

**Coconut Husk Grading System Using Image Processing.
IoT Automation for Coco Peat Quality Assurance**

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Dissertation submitted in partial fulfillment of the requirements for the Bachelor of
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DECLARATION

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ABSTRACT

This research presents a novel, IoT-driven approach to enhancing quality control in coconut husk processing. By integrating automated husk grading and moisture-level monitoring, the system addresses longstanding challenges in achieving consistent product quality while reducing labor dependency. The husk grading module employs an ESP32-CAM combined with an HC-SR04 ultrasonic sensor to capture images of coconut husks under natural daylight. Using a streamlined image processing algorithm based on the green ratio, husks are classified into “Qualified,” “Accepted,” and “Disqualified” categories with distinct thresholds. In parallel, the moisture monitoring system utilizes an ESP32-based device paired with calibrated soil moisture sensors and an ultrasonic sensor for water tanks. This module samples moisture every 15 minutes and transmits real-time data to a web dashboard via MQTT, enabling continuous oversight of drying conditions and water usage. Experimental evaluations confirm that the proposed solutions are both cost-effective and scalable, resulting in improved process efficiency, enhanced product quality, and reduced manual oversight. The findings pave the way for broader industrial adoption and set a foundation for future work aimed at integrating additional environmental parameters to further optimize coconut husk processing.

Keywords - Coconut Husk, IoT Automation, ESP32, Image Processing, Green Ratio, Moisture Monitoring, MQTT, Quality Control, Coconut Coir, Cocopeat

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LIST OF ABBREVIATIONS

Abbreviation	Description
AI	Artificial Intelligence
CV	Computer Vision
CVAT	Computer Vision Annotation Tool
IOT	Internet of Things
MQTT	Message Queuing Telemetry Transport
RGB	Red, Green, Blue
SSD	Single Shot MultiBox Detector
YOLO	You Only Look Once
mAP	Mean Average Precision
IP	Ingress Protection

1. INTRODUCTION

1.1 Background Literature

In many tropical and subtropical areas, coconuts are a significant agricultural resource that support a variety of sectors, including food & beverage, cosmetics, and biofuel. The husk is one part of the coconut value chain that is frequently disregarded, but with the right processing, it may provide a number of goods with added value. Coconut husks are positioned as a prospective source of sustainable raw materials due to recent industry developments that show an increasing need for eco-friendly products worldwide.

Studies in related fields have demonstrated the effective use of image processing techniques for quality assessment in agriculture. For instance, Chiu and Fong [1] successfully applied image processing for fruit classification, while Hemachandran [6] explored similar approaches in agricultural contexts, establishing a strong foundation for such applications in coconut husk grading. Furthermore, Gupta and Anjum [2] and Pavithra et al. [3] have illustrated the power of color analysis techniques to detect critical quality markers in diverse products, underscoring the potential to extend these methodologies to husk classification.

Coconut husks, traditionally regarded as waste or used as a low-grade fuel, have become increasingly valuable due to their fibrous composition and naturally high lignin content. These characteristics allow husks to be transformed into **coir fiber** for rope, mats, brushes, and geotextiles, as well as **coconut peat** (also known as cocopeat) for horticultural uses such as soil conditioners and potting mixes. Consequently, a thriving market has emerged around husk-derived materials, driven by consumer preference for biodegradable and renewable products.

In addition, research such as that by Pandey [4] highlights the integration of image processing with automated systems and robotics for quality assurance in production environments, offering insights relevant to the mechanization of husk grading processes.

Coconut husks can be used to make a wide range of goods, not just coir. Because of their resilience and cushion-like qualities, husk fibers are also used in the automotive sector for insulation and seat padding. Because of its ability to retain water, cocopeat is a very appealing material for horticultural projects such as urban farming, greenhouse growing, and landscaping. More study into optimizing yields and enhancing product consistency has been spurred by these uses, which have opened the door for more commercialization and international export prospects.

The first step in quality control is to choose husks that satisfy predetermined standards for moisture content, fiber strength, maturity, and most importantly color. Because it reflects the husk's natural characteristics and developmental stage, color is frequently used by manufacturers as an early quality indicator,

1. Green husks

Green husks are thought to be ideal because of their higher moisture content, desirable fiber maturity, and tendency to produce lower amounts of undesired debris and superior tensile strength in coir. For producing high-quality rope, twine, and coir-based goods, they are therefore the go-to option.

2. Green- yellow husks(less green)

These husks are a little more mature than totally green ones, but they still have fiber qualities suitable for the majority of commercial uses. These husks are nevertheless appropriate for a wide variety of value-added products, despite the tiny color differences that may reflect slight changes in the amount of lignin or moisture present.

3. Brown husks

Brown husks can result in lower-quality coir with less elasticity and strength; they are frequently linked to drier fibers and an advanced stage of development. Since they can lead to discrepancies that increase production costs and decrease overall reliability, many manufacturers believe they are inappropriate for high-end or performance-critical items.

Selecting the right coconut husks at the beginning—and rejecting those that do not meet color and maturity standards—forms a cornerstone of effective quality assurance in the coconut product industry. By implementing clear color-based selection guidelines, producers can avoid incorporating subpar husks into the manufacturing process, which improves the consistency and performance of coir products and cocopeat substrates, as well as profitability and market competitiveness.

Coconut husks are initially manually sorted at designated stations in many processing facilities. Here, skilled personnel examine each husk in person to see if it is suitable for additional processing. When workers pick up each husk, they look for bright greens or green-yellow hues, which usually signal the best fiber properties. On the other hand, brown or blackened husks indicate lower-quality fibers and over-maturity. After inspection, each husk will be categorized as qualified, accepted and disqualified.

This method of manual grading has been routinely applied in industry; however, it introduces significant subjectivity and variability, as highlighted by numerous studies in the literature [1], [3], [4]. Automated image processing techniques, as suggested by Babica et al. [5] and Hemachandran [6], offer a promising alternative, potentially reducing errors and increasing throughput.

1. Husk Transfer to Cutting Machines

The coconut husks are sent to specialist cutting machines once they have passed the grading step, where only those that satisfy particular quality and color requirements are accepted. In order to separate the coir fibers from the outer husk layers, these machines are made to

effectively reduce the husks to tiny bits. This mechanical procedure minimizes waste while guaranteeing the optimum extraction of valuable material.

2. Separation of Cocopeat

The finer dust-like material known as cocopeat (also called coir pith) spontaneously separates from the fibrous components (coir) during cutting and grinding. The lighter peat particles separate and gather separately from the coarser coir strands as a result of the machinery ripping and mixing the husks.

3. Washing process

The freshly extracted cocopeat is then transported its way to a sizable washing station or tank area, frequently via a conveyor system. During this stage,

Water is sprayed or soaked into the cocopeat by workers or automated machinery to eliminate any remaining dirt, salts, and other contaminants.

At regular intervals, the peat's moisture content is checked. This makes sure the peat isn't too saturated, which could slow down the drying process, or not washed enough, which could leave unwanted pollutants.

4. Soaking and Settling

To ensure complete washing and the removal of surplus salts, the cocopeat is placed in water and let to soak for a predetermined amount of time. To help release any leftover debris and spread moisture levels uniformly, operators can shake or mix the peat during this period.

5. Open-Air Drying

The cocopeat is moved to a large open area and laid out in thin layers in the sun once the washing cycle is over. This stage of drying is essential because.

The sun offers an economical and sustainable method of reducing moisture content.

To determine whether the peat has attained its ideal dryness, operators regularly check the moisture content. While too-dry peat can become brittle and lose some of its advantageous qualities, too-wet cocopeat might grow mold or other microbiological problems.

Finally The coco peat is gathered into bags during the drying process and will be shipped to the exporters.

1.2 Research Gap

Current research and industry practices reveal significant limitations in the way husk quality is evaluated and controlled, despite the growing significance of coconut husks in the creation of environmentally beneficial coir and cocopeat products as well as their rising demand worldwide.

1. Lack of End-to-End Automation in Quality Assessment

Current research and industrial configurations only use manual grading, which is completed visually by skilled personnel, without automating the entire procedure. Important tasks like,

- Visual inspection for **color and maturity**
- **Tactile evaluation** of fiber texture
- **Moisture content estimation**
- Manual sorting into “Accepted” or “Rejected” categories

2. No Application of Image Processing or Computer Vision in This Domain

The classification of coconut husks lacks the technological application of image processing and computer vision, which have transformed quality control in other agricultural industries, such as automated fruit ripeness detection, rice color sorting, or leaf disease recognition.

- **Color analysis** algorithms to detect husk maturity levels
- **Computer vision models** trained to distinguish green, yellow-green, and brown husks
- **Sensor integration** to estimate **real-time moisture levels** and determine processing readiness

3. No Intelligent Feedback Mechanism or Data Logging in Manual Systems

Current grading systems also lack,

- **Data collection**, tracking, or reporting features
- **Objective record-keeping** of quality metrics per batch
- **Predictive feedback** or alerts for husk quality trends

2. RESEARCH PROBLEM

2.1 Husk Grading Process

Choosing coconut husks by hand using color and surface examination has a number of serious disadvantages.

1. Subjectivity and Human Error

Employees with various levels of expertise may classify the same item in different ways because the grading system depends on personal judgment. Because some inferior husks may pass inspection while others of good quality may be wrongly dismissed, this discrepancy may result in differences in the quality of the final product.

2. Reliance on Skilled Labor

The efficiency of hand sorting depends on having employees who are knowledgeable on husk quality indicators. In the current labor market, it has become more and more challenging to find or train employees with the requisite competence. Because of this, businesses could find it difficult to retain a steady workforce that can grade husks accurately and effectively.

3. Direct Impact on End-Product Quality

Any mistake in husk selection, whether brought on by inexperience, exhaustion, or a lack of rigorous quality standards, has a ripple impact on the performance of the finished product. Compromised husks can lower the purity of cocopeat or the tensile strength of coir fibers, which can result in less-than-ideal results, increased rejection rates, and possible harm to one's reputation in cutthroat marketplaces.

Given the limitations of a selection procedure that is entirely human, automating this process will have an important beneficial effect.

1. Consistency and Accuracy

Husk quality can be objectively assessed by automated systems that measure color, size, moisture content, and other factors. These systems usually depend on sensors, image technologies, or machine learning algorithms. This improves overall consistency by removing a large portion of the subjectivity that comes with manual grading.

2. Labor Efficiency

Automation reduces the need for significant workforces assigned just to husk inspection. This can greatly reduce labor costs and make it easier to hire staff with specific knowledge, which is a problem that many facilities are now facing.

3. Scalability and Throughput

Automated grading machines are capable of **24/7 operation** with minimal downtime, enabling

processors to handle larger volumes of husks more quickly. This increased throughput can support **industrial-scale production**, vital for meeting growing global demand for coconut-based products.

4. Higher Product Quality

Only husks that satisfy the required specifications get forward in the production line through automated processes that consistently enforce higher quality standards. This results in cocopeat and coir fibers that are more dependable, which eventually improves the product's and the producer's reputation.

5. Data and Traceability

During the grading process, real-time data can be captured using contemporary automation solutions. In addition to facilitating prompt decision-making, this type of data enables long-term quality analytics and ongoing enhancement of product standards.

2.2 Moisture Checking Process

Moisture checking of the coco peat in both washing and drying stages are necessary in order to maintain a good quality and there can be requirements for coco peat with different moisture levels. So using workers, the moisture levels are being checked consistently. In order to check the levels, workers need to go to the both washing and drying areas and do the checking using a device which able to track the moisture of the coco peat. Then those data needs to be written down on a book in order to track the moisture changes.

One of the issues of this manual process is there can be lack of consistency of from the human side. Workers may not able to check the moisture levels properly and there can be human errors while noting down the moisture levels. The second issues is that in order to make sure that the process is done well, there needs to be a person in charge on site all the time whenever this process is done. Its not practical to stay on the site for a person in charge like this. These kinds of issues leads to not meeting the proper requirements for the coco peats.

As a solution, automating this process will have an important beneficial effect.

1. Consistency and Accuracy

Automating this moisture level checking process ensure that the moisture levels being checked properly and it able to store accurate data properly.

2. Labor Efficiency

Since this whole process is being done and monitored automatically, workers no more need to manually involve in the process and theres no need someone in charge to be there all the time. This reduce the amount of labors needs to this process.

3. Higher product quality

Since the moisture levels are being checked consistently and properly, it enables the ability to get the quality coco peat with proper moisture levels depending on the exporter requirements. When the exporter's requirements are always being met. It increases the quality of the service.

4. Data and Traceability

During the moisture level checking process, real-time data can be captured using contemporary automation solutions. In addition to facilitating prompt decision-making, this type of data enables long-term quality analytics and ongoing enhancement of product standards.

3. RESEARCH OBJECTIVES

3.1 Main Objectives

1. Automating Husk Grading Process
2. Automating Moisture Level Tracking System

3.2 Specific Objectives

1. Automate Husk Transport
2. Identify Suitable Computer Vision Modules
3. Assess Image Processing Algorithms
4. Determine The Most Effective Grading Approach
5. Select Appropriate IOT Hardware
6. Implement Algorithm For The Husk Classification
7. System Implementation
8. Determine Optimal Sensor Placement
9. Implement The Moisture Monitoring Solution
10. Finalize Device Specifications

3.3 General Objectives

1. Establish a comprehensive framework for end-to-end automation in coconut husk processing, from grading to final moisture regulation.
2. Assess the impact of automation on throughput, product quality, labor requirements, and cost-effectiveness within a typical coconut processing facility.
3. Provide data-driven insights and recommendations to industry stakeholders for adopting or scaling automated husk processing solutions.

4. METHODOLOGY

4.1 Methodology

1. Automating husk grading process

1.1 Automate husk transport

1.1.1 System Overview

An end-to-end automated process requires that the husks move smoothly from the site of arrival (transport truck containers) to the station where they are sorted into the appropriate bins after being graded. To do this, a number of carefully planned mechanical processes that limit human involvement, lower labor expenses, and boost overall productivity are needed.

Container placement

Husks are dropped off in big containers by transport vehicles. Gravity helps move the husks onto a slider by carefully tilting these containers, eliminating the need for extra mechanical pushers. In order to allow husks to naturally glide toward the exit, each container is positioned at a slight angle.

Angle Slider (Tray) Mechanism

The width of the slider is made to fit only one husk at a time. This guarantees a steady, level flow of husks by avoiding blockages or irregular pulling. Husks slide more easily when made of low-friction materials, such as stainless steel or specialty plastic. As an alternative, if the husks are moist or have an odd form, a gentle vibrating mechanism can be added to avoid blockages. The benefits are Because gravity-driven movement eliminates the need for motors or other power-hungry devices, daily operations become simpler.

1.1.2 Conveyor Belt Integration

Husks are sent to the grading device by a conveyor belt after passing through the angled tray. One of the main parts of the automation system is this belt.

Conveyor Design & Construction

For durability and simplicity of cleaning, a rubberized or PVC belt is typically utilized. Additionally, the belt must endure wear from fibrous materials and sporadic wetness. The belt is pushed by an electric motor, usually AC with a variable frequency drive. The motor's frequency can be changed to fine-tune the speed to correspond with the grading throughput. Husks are kept in the center of the belt by low-profile guard rails along the conveyor edges, ensuring a constant, predictable flow beneath the grading mechanism.

The benefits are Depending on the facility's capacity, conveyor length and speed can be changed. and well-established technique that handles husks with little modification.

1.1.3 Color Detection and Classification Device (High-Level)

The originality of the entire system is largely due to the husk grading device, although this section just offers a high-level overview because a special chapter will describe the specific algorithms and image hardware.

Positioning and Lighting

To ensure that every husk is visible, the grading equipment is positioned at the ideal height above the conveyor. Consistent color detection is ensured by uniform lighting, which lowers errors brought on by reflections or shadows.

Grading Output

This process uses color to classify each husk as either "Qualified," "Accepted," or "Disqualified." The sorting arms downstream get a digital output from the grading device once a husk has been classified.

A significant field of research is the choice and improvement of computer vision or machine learning methods. Its novelty and importance is highlighted by its individual section.

1.1.4 Automated Sorting Arm Mechanism

After the grading mechanism has identified a husk's category, it proceeds along the conveyor until it comes to a row of three piston-driven arms, each of which represents one of the three grading categories:

Three-Armed Actuation

The piston designated for a certain category rapidly extends and forces the husk off the conveyor and into the appropriate bin when the grading system indicates that an incoming husk falls into that category (such as Qualified, Accepted, or Disqualified). In industrial applications, pneumatic pistons are frequently selected because to their direct linear motion, quick reaction, and dependability.

Bin Replacement

Each bin is positioned adjacent to the conveyor, in alignment with its respective piston. Simple guide rails or angled chutes can help funnel the husk directly into the bin, minimizing spillage.

Containers are clearly marked as **Qualified**, **Accepted**, or **Disqualified** to ensure organizational clarity for downstream processing or disposal.

Feedback Control

Limit switches or simple optical sensors can verify that the piston has fully extended and retracted, preventing collisions or double pushes.

1.1.5 Design Justifications & Advantages

Gravity Utilization

The angled container and slider tray reduce mechanical complexity and energy consumption. This design also ensures a consistent, **single-file** flow of husks.

Conveyor Throughput

Employing a conveyor belt leverages widely used industrial technology with a long record of reliable performance and easy maintenance. Variable motor control allows the production line's speed to be matched to the **capacity** of the grading system.

Modular Setup

Separating the stages, slider tray, conveyor belt, grading station, and sorting arms makes **maintenance** and **future upgrades** more straightforward. It also allows each module to be tested and refined independently.

1.2 Identify Suitable Computer Vision Modules

1.2.1 Overview of Common Object Detection Modules

A critical step in automating the coconut husk grading process is selecting a robust computer vision module that can reliably detect and classify husks based on their color and maturity stage. Multiple frameworks and algorithms exist for object detection and classification, each differing in speed, accuracy, and resource requirements. This section evaluates three popular methods, **R-CNN (Regions with Convolutional Neural Networks)**, **SSD (Single Shot MultiBox Detector)**, and **YOLO (You Only Look Once)**.

R-CNN Family

- **Concept:** R-CNN and its variants (Fast R-CNN, Faster R-CNN) use a two-stage approach,
 1. **Region Proposal:** First, the algorithm generates potential bounding boxes (regions) where objects might be located.
 2. **Classification:** A CNN then classifies those regions into object categories (or background).
- **Strengths**
 1. Tends to yield **high accuracy** for complex object detection.
 2. Well-established framework with many pre-trained models available.
- **Limitations**
 1. **Region Proposal:** First, the algorithm generates potential bounding boxes (regions) where objects might be located.

2. **Classification:** A CNN then classifies those regions into object categories (or background).

SSD (Single Shot MultiBox Detector)

- **Concept:** SSD performs object localization and classification in a single forward pass of a CNN. Different feature maps at various scales are used to detect objects, making it faster than R-CNN-based methods.
- **Strengths**
 1. **Real-time capability** (faster than region-based detectors).
 2. Multi-scale feature maps help detect objects of different sizes.
- **Limitations**
 1. May have lower accuracy than two-stage methods (like Faster R-CNN) when detecting very small objects.
 2. Hyperparameter tuning can be more delicate to balance speed and accuracy.

YOLO (You Only Look Once)

- **Concept:** YOLO treats detection as a **single regression** problem, taking an input image and directly predicting bounding boxes and class probabilities in a single CNN forward pass. The image is divided into a grid, and each grid cell is responsible for predicting objects within that region.
- **Strengths**
 1. **High FPS (frames per second)** suitable for real-time applications.
 2. End-to-end training: entire model learns bounding box coordinates and class probabilities simultaneously.
 3. Generally simpler pipeline compared to the region proposal + classification approach.
- **Limitations**
 1. Potentially less precise for very small objects or crowded scenes compared to two-stage methods.
 2. Requires careful selection of anchor boxes to improve detection accuracy.

1.2.2 Comparative Analysis for Husk Detection

In the context of coconut husk grading, three factors significantly influence which detector is best suited:

1. **Speed / Throughput:** Production lines may process hundreds of husks per hour, so real-time or near real-time detection is essential.
2. **Accuracy:** Husk classification depends heavily on **color** indicator. Missing or misclassifying husks could directly impact quality assurance.

3. **Computational Resources:** Many factories or field installations have limited GPU/CPU capacity. Hence, the chosen solution should be lightweight enough to run on available hardware or on an edge device without large overhead.

Factor	R-CNN	SSD	YOLO
Speed (FPS)	Moderate to Low	Moderate to High	High (suitable for real-time)
Accuracy	High for complex detection	Good for most objects	Good to High (with proper tuning)
Resource Usage	Higher	Lower than R-CNN, but can vary	Lower overall, very efficient
Ease of Deployment	Well-established, but more steps	Straightforward single-shot	One-pass end-to-end training
Edge Device Friendly	Often too heavy for edge unless optimized	Reasonable with some optimization	Well suited especially YOLOv5, YOLOv8 on smaller models

1.2.3 Rationale for Choosing YOLO

Based on the above comparison, **YOLO** emerged as the most suitable framework for our automated husk grading system. Three main justifications support this decision

1. Real-Time Detection

The husk grading line demands a constant flow of items. A detector that processes images quickly ideally above 30 FPS ensures **minimal bottlenecks**. YOLO's one-shot detection design easily meets high throughput requirements.

2. Resource Efficiency

Many YOLO implementations, including newer versions (YOLOv5, YOLOv8), offer **lightweight architectures** that can run on modest GPUs or even CPUs with some trade-offs. This helps contain hardware costs and complexity a major consideration for industrial deployments.

3. Simplicity of Implementation

YOLO's single-pass approach is typically easier to integrate into a real-time pipeline. By generating bounding boxes and class probabilities in a single neural network pass, YOLO avoids the overhead of separate region proposals, leading to **faster inference** and a more straightforward architecture to maintain.

1.2.4 Building the YOLO Module

Dataset Preparation

We compiled approximately **500 images** depicting coconut husks on a conveyor, spanning different angles and distances. Images were taken in consistent daylight conditions to minimize lighting variance and ensure color consistency.

Annotation Process

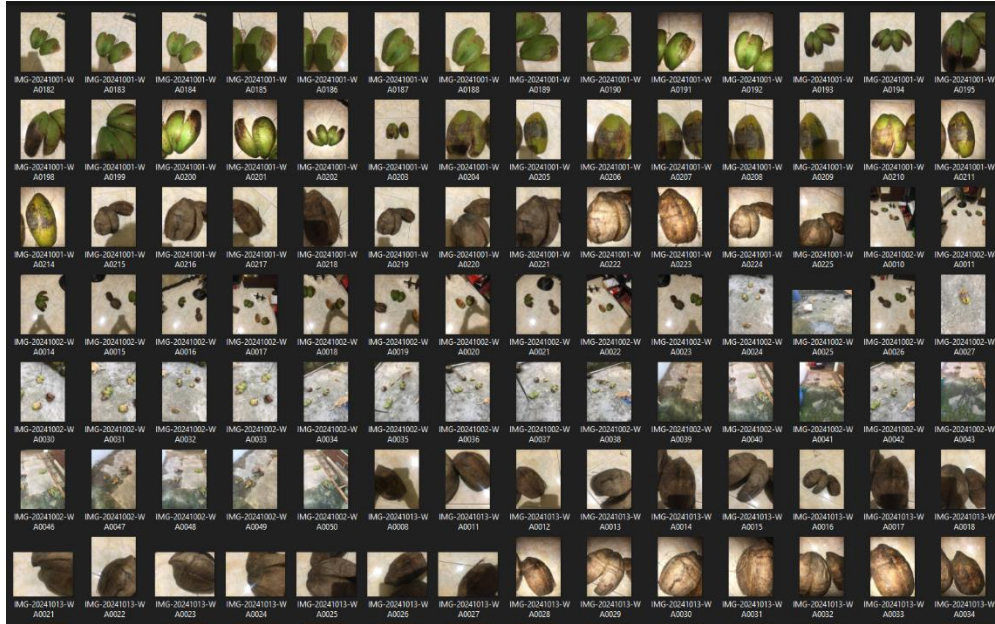


Figure 1 Dataset preparation

We used CVAT(Computer Vision Annotation Tool) to draw bounding boxes around each husk and assign the correct class label. Each bounding box covers the entire visible husk. Subcategories (e.g., partial browning) were still grouped under the main color category closest to its dominant hue. The final annotations were saved in the YOLO format (text files containing box coordinates and class indices).

Training the YOLO Model

We implemented and trained our YOLO model using the Ultralytics Python package, which provides a streamlined interface for model configuration, training, and inference. Below is the core code snippet that demonstrates how the training was conducted

```
from ultralytics import YOLO

# Load a model
model = YOLO("yolo11n.pt")

# Train the model
train_results = model.train(
    data="config.yaml", # path to dataset YAML
    epochs=20, # number of training epochs
    imgsz=640, # training image size
    device="cpu", # device to run on, i.e. device=0 or device=0,1,2,3 or device=cpu
)
```

Figure 2 YOLO training model

Model Evaluation

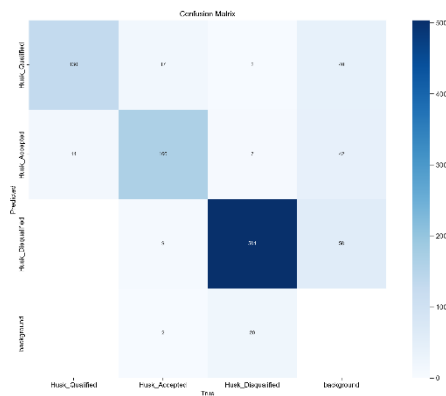


Figure 4 confusion matrix

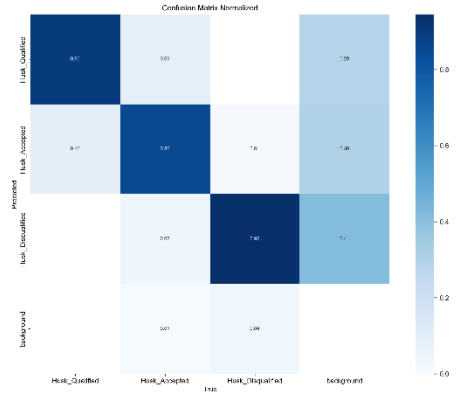


Figure 3 confusion matrix normalized

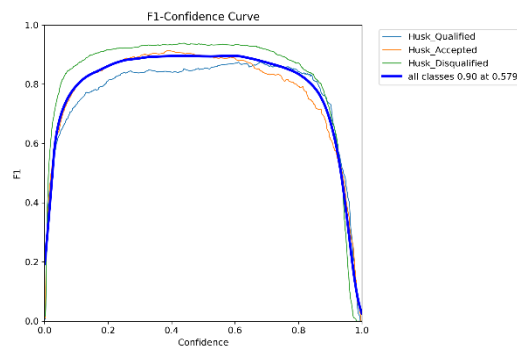


Figure 5 F1 curve

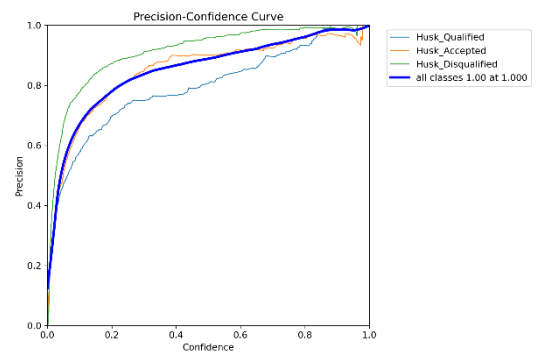


Figure 6 P curve

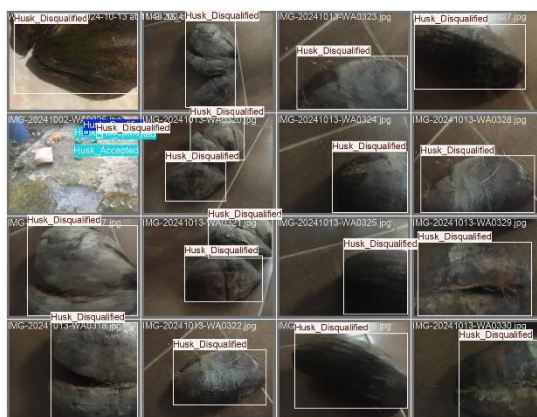
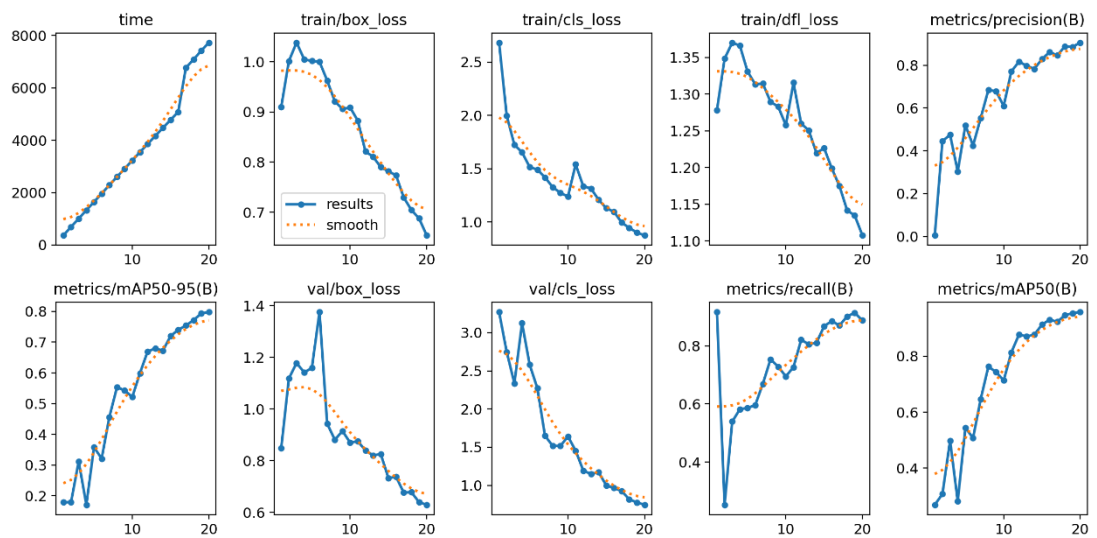
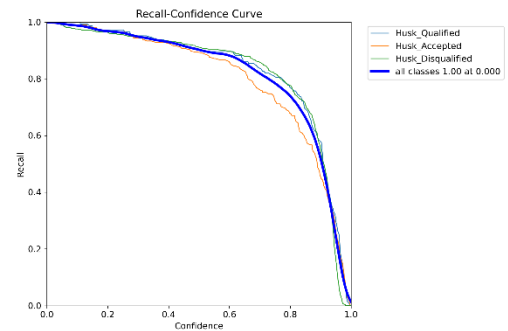
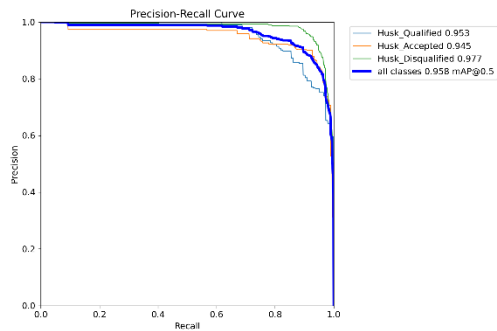


Figure 11 training batch

Figure 10 Training batch

Model Testing

```

import time
import psutil
from ultralytics import YOLO

# Load the trained YOLO model
model = YOLO("/Codings/Husk_grading/Scripts/runs/detect/train4/weights/best.pt") # Path to the best-trained model

# Measure initial memory usage
process = psutil.Process()
initial_memory = process.memory_info().rss / (1024 ** 2) # Convert to MB
print(f"Initial Memory Usage: {initial_memory:.2f} MB")

# Measure initial CPU usage
initial_cpu = psutil.cpu_percent(interval=0.1)
print(f"Initial CPU Usage: {initial_cpu:.2f}%")

# Start tracking inference time
start_time = time.time()

# Test the model on a single image
results = model.predict(source="/SLIIT/Research/Test/test3.jpg", save=True, imgsz=640)

# End tracking inference time
end_time = time.time()

# Calculate inference time
inference_time = end_time - start_time
print(f"Inference Time: {inference_time:.4f} seconds")

# Measure memory usage after inference
final_memory = process.memory_info().rss / (1024 ** 2) # Convert to MB
print(f"Memory Usage After Inference: {final_memory:.2f} MB")

# Measure CPU usage after inference
final_cpu = psutil.cpu_percent(interval=0.1)
print(f"CPU Usage After Inference: {final_cpu:.2f}%")

# Analyze results
detections = results[0].boxes if results else None # Get bounding box details

```

Figure 12 Yolo model testing code

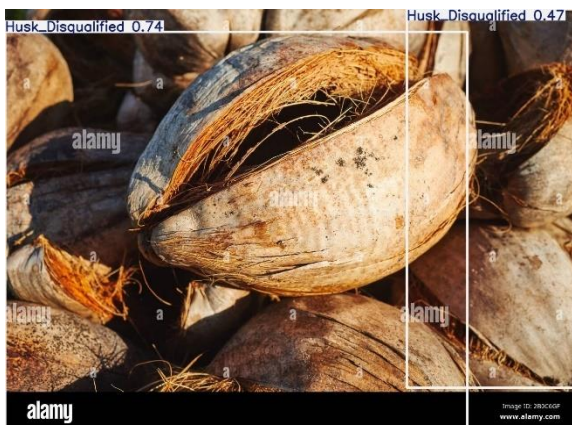


Figure 14 testing results



Figure 13 testing results

1.3 Assess Image Processing Algorithms

Accurate identification of coconut husk color is critical for determining whether the husk meets the desired quality criteria (e.g., green, green-yellow, or brown). To achieve reliable color segmentation and boundary identification, we evaluated two different image processing approaches:

Basic Color Thresholding

- **Overview:** Color thresholding is a foundational image processing method where pixels are classified based on their intensity within a specified color space (e.g., RGB, HSV). For coconut husks, it's typically done by setting upper and lower bounds for particular hues associated with green, green-yellow, and brown.
- **Advantages**
 1. Straightforward to implement and requires minimal computational overhead.
 2. Very fast since it involves direct comparisons for each pixel.
 3. Adjusting the hue, saturation, and value ranges can typically be done quickly with an interactive tool or incremental testing.
- **Limitations**
 1. If the lighting conditions vary significantly, a fixed threshold range may misclassify pixels.
 2. Pure color thresholding cannot distinguish between objects of the same color or handle complex boundaries effectively.
 3. Overlapping colors (like green-yellow variations or partial browning) might produce false positives or partial segmentation errors.

- **Basic Color Thresholding Implementation**

To thoroughly evaluate this image processing technique, I captured a total of **50 images per category** (green, green-yellow, brown) using my personal camera. All images were taken under **consistent daylight conditions** to maintain uniformity in lighting and reduce variability caused by artificial light sources. This choice was made to focus exclusively on the color-based segmentation challenges, rather than confounding factors like changing illumination. Once captured, each image was **converted from RGB to HSV color space** to facilitate more robust color thresholding, given that HSV can better handle slight variations in brightness and contrast. By employing a single, well-controlled lighting setup and applying HSV conversion, I ensured that any observed differences in segmentation quality were primarily attributable to the algorithms themselves, rather than inconsistencies in image acquisition.



Figure 16 qualified husk image



Figure 17 accepted husk image



Figure 15 disqualified husk image

```

import cv2
import numpy as np
import matplotlib.pyplot as plt

#HSV ranges for each category

qualified_hue_min, qualified_hue_max = 35, 85
qualified_sat_min, qualified_val_min = 50, 50

accepted_hue_min, accepted_hue_max = 15, 35
accepted_sat_min, accepted_val_min = 80, 80

disqualified_sat_max = 45 # Low saturation
disqualified_val_max = 85 # Low value (dark)

3 usages  ▲ RanminiManditha
def classify_husk(image_path):
    #Load and convert image to HSV
    image = cv2.imread(image_path)
    hsv_image = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)

    #Mask for Qualified (Greenish)
    qualified_mask = cv2.inRange(
        hsv_image,
        (qualified_hue_min, qualified_sat_min, qualified_val_min),
        (qualified_hue_max, 255, 255)
    )

    #Mask for Accepted (Yellowish/Brownish)
    accepted_mask = cv2.inRange(
        hsv_image,
        (accepted_hue_min, accepted_sat_min, accepted_val_min),
        (accepted_hue_max, 255, 255)
    )

    #Mask for Disqualified (Dark/Brownish)
    disqualified_mask = cv2.inRange(

```

Figure 18 Basic color thresholding code

1. Loading and HSV Conversion

The script reads each image via `cv2.imread`, then converts it from BGR (OpenCV's default) to **HSV** using `cv2.cvtColor`. HSV often proves more robust for color-based segmentation than RGB because hue and saturation are less affected by varying brightness.

2. Defining Thresholds

Each category **Qualified** (greener husks), **Accepted** (yellow/brown husks), and **Disqualified** (dark or overly mature) has distinct hue, saturation, and value boundaries. For instance, a greenish husk typically falls between hue 35–85 with moderate saturation/value, while a darker brownish husk has low saturation/value.

3. Mask Generation

Using `cv2.inRange`, the script creates **binary masks** that isolate pixels matching each category's HSV range. If a pixel lies within the specified bounds, that pixel becomes white (255) in the

mask; otherwise, it remains black (0).

4. Pixel Counting & Classification

`cv2.countNonZero` measures how many pixels in each mask are white. Whichever mask has the largest non-zero count indicates the **dominant color** of the husk, driving the final classification. This approach works best when the husk's color is relatively uniform and the lighting is consistent.

5. Visualization

The script displays each mask in a **matplotlib** subplot, making it easy to see which parts of the image matched the thresholds. This step helps diagnose whether the chosen HSV ranges are appropriate or need fine-tuning.

- **Results**

```
D:\Codings\ImageProcessing_Thresholding\Scripts\python.exe D:\
Classification for Qualified Image: Qualified
Classification for Accepted Image: Accepted
Classification for Disqualified Image: Disqualified
```

Figure 19 basic thresholding results

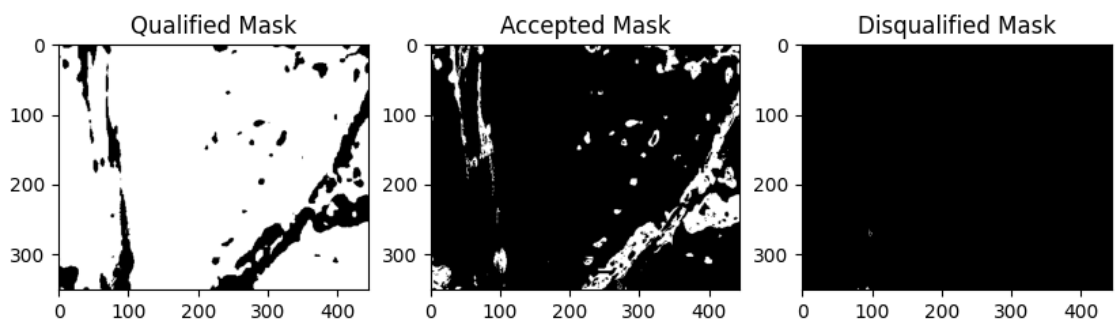


Figure 20 qualified masking

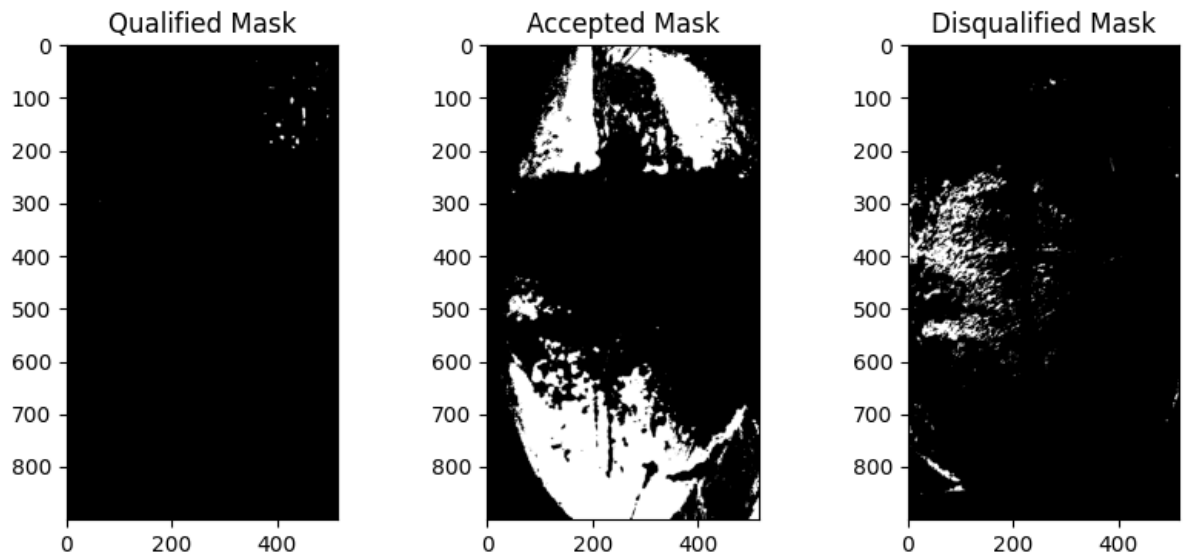


Figure 21 accepted mask

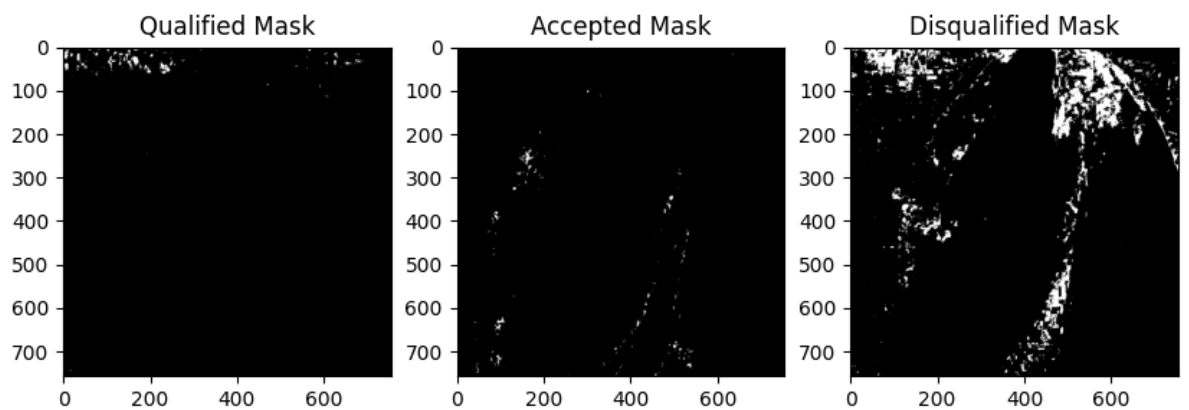


Figure 22 disqualified masking

Color Thresholding + Edge Detection

- Overview:** To enhance the reliability of pure color-based segmentation, we tested a combined approach: apply basic color thresholding first to isolate husk-colored regions, then use an edge detection algorithm (e.g., Canny or Sobel) to refine the boundaries and filter out noise.
 - Color Thresholding
Convert image to HSV, apply color thresholds to highlight the husk pixels.
 - Edge Detection
Canny (most common) or **Sobel** (gradient-based) algorithms find abrupt intensity

changes in the masked image. This step helps us detect the **outer contours** of the husk, reducing random pixel noise that might slip through color-based segmentation.

- **Advantages**

1. By combining color information with edge detection, you can more precisely separate the husk from the background or overlapping objects.
2. Random color fluctuations within the threshold range are often removed once you verify a coherent contour (like a husk shape).
3. If the husk has slight variations (e.g., green turning to brown), the edge detection can help outline the actual boundary, preventing partial misclassifications based solely on color.

- **Limitations**

1. Adding edge detection means additional image processing steps, which could slow down the pipeline if you need high real-time throughput.
2. Though edge detection can help mitigate some color issues, extreme shadowing or glare might affect gradient detection and require more sophisticated pre-processing (e.g., illumination correction).

- **Color Thresholding + Edge Detection Implementation**

The same pictures that we used for the basic color thresholding algorithm are used here.

```

import cv2
import numpy as np
import tracemalloc # For memory usage tracking
import time # For execution time tracking
import psutil # For CPU usage tracking

# Define HSV color ranges for each category
qualified_hsv_range = [(40, 60, 60), (75, 255, 255)] # Greenish (Qualified)
accepted_hsv_range = [(20, 60, 60), (30, 200, 200)] # Narrowed Yellowish/Brownish (Accepted)
disqualified_hsv_range = [(0, 0, 0), (20, 50, 85)] # Dark brownish tones (Disqualified)

1 usage  ▲ RanminiManditha
def load_image(image_path):
    """Load and preprocess an image."""
    image = cv2.imread(image_path)
    hsv_image = cv2.cvtColor(image, cv2.COLOR_BGR2HSV)
    return hsv_image

3 usage  ▲ RanminiManditha
def apply_threshold(hsv_image, lower, upper):
    """Apply color thresholding and edge detection."""
    mask = cv2.inRange(hsv_image, np.array(lower), np.array(upper))
    edges = cv2.Canny(mask, 50, 150)
    combined = cv2.bitwise_and(mask, mask, mask=edges)
    return combined

1 usage  ▲ RanminiManditha
def classify_husk(image_path):
    """Classify a husk image as Qualified, Accepted, or Disqualified."""

    # Track execution time
    start_time = time.time()

```

Figure 23 Color Thresholding + Edge Detection algorithm

1. Loading & HSV Conversion

The `load_image` function reads the image, then converts it to **HSV** via `cv2.cvtColor`. HSV often yields better segmentation for tasks involving distinct color regions.

2. Color Thresholding + Edge Detection

In `apply_threshold`, `cv2.inRange` first creates a **binary mask** from hue/saturation/value boundaries. Next, **Canny edge detection** (`cv2.Canny`) highlights the edges within that mask. Finally, `cv2.bitwise_and` merges the two, allowing only **edges within** the thresholded region to persist. This step refines segmentation by excluding stray regions in the mask without strong boundaries.

3. Classification Logic

Each category (Qualified, Accepted, Disqualified) has a corresponding mask derived from

unique HSV ranges + edges. By summing each mask's white pixels ($\text{np.sum}(\text{mask}) / 255$), the code obtains a **score** reflecting how strongly the image matches that category. The category with the **highest** score becomes the final classification.

4. Result & Metrics Output

After classification, the script prints both the final **classification** (Qualified, Accepted, or Disqualified)

- **Results**



Figure 24 used image for classification

```
Qualified Score: 944.0  
Accepted Score: 1498.0  
Disqualified Score: 0.0
```

Figure 25 result for the image

1.4 Determine the Most Effective Grading Approach

After building and testing both a **computer vision–based approach (e.g., YOLO)** and two **custom image processing algorithms** (basic thresholding vs. color thresholding + edge detection), I compared their **performance** in terms of accuracy, speed, resource usage (CPU/memory), and cost-effectiveness.

Method	Execution Time	Memory Usage	CPU Usage	Key Observations
Basic Thresholding (HSV)	~0.65–0.76 s (avg.)	~3–4 MB current (Peaks ~11–14 MB)	~26%–52%	- Straightforward HSV thresholds - Works well under stable lighting - Minimal overhead
Thresholding + Edge Detection (HSV)	~0.05–0.06 s (some tests)	~1–3 MB current (Peaks up to ~4 MB)	Up to ~60%	- Adds Canny edges for better boundary precision - Still lighter than YOLO - Slightly higher CPU load
YOLO (Computer Vision Model)	~7.51 s (single image)	256–319 MB (significantly higher)	~38%–50%	- Robust object detection - Overkill for simple color-based tasks - Requires more advanced hardware

Considering **cost constraints** and the **specific nature** of our husk grading—where color alone is the primary indicator of maturity—**image processing** is the most **practical** and **cost-effective** method. Purely color-based thresholding and the enhanced threshold+edge approach both provide **fast** and **reliable** segmentation, requiring minimal hardware and coding overhead compared to advanced object detection frameworks.

Between the two image processing solutions:

- **Basic thresholding** is extremely quick and resource-light, ideal for stable lighting conditions and clear color boundaries.
- **Thresholding + edge detection** yields more precise segmentation in variable conditions but slightly increases CPU usage.

Given our **consistent lighting setup** and the fact that the majority of husks show **distinct** color differences, **basic color thresholding** emerges as the simplest, fastest, and most cost-efficient solution for our grading system. Any future requirements for finer shape-based classification could revisit edge detection or more advanced CV, but for now, the **basic thresholding approach** sufficiently meets all

```
Initial Memory Usage: 255.68 MB
Initial CPU Usage: 37.90%

image 1/1 D:\SLIIT\Research\Test\test3.jpg: 480x640 2 Husk_Disqualifieds, 2098.8ms
Speed: 302.9ms preprocess, 2098.8ms inference, 176.6ms postprocess per image at shape (1, 3, 480, 640)
Results saved to runs\detect\predict9
Inference Time: 7.5126 seconds
Memory Usage After Inference: 318.77 MB
CPU Usage After Inference: 50.00%
Total Detections: 2
Detection 1:
  - Class ID: 2.0
  - Confidence: 0.7439
  - Bounding Box: [0.0, 51.0279655456543, 1041.1875, 951.0]
Detection 2:
  - Class ID: 2.0
  - Confidence: 0.4737
  - Bounding Box: [905.5880126953125, 0.0, 1297.48583984375, 851.9649658203125]
```

Figure 26 computer vision performances

performance and reliability goals.

1.5 Select Appropriate IoT Hardware

In order to integrate our image processing solution into a **compact, low-power** device for automated husk grading, I evaluated three widely used IoT hardware platforms: **ESP32**, **Arduino**, and **Raspberry Pi**. The primary considerations included **processing power**, **memory capacity**, **power consumption**, **ease of development**, and overall **cost**.

```
D:\Codings\ImageProcessing_Thresholding\Scripts\python.exe D:\Codings\ImageProcessing_Thresholding\Scripts\test_basicThresholding.py
Execution Time: 0.304084 seconds
Memory Usage (Current): 4180.41 KB
Memory Usage (Peak): 12139.04 KB
CPU Usage: 16.70%
Classification Per Qualified Image: Qualified
Execution Time: 0.467050 seconds
Memory Usage (Current): 5158.50 KB
Memory Usage (Peak): 12129.42 KB
CPU Usage: 18.00%
Classification Per Accepted Image: Accepted
Execution Time: 0.403868 seconds
Memory Usage (Current): 3557.13 KB
Memory Usage (Peak): 14467.83 KB
CPU Usage: 11.50%
Classification Per Disqualified Image: Disqualified
```

Figure 27 basic thresholding performances

```
D:\Codings\ImageProcessing_Thresholding\Scripts\python.exe D:\Codings\ImageProcessing_Thresholding\Scripts\test_imageSegmentation.py
Qualified Score: 2464.0
Accepted Score: 3023.0
Disqualified Score: 0.0

--- Performance Metrics ---
Execution Time: 0.0569 seconds
Current Memory Usage: 907.86 KB
Peak Memory Usage: 1288.70 KB
CPU Usage: 69.00%
The husk in the image is classified as: Accepted

Process finished with exit code 0
```

Figure 28 basic thresholding + image segmentation performances

Hardware	CPU & Speed	Memory	Power Consumption	Cost Range	Key Strengths	Limitations
ESP32	Dual-core Tensilica (~160–240 MHz)	~520 KB SRAM + some flash	Very low; suitable for battery/solar setups	\$5–\$10 (depending on module)	<ul style="list-style-type: none"> - Wi-Fi + Bluetooth built-in - Good for basic to moderate tasks - Very cost-effective, easy to program (Arduino-like) 	<ul style="list-style-type: none"> - Limited RAM/flash vs. Pi - Not ideal for heavy vision tasks (but sufficient for simpler algorithms)
Arduino (e.g., Uno, Mega)	8-bit AVR (~16 MHz)	2 KB–8 KB SRAM (model dependent)	Very low; often used with batteries	\$5–\$30 (depending on model)	<ul style="list-style-type: none"> - Extremely low power - Huge community, easy for sensors - Great for basic control/logic tasks 	<ul style="list-style-type: none"> - Very limited memory & speed - Not well-suited for image processing - Typically no built-in Wi-Fi/BLE
Raspberry Pi (e.g., Pi 4)	Quad-core ARM Cortex (~1.5 GHz)	1–8 GB RAM (model dependent)	Moderate to high (Requires stable 5V supply)	\$35–\$75+ (depending on model)	<ul style="list-style-type: none"> - Can run full Linux OS - Ideal for advanced edge computing - Large memory for ML tasks 	<ul style="list-style-type: none"> - Higher cost - Consumes more power - Overkill if only simple color detection is needed

- Matching Hardware to Image Processing Requirements

Since we decided to use **simple HSV-based thresholding** (with or without edge detection), the **computational demands** are moderate. The tasks involve pixel-level operations but do **not** require

complex deep learning frameworks. Therefore,

ESP32: Offers enough processing power to handle **basic real-time** color thresholding, especially if images are captured at lower resolution (e.g., 320×240 or 640×480) and processed sequentially. Its built-in Wi-Fi/Bluetooth simplifies sending classification signals to the mechanical sorting arms or any central server if needed. Additionally, **low cost** (often under \$10) and low power consumption make it attractive for large-scale deployment.

Arduino: Excellent for **simple control** and sensor reading, but the limited CPU speed (16 MHz) and **minimal RAM** (2–8 KB) severely restrict image processing capabilities. To handle even basic image thresholding, extra shields or modules might be required, quickly eroding its low cost advantage and complicating the system.

Raspberry Pi: Offers a **full Linux environment** and can easily handle advanced image processing or even YOLO-based computer vision. However, it comes at a higher price point (\$35–\$75) and consumes more power. This is often **overkill** when simpler color detection is sufficient.

- Rationale for Choosing ESP32,

Although the ESP32 is not as powerful as the Raspberry Pi, it can comfortably run the **basic image processing** routines I have developed. By using efficient libraries and lower-resolution images, the performance remains acceptable for real-time husk grading.

The ESP32 module is **significantly cheaper** than a Raspberry Pi, and its ultra-low-power modes allow battery or solar operation, valuable if the grading system is deployed in remote or large-scale settings.

Native **Wi-Fi** (and optionally **Bluetooth**) support makes it straightforward to send classification data to servers, log results in the cloud, or control external devices. Arduino boards often require **additional** Wi-Fi modules or shields.

The ESP32 can be programmed via the familiar Arduino IDE or PlatformIO, with a rich ecosystem of tutorials and libraries. This ensures **rapid prototyping** and straightforward integration with sensors, conveyors, or sorting actuators.

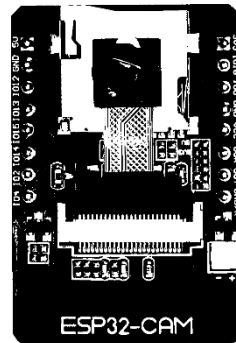


Figure 30 ESP 32 cam module



Figure 29 Arduino Board

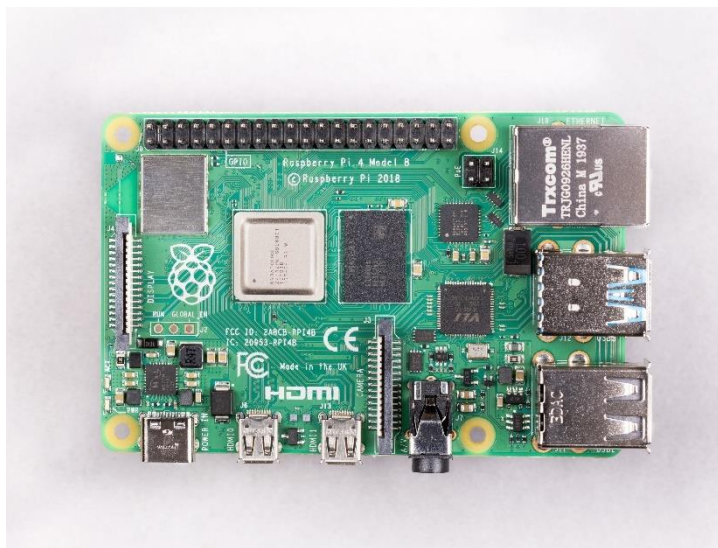


Figure 31 raspberry pi

1.6 Implement Algorithm for the Husk Classification in the ESP32

To bring the husk classification algorithm onto a compact, **IoT-based platform**, I initially tried running all detection, image capture, and classification tasks on a **single ESP32** module. The workflow required:

- **Object Detection:** Detect when a coconut husk passes in front of a sensor (e.g., ultrasonic HC-SR04), alerting the ESP32.

- **Camera Initialization:** Power up and activate the ESP32-CAM to capture a frame of the husk.
- **Running the Algorithm:** Apply the basic color thresholding classification model to determine if the husk is “Qualified,” “Accepted,” or “Disqualified.”
- **Data Tracking:** Keep a cumulative count of husks in each category.
- **Data Reporting:** Transmit these counts to a **HIVE server** for logging or analytics.

Memory and Performance Constraints

Although the ESP32 has sufficient **clock speed** and memory for basic image processing, it proved challenging to manage **all** required tasks object detection, camera operations, classification, and real-time data transmission within a single device. Image buffers, along with the overhead of continuous sensor polling, exhausted the ESP32’s resources, causing **instability** and inconsistent classification results.

Dual-Module Setup

To mitigate these limitations, I opted for **two ESP32 modules**:

1. Standard ESP32

- Interfaces with the **HC-SR04** or equivalent sensor to detect an incoming husk.
- Powers up the ESP32-CAM **on-demand** via a **relay module** (minimizing idle power consumption).
- Maintains internal counters for each category (Qualified, Accepted, Disqualified).
- Communicates final husk counts to the **HIVE server** for data logging.

2. ESP32-CAM

- Activated only when the standard ESP32 detects a husk and energizes the relay(relay module).
- Initializes the onboard camera, captures the image, and runs the **lightweight** classification algorithm.
- Sends classification results back to the primary ESP32 over **UART** (wired serial).
- Powers down once classification completes, reducing overall resource usage.

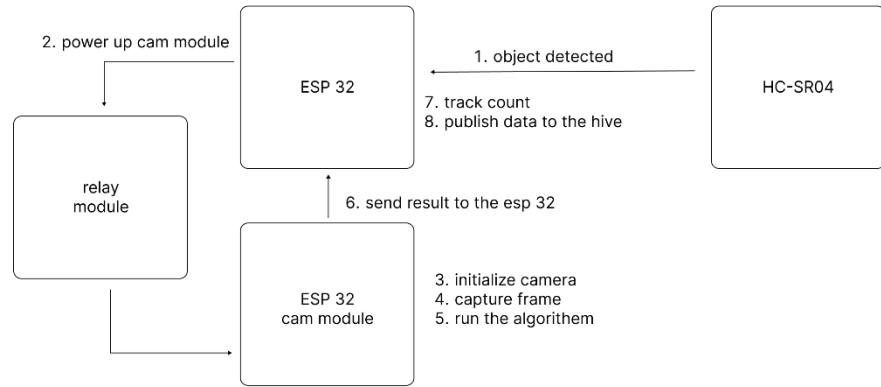


Figure 33 system architecture

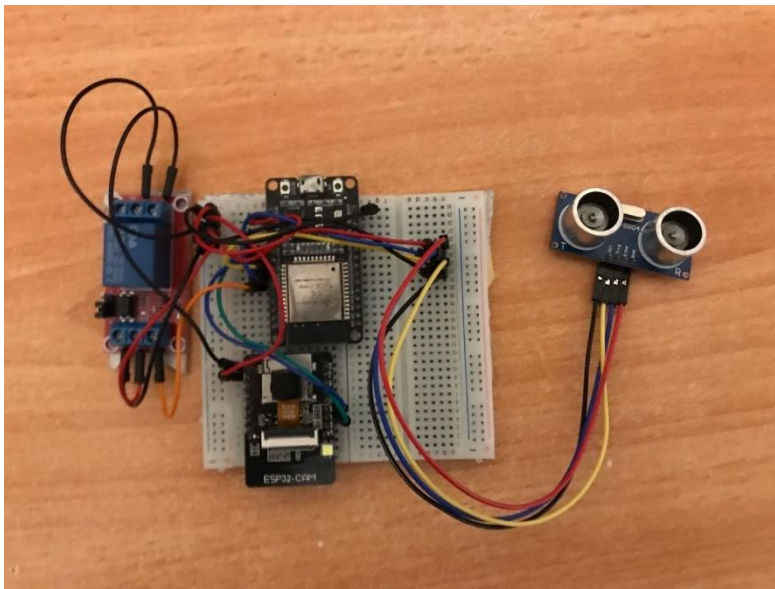


Figure 32 real time module

Architecture and Issues Encountered

Despite this design partially offloading the workload, image quality and algorithmic accuracy on the ESP32-CAM remained problematic. The built-in camera's resolution and sensor quality, combined with limited processing overhead, led to inconsistent or imprecise husk segmentation, especially under variable lighting. Consequently, classification accuracy suffered.

2. Automating Moisture Level Tracking System

Maintaining optimal moisture levels is critical for both drying coconut husks and managing water supply in soaking or washing processes. This second major component of the research aims to develop and deploy an automated monitoring solution capable of measuring and transmitting real-time moisture data to an online dashboard for timely intervention and process optimization. By placing robust sensors in both drying areas and water storage tanks, stakeholders can effectively track

conditions, ensure quality control, and conserve resources.

2.1 Determine Optimal Sensor Placement

I began by surveying the **drying yards** to pinpoint zones where coconut husks typically retain or lose moisture at varying rates. Capacitive sensors were placed at strategic depths to capture meaningful readings in these critical spots, while an ultrasonic sensor was reserved for measuring water levels in key tanks. This layout ensures each location is monitored where it matters most, minimizing blind spots and providing actionable insights around the clock.

Water Tank view

● → Device

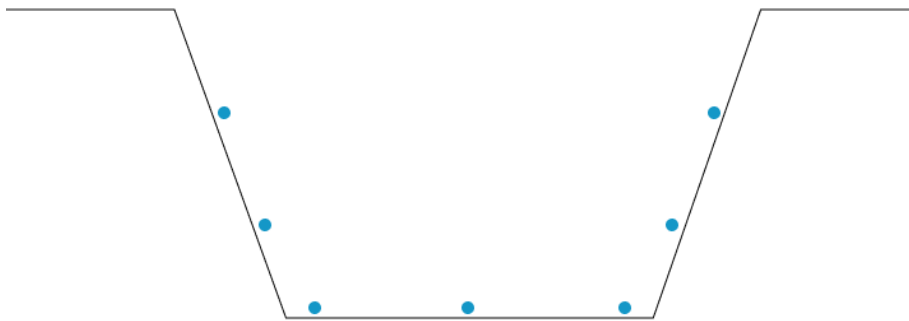


Figure 34 water tank view

Drying area view

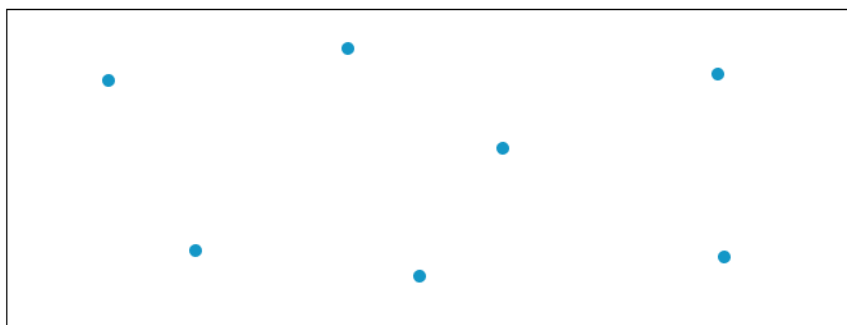


Figure 35 drying area view

4.2 Commercialization Aspects of the Product

1. Husk Classification Automated System

1. Target Market and Value Proposition

- **Primary Audience:** Coconut processing plants, exporters, and large-scale husk product manufacturers requiring consistent grading based on maturity or color.
- **Value:** By automating husk classification, factories can reduce labor expenses, achieve more consistent product quality, and enhance throughput. The system is compact, cost-friendly (ESP32-CAM), and well-suited for continuous production lines.

2. Cost Structure and Pricing

- **Hardware Cost:** Each ESP32-CAM device, plus a simple ultrasonic or photoelectric sensor, typically falls under \$25–\$35 per unit (depending on bulk discounts). Basic installation materials (mounts, cables) remain minimal.
- **ROI:** Clients can see a return on investment through reduced manual inspection, minimized error rates, and faster sorting. Smaller factories benefit from labor cost savings, while larger facilities gain scale-up efficiency.

3. Scalability and Marketing Strategy

- **Modular Deployment:** Facilities can start with a few lines and expand as throughput grows, each line adding an additional ESP32-CAM kit.
- **Branding & Promotion:** Emphasize “low-cost, high-consistency husk grading.” Demonstrating actual ROI like time-savings, labor reallocation, or improved product uniformity bolsters credibility.
- **Service & Maintenance:** Beyond the initial sale, recurring revenue might stem from periodic firmware upgrades, sensor replacements, or extended warranties.

2. Moisture-Level Tracking System

1. Target Market and Business Potential

- **Primary Audience:** Coconut husk drying operators, large-scale farms, and even broader agricultural sectors (like coffee, cocoa, or grain) needing continuous moisture tracking.
- **Value:** Real-time moisture data improves drying accuracy, prevents product spoilage, and optimizes water usage in washing/soaking processes. This equates to tangible cost savings and improved product quality.

2. Cost Elements and Pricing Model

- **Hardware:** Each sensor node (ESP32, moisture/ultrasonic sensors, LM2596, enclosures) roughly ranges from \$25–\$50, depending on sensor quality (accuracy) and power choices (battery vs. solar).

- **Data Connectivity:** A small monthly fee could be charged for cloud hosting or advanced analytics dashboards that aggregate sensor data from multiple nodes.
- **Long-Term ROI:** Users see a return via reduced waste (over-drying or rewetting), better resource allocation (water, labor), and minimized risk of product losses. By presenting historical data, it's easier for stakeholders to fine-tune operations, reinforcing the system's ongoing value.

3. Deployment, Branding, and Maintenance

- **Rapid Deployment:** Pre-calibrated sensor kits can be installed quickly in drying yards or water tanks. Step-by-step instructions and a user-friendly interface expedite the setup process for non-technical staff.
- **Maintenance Program:** Annual or biannual service packages can be sold, covering sensor recalibration, firmware updates, and potential hardware replacements. This model fosters a steady service-based revenue stream.
- **Marketing Strategy:** Highlight proven field results—for instance, how real-time moisture tracking prevents over-drying or resource misallocation. Testimonials from early adopters in the coconut or broader agricultural sector will validate reliability and cost-effectiveness.

4. Scalability and Expansion

- **Add-On Features:** As demand grows, or for different agricultural processes, you could offer advanced features (like temperature, pH sensors) in the same integrated dashboard.
- **Cross-Sector Potential:** Moisture monitoring is widely needed in all sorts of agricultural commodities. By demonstrating success in coconut husk processing, the system can pivot to other markets (grain storage, coffee drying), extending the product's lifespan and market footprint.

5. Testing & Implementation

5.1 Implementation

Refining the Algorithm: Green Ratio Classification

Given the **ESP32-CAM**'s limited image quality and processing capacity, I shifted from broad HSV color thresholding to a **simpler metric: the green ratio** in each captured frame. This streamlined approach directly measures how much of the image exhibits "green" pixels, then uses **fixed thresholds** to decide whether the husk is "Qualified," "Accepted," or "Disqualified."

1. Motivation for the Green Ratio

- **ESP32-CAM Constraints:** Due to its modest camera sensor and memory, standard color segmentation proved inconsistent. Introducing advanced filters or multiple color checks quickly exhausted resources.
- **Dominant Feature (Green):** In practice, "Qualified" husks tend to have more visible green, while "Accepted" husks are largely yellowish-brown with traces of green, and "Disqualified" husks show little to no green.
- **Cleaner Separation:** Preliminary tests on actual ESP32-CAM snapshots revealed distinct "clusters" of green ratios for each category. This natural spread made it straightforward to define numeric cutoffs.

2. Deriving Category Ranges from ESP32-CAM Images

To establish reliable thresholds for "Qualified," "Accepted," and "Disqualified" husks, I first **collected a sample set** of images directly using the **ESP32-CAM** under typical operating conditions. This ensured the captured frames reflected the **real-world resolution, color fidelity, and lighting** the module would encounter during actual grading

1. Image Capture

- Each image was taken when a husk was placed before the ESP32-CAM.
- The camera's configuration mirrored final deployment to capture realistic color data specific for the ESP-32.

2. Green Ratio Computation

- For each image, I iterated over all pixels to **quantify** how many qualified as "green." Typically, this involved checking if the green channel (in RGB) or the hue (in HSV) surpassed certain thresholds relative to red/blue.

3. Data Analysis & Clustering

- After generating a green ratio for each image, I grouped them by *intended* label: "Qualified," "Accepted," or "Disqualified."
- Observing the results revealed **natural gaps** in green ratio values clear clusters emerged, with each category occupying a distinct range.

4. Final Ranges

- **Qualified** consistently exhibited the **highest** green ratios, often above 0.25.
- **Accepted** images showed a **moderate** green coverage (~0.07–0.12).
- **Disqualified** almost **lacked** visible green (often below 0.02).
- These findings allowed me to define **cutoff thresholds** with minimal overlap—for instance,
 1. **green_ratio > 0.20** → "Qualified"
 2. **0.03 < green_ratio ≤ 0.20** → "Accepted"
 3. **green_ratio ≤ 0.03** → "Disqualified"

3. Practical Workflow of the ESP32-CAM with HC-SR04

In the finalized system, **one** ESP32-CAM module orchestrates both **object detection** and **image-**

based classification

1. Husk Detection (HC-SR04)
 - The **HC-SR04 ultrasonic sensor** faces the conveyor path.
 - When the sensor's distance reading indicates a husk is within range, the ESP32-CAM triggers its internal routine to capture and analyze an image.
2. Camera Initialization & Frame Capture
 - The ESP32-CAM's built-in camera module wakes up or switches into capture mode.
 - It grabs a **single frame** of the husk in its field of view at a low-to-moderate resolution (e.g., 320×240) to balance clarity with memory constraints.
3. Green Ratio Calculation
 - The captured frame is processed to count how many pixels are "green.",
4. Classification
 - Based on the green ratio, the algorithm compares the result against predetermined thresholds
 - This simplified approach lets the ESP32-CAM manage classification without exceeding its limited memory or processing budget.
5. Data Handling
 - Once the category is determined, the ESP32-CAM can locally increment counters (if needed) and transmit the classification result to a remote server.



Figure 37 qualified husk images taken by esp 32 cam



Figure 38 accepted husk images taken by esp 32 cam



Figure 36 disqualified husk images taken by esp 32 cam


```

import cv2
import numpy as np
import glob
import os

lower_green = np.array([35, 40, 40], dtype=np.uint8)
upper_green = np.array([85, 255, 255], dtype=np.uint8)

1 usage
def compute_green_ratio(image_path):

    img = cv2.imread(image_path)
    if img is None:
        print(f"Error: Could not open {image_path}")
        return None

    # Convert BGR -> HSV
    hsv = cv2.cvtColor(img, cv2.COLOR_BGR2HSV)

    # Create a mask for pixels within [lower_green, upper_green]
    mask = cv2.inRange(hsv, lower_green, upper_green)

    # Count 'white' (green) pixels
    green_pixels = cv2.countNonZero(mask)
    total_pixels = img.shape[0] * img.shape[1]

    return green_pixels / float(total_pixels)

3 usages
def analyze_directory(folder_path, label):

    patterns = [
        "*.jpg", "*.jpeg", "*.png",
        "*.JPG", "*.JPEG", "*.PNG"
    ]

    image_paths = set()

```

Figure 40 green analyzing code

```

--- Analyzing category: Qualified ---
D:/SLIIT/Research/analyze green/qualified\2.jpg: green_ratio=0.3018
D:/SLIIT/Research/analyze green/qualified\3.jpg: green_ratio=0.2592
D:/SLIIT/Research/analyze green/qualified\5.png: green_ratio=0.5921
D:/SLIIT/Research/analyze green/qualified\6.png: green_ratio=0.2466
D:/SLIIT/Research/analyze green/qualified\1.jpg: green_ratio=0.3462

--- Analyzing category: Accepted ---
D:/SLIIT/Research/analyze green/accepted\2.jpg: green_ratio=0.0697
D:/SLIIT/Research/analyze green/accepted\3.jpg: green_ratio=0.1232
D:/SLIIT/Research/analyze green/accepted\4.jpg: green_ratio=0.1115

--- Analyzing category: Disqualified ---
D:/SLIIT/Research/analyze green/disqualified\4.png: green_ratio=0.0174
D:/SLIIT/Research/analyze green/disqualified\3.png: green_ratio=0.0077
D:/SLIIT/Research/analyze green/disqualified\1.jpg: green_ratio=0.0015

```

Figure 39 green analyzed results

System implementation

In the final design, the **ESP32-CAM module** serves as both the **sensor controller** and **image processor**, while an **HC-SR04 ultrasonic** sensor detects incoming husks. Once a husk is detected, the ESP32-CAM captures and analyzes the frame, classifies the husk by its green ratio, and communicates the results (including a running count) to a **HiveMQ** server via MQTT.

1. Hardware Connections

1. ESP32-CAM Module

- Powered by a 5V supply(USB Cable)
- Configured to run in station mode for Wi-Fi connectivity, enabling data transmission to the HiveMQ server.

2. HC-SR04 Ultrasonic Sensor

- **VCC** and **GND** connected to the ESP32-CAM's 5V and ground pins.
- **Trigger Pin (TRIG)** and **Echo Pin (ECHO)** wired to GPIO 13 and GPIO 12, with necessary level shifting.
- Continuously measures distance to detect the presence of a coconut husk in front of the camera.

3. MQTT Connectivity

- The ESP32-CAM uses built-in Wi-Fi to connect to the local network.
- MQTT library installed for publishing classification results to the **HiveMQ** server.

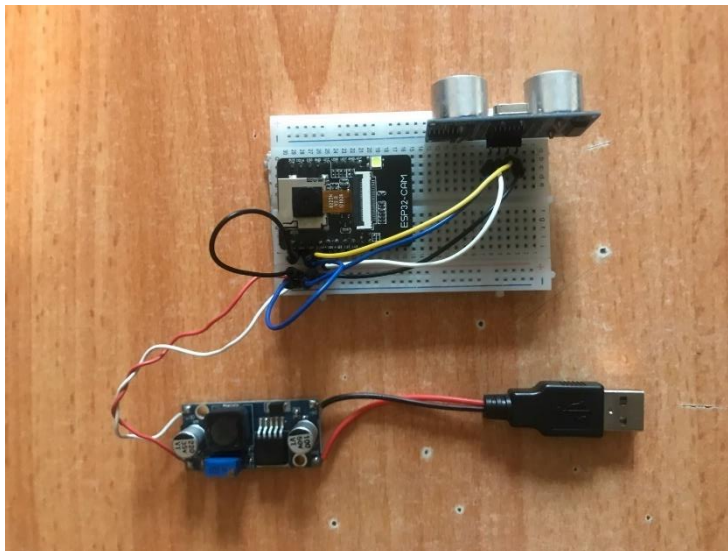


Figure 41 hardware model

2. System Workflow

1. Object Detection via HC-SR04

- The ultrasonic sensor sends out pulses. If the returning echo indicates a distance less than 10cm, the system infers that a husk is near the camera.

```
// Ultrasonic pins
#define TRIG_PIN 13
#define ECHO_PIN 12

// Distance threshold (in cm) to detect a husk
#define DIST_THRESHOLD_CM 10
```

Figure 42 module pins

```
//
long getDistanceCM() {
    // Clear trigPin
    digitalWrite(TRIG_PIN, LOW);
    delayMicroseconds(2);

    // Send 10us pulse on trigPin
    digitalWrite(TRIG_PIN, HIGH);
    delayMicroseconds(10);
    digitalWrite(TRIG_PIN, LOW);

    // Measure the time for echoPin
    long duration = pulseIn(ECHO_PIN, HIGH, 30000UL); // 30ms timeout => ~5m max
    if (duration == 0) {
        // No echo -> out of range
        return 9999;
    }

    // Calculate distance in cm
    long distanceCM = duration / 29 / 2;
    return distanceCM;
}
```

Figure 43 object detection code

2. Camera Initialization & Frame Capture

- Upon detecting a husk, the ESP32-CAM initializes its camera module.
- Captures a single frame of the husk at a modest resolution (e.g., 320×240) to balance detail with memory constraints.

```

void initCamera() {
    camera_config_t config;
    config.ledc_channel = LEDC_CHANNEL_0;
    config.ledc_timer = LEDC_TIMER_0;
    config.pin_d0 = Y2_GPIO_NUM;
    config.pin_d1 = Y3_GPIO_NUM;
    config.pin_d2 = Y4_GPIO_NUM;
    config.pin_d3 = Y5_GPIO_NUM;
    config.pin_d4 = Y6_GPIO_NUM;
    config.pin_d5 = Y7_GPIO_NUM;
    config.pin_d6 = Y8_GPIO_NUM;
    config.pin_d7 = Y9_GPIO_NUM;
    config.pin_xclk = XCLK_GPIO_NUM;
    config.pin_pclk = PCLK_GPIO_NUM;
    config.pin_vsync = VSYNC_GPIO_NUM;
    config.pin_href = HREF_GPIO_NUM;
    config.pin_sscb_sda = SIOD_GPIO_NUM;
    config.pin_sscb_scl = SIOC_GPIO_NUM;
    config.pin_pwdn = PWDN_GPIO_NUM;
    config.pin_reset = RESET_GPIO_NUM;
    config.xclk_freq_hz = 20000000;
    config.pixel_format = PIXFORMAT_RGB565;
    config.frame_size = FRAMESIZE_QVGA;
    config.jpeg_quality = 12;
    config.fb_count = 1;

    esp_err_t err = esp_camera_init(&config);
    if (err != ESP_OK) {
        Serial.printf("Camera init failed with error 0x%x\n", err);
    } else {
        Serial.println("Camera initialized.");
    }
}

```

Figure 44 camera setup

3. Green Ratio Computation

- Converts the captured frame into RGB or HSV.
- Determines how many pixels qualify as “green”

```

void RGBtoHSV(uint8_t r, uint8_t g, uint8_t b,
              uint8_t &h, uint8_t &s, uint8_t &v)
{
    uint8_t maxVal = max(r, max(g, b));
    uint8_t minVal = min(r, min(g, b));
    uint8_t delta = maxVal - minVal;

    v = maxVal; // 0..255

    if (delta == 0) {
        s = 0;
        h = 0;
        return;
    }

    s = (uint16_t)delta * 255 / maxVal;

    if (r == maxVal) {
        h = 0 + 43 * (g - b) / delta;
    }
    else if (g == maxVal) {
        h = 85 + 43 * (b - r) / delta;
    }
    else {
        h = 170 + 43 * (r - g) / delta;
    }
    if ((int)h < 0) {
        h += 180;
    }
}

// Range check for "green" in HSV
bool isGreenHSV(uint8_t h, uint8_t s, uint8_t v) {
    // Adjust these as per your husk color
    if (h >= 35 && h <= 85 &&
        s >= 40 && s <= 255 &&
        v >= 40 && v <= 255) {
        return true;
    }
    return false;
}

```

Figure 45 green ratio checking

4. Classification

- The green ratio is compared to **two numeric thresholds** to assign the husk to one of three categories

- The logic stems directly from empirical testing with the ESP32-CAM, ensuring **minimal overlap** among categories.

```
String category;
if (green_ratio > 0.25f) {
  category = "Qualified";
} else if (green_ratio > 0.05f) {
  category = "Accepted";
} else {
  category = "Disqualified";
}
Serial.println(" => " + category);
return category;
```

Figure 46 classification

5. Counting & Data Handling

- The ESP32-CAM increments an **internal counter** for each classification type
- These counters are stored in memory and updated after every new husk classification.

```
long huskCount = 0;
```

Figure 47 husk count

```
String result = classifyHusk();
if (result != "CameraFail" && result != "FormatError") {
  huskCount++;
  // 3) Publish classification + count
  // e.g. "Qualified" or "Accepted" or "Disqualified"
  mqttClient.publish(TOPIC_CLASSIFICATION, result.c_str());

  // Convert huskCount to string
  char buf[10];
  snprintf(buf, sizeof(buf), "%ld", huskCount);
  mqttClient.publish(TOPIC_COUNT, buf);

  Serial.println("MQTT published: classification + huskCount");
}
```

Figure 48 counting husks

6. Publishing to HiveMQ

- After updating counts, the ESP32-CAM formats a short JSON or text payload and publishes it to a **HiveMQ** server via MQTT.
- This allows any remote application to receive real-time updates on how many husks have been classified in each category.

```

void connectMQTT() {
  while (!mqttClient.connected()) {
    Serial.print("Attempting MQTT connection...");

    if (mqttClient.connect("ESP32HuskClient")) {
      Serial.println("connected");
    } else {
      Serial.print("failed, rc=");
      Serial.print(mqttClient.state());
      Serial.println(" retry in 2 seconds");
      delay(2000);
    }
  }
}

```

Figure 49 MQTT connection

7. Idle State

- If no husk is detected, the ESP32-CAM optionally power down or enter a low-power standby to conserve energy, only reactivating the camera once the ultrasonic sensor registers a new object.

In summary, this **ESP32-CAM-based** system autonomously detects each husk via an ultrasonic sensor, captures a frame, classifies the husk by a **green ratio** threshold, maintains category counts, and **publishes** the data to **HiveMQ** for real-time monitoring or long-term analytics. This design strikes a **practical** balance between minimal hardware complexity, **cost**, and **functional** requirements for automated coconut husk grading.

Implementing the Moisture Monitoring Solution

1. Hardware Integration

1. ESP32 Microcontroller

- Chosen for its **built-in Wi-Fi** and sufficient I/O pins, the ESP32 reads the soil moisture sensor via one of its **analog pins**. I found it robust enough to handle basic data processing while still offering **real-time connectivity** to our web dashboard.
- The board is powered at **3.3V**, which makes accurate voltage regulation essential.

2. Soil Moisture Sensor

- Placed outside of the device, this sensor detects current moisture content by measuring the **electrical conductivity** in the substrate.

3. LM2596 DC-DC Buck Converter

- The LM2596 module steps down higher DC voltages to the **3.3V** required by the ESP32. This regulator efficiently handles voltage drops with minimal heat loss, preserving overall system longevity.

- By adjusting the built-in potentiometer and monitoring output with a multimeter, I fine-tuned the LM2596's output to ensure **stable power** at ~3.3V, preventing brownout resets or sensor inaccuracies that can result from fluctuating voltages.

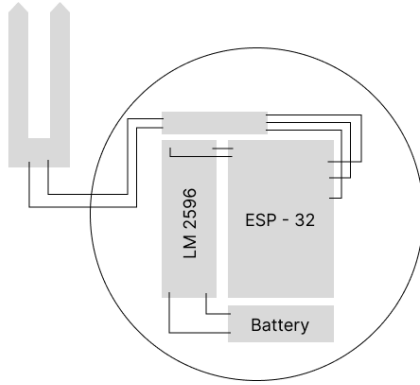


Figure 51 system architecture

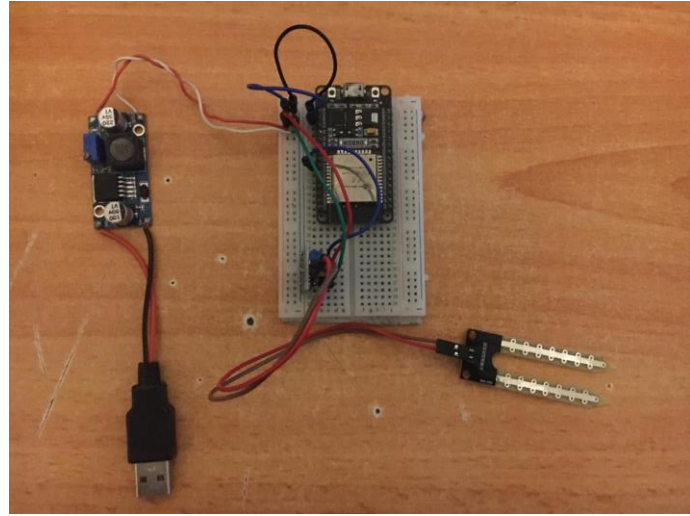


Figure 50 system module

2. Data Processing & Transmission

To ensure timely insights while conserving resources, each device **samples the moisture sensor** every 15 minutes. Once a reading is obtained, the system applies basic filtering to stabilize the measurement. This filtered value is then **packaged** with metadata such as the **device name**, **timestamp**, and the **sensor reading** and transmitted to the central dashboard via Wi-Fi.

1. Sampling Interval

- Each device awakens from low-power mode every 15 minutes, powers the moisture sensor, and performs a brief reading sequence
- Basic arithmetic operations refine the raw data into a single, more reliable measurement..

2. Data Preparation

- After finalizing the moisture reading, the system compiles the **device name**, **time** of measurement, and the **data** value into a lightweight JSON.

3. Dashboard Integration

- Once received by the server, each data entry is stored and displayed in a **table** within the dashboard, where columns correspond to,

1. **Device Name:** Easily identifies which node (e.g., "D1,D2") provided the reading.
2. **Time:** Specifies when the measurement was taken, enabling historical tracking and trend analysis.
3. **Data:** Shows the final moisture value, allowing users to quickly scan for anomalies.


```

const char* ssid = "SLT_FIBRE";
const char* password = "SLT_FIBRE";

// Change these to match your setup
const char* deviceName = "ESP32_A1";
#define MOISTURE_SENSOR_PIN 34

#define SLEEP_INTERVAL_MINUTES 15
#define uS_TO_S_FACTOR 1000000ULL

// Placeholder server endpoint (if needed for future HTTP transmissions)
const char* serverURL = "http://yourserver.com/api/moisture";

void setup() {
  Serial.begin(115200);
  delay(1000);

  pinMode(MOISTURE_SENSOR_POWER_PIN, OUTPUT);
  digitalWrite(MOISTURE_SENSOR_POWER_PIN, HIGH);
  delay(100);

  // Connect to Wi-Fi
  WiFi.mode(WIFI_STA);
  WiFi.begin(ssid, password);

  Serial.print("Connecting to WiFi");
  while (WiFi.status() != WL_CONNECTED) {
    delay(500);
    Serial.print(".");
  }
  Serial.println("\nWiFi connected!");

  int filteredReading = getFilteredMoistureReading();

  String timestamp = "2025-05-10T07:30:00Z";

  String payload = "{";
  payload += "\"device\": \"" + String(deviceName) + "\", ";
  payload += "\"timestamp\": \"" + timestamp + "\"";
}

```

Figure 54 code snippet 1

```

HTTPClient http;
http.begin(serverURL);
http.addHeader("Content-Type", "application/json");
int httpResponseCode = http.POST(payload);
Serial.print("HTTP Response code: ");
Serial.println(httpResponseCode);
http.end();

// Print done message
Serial.println("Data acquisition complete. Going to deep sleep...");

// Schedule deep sleep
esp_sleep_enable_timer_wakeup(SLEEP_INTERVAL_MINUTES * 60ULL * uS_TO_S_FACTOR);
esp_deep_sleep_start();

void loop() {
  delay(1000);

  int getFilteredMoistureReading() {
    const int NUM_SAMPLES = 5;
    int readings[NUM_SAMPLES];

    // Take multiple samples
    for (int i = 0; i < NUM_SAMPLES; i++) {
      readings[i] = analogRead(MOISTURE_SENSOR_PIN);
      delay(200); // small delay between readings
    }

    // Sort the array (simple Bubble Sort for illustration)
    for (int i = 0; i < NUM_SAMPLES - 1; i++) {
      for (int j = 0; j < NUM_SAMPLES - i - 1; j++) {
        if (readings[j] > readings[j + 1]) {
          int temp = readings[j];
          readings[j] = readings[j + 1];
          readings[j + 1] = temp;
        }
      }
    }
  }
}

```

Figure 53 code snippet 2

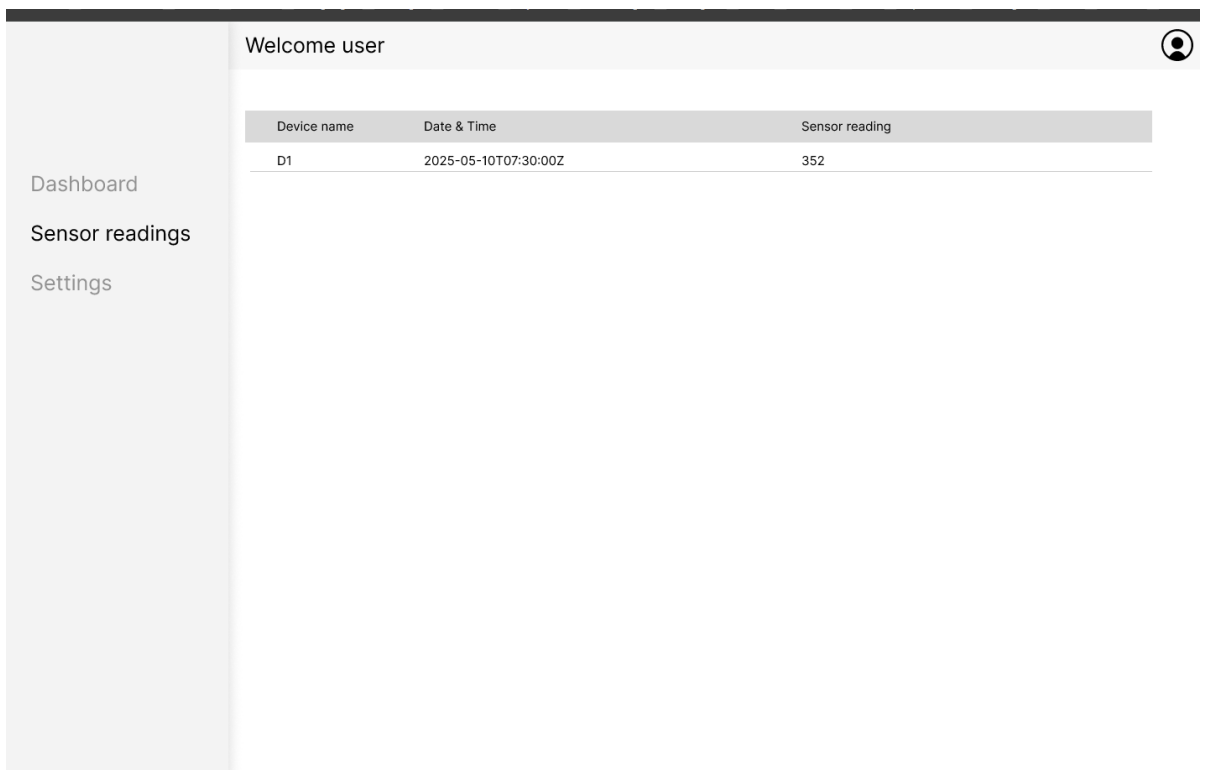


Figure 52 dashboard integration

5.2 Testing

5.2.1 Test Cases

1. Husk classification

Test Case Id	HG-01
Test Case	Detect Husk & Classify (Qualified)
Test Scenario	Confirm the system tags a partially green/yellow husk as “Qualified.”
Input	Husk with green ratio > 0.20
Expected Output	Output classification: Qualified
Actual Result	<pre>Waiting for a husk.. Husk detected! Initializing camera Capturing frame Frame Captured! Husk classifying.. Result - Qualified</pre>
Status (Pass/Fail)	Pass

Test Case Id	HG-02
Test Case	Detect Husk & Classify (Accepted)
Test Scenario	Confirm the system tags a partially green/yellow husk as “Accepted.”
Input	Husk with green ratio ~0.10–0.12
Expected Output	Output classification: Accepted
Actual Result	<pre>Waiting for a husk.. Husk detected! Initializing camera Capturing frame Frame Captured! Husk classifying.. Result - Accepted</pre>

Status (Pass/Fail)	Pass
--------------------	------

Test Case Id	HG-03
Test Case	Detect Husk & Classify (Disqualified)
Test Scenario	Confirm the system tags a partially green/yellow husk as “Disqualified.”
Input	Husk with green ratio near zero
Expected Output	Output classification: Disqualified
Actual Result	<pre>Waiting for a husk.. Husk detected! Initializing camera Capturing frame Frame Captured! Husk classifying.. Result - Disqualified</pre>
Status (Pass/Fail)	Pass

Test Case Id	HG-04
Test Case	No Husk Present (Idle State)
Test Scenario	Ensure the system remains idle if no object is detected by ultrasonic sensor.
Input	No object in front of camera Distance > threshold
Expected Output	The ESP32-CAM does not trigger the camera or classification
Actual Result	<pre>Waiting for a husk.. 2 minutes passed, no husk detected Waiting for a husk..</pre>
Status (Pass/Fail)	Pass

2. Moisture level tracking

Test Case Id	MC-01						
Test Case	Very Dry Condition						
Test Scenario	Check system behavior at minimal moisture levels.						
Input	Sensor in a very dry substrate						
Expected Output	Dashboard displays reading < 200 as “Very Dry” in the data column.						
Actual Result	<table><tr><th>Device name</th><th>Date & Time</th><th>Sensor reading</th></tr><tr><td>D1</td><td>2025-05-10T07:32:03Z</td><td>172</td></tr></table>	Device name	Date & Time	Sensor reading	D1	2025-05-10T07:32:03Z	172
	Device name	Date & Time	Sensor reading				
	D1	2025-05-10T07:32:03Z	172				
Status (Pass/Fail)	Pass						

Test Case Id	MC-02									
Test Case	Very Wet Condition									
Test Scenario	Check system behavior at maximum moisture levels.									
Input	Sensor immersed or near saturation									
Expected Output	Dashboard displays reading very high in the data column.									
Actual Result	<table><tr><th>Device name</th><th>Date & Time</th><th>Sensor reading</th></tr><tr><td>D1</td><td>2025-05-10T07:32:03Z</td><td>172</td></tr><tr><td>D1</td><td>2025-05-10T07:35:32Z</td><td>657</td></tr></table>	Device name	Date & Time	Sensor reading	D1	2025-05-10T07:32:03Z	172	D1	2025-05-10T07:35:32Z	657
Device name	Date & Time	Sensor reading								
D1	2025-05-10T07:32:03Z	172								
D1	2025-05-10T07:35:32Z	657								
Status (Pass/Fail)	Pass									

Test Case Id	MC-03												
Test Case	Mid Condition												
Test Scenario	Check system behavior at mid moisture levels.												
Input	Sensor in a mid moistured substrate												
Expected Output	Dashboard displays reading around 300-400 in the data column.												
Actual Result	<table><tr><th>Device name</th><th>Date & Time</th><th>Sensor reading</th></tr><tr><td>D1</td><td>2025-05-10T07:32:03Z</td><td>172</td></tr><tr><td>D1</td><td>2025-05-10T07:35:32Z</td><td>657</td></tr><tr><td>D1</td><td>2025-05-10T07:41:49Z</td><td>369</td></tr></table>	Device name	Date & Time	Sensor reading	D1	2025-05-10T07:32:03Z	172	D1	2025-05-10T07:35:32Z	657	D1	2025-05-10T07:41:49Z	369
Device name	Date & Time	Sensor reading											
D1	2025-05-10T07:32:03Z	172											
D1	2025-05-10T07:35:32Z	657											
D1	2025-05-10T07:41:49Z	369											
Status (Pass/Fail)	Pass												

6. RESULTS AND DISCUSSIONS

6.1 Results

The implemented systems were evaluated on a series of controlled tests and field deployments. The husk grading system and the moisture tracking system were each tested under realistic conditions that mimic daily operations in a coconut husk processing facility.

Husk Grading System

1. Detection and Classification

1. Image-Based Classification:

- Using the ESP32-CAM in conjunction with an HC-SR04 sensor, the system captured frames of coconut husks and computed the green ratio.
- The classification algorithm, based on empirically determined thresholds, yielded consistent results.

2. Performance Metrics:

- Average Execution Time: Approximately 0.7 seconds per image for the complete process
- Resource Usage: The algorithm operated within the ESP32's limitations, with measured memory peaks around 4 MB and CPU usage fluctuating between 26–52%.

3. Test Outcomes:

- Test images from each husk category consistently produced classification results that matched manual visual assessments.
- Visual outputs confirmed distinct separation among categories, with minimal overlap between the ranges.

2. Data Transmission

- The classification results, along with timestamped counts for each category, were successfully transmitted to the HiveMQ server via MQTT.

Moisture Tracking System

1. Sensor Readings

1. Coco Peat Moisture:

- Sensors deployed in the drying areas recorded values consistent with expected ranges: very dry conditions (~150–200), optimal moisture (300–400), and saturated conditions (~600–700) on a 0–1023 scale.

2. Data Sampling:

- Readings were reliably transmitted at 15-minute intervals, and the real-time dashboard correctly displayed each sensor's output in a tabular format.

2. System Performance

- The moisture reading system maintained stable connectivity throughout extended field testing, showing no significant data loss during intermittent network fluctuations.
- Power consumption was effectively managed through deep sleep cycles, and the LM2596 ensured a steady 3.3V supply, preventing undervoltage issues.

6.2 Research Findings

1. Husk Grading Findings

- The green ratio-based classification produced distinct clusters of values for each category, with "Qualified" husks consistently exhibiting higher green ratios compared to "Accepted" and "Disqualified".
- The integrated workflow proved reliable, though minor delays were noted during sensor-triggered activation.
- Although advanced computer vision techniques were considered, the simplified image processing algorithm provided cost-effective performance with acceptable accuracy for the grading task.

2. Moisture Tracking Findings

- Sensor calibration confirmed that capacitive soil moisture values accurately matched known reference points, and the derived thresholds reliably distinguished among very dry, optimal, and very wet conditions in coco peat.
- The system's ability to log readings at fixed 15-minute intervals and transmit this data successfully to the dashboard demonstrates strong potential for real-time moisture management.
- Field tests indicated that the deployment of weatherproof enclosures and the efficient power management via the LM2596 contributed to the overall stability and low maintenance of the system.

6.3 Discussion

- **Balancing Simplicity with Functionality**

The husk grading system's reliance on a simple color detection metric has proved efficient.

Although more complex computer vision models could enhance detection granularity, the basic image processing algorithm offers a compelling trade-off between hardware complexity, speed, and cost. The resulting classification is robust under controlled conditions, which is sufficient given our system's reliance on consistent daylight for image capture.

- **Cost-Effectiveness and Scalability**

Both the ESP32-CAM based grading system and the moisture tracking system are built upon affordable, readily available components. This cost-effectiveness, combined with the modular nature of the design, allows for scalable deployment across multiple lines or in different facilities. The use of MQTT for data transmission and a cloud-based dashboard further simplifies future expansions and integration into existing processing workflows.

- **Real-World Applicability**

The moisture tracking system's performance under field conditions confirms that real-time monitoring is achievable even with sensor and hardware limitations. By ensuring that both the grading and moisture systems can operate continuously and report data reliably, the overall design supports a comprehensive quality control mechanism that addresses key production challenges like inconsistent drying and resource inefficiency.

7. CONCLUSIONS

This project successfully developed and validated a dual-module system designed for the automation of coconut husk processing, specifically through husk classification and moisture level tracking. By integrating an ESP32-CAM-based husk grading system with a simplified green ratio algorithm and an automated moisture monitoring solution using an ESP32 with capacitive sensors, the research demonstrates a cost-effective, scalable, and robust approach to addressing quality control in coconut-based production environments.

The **husk grading system** leverages consistent daylight imaging and a lightweight image processing method to classify husks into “Qualified,” “Accepted,” or “Disqualified” categories based on a computed green ratio. Extensive testing confirmed that the green ratio ranges derived from ESP32-CAM images allow for clear, non-overlapping categorization. Although more complex computer vision models, such as YOLO, were evaluated, the simple threshold-based approach proved sufficient for the application, balancing performance with minimal hardware complexity and cost.

Similarly, the **moisture tracking module** was implemented using calibrated soil moisture sensors and an ESP32 board, supported by an LM2596 DC-DC converter for power regulation. Real-time sensor readings collected at 15-minute intervals were reliably transmitted to a web dashboard via MQTT, enabling continuous monitoring of both the drying areas and water tanks. This system provides vital information that not only helps maintain the ideal moisture conditions for optimal product quality but also contributes to operational efficiency by reducing resource wastage and enabling proactive interventions.

The project’s results and subsequent analysis confirm that both modules meet the fundamental requirements for industrial application. The husk grading module ensures precise and efficient classification under controlled lighting conditions, while the moisture monitoring system delivers accurate, actionable data for managing environmental variables in the production line. Although challenges remain particularly regarding sensor calibration under varying conditions and the inherent limitations of the ESP32-CAM’s image quality the overall system offers a substantial leap forward in automating coconut husk processing.

Future work will focus on further optimizing the image processing algorithm to improve resilience against minor lighting fluctuations and enhance classification accuracy. Additionally, expanding sensor integration to include complementary parameters, such as ambient temperature and humidity, may further refine moisture control and improve system robustness. With these enhancements, the proposed solution has the potential to drive significant improvements in efficiency, quality, and cost savings in the coconut husk production industry.

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9. APPENDICES