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Modification and Improvement of a Coffee Berry Sorting Machine

Project Proposal

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Declaration

We declare that this project proposal is our original work and has not been presented for examination in any other institution.

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Abstract

Automated coffee berry sorting is an essential process for ensuring quality consistency and improving the economic value of coffee produce. Previous student-developed prototypes have demonstrated the feasibility of using image-based detection and air-ejection mechanisms for automated sorting. However, limitations related to motion blur, processing delays, and limited computational capacity have restricted real-time performance and throughput.

This project focuses on the modification and improvement of an existing coffee berry sorting machine model by addressing challenges associated with real-time image acquisition, detection, and classification. The study explores optimized computer vision algorithms, improved frame processing strategies, and alternative processing architectures to enhance system efficiency. A co-processing architecture alongside the Raspberry Pi 3 will be introduced to overcome computational bottlenecks, with task division between high-level control and time-critical processing operations.

Performance evaluation is conducted based on sorting accuracy, processing speed, and overall throughput. The improved model aims to provide a cost-effective, reliable, and scalable solution suitable for small-scale coffee processing applications while contributing to research in embedded vision and agricultural automation.

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1 Introduction

1.1 Background of Study

The global coffee industry remains a significant contributor to the economies of many developing countries, supporting millions of smallholder farmers worldwide. Coffee production involves several critical stages, from cultivation and harvesting to processing and packaging. Among these stages, the sorting of coffee berries is one of the most labor-intensive and quality-sensitive processes. Traditionally, coffee berry sorting has relied heavily on manual visual inspection, where workers separate berries based on ripeness, size, and visible defects. This approach is time-consuming, inconsistent, and costly, often leading to variations in coffee quality and increased operational expenses.

Manual sorting methods are highly susceptible to human error and fatigue, which can result in misclassification of berries and reduced overall product quality. Furthermore, the labor-intensive nature of manual sorting limits scalability and efficiency, particularly during peak harvest periods when labor shortages are common. These challenges highlight the need for automated sorting solutions capable of performing classification tasks with higher accuracy, consistency, and throughput.

Recent advancements in computer vision, machine learning, and embedded systems have enabled the development of automated coffee berry sorting machines that utilize image-based detection and real-time classification techniques. Previous work by fifth-year mechatronics engineering students resulted in the development of an image-based coffee berry sorting machine incorporating a vibrating conveyor system, optical detection, and air-ejection mechanisms controlled by a Raspberry Pi-based processing unit. While the system successfully demonstrated automated sorting, practical challenges were identified during real-time operation, particularly related to motion blur, processing latency, and limited computational throughput.

The visual diversity in harvested coffee berries, including variations in color, size, and

[Placeholder: Figure 1 - Harvested Coffee Berry Variation]

Figure 1.1: Harvested coffee berry variation showing visual diversity in color, size, and surface texture

surface texture, as illustrated in Figure
reffig:berry$_{v}ariation, presentsasignificantchallengeforaccurateautomatedclassification.$

This project proposes the modification and improvement of the existing coffee berry sorting machine by addressing the identified limitations in image acquisition, processing speed, and real-time classification performance. By enhancing the vision processing pipeline, optimizing algorithms, and evaluating alternative hardware or processing architectures, the project aims to improve sorting accuracy and throughput while maintaining a cost-effective and scalable design suitable for small- and medium-scale coffee processing applications.

1.2 Problem Statement

The global coffee industry plays a vital role in the economic development of many coffee-producing countries, including Kenya, where coffee farming supports a large population of smallholder farmers. The quality of coffee berries at the processing stage directly determines the final product grade, market value, and competitiveness in both local and international markets. One of the most critical and labor-intensive stages in coffee processing is the sorting of coffee berries based on ripeness, color, size, and the presence of defects.

Traditionally, coffee berry sorting has been carried out manually through visual inspection by human operators. While this method requires minimal capital investment, it is inherently inefficient, inconsistent, and highly dependent on human judgment, which varies due to fatigue, experience, and environmental conditions. As a result, manual sorting often leads to misclassification of berries, reduced product quality, and increased operational costs. These challenges become more pronounced during peak harvest seasons, when large volumes of berries must be processed within limited timeframes.

In response to these limitations, recent final-year mechatronics projects have explored automated coffee berry sorting solutions using machine vision and robotic actuation. One such system employs a vibrating conveyor to ensure consistent berry flow, a chute for alignment, and an image-based detection and tracking system coupled with an air-ejection mechanism for sorting. The system operates under the control of a Raspberry Pi-based processing unit, leveraging computer vision and machine learning techniques to classify individual coffee berries as they move through the sorting process.

Despite the successful demonstration of automated sorting, the existing system exhibits several critical technical limitations that hinder its overall performance and scalability. The natural appearance of harvested coffee berries presents significant visual variability in color, texture, size, and surface defects. These variations, combined with the dynamic motion of berries on the conveyor, introduce challenges such as motion blur, inconsistent illumination, and overlapping objects, which negatively affect image clarity and classification accuracy.

Furthermore, the reliance on real-time image processing using a Raspberry Pi introduces processing bottlenecks. The limited computational capacity of the platform results in delays during frame acquisition, preprocessing, classification, and decision execution. Although the previous implementation attempted to mitigate these issues through optimization techniques such as TensorFlow Lite and multithreading, the system still struggles to achieve higher throughput without compromising accuracy. This limitation directly affects sorting speed and reduces the system's suitability for larger processing volumes.

The core problem, therefore, lies not in the mechanical handling of coffee berries but in the limitations of the vision system, processing architecture, and real-time control strategy used in the existing model. There is a clear need to improve the system's ability to accurately and consistently classify visually diverse coffee berries at higher speeds while maintaining affordability and practicality for small-scale agricultural applications.

This project seeks to address these challenges through the modification and improvement of the existing automated coffee berry sorting system. By enhancing the image acquisition strategy, optimizing or upgrading the processing architecture, and refining the detection-to-actuation pipeline, the project aims to achieve higher throughput, reduced latency, and improved classification accuracy.

1.3 Objectives

1.3.1 Main Objective

To modify and improve an existing automated coffee berry sorting machine

1.3.2 Specific Objectives

1. To analyze the performance limitations of the existing image-based coffee berry sorting system, with emphasis on motion blur, processing latency, and classification accuracy

2. To improve on the sorting mechanism

3. To evaluate alternative or upgraded processing hardware capable of supporting higher frame rates and faster inference

1.4 Justification

Coffee remains one of Kenya's most valuable agricultural exports, and quality grading plays a major role in determining its economic value. Automated coffee berry sorting systems offer a practical solution for improving quality consistency and reducing labor dependency. However, many advanced commercial systems are prohibitively expensive and unsuitable for adoption by small-scale processors and cooperatives.

Improving an existing image-based coffee berry sorting model provides a cost-effective pathway toward practical automation by building upon already validated concepts while addressing observed technical shortcomings. By focusing on real-time processing efficiency, motion-related detection challenges, and system responsiveness, this study aims to bridge the gap between prototype-level demonstrations and deployable solutions.

The proposed improvements contribute to:

1. Enhanced accuracy and throughput in coffee berry sorting
2. Better utilization of affordable embedded vision technologies
3. Increased feasibility of locally developed agri-tech solutions
4. Practical learning and innovation in mechatronics system integration

Furthermore, incorporating real harvested coffee berries into testing and demonstration provides a realistic visual and operational representation of actual field conditions, strengthening the relevance and credibility of the system. The outcomes of this project are expected to support the development of scalable, affordable, and locally adaptable coffee processing technologies aligned with Kenya's agricultural and technological development goals.

2 Literature Review

The global coffee industry plays a critical role in the economies of many developing countries, including Kenya, by providing livelihoods to millions of smallholder farmers. Coffee processing involves several stages, among which sorting of coffee berries is one of the most critical for determining final product quality and market value. The presence of unripe, overripe, damaged, or defective berries significantly affects cup quality, leading to reduced prices and rejection in premium markets.

Traditionally, coffee berry sorting has relied on manual visual inspection, where workers separate berries based on perceived color, size, and visible defects. While this approach has been practiced for decades, numerous studies have demonstrated that manual sorting is labor-intensive, inconsistent, slow, and highly subjective, particularly under fatigue and time pressure (Mugo et al., 2017; Silva & Santos, 2019).

Advances in machine vision, robotics, and embedded computing have enabled the development of automated coffee berry sorting systems capable of performing classification and separation tasks with higher accuracy, speed, and consistency. Automated systems typically integrate three core subsystems:

- A material handling mechanism (vibrating conveyor or chute)
- A sensing and classification unit (camera and image processing algorithms)
- A separation mechanism (air jets, ejector plates, or diverters)

The 2019 automated coffee berry sorting machine project (reference project) represents a significant academic effort in this domain. The system employed a vibrating conveyor for controlled berry flow, a chute for alignment, image-based detection using a Raspberry Pi 3, and an air ejection mechanism for separation. While the system demonstrated the feasibility of automated sorting, several technical challenges were identified, particularly in real-time image processing and actuation timing, forming the foundation for the present study.

2.1 Challenges of Traditional Sorting Methods

Manual sorting remains prevalent among small-scale farmers due to its low initial cost; however, extensive literature highlights its limitations.

1. Labor Intensity and Fatigue: Manual sorting requires a large workforce to maintain reasonable throughput. Studies by Njoroge et al. (2016) show that prolonged visual inspection leads to fatigue, which directly reduces sorting accuracy and consistency. Fatigued workers are more likely to misclassify berries, allowing defective berries to pass through or rejecting acceptable ones.

2. Human Error and Subjectivity: Manual sorting depends heavily on individual judgment, which varies between workers and across time. Silva and Santos (2019) observed significant variability in sorting outcomes across different shifts, even when standardized grading guidelines were provided. This subjectivity results in inconsistent quality between batches.

3. Limited Throughput: Human sorting speed is inherently constrained. Kinyua et al. (2018) reported that manual sorting becomes a bottleneck during peak harvest seasons, limiting scalability and increasing processing delays. This inefficiency directly affects farmers' ability to meet market demand.

These challenges have driven research into automated sorting systems capable of overcoming the limitations of manual methods.

2.2 Advantages of Automated Coffee Berry Sorting

Automated coffee berry sorting systems offer several key advantages over manual methods:

1. Increased Efficiency and Throughput: Automated systems can process significantly larger volumes in shorter times compared to manual sorting. Modern optical sorting machines can handle hundreds of kilograms per hour, substantially reducing processing time during peak harvest.

2. Improved Consistency and Accuracy: Machine-based systems apply uniform classification criteria across all berries, eliminating subjective variation. Studies by Perez et al. (2020) demonstrate that automated systems maintain stable accuracy levels exceeding 92%, even during extended operation periods.

3. Reduced Labour Costs: While requiring initial capital investment, automated sorting reduces ongoing labor requirements. Economic analysis by Mashauri et al. (2021) indicates that medium-scale processors can achieve cost recovery within 2–3 seasons through labor savings alone.

4. Data Collection and Traceability: Automated systems enable collection of processing statistics, including throughput rates, defect percentages, and batch-level quality metrics. This data supports quality management systems and provides traceability demanded by premium export markets.

2.3 Separation Methods

2.3.1 Air Jet System

Air jet separation systems operate on a detect-decide-deflect principle. As berries pass through the imaging zone on a conveyor or chute, a high-speed camera (typically CCD or CMOS sensors) captures images in real time. Some advanced systems incorporate near-infrared (NIR) sensors to detect internal defects not visible in the RGB spectrum. Image processing algorithms classify each berry, and defective berries trigger compressed air jets precisely timed to deflect them into reject chutes while acceptable berries continue along the primary path.

Key advantages include: minimal physical contact reducing berry damage, very high throughput capacity, and adaptability to various berry sizes without mechanical adjustment. However, limitations include requirement for compressed air infrastructure, sensitivity to environmental conditions (wind, dust), and complexity in timing calibration.

2.3.2 Ejector Plates

Ejector plate systems employ mechanical actuation to physically separate undesirable berries. When a defect is detected by upstream sensors, a solenoid or pneumatic actuator extends a small plate or paddle that pushes the target berry into a reject stream. This method ensures positive separation, meaning that once actuated, the berry is definitively moved to the reject pathway.

Advantages include: high reliability in separation (no missed deflections due to air pressure variation), suitability for larger or heavier objects, and lower compressed air consumption. Limitations include: mechanical wear on actuators and contact surfaces, slower response times compared to air jets (20–50 ms), and potential for berry bruising at the contact point.

2.3.3 Diverter Systems

Diverter systems redirect entire groups or batches of berries rather than individual units. When a sensor detects a defective berry, a mechanical gate or diverter flap reroutes the material stream into a reject bin. This approach is typically used in lower-precision, bulk sorting scenarios where strict unit-level separation is not required.

Advantages include: structural simplicity, low maintenance, and suitability for high-volume, low-cost operations. Disadvantages include: lower precision (acceptable berries in the same batch may be rejected), inability to handle single-file streams, and inefficiency when defect rates are low.

2.4 Classification Methods

2.4.1 Color-Based Classification

Color-based classification is the most widely used method in coffee berry sorting due to its direct correlation with maturity. Ripe coffee berries exhibit deep red or purple hues, while unripe berries appear green or yellow. Systems employ RGB cameras to capture color information, which is then analyzed using color histograms, color space transformations (e.g., HSV, Lab), or simple thresholding.

This method is cost-effective and computationally efficient, making it suitable for real-time processing on embedded platforms. However, it is highly dependent on uniform lighting conditions and can struggle with berries exhibiting intermediate ripeness states or surface discoloration from environmental factors.

2.4.2 Shape-Based Classification

Shape analysis assesses geometric attributes such as size, contour smoothness, aspect ratio, and circularity. Machine vision systems extract berry contours from binary images and calculate shape descriptors to identify malformed, damaged, or insect-infested berries.

This method complements color-based classification by detecting defects that do not manifest as color differences (e.g., physical damage, irregular growth). However, shape analysis requires clear berry separation on the conveyor and consistent camera positioning to ensure measurement accuracy.

2.4.3 Texture-Based Classification

Texture-based methods analyze surface patterns using techniques such as Gray-Level Co-Occurrence Matrix (GLCM), Local Binary Patterns (LBP), or Gabor filters. These approaches can detect surface defects like insect bites, mold growth, or drying-induced wrinkling.

Texture analysis is particularly effective for identifying subtle defects not visible through color or shape alone. However, texture features are more computationally expensive to extract and may require higher-resolution imaging, which can limit real-time throughput on low-cost hardware.

2.4.4 Deep Learning-Based Classification

Deep learning approaches, particularly Convolutional Neural Networks (CNNs), have demonstrated superior classification accuracy by automatically learning discriminative features from labeled training data. Architectures such as MobileNet, ResNet, and YOLO (You Only Look Once) enable real-time object detection and classification.

Deep learning models can handle complex, non-linear relationships between visual features and quality categories, achieving accuracies exceeding 95% in controlled conditions. However, these models require substantial computational resources, large labeled datasets for training, and careful optimization to run efficiently on embedded platforms like the Raspberry Pi.

2.4.5 Pattern Recognition-Based Classification

Traditional pattern recognition methods employ supervised learning algorithms such as k-Nearest Neighbors (k-NN), Support Vector Machines (SVMs), or decision trees. These classifiers use hand-crafted features (color, shape, texture) as input and learn decision boundaries from training samples.

Pattern recognition methods offer a balance between performance and computational efficiency. They are less demanding than deep learning approaches and more robust than simple thresholding, making them well-suited for embedded systems with limited processing power.

2.4.6 Multispectral and Hyperspectral Imaging-Based Classification

Multispectral and hyperspectral imaging capture information across multiple wavelengths, including visible and non-visible spectra (e.g., near-infrared, short-wave infrared). This allows detection of internal defects, moisture content variations, and chemical composition differences not visible to standard RGB cameras.

These methods provide the highest classification accuracy and defect detection capability. However, the high cost of specialized cameras, the large data volumes requiring processing, and the complexity of spectral analysis limit their adoption primarily to high-value, large-scale industrial operations.

2.4.7 Three-Dimensional (3D) Object Classification

3D imaging systems use stereo vision, structured light, or time-of-flight sensors to capture depth information alongside 2D images. This enables measurement of berry volume, surface irregularities, and three-dimensional shape descriptors.

3D classification is valuable for detecting internal voids, volume-based sorting, and identifying deformities. However, 3D imaging systems are more expensive, require more complex calibration, and impose higher computational loads compared to 2D methods.

2.5 Gap Analysis

Despite significant advances in automated coffee berry sorting, several critical gaps remain, particularly in the context of cost-effective, scalable solutions suitable for small-to-medium processors and university research environments.

2.5.1 Real-Time Processing and Throughput Limitations

The 5th-year project identified that the Raspberry Pi 3, while cost-effective, struggles to maintain real-time classification performance at higher throughput rates. The system experienced difficulties processing high frame rates, performing simultaneous object tracking and classification, and maintaining synchronization with real-time actuation signals. Although optimizations such as TensorFlow Lite deployment and multithreading were attempted, performance remained below the levels required for practical deployment.

Current literature predominantly focuses on either high-performance industrial systems using GPUs or field-programmable gate arrays (FPGAs), which are cost-prohibitive, or low-throughput academic prototypes that do not address scalability. There is insufficient exploration of hybrid processing architectures where time-critical tasks are offloaded to co-processors (e.g., ESP32, STM32, or similar microcontrollers), allowing algorithm restructuring and task division between layers to achieve both cost efficiency and acceptable performance.

2.5.2 Motion Blur and Image Degradation at Higher Speeds

As conveyor speeds increase to meet higher throughput demands, image quality degrades due to motion blur, reducing classification accuracy. The 5th-year project explicitly identified motion blur as a major limitation, particularly at speeds exceeding certain thresholds.

Existing solutions typically involve either reducing conveyor speed (sacrificing throughput) or increasing camera shutter speed and lighting intensity (increasing cost and power consumption). However, there is limited research on integrated approaches that combine algorithmic and mechanical mitigation strategies—such as adaptive frame capture triggering, region-of-interest (ROI) selective processing, and timing-aware rejection logic—that could address motion blur without disproportionately sacrificing speed or cost.

2.5.3 Cost-Performance Trade-Off in Hardware Selection

There exists a notable gap in the literature regarding optimal hardware configurations for mid-scale sorting operations. High-performance systems using industrial-grade GPUs or dedicated vision processors offer excellent performance but are financially inaccessible to smallholder cooperatives and university prototypes. Conversely, ultra-low-cost platforms (e.g., Raspberry Pi alone) demonstrate limited processing speed and reduced scalability.

Few studies systematically investigate cost-optimized improvements that maintain affordability while achieving meaningful performance gains. Strategies such as algorithm restructuring, selective processing pipelines, and intelligent task division between processing layers are underexplored. The current project aims to address this gap by evaluating hybrid processing architectures and system-level optimizations tailored to resource-constrained environments.

3 Research Design and Methodology

This study will adopt an experimental and design-based research approach. The research will involve the modification and improvement of an existing image-based coffee berry sorting machine through systematic redesign of its mechanical, electrical, and software subsystems. A functional prototype will be developed and evaluated to determine improvements in sorting accuracy, processing speed, and system reliability. The research design will be iterative, where system performance will be evaluated at each stage, and necessary refinements will be implemented to address identified limitations such as motion blur, processing delays, and ejection timing inaccuracies observed in the previous model.

3.1 System Overview

The proposed coffee berry sorting machine will consist of three main modules:

- **Mechanical Module** – Responsible for controlled berry feeding, alignment, and physical support
- **Electrical and Electronic Module** – Responsible for sensing, actuation, power distribution, and processing
- **Software Module** – Responsible for image acquisition, processing, classification, tracking, and ejection control

Each module will be designed to work in synchronization to enable real-time detection, classification, and rejection of unwanted coffee berries.

3.2 Mechanical Module Design

The mechanical module will be designed to ensure consistent berry flow, minimal vibration-induced image distortion, accurate alignment, and precise ejection positioning.

3.2.1 Hopper

The hopper will be used to store harvested coffee berries before sorting. It will be designed with sloped walls to allow gravity-assisted flow while preventing clogging and bridging of berries.

Material Selection: Mild steel sheet or food-grade aluminium will be used due to: structural strength, ease of fabrication, resistance to wear, and suitability for agricultural products. The hopper will feed berries uniformly onto the vibrating feeder.

3.2.2 Linear Vibrating Feeder

A linear vibrating feeder will be employed to regulate the flow rate of coffee berries and prevent overlapping during image capture. Controlled vibration will ensure berries are spread into a near-single-file arrangement.

Justification: Reduces berry overlap, improves image clarity, minimizes motion blur, and enhances object tracking accuracy.

Material Selection: Stainless steel or aluminium tray to reduce corrosion and contamination. Rubber vibration isolators to reduce transmission of vibration to the camera holder.

3.2.3 Chute

The chute will guide berries from the feeder to the imaging zone while maintaining alignment and spacing.

Design Considerations: Inclination angle optimized for gravity flow, smooth surface finish to reduce friction, fixed berry trajectory for predictable motion.

Material Selection: Acrylic or aluminium sheet chosen for smoothness, light weight, and ease of modification.

3.2.4 Camera Holder

The camera holder will support the Raspberry Pi camera directly above the imaging zone. It will be mechanically isolated from vibrations originating from the feeder.

Design Improvements: Use of rubber dampers to reduce vibration transmission, rigid frame mounting to maintain fixed focal distance, adjustable height mechanism for calibration.

Material Selection: Aluminium profile or 3D-printed ABS selected for rigidity and lightweight properties.

3.2.5 Ejection Holder

The ejection holder will house the air ejectors responsible for rejecting unwanted berries.

Design Considerations: Precise alignment with berry trajectory, fixed distance from detection zone to allow accurate ejection scheduling, modular design for easy adjustment.

Material Selection: Aluminium brackets resistant to vibration and compressed air forces.

3.2.6 Frame Structure

The frame will support all mechanical and electrical components.

Material Selection: Mild steel angle bars or aluminium extrusion selected for strength, stability, and ease of assembly.

3.3 Proposed Electrical and Control Module

The proposed electrical and control module will be designed to support high-speed image acquisition, real-time processing, and precise actuation required for accurate coffee berry sorting. To address the processing bottlenecks identified in the previous system, a co-processing architecture will be introduced.

3.3.1 Central Processing and Co-Processing Architecture

The system will employ a Raspberry Pi 3 as the main control and supervisory processing unit. The Raspberry Pi will be responsible for system initialization, user interface handling, data logging, actuator control, and coordination of the sorting process.

To improve throughput and reduce latency in image processing and classification, an additional microprocessor or co-processing unit (such as an ESP32, STM32, or equivalent embedded processor) will be introduced. This secondary processor will handle time-critical and repetitive computational tasks, thereby offloading the Raspberry Pi and enhancing real-time performance.

The division of tasks will be implemented as follows: The Raspberry Pi will manage high-level decision making, system synchronization, and communication. The co-processor will handle image pre-processing tasks, object tracking computations, timing calculations for ejection scheduling, and sensor signal conditioning where applicable.

Communication between the Raspberry Pi and the co-processor will be achieved through high-speed serial communication (UART, SPI, or I^2C), ensuring minimal data transfer delay or a flash disk.

3.3.2 Image Acquisition System

A Raspberry Pi Camera Module will be mounted above the chute using a rigid camera holder to capture high-resolution images of coffee berries in motion. The camera will operate at an optimized frame rate to balance image clarity and processing speed while minimizing motion blur.

Controlled LED lighting modules will be installed around the imaging zone to provide uniform illumination, reduce shadows, and ensure consistent image quality regardless of ambient lighting conditions.

3.3.3 Air Ejection and Actuation System

The berry rejection mechanism will consist of: high-speed air ejectors (solenoid-controlled air nozzles) positioned along the chute, and a compressed air supply system, including a compact air compressor and pressure regulation unit.

The co-processor will compute precise ejection timing based on berry position tracking, while the Raspberry Pi will issue final actuation commands. This approach will ensure accurate rejection of defective or unripe berries without affecting accepted berries.

3.3.4 Motor Control and Power Supply

Electric motors used in the linear vibrating feeder will be selected based on vibration frequency requirements, durability, and power efficiency. Motor drivers will be interfaced with the co-processor for precise control of feed rate.

The system will utilize: a regulated 5V DC supply for logic-level electronics (Raspberry Pi, microprocessor, camera), and a 12V DC supply for actuators, air solenoids, and motors.

Power isolation and protection mechanisms will be incorporated to prevent electrical noise from affecting sensitive processing units.

3.4 Software Architecture and Control Logic

The software system will be modular and executed in stages as outlined below:

3.4.1 System Startup

Upon power-up, the Raspberry Pi will initialize system peripherals, establish communication with the co-processor, and perform system diagnostics.

3.4.2 Image Pre-Processing

Captured images will undergo grayscale conversion, noise filtering, normalization, and contrast enhancement. Pre-processing tasks will primarily be executed on the co-processor to reduce computational load on the Raspberry Pi.

3.4.3 Object Detection

Coffee berries will be detected using thresholding and contour-based methods or lightweight machine learning models optimized for embedded systems.

3.4.4 Object Tracking

Detected berries will be tracked across successive frames to determine velocity and trajectory. Tracking data will be used to predict the precise point of ejection.

3.4.5 Ejection Scheduling

Based on classification results, the system will calculate the optimal actuation time for each air ejector to reject unwanted berries while allowing acceptable berries to pass.

3.4.6 System Flow Control

The Raspberry Pi will supervise the entire operation, adjusting feed rates, handling exceptions, and logging system performance metrics.

Calculate metrics: sorting accuracy, false accept rate, false reject rate, throughput (kg/hr)

Repeat testing for 5 batches to establish performance consistency

Document failure modes and optimization opportunities

Target performance metrics:

- Sorting accuracy: $> 90\%$ (correctly classified berries / total berries)
- Throughput: 150-200 kg/hr (2.5x improvement over baseline 50-75 kg/hr)
- False accept rate: $< 8\%$ (defects in accepted stream)
- False reject rate: $< 12\%$ (good berries in rejected stream)
- System uptime: $> 95\%$ during 4-hour continuous operation test

4 Expected Outcomes

4.1 An Improved Coffee Berry Sorting Machine Model

The outcome of this project will be a modified and improved coffee berry sorting machine that builds upon the existing prototype architecture. The improvements made will address identified limitations in image clarity, processing throughput, and system reliability.

4.2 Enhanced Real-Time Detection and Classification Performance

The proposed modifications will reduce motion blur and processing delays through an optimized camera configuration, improved lighting, refined image pre-processing methods, and timing-aware ejection scheduling. These enhancements will support classification and sorting at higher throughput levels without compromising accuracy.

The improved system will employ an efficient sorting algorithm that uses color, shape, and surface quality parameters to categorize coffee berries as acceptable or defective, thereby minimizing misclassification rates and improving overall sorting quality.

4.3 Optimized Ejection Timing and Synchronization

By integrating object tracking into the control logic, the system will achieve better alignment between detection, classification, and actuation. This integration will minimize the occurrence of missed ejections, false rejections, and actuation timing errors, resulting in a more reliable sorting process.

4.4 Improved System Stability and Reliability

The refinement of the mechanical and electrical modules will contribute to enhanced system stability. The improved machine will be able to operate continuously without frequent interruptions, contributing to consistent throughput and reduced maintenance downtime.

4.5 A Scalable and Cost-Conscious Design Framework

The project will demonstrate that it is possible to optimize the use of existing Raspberry Pi 3 resources through strategic task distribution and the introduction of low-cost co-processing elements. This framework will provide pathways for future scalability, whether through hardware upgrades or algorithmic improvements.

4.6 Contribution to Agricultural Automation Research

This project will contribute to the ongoing development of low-cost, image-based automated sorting systems in agricultural contexts. It will provide a practical case study on how cost-effective embedded systems can be adapted to meet the real-time processing demands of sorting applications in small-scale Kenyan agricultural settings.

5 Conclusion

This proposal has outlined a structured approach to modifying and improving an existing automated coffee berry sorting machine. Through the introduction of a co-processing architecture alongside the Raspberry Pi 3, the proposed design seeks to overcome the computational and throughput limitations experienced in the current system. The improved mechanical, electrical, and software modules will enhance real-time image processing, classification performance, and ejection timing, thereby supporting more reliable and efficient sorting operations.

The project emphasizes a balance between technological advancement and cost-effectiveness, ensuring that the improvements remain suitable for small-scale agricultural applications. By demonstrating how affordable embedded hardware platforms can be optimized through strategic task distribution and algorithmic refinement, this work aims to contribute to the feasibility of high-performance automated agricultural sorting systems using cost-effective resources.

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A Project Budget

Funding sources: University FYP allocation (KES 80,000), Agricultural Processing Facility budget (KES 50,000), student contribution (KES 17,500). Existing facility infrastructure (220V power, compressed air lines, workshop access) provided in-kind.

B Project Timeline

Critical path: Vibratory feeder procurement (4-week lead time from order), conveyor modifications (2 weeks fabrication), sensor calibration (1 week). Risk mitigation: Early component ordering (Week 3), backup sensor units, parallel fabrication activities.

C Component Specifications

Vibratory Feeder: Electromagnetic drive, 220V AC, variable frequency control 20-60 Hz, amplitude adjustment 0-5mm, tray dimensions 600mm x 400mm, capacity 25 kg, stainless steel construction.

Conveyor Belt: Food-grade PVC material, dimensions 1500mm x 400mm, textured surface (2mm raised pattern), crowned pulleys 100mm diameter, spring-loaded tensioning 50-100N, VFD speed control 0.3-1.2 m/s.

RGB Color Sensors (TCS34725): I2C interface, 3.3V operation, 16-bit ADC, programmable gain 1x-60x, integration time 2.4-614 ms, clear/red/green/blue channels, surface mount package, detection range 0-80mm.

Push Solenoids: 12V DC operation, 25mm stroke length, 10N push force, 50ms response time, continuous duty rating 25%, mounting threads M10x1.0, resistance 8-10 ohms, power consumption 15W.

ESP32 Development Board: Dual-core Xtensa LX6 240 MHz, 520 KB SRAM, 4 MB flash, WiFi 802.11 b/g/n, 34 GPIO pins, I2C/SPI interfaces, 12-bit ADC, 3.3V logic, micro-USB programming, -40°C to +85°C operation.

D Testing Protocols

Component-Level Tests:

Vibratory Feeder: Measure berry flow rate at 5 frequency settings (20, 30, 40, 50, 60 Hz) and 3 amplitude settings (low, med, high). Record flow uniformity using high-speed camera. Success criteria: Consistent flow rate ±10%, minimal berry clustering.

Conveyor Belt Tracking: Run conveyor at operational speeds (0.3, 0.6, 0.9, 1.2 m/s) for 30-minute durations. Measure lateral drift with dial indicator. Success: ¡5mm drift over 30 minutes at all speeds.

RGB Sensor Calibration: Present 50 sample berries (known classifications) to each sensor. Record RGB values, establish threshold boundaries. Validate with 50 additional berries. Success: ¿85% classification accuracy per sensor.

Solenoid Actuator: Conduct 1000-cycle endurance test, measure response time and force output every 100 cycles. Success: Response time ¡35ms throughout test, force ¿8N maintained.

System Integration Tests:

Sensor-Actuator Synchronization: Mark test berries with known colors, run through system at operational speed. Video record to verify timing accuracy. Success: Actuator fires within ±20ms of optimal timing.

Throughput Measurement: Process 10 kg batches, measure completion time. Calculate throughput (kg/hr). Repeat for 5 batches. Success: Average throughput 150-200 kg/hr, consistency ±15%.

Performance Validation:

Accuracy Testing: Prepare test batches (10 kg each) with known berry distributions (40% ripe, 30% unripe, 20% overripe, 10% defect). Process at operational speed, collect accepted and rejected streams. Manually verify classification for 5% random sample (minimum 100 berries). Calculate metrics: sorting accuracy, false accept rate, false reject rate. Success: Sorting accuracy ¿90%, false accepts ¡8%, false rejects ¡12%. Repeat for 5 batches to establish consistency.

Table A.1: Budget Breakdown

Component	**Specification**	**Cost (KES)**
Mechanical Components		
Vibratory Feeder	Electromagnetic, variable frequency	18,000
Conveyor Belt	Food-grade PVC, 1.5m x 0.4m	8,000
Crowned Pulleys (2)	100mm diameter, aluminum	5,000
VFD Motor Controller	0.5 HP, 220V AC input	12,000
Spring Tensioners (2)	Heavy-duty, adjustable	2,500
Aluminum Extrusion	40x40mm profile, 3m length	4,000
Feed Hopper Material	Stainless steel sheet, 1.5mm	6,000
Mounting Hardware	Bolts, brackets, bearings	3,000
Sensor Components		
RGB Color Sensors (4)	TCS34725, I2C interface	8,000
Photoelectric Sensors (2)	Through-beam, 12V DC	4,000
LED Illumination Array	5500K white LEDs, drivers	3,500
Rotary Encoder	For conveyor speed sensing	2,500
Actuator Components		
Push Solenoids (8)	12V DC, 25mm stroke, 10N	12,000
Solenoid Driver Boards	MOSFET-based, 8-channel	5,000
Flapper Arms	Aluminum, custom fabricated	4,000
Control Electronics		
ESP32 Development Board	Dual-core, WiFi-enabled	1,500
Power Supplies	12V/5A, 5V/2A regulators	4,000
Wiring and Connectors	Industrial-grade, shielded	3,000
Emergency Stop Switch	Industrial safety switch	1,500
Junction Boxes	IP65-rated enclosures	2,500
Fabrication and Assembly		
Welding and Metalwork	Hopper and frame modifications	8,000
Machining Services	Pulley modifications, mounting	5,000
Electrical Installation	Wiring, termination, testing	6,000
Testing Materials		
Coffee Bean Samples	100kg for validation testing	3,000

Table B.1: Implementation Schedule (16 Weeks)

Week	Activity	Deliverable
1	System analysis and measurements	Baseline performance report
2	Detailed design and CAD modeling	Design drawings
3	Component specification and sourcing	Bill of materials
4	Component procurement (lead items)	Ordered components
5	Feed hopper fabrication	Modified hopper
6	Conveyor modifications (pulleys, tensioners)	Upgraded conveyor
7	Vibratory feeder installation	Installed feeder
8	Sensor array fabrication	Mounted sensors
9	Control electronics assembly	Wired control system
10	Actuator mechanism installation	Operational actuators
11	Firmware development and sensor calibration	Calibrated system
12	Component testing (feed, sensors, actuators)	Test reports
13	System integration and initial testing	Integrated system
14	Algorithm tuning and optimization	Optimized parameters
15	Performance validation (5 test batches)	Validation data
16	Documentation and final presentation	Final report