Modification and Improvement of a Coffee Berry Sorting Machine

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1 Declaration

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2 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. 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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Figure 1: Harvested coffee berry variation

3 Introduction

3.1 Background

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 surface texture, as illustrated in Figure 1.1, presents a significant challenge for accurate automated classification.

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.

3.2 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, as shown in Figure 1, 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.

Additional challenges identified include difficulties in integrating certain electronic components, such as optocouplers, which were not readily available or reliable during implementation. These constraints affected synchronization between object detection, tracking, and actuation, leading to timing inaccuracies in the air-ejection mechanism. Consequently, some berries were incorrectly sorted or missed entirely during high-speed operation.

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. The improved system will better accommodate the natural variability of harvested coffee berries while remaining cost-effective and suitable for adoption by smallholder farmers and cooperatives.

3.3 Objectives

Main Objective

- To modify and improve an existing automated coffee berry sorting machine

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.

3.3.1 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, and
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.

4 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.

4.1 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.

4.2 Advantages of automated coffee berry sorting over traditional methods

1. Increased Efficiency and Throughput Automated systems operate continuously without fatigue, enabling significantly higher throughput. The previous project demonstrated that image-based systems can maintain consistent conveyor speeds, eliminating delays caused by human limitations.

2. Improved Consistency and Accuracy Automated vision systems apply predefined classification criteria uniformly. According to Perez et al. (2020), machine vision reduces variability between batches and ensures consistent grading standards. This was evident in the uploaded report, where automated sorting achieved repeatable classification under controlled lighting.

3. Reduced Labour Costs By minimizing reliance on manual labour, automated sorting lowers operational costs in the long term. Although initial investment may be higher, Mashauri et al. (2021) argue that automation offers better cost-efficiency for scalable operations.

4. Data Collection and Traceability Modern automated systems allow real-time data collection on berry quality, size, and defect rates. The uploaded report highlights how captured image data can be reused to refine classification algorithms and support decision-making.

4.3 Separation Methods

Separation methods in coffee berry sorting have evolved from simple mechanical diverters to sophisticated pneumatic and electromechanical systems. The choice of separation mechanism influences system speed, reliability, cost, and maintenance requirements. Research shows that effective separation must be tightly synchronized with the classification algorithm to ensure correct berry rejection or acceptance.

4.3.1 Air Jet System

Air jet separation is a high-speed, non-contact separation technique widely applied in agricultural and industrial sorting processes, particularly in coffee berry and bean sorting. The method operates on a detect–decide–deflect principle, where individual particles are first inspected using optical or sensor-based systems, classified by a control unit, and selectively redirected using short bursts of compressed air.

In coffee processing, air jet systems are commonly integrated into optical sorting machines. Coffee berries or beans are fed into the system in a controlled, single-file manner to ensure accurate inspection. Detection units such as CCD/CMOS cameras and near-infrared sensors analyze key quality attributes including color, size, shape, and internal defects. Based on predefined quality thresholds, the control system determines whether each berry meets acceptance criteria.

Separation is achieved through precisely timed air pulses emitted from strategically positioned nozzles. Acceptable berries follow a natural free-fall trajectory into a collection chute, while defective or foreign materials are deflected sideways by the air jet into a reject channel. The accuracy of separation depends on rapid signal processing, precise timing, and controlled air pressure, typically supplied by a compressed air system.

Air jet separation offers several advantages over traditional mechanical and manual sorting methods. It minimizes physical contact, thereby reducing damage to coffee beans, and enables high throughput with consistent sorting accuracy. The technique is highly adaptable, allowing operators to adjust sensitivity, air pressure, and timing parameters to meet varying quality requirements. However, its performance is dependent on proper calibration, clean compressed air, and reliable power supply.

Overall, air jet separation has become a critical method in modern coffee processing due to its efficiency, precision, and ability to meet stringent quality standards, particularly in specialty and export-grade coffee production.

4.3.2 Ejector Plates

Ejector plates are a mechanical separation method commonly used in sorting systems to divert selected items from a main material flow based on predefined quality or classification criteria. Unlike non-contact methods such as air jet separation, ejector plate systems rely on direct physical interaction to achieve separation, making them suitable for applications where object size, weight, and mechanical robustness permit controlled contact.

In agricultural sorting applications, including coffee berry and bean processing, ejector plates are typically positioned along a conveyor or chute system. As individual berries move past a detection or inspection zone—often incorporating optical sensors or machine vision—the control unit evaluates each item against established acceptance thresholds. When a defective or unwanted berry is identified, the system activates an ejector plate at the appropriate moment.

The ejector plate, driven by an actuator such as a solenoid, pneumatic cylinder, or servo mechanism, rapidly extends into the product stream to deflect the targeted berry into a separate reject chute. Acceptable berries continue along the primary path without interruption. Precise synchronization between the detection system and plate actuation is essential to ensure accurate separation, particularly at higher processing speeds.

Ejector plate separation systems offer advantages including mechanical simplicity, ease of maintenance, and reliable operation in environments where compressed air availability is limited. They are generally robust and capable of handling heavier or irregularly shaped materials. However, due to direct contact with the product, ejector plates may introduce a higher risk of mechanical wear and potential product damage compared to air-based methods. Additionally, their operational speed is typically lower, limiting throughput in high-capacity sorting applications.

Despite these limitations, ejector plate systems remain a viable separation method in small- to medium-scale sorting operations and in processing stages where high precision and ultra-fast response times are not critical. Their continued use reflects a balance between cost, mechanical reliability, and acceptable sorting accuracy in specific industrial contexts.

4.3.3 Diverter systems

Diverter systems are mechanical separation methods used to redirect materials from a primary flow path into alternative channels based on predefined classification criteria. They are commonly employed in industrial and agricultural sorting processes where controlled redirection of products is required rather than high-speed, individual-item ejection. Diverter systems function by altering the trajectory of materials using movable guides, gates, flaps, or switch mechanisms.

In agricultural applications such as coffee berry and bean sorting, diverter systems are typically integrated into conveyor-based or chute-fed processing lines. After the product passes through a detection or inspection stage—often using optical sensors or machine vision—the control unit determines whether the material should proceed along the main path or be redirected. Upon receiving a control signal, the diverter mechanism actuates to guide the selected berries into a designated reject or alternative processing channel.

Separation in diverter systems is achieved through controlled mechanical motion rather than rapid impulses. Common actuation mechanisms include pneumatic cylinders, electric motors, or servo-driven arms. Because diverters generally act on groups of items or sequential product flow rather than individual particles, their response time and precision are lower compared to air jet or ejector plate systems. As a result, diverter systems are more suitable for moderate-speed operations or for coarse separation tasks.

Diverter systems offer advantages such as structural simplicity, durability, and the ability to handle larger volumes or bulk material with minimal risk of misalignment. They are also less sensitive to timing errors and are easier to integrate into existing material handling infrastructure. However, direct contact with the product increases the potential for mechanical wear and product damage, and their lower sorting resolution limits their effectiveness in high-precision or high-throughput applications.

Overall, diverter systems remain an effective separation method in applications where robustness, simplicity, and bulk redirection are prioritized over fine-grained accuracy. In coffee processing, they are often used in preliminary or secondary sorting stages, complementing more precise separation techniques such as air jet or optical sorting systems.

4.4 Classification methods

4.4.1 Color-Based Classifiction

Color-based classification is one of the most widely used methods in agricultural product sorting, including coffee berry classification. The method relies on analyzing color features extracted from digital images to differentiate products based on maturity, ripeness, or defects. In coffee processing, color information is commonly used to distinguish ripe berries from unripe (green), overripe, or defective berries. Image acquisition is typically performed using RGB cameras under controlled lighting conditions, and classification is achieved by comparing pixel intensity values or color histograms against predefined thresholds. While color-based classification is computationally efficient and easy to implement, its performance is highly dependent on stable illumination and surface cleanliness, limiting its robustness in variable operating environments.

4.4.2 Shape-Based Classification

Shape-based classification focuses on geometric attributes such as size, contour, aspect ratio, and roundness to identify and classify objects. In coffee berry and bean sorting, this method is useful for detecting malformed, broken, or undersized beans. Shape features are extracted using image segmentation and edge detection techniques, followed by feature measurement and comparison with reference models. Shape-based classification is effective in identifying physical deformities but is less capable of detecting internal defects or subtle quality variations. Its accuracy is also influenced by object orientation and overlap during image acquisition.

4.4.3 Texture-Based Classification

Texture-based classification analyzes surface patterns and spatial intensity variations to distinguish between different object conditions. In coffee processing, texture features can help identify defects such as insect damage, mold growth, or surface roughness. Common texture descriptors include gray-level co-occurrence matrices (GLCM), local binary patterns (LBP), and statistical measures of pixel distribution. Texture-based methods provide richer descriptive information than color alone but are more computationally demanding and sensitive to image noise and resolution. Proper feature selection and preprocessing are essential for reliable classification performance.

4.4.4 Deep Learning-Based Classification

Deep learning-based classification employs artificial neural networks, particularly convolutional neural networks (CNNs), to automatically learn discriminative features from raw image data. In coffee berry sorting and similar applications, deep learning models can simultaneously capture color, shape, and texture information, enabling highly accurate classification of complex defects and quality variations. These systems reduce reliance on handcrafted features and improve adaptability to diverse datasets. However, deep learning approaches require large labeled datasets, substantial computational resources, and careful model training to avoid overfitting. Despite these challenges, they represent the current state-of-the-art in automated classification systems.

4.4.5 Pattern Recognition-Based Classification

Pattern recognition-based classification involves identifying recurring structures or feature combinations within data to categorize objects. This approach typically integrates multiple features such as color, shape, and texture, which are processed using classifiers like k-nearest neighbors (k-NN), support vector machines (SVMs), or decision trees. In agricultural sorting systems, pattern recognition techniques provide a balance between computational efficiency and classification accuracy. Their performance depends on effective feature extraction and classifier selection, and they generally require prior domain knowledge to define meaningful feature sets.

4.4.6 Multispectral and Hyperspectral Imaging-Based Classification

Multispectral and hyperspectral imaging-based classification extends conventional imaging by capturing information across multiple wavelengths, including visible and non-visible spectra. In coffee quality assessment, these methods enable the detection of internal defects, moisture content, and chemical composition that are not discernible through standard RGB imaging. Multispectral systems capture a limited number of spectral bands, while hyperspectral systems acquire continuous spectral data across a wide range of wavelengths. Although these techniques offer superior classification accuracy and material discrimination, their high cost, complex data processing requirements, and large data volumes limit widespread industrial adoption.

4.4.7 Three-Dimensional (3D) Object Classification

Three-dimensional object classification utilizes depth information obtained from stereo vision, structured light, or laser scanning systems to analyze object geometry in three dimensions. In coffee sorting, 3D classification can enhance size estimation, volume measurement, and shape analysis, particularly for distinguishing overlapping or clustered objects. By incorporating depth data, 3D systems improve robustness against orientation and lighting variations. However, they introduce additional system complexity, increased processing requirements, and higher hardware costs, which can constrain their use in high-speed commercial sorting lines.

4.5 Gap Analysis

Despite significant progress in automated coffee berry sorting technologies, several technical, economic, and implementation gaps remain, particularly for small- to medium-scale systems intended for developing-country contexts.

- Real-Time Processing and Throughput Limitations

Most low-cost vision-based sorting systems, including the existing 5th-year coffee berry sorting project, rely on embedded platforms such as the Raspberry Pi 3, which struggle with: High frame rates, Simultaneous object tracking and classification, Real-time actuation timing for rejection mechanisms. Although TensorFlow Lite and multithreading were used to mitigate processing delays, classification latency still limits achievable conveyor speed, directly affecting throughput. Gap:

There is insufficient exploration of efficient, hybrid processing architectures (e.g., task offloading, algorithm simplification, edge-accelerated logic) that improve throughput without resorting to expensive high-end hardware.

- Motion Blur and Image Degradation at Higher Speeds

Studies consistently report that image-based sorting accuracy degrades as conveyor speed increases. The reviewed 5th-year project explicitly identified motion blur as a major challenge when attempting to increase system throughput. Gap: Most existing systems address motion blur only through: Reduced conveyor speed, or Increased camera shutter speed and lighting, both of which introduce new constraints. There is a lack of integrated algorithmic–mechanical mitigation strategies, such as adaptive triggering, selective region-of-interest processing, or timing-aware rejection logic.

- Cost–Performance Trade-Off in Hardware Selection

High-performance solutions using GPUs or industrial vision controllers achieve excellent results but are cost-prohibitive for smallholder farmers and university-scale prototypes. Conversely, low-cost platforms suffer from: Limited processing speed, Reduced scalability. Gap: There is insufficient focus on cost-optimized performance improvements, such as: Algorithm restructuring, Selective processing pipelines, Division of tasks between sensing, classification, and actuation layers.

5 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. 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.

5.1 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.

- 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 Suitability for agricultural products The hopper will feed berries uniformly onto the vibrating feeder.

- 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 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

- 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

- 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

- 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

- 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

5.2 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.

- 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 flshdisk.

- 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.

- Air Ejection and Actuation System

The berry rejection mechanism will consist of: High-speed air ejectors (solenoid-controlled air nozzles) positioned along the chute 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.

- 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) 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.

5.3 Software Architecture and Control Logic

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

- System Startup

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

- 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.

- Object Detection

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

- 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.

- 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.

- System Flow Control

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

6 Expected Outcomes

Upon successful implementation of this project, the following outcomes are expected:

- An Improved Coffee Berry Sorting Machine Model

The project is expected to produce a modified and improved coffee berry sorting machine model that builds upon the existing image-based sorting architecture. The improved system will incorporate optimized image acquisition, processing, object tracking, and ejection scheduling to achieve higher throughput and reliability.

- Enhanced Real-Time Detection and Classification Performance

The proposed improvements are expected to significantly reduce motion blur effects and processing delays observed in the previous implementation. Through optimized camera positioning, controlled lighting, refined image pre-processing techniques, and improved software scheduling, the system will achieve more accurate real-time detection and classification of coffee berries.

- Improved Sorting Algorithm with Clear Acceptance and Rejection Logic

A refined sorting algorithm will be developed to clearly distinguish between accepted and rejected coffee berries based on defined quality parameters such as color, shape, and surface characteristics. This will result in more consistent rejection of unripe, defective, or unwanted berries while ensuring minimal misclassification of acceptable berries.

- Optimized Ejection Timing and Synchronization

The integration of object tracking with precise ejection scheduling is expected to improve synchronization between detected berries and the air ejection mechanism. This will minimize missed ejections, false rejects, and timing errors that were identified as challenges in the previous system.

- Improved System Stability and Reliability

By refining both the mechanical and electrical modules—including the feeder, chute alignment, camera mounting, lighting, and air ejection system—the overall system stability and operational reliability will be improved during continuous operation.

- A Scalable and Cost-Conscious Design Framework

The improved model is expected to demonstrate a balance between performance and cost by optimizing the use of available hardware resources such as the Raspberry Pi 3, while identifying clear pathways for future scalability to higher-performance processing platforms if required.

- Contribution to Agricultural Automation Research

The outcomes of this study are expected to contribute valuable insights into low-cost, image-based agricultural sorting systems, particularly for small-scale coffee processing contexts relevant to Kenya and other coffee-producing regions.

7 Conclusion

This proposal presents a structured approach to the modification and improvement of a coffee berry sorting machine through the integration of advanced mechatronic design principles. By introducing a co-processing architecture alongside the Raspberry Pi 3, the proposed system aims to overcome the computational and throughput limitations observed in previous implementations. The improved electrical, mechanical, and software modules will collectively enhance real-time image processing, classification accuracy, and ejection timing, thereby improving overall system performance. The proposed design maintains a balance between technological advancement and cost-effectiveness, ensuring suitability for small-scale coffee processing applications. Successful implementation of this project will demonstrate the feasibility of high-performance, automated agricultural sorting systems using affordable embedded hardware, contributing to improved coffee quality, reduced labor dependence, and increased value addition within the coffee industry.

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Component	Quantity	Price
Raspberry Pi 3	1	5500
Camera	1	1500
Power Supply	1	3000
Air Ejectors	3	2500
Vibrating Motor	12v 200W (1)	1500
Relay	1	100
Misclenous		2000
TOTAL		16,100

Figure 2: Budget

9 Appendices

9.1 Budget