconuts) and generates output features.
• Feature Database: The model's output is stored or referred to for further decision making.
• Harvesting Information and Maturity Report: Based on the detected objects, the system evaluates the maturity of, determining whether they are ready for harvesting.
• Classification: The objects are classified, and the model produces bounding boxes with regression values and a confidence score for each detection.

C. Robotic System Architecture

1) Ground Station
• Joystick and Switch HCL: Used by the operator to control the robotic system remotely.
• Power Management: Ensures power distribution for various components.
• Transmitter and Receiver: Responsible for transmitting control signals and receiving real-time data from the robotic platform.
• Monitor: Displays live video feed from the robotic climber's camera, aiding the operator in manual control.

2) Robotic Climber
• Camera: Captures real-time images of the coconuts and sends them to the ground station.
• Controller: Controls the climber's movement and coordination with other robotic parts.

• Power Management: Manages the power needed to operate the motors and control units.
• Motor Drivers and Power Drivers: Control the motors and actuators responsible for climbing.

3) Robotic Arm
• Receiver: Receives control signals from the ground station.
• Controller: Processes these signals and moves the arm to the correct position.
• Motor Driver: Drives the motors for the arm's movement.
• Power Management: Ensures efficient operation of the robotic arm. The harvested coconuts are dropped, completing the process.

VI. RESULT

The Coconut Maturity Detection and Harvesting System successfully automated the process of coconut classification and harvesting by integrating AI-driven image processing and robotic mechanisms. The system's YOLOv5 deep learning model, trained on over 5000 images, demonstrated high accuracy in classifying coconuts as mature, premature, or potential. The camera efficiently captured images under various lighting conditions, ensuring reliable input for the detection model. The classification results, displayed on a HTML web dashboard, provided users with real-time monitoring, including bounding boxes and confidence scores, making the system both interactive and user-friendly.

The robotic harvesting mechanism, controlled by an Arduino Uno, performed precise movements to ensure accurate cutting of mature coconuts. The motor-driven robotic arm successfully positioned the cutting tool using X and Y directional movement, while the 43cc 2-stroke engine powered climbing mechanism allowed smooth tree ascension.

The power transmission system efficiently distributed energy, ensuring stable operation throughout the harvesting process. The combination of these hardware components contributed to a significant reduction in manual labor, improved safety, and increased efficiency in coconut harvesting.

Field tests validated the system's reliability and scalability, proving that it could operate under real-world farming conditions with minimal errors. The automated detection and harvesting process not only reduced human intervention but also optimized yield collection by ensuring that only fully matured coconuts were harvested. Additionally, the system's ability to store and update its dataset enabled continuous learning, improving detection accuracy over time. Overall, the project successfully provided an innovative, cost-effective, and scalable solution for modern coconut farming, making harvesting safer, faster, and more efficient.

The figure 2, shows the login page of the user interface for coconut maturity detection. The page features a minimalist layout with a central focus on the login form, which is housed in a neatly designed container with rounded corners and subtle box shadows to create a sense of depth. The background color is kept light and neutral, contributing to a calm and professional aesthetic, while the form fields for username and password are clearly labeled and easily accessible. Each input field is styled with ample padding and spacing to enhance usability, while a simple button prompts users to log in.

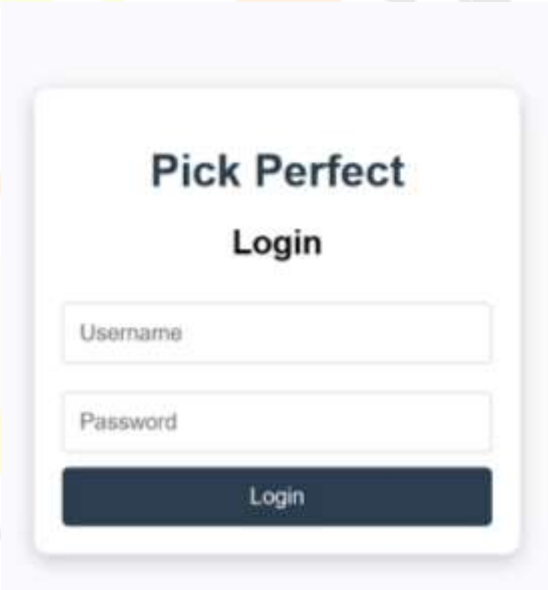

Figure 2. Login Page.

The user interface (UI) of the detection page, shown in figure 3, is designed to be both functional and visually appealing, providing users with easy access to the coconut detection live feed. Upon successful login, users are greeted with a clean layout that features a real-time video stream at the center, showcasing the detection process in action.

Figure 3. Detection Page.

Figure 4 demonstrates the use of YOLOv5 for detecting mature coconuts, an essential step in automating the harvesting process. The model's ability to accurately identify mature coconuts in real-time enables more efficient decision-making for harvesting, reducing human effort and improving the overall productivity of coconut farms.

Figure 4. Mature Coconut Detection.

Figure 5 illustrates YOLOv5 detecting and classifying red mature coconuts, a variety that is the advancement of this project. The model is trained specifically to recognize the distinct characteristics of red mature coconuts, which are crucial for accurate harvesting decisions.

Figure 5. Mature Red Coconut Detection.

Figure 6. illustrates YOLOv5 detecting potential coconuts, an essential step in automating the harvesting process. The model's ability to identify coconuts in various stages of maturity allows for more precise harvesting decisions, improving efficiency and reducing the need for manual labor.

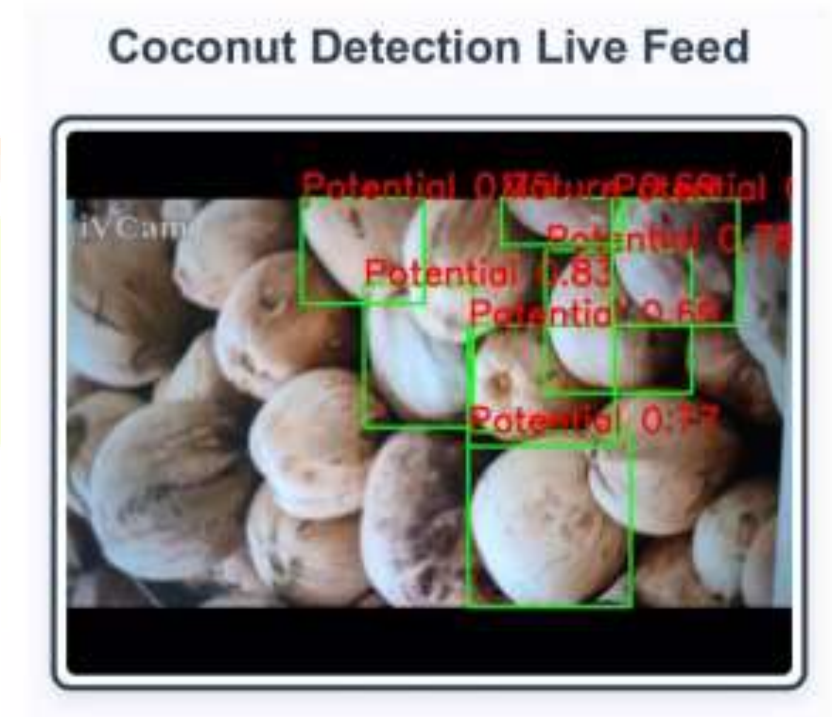

Figure 6. Potential Coconut Detection

Figure 7. illustrates YOLOv5 detecting premature coconuts, which is crucial for making informed automated harvesting decisions. By accurately identifying coconuts that are not yet mature, the system helps prevent premature harvesting, ensuring only fully developed coconuts are collected.

Figure 7. Premature Coconut Detection.

A 775 DC motor fitted with a wood-cutting blade shown in figure 8, is used to effectively chop off the coconut's inflorescence.

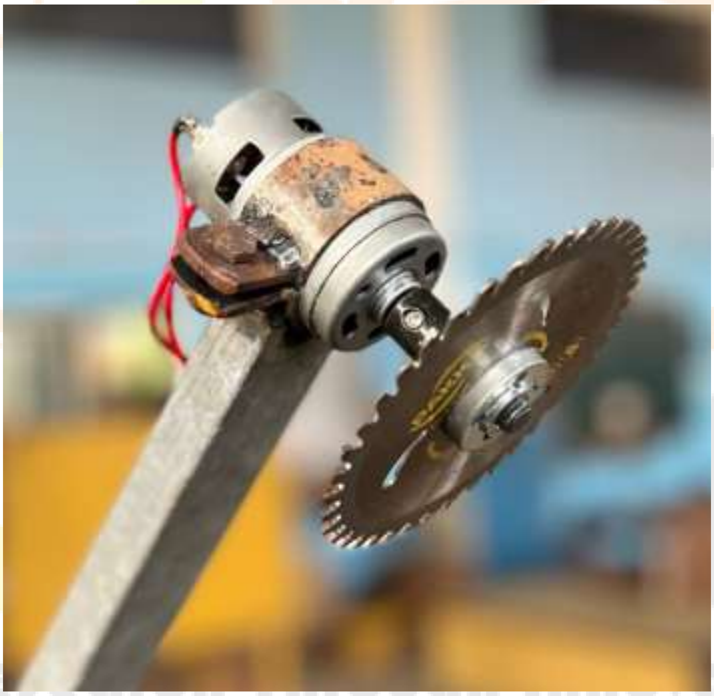

Figure 8. Cutter Blade for Robotic Arm.

A FlySky FS-CT6B remote control system in the figure 9, was used to manually control the robotic arm during testing. This allowed for real-time movement adjustments and ensured flexibility in operations before full automation.

Figure 9. FS-CT6B Remote Control.

The robotic arm shown in the figure 10, was designed with a mechanical structure that includes gears, motors, and a cutting mechanism. The arm was mounted on a climbing frame to reach coconuts at different heights

Figure 10. Prototype of the Robotic Arm Structure.

The harvesting mechanism consists of a motorized blade that is capable of cutting mature coconuts from trees. The system in the figure 11, was designed with an adjustable arm to control the cutting angle. High-torque motors were used to ensure smooth operation.

Figure 11. Harvesting Machine.

The confusion matrix in Figure 12 demonstrates strong classification performance, with high accuracy for Mature (81%), Potential (75%), and Premature (76%) cases, though further optimization is needed to reduce misclassification, particularly in differentiating the Background category.

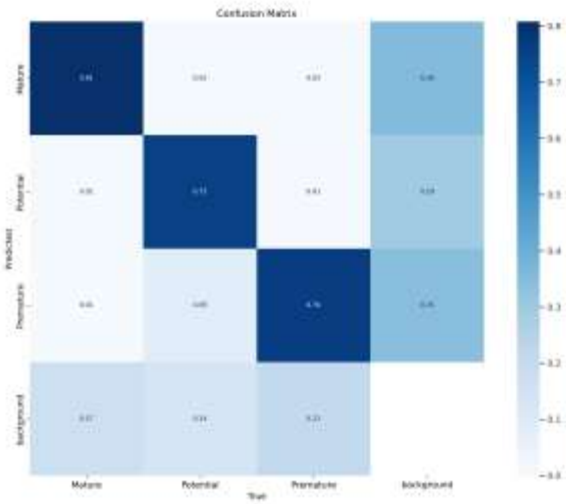

Figure 12. Confusion Matrix.

The figure 13, displays multiple training and validation performance metrics for the object detection model across training epochs. The model shows progressive improvement, with decreasing losses and increasing performance metrics.

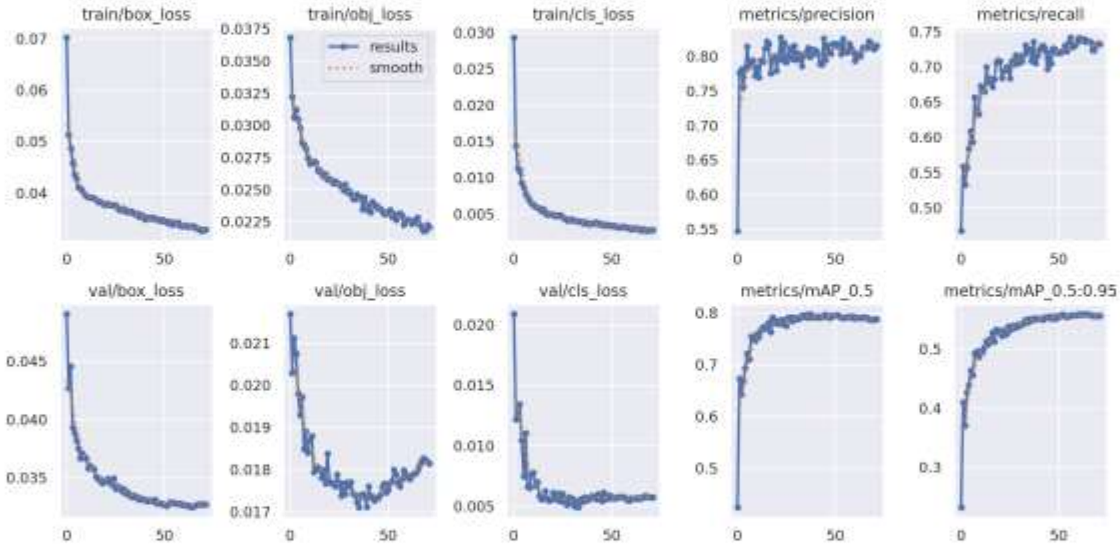

Figure 13. Overall Result.

VII. CONCLUSIONS

The development of an AI-based coconut harvesting system represents a significant step forward in modernizing traditional farming methods and addressing the unique challenges faced by coconut farmers. By integrating advanced artificial intelligence and deep learning, this system offers an efficient, safe, and data-driven approach to harvesting, ensuring that only ripe coconuts are picked while reducing labor strain and minimizing the risks involved in manual climbing. Furthermore, the project's focus on sustainability and collaboration underscores a commitment to creating long-term benefits for farmers, workers, and the environment. Through the combined power of technology and community engagement, this initiative aims to set a new standard in coconut farming that not only meets the growing demand for coconuts but also enhances productivity and promotes sustainable agricultural practices. Looking ahead, this project opens the door to further advancements in precision agriculture, where AI and deep learning can be applied to other aspects of coconut farming, such as pest control, yield prediction, and resource management. By continuously refining and expanding the technology, we can build a comprehensive system that supports farmers in making data-informed decisions across the entire crop cycle, optimizing resource use and minimizing environmental impact.

Additionally, the AI-based coconut harvesting system has the potential to inspire broader adoption of technology-driven solutions across the agricultural sector. By demonstrating the practical and economic advantages of AI in farming, this project could encourage the development of similar tools for other crops and farming environments, fostering a proactive, sustainable approach to farm management that reduces waste and boosts yield. The success of this initiative will highlight the value of cross-disciplinary collaboration, combining engineering, agriculture, and environmental science to create solutions that are both technically sophisticated and farmer-friendly. Ultimately, this project lays the foundation for a future where coconut farming is both technologically advanced and aligned with principles of ecological and economic sustainability offering an agricultural model that is innovative, inclusive, and resilient for generations to come.

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