

Prototype Development of Sorting System for Coffee Cherries Using Computer Vision

การพัฒนาต้นแบบระบบคัดแยกผลเชอร์รี่กาแฟด้วยคอมพิวเตอร์วิทัศน์

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บทคัดย่อ: ตลาดกาแฟของประเทศไทยมีการเติบโตอย่างโดดเด่น โดยมีอัตราการเติบโตต่อเนื่องที่ร้อยละ 7.3 ระหว่างปี พ.ศ. 2560 ถึง 2566 มีมูลค่าตลาดถึง 34 ล้านบาท ด้วยการเติบโตดังกล่าว การควบคุมคุณภาพกาแฟให้สม่ำเสมอจึงมีความสำคัญมากขึ้น โดยเฉพาะอย่างยิ่งในขั้นตอนแรกของการคัดแยกผลเชอร์รี่กาแฟ คุณภาพของผลเชอร์รี่กาแฟส่งผลโดยตรงต่อคุณภาพของเมล็ดกาแฟ ทำให้การคัดแยกที่มีประสิทธิภาพและแม่นยำเป็นสิ่งจำเป็นสำหรับการผลิตกาแฟคุณภาพพรีเมียม งานวิจัยนี้ศึกษาแนวทางนวัตกรรมในการจำแนกผลเชอร์รี่กาแฟโดยใช้เทคนิคการประมวลผลภาพได้พัฒนาและเปรียบเทียบแบบจำลองการเรียนรู้ของเครื่องสี่รูปแบบ ได้แก่ Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), และ Convolutional Neural Network (CNN) แบบจำลองแต่ละตัวได้รับการประเมินด้านความแม่นยำในการจำแนกและความเร็วในการประมวลผล ผลการทดลองแสดงให้เห็นว่าแบบจำลอง CNN มีประสิทธิภาพในการจำแนกสูงสุดอย่างมีนัยสำคัญ โดยมีความแม่นยำถึงร้อยละ 94 และมีเวลาประมวลผลที่ 0.532 วินาทีต่อภาพ นอกจากนี้ เมื่อนำแบบจำลอง CNN มาประยุกต์ใช้ในระบบคัดแยกต้นแบบพบว่าให้ผลลัพธ์ที่น่าพอใจทั้งในด้านความแม่นยำและกำลังการผลิต โดยมีความแม่นยำในการคัดแยกภาพรวมที่ร้อยละ 81.73 และมีกำลังการผลิตประมาณ 120 ผลต่อนาที (ประมาณ 2 กิโลกรัมต่อชั่วโมง) ผลการวิจัยนี้ชี้ให้เห็นว่าการตรวจสอบด้วยภาพแบบอัตโนมัติโดยใช้ CNN สามารถพัฒนาประสิทธิภาพและความสม่ำเสมอในการคัดแยกผลเชอร์รี่กาแฟ ซึ่งมีศักยภาพในการนำไปประยุกต์ใช้เพื่อยกระดับมาตรฐานการผลิตของวิสาหกิจชุมชนและเกษตรกรรายย่อยได้อย่างมีนัยสำคัญ

คำสำคัญ: การคัดแยกผลเชอร์รี่กาแฟ การประมวลผลภาพ โครงข่ายประสาทเทียมแบบคอนโวลูชัน การตรวจจับวัตถุ ระบบคัดแยกอัตโนมัติ

Abstract: Thailand's coffee market has experienced remarkable growth, with a consistent annual increase of 7.3% from 2017 to 2023, reaching a market valuation of 34 million Baht. Given this growth, assuring consistent coffee quality has become increasingly critical, particularly at the initial stage of coffee cherry selection. The quality of coffee cherries directly impacts the final coffee bean quality, making efficient and accurate sorting essential for premium coffee production. This research explores an innovative approach to coffee cherry classification using image processing techniques. We developed and compared four machine learning models: Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN). Each model was evaluated based on classification accuracy and processing speed. The experimental results revealed that the CNN model significantly outperformed other approaches, achieving an overall operational accuracy of 81.73% and a throughput of approximately 120 cherries per minute (about 2 kg per hour). These findings suggest that automated visual inspection using CNN-based methods can substantially improve the efficiency and consistency of coffee cherry sorting, demonstrating strong potential for practical implementation in small- to medium-sized specialty coffee community enterprises.

Keywords: coffee cherry sorting, image processing, convolutional neural network, object detection, automated sorting system

Introduction

The global coffee industry represents a significant agricultural sector, with Thailand emerging as a key producer in the Southeast Asian market. From 2017 to 2023, the Thai coffee market demonstrated a consistent annual growth rate of 7.3% (Euromonitor, 2023). However, ensuring consistent coffee bean quality remains an important challenge. The quality control process must begin at the initial stages of harvesting and sorting, as the physical condition and ripeness of coffee cherries directly influence the final sensory attributes of the coffee (Haile and Kang, 2019; Iriondo-DeHond *et al.*, 2020; Velásquez *et al.*, 2021). Traditionally, cherry sorting has relied heavily on manual labor, which is not only labor-intensive but also susceptible to human error and inconsistency. This careful attention to sorting and processing is essential, as it directly affects

the flavor and aroma coffee enthusiasts anticipate in their brew (Santos *et al.*, 2020; Fracarolli *et al.*, 2021; Klingel *et al.*, 2020; Soedibyo *et al.*, 2010; Stanley-Foreman, 2023).

Coffee production in northern Thailand is shaped by ecological suitability and biological complexity. Arabica coffee thrives in the highland regions of Chiang Mai, Chiang Rai, and Nan due to cool temperatures and favorable elevations, yet the crop is far from genetically uniform — recent studies reveal substantial variation among accessions in the Royal Project system, reflecting multiple genetic backgrounds rather than a single cultivar population (Anonymous, 2024; Techanan *et al.*, 2023; ULKA, 2025). This diversity directly influences yield, cup quality, disease response, and climate adaptation, making it especially significant given the pressures growers face from pests, leaf rust, aging trees, and shifting weather conditions. As a result, agronomic performance in

northern Thailand depends not just on variety name but on genotype, site conditions, and management practices combined (Chumprasert *et al.*, 2020; Techanan *et al.*, 2023).

Agricultural technology for coffee production has advanced, but many solutions remain only partially ready for real farm use. Mechanized harvesting, fruit-processing systems, solar drying, and digital farming tools have been developed to boost efficiency and reduce labor, yet widespread adoption is constrained by high costs, maintenance demands, and the need for reliable performance under variable field conditions. The core challenge, therefore, is to identify and develop post-harvest technologies that are not only technically promising but economically and operationally viable for local farmers, which is essential for improving the long-term sustainability of the region's coffee sector.

To automate the sorting and grading process, previous studies have increasingly applied computer vision and machine learning techniques to enhance efficiency and ensure consistent coffee quality (Anita and Albarda, 2020; Santos *et al.*, 2020; Fracarolli *et al.*, 2021; Stanley-Foreman, 2023). In the coffee industry, several research efforts have explored the use of integrated image processing and back-propagation Artificial Neural Network (ANN) to evaluate and classify coffee beans (Balbin *et al.*, 2020; Soedibyo *et al.*, 2010). Specifically, for categorizing coffee cherries into different quality grades, researchers have successfully deployed the Gray-Level Co-occurrence Matrix (GLCM) algorithm for feature extraction alongside classification algorithms such as K-Nearest Neighbors (KNN) and Artificial Neural Network (ANN) (Anita and Albarda, 2020; Peña *et al.*, 2014;

Pei *et al.*, 2019; Velásquez *et al.*, 2019). However, despite these advancements, existing models predominantly focus on evaluating already processed green coffee beans or utilizing stable, single images in controlled laboratory environments. There remains a significant research gap concerning the development of a practical sorting system tailored to the specific traits of Thai Arabica coffee (*Coffea arabica*) cultivated in the northern highlands, such as Chiang Mai and Doi Chang. These local varieties, including Catimor, Red and Yellow Caturra, and Bourbon, present highly variable skin color spectrums (Techanan *et al.*, 2023; ULKA, 2025). Furthermore, local harvesting practices often result in uneven branch ripening, yielding a complex mixture of unripe green, semi-ripe, fully ripe red, and defective cherries, particularly those damaged by the coffee berry borer (*Hypothenemus hampei*). Currently, no existing literature demonstrates a physical prototype that integrates edge-computing AI via low-cost single-board computers, such as the Raspberry Pi 5, to perform real-time visual inspection and electromechanical segregation under the actual, dynamic conditions of small-to-medium Thai specialty coffee farms.

Therefore, this study aims to develop a prototype of a sorting line system for Thai coffee cherries using computer vision and edge computing algorithms. Specifically, this research investigates the effectiveness of a Convolutional Neural Network (CNN) compared to traditional machine learning models (Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Artificial Neural Network (ANN)) in accurately classifying coffee cherries based on their visual characteristics. The goal is to integrate the most effective classification model into a real-time

physical prototype controlled by a single-board computer to automate the sorting process, thereby enhancing the quality and consistency of Thai specialty coffee production from the initial post-harvest stage.

Materials and Methods

The research and development of the coffee cherry sorting prototype using computer vision are organized into a sequential pipeline of five main stages: dataset preparation, image representation and feature extraction, model training, model deployment, and prototype sorting operation.

2.1 Dataset Preparation and Class Labeling: To ensure evaluation accuracy and model transparency, the dataset acquisition was separated into two distinct sets with different objectives:

Dataset A (Static Model Comparison Dataset): This dataset comprises 400 static images of coffee cherries captured under uniform lighting and controlled laboratory conditions. It was utilized to test and compare the preliminary

image classification performance among the SVM, KNN, ANN, and CNN models. The input images were resized into three dimensions: 64 × 64, 128 × 128, and 256 × 256 pixels.

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Class Labels: The class definitions were established consistently throughout the study based on physical characteristics and quality requirements (Figure 1)

Class 0: Substandard Cherries (Unripe & Defective). This class represents substandard coffee cherries that must be rejected. It includes unripe cherries with green or green-yellow skin, as well as ripe cherries with prominent physical defects, such as being moldy, withered, black, or damaged by pests (e.g., the coffee berry borer).

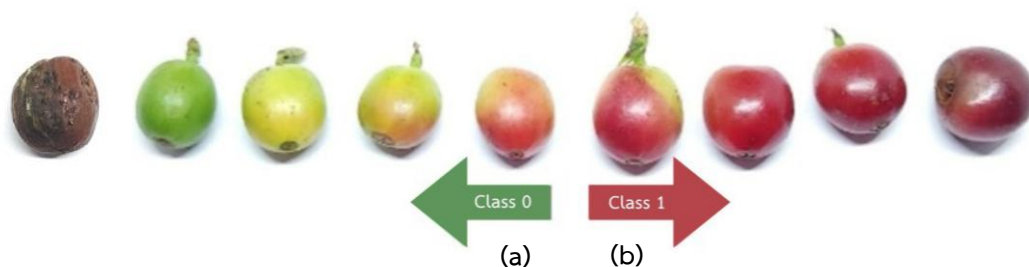


Figure 1. Visual classification standards for the automated sorting dataset: (a) Class 0 representing substandard green-yellow/unripe and insect-damaged cherries, and (b) Class 1 representing premium ripe/red cherries.

2.2 Image Representations and

Feature: Descriptors To accurately evaluate the computational complexity, the preprocessed images were transformed and extracted using distinct computer vision techniques. These techniques are strictly categorized according to their theoretical frameworks:

Color Spaces and Intensity Representations:

- **HSV (Hue, Saturation, Value):** Applied as a Color Space, which effectively separates color information from lighting intensity, helping to reduce the influence of shadows on the spherical surface of coffee cherries.
- **Grayscale:** Applied as a Single-channel Intensity Image Representation.
- **HOG (Histogram of Oriented Gradients):** Applied as a Gradient-based Shape Feature Descriptor that extracts structural and edge information based on light intensity gradients.
- **LBP (Local Binary Patterns):** Applied as a Texture Feature Descriptor used to describe the intricate surface patterns and texture of the objects.

2.3 CNN Architecture and Model

Training: The CNN architecture was implemented using the TensorFlow framework. The structure processes input images through sequential Conv2D layers for spatial feature extraction, followed by MaxPooling layers to reduce the dimensionality of the feature maps. To prevent the model from overfitting during the training phase, a Dropout layer with a rate of 0.3 was incorporated before passing the data to the final dense layers. The model training parameters were optimized using the Adam optimizer along with a Binary cross-entropy loss function. (Figure 2)

2.4 Model Deployment via TensorFlow

Lite To deploy the selected CNN object detection model for practical edge computing, the model

underwent a quantization process. This conversion process transformed the trained CNN model into a lightweight TensorFlow Lite (.tflite) file format. This critical step significantly accelerated the inference speed and reduced computational weight, enabling real-time operation on a small single-board computer like the Raspberry Pi 5.

2.5 Prototype Sorting Operation and

Hardware Control Logic: The physical prototype sorting machine is composed of three main sections: a cleaning section (to brush off dust and debris), a specific gravity separation section (using water density to separate light, withered cherries and twigs), and the optical sorting section. (Figure 3)

The hardware control logic is governed by a synchronized multi-threaded architecture on the Raspberry Pi 5 to ensure continuous, real-time operation without processing bottlenecks:

Thread 1 (Object Detection Thread): This thread continuously retrieves live images from the PiCamera, detects, coordinates, and runs inference through the TFLite model. If a coffee cherry is detected with a confidence score greater than or equal to 0.7 (Confidence ≥ 0.7), the system classifies it and writes the result (Class 0 or Class 1) into a shared data queue.

Thread 2 (Sorting Control Thread): Operating in parallel, this thread monitors an infrared (IR) sensor interfaced via an Arduino microcontroller. When the IR sensor detects a cherry passing through the sorting zone, it triggers the Raspberry Pi to pull the latest prediction value from the queue. If the value is Class 0, it sends a command to actuate the mechanical rejection system (servo motor) to sweep the substandard cherry off the conveyor. If the value is Class 1, the mechanism remains idle, allowing the premium cherry to pass through.

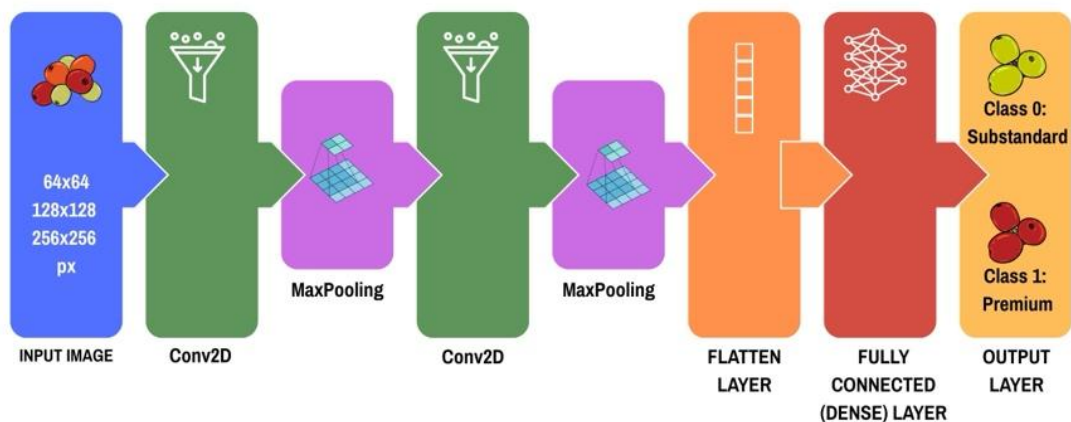


Figure 2. Architecture of the CNN model utilized for coffee cherry classification, illustrating the input dimensions, feature extraction layers, dropout regularization, and standardized output classes.

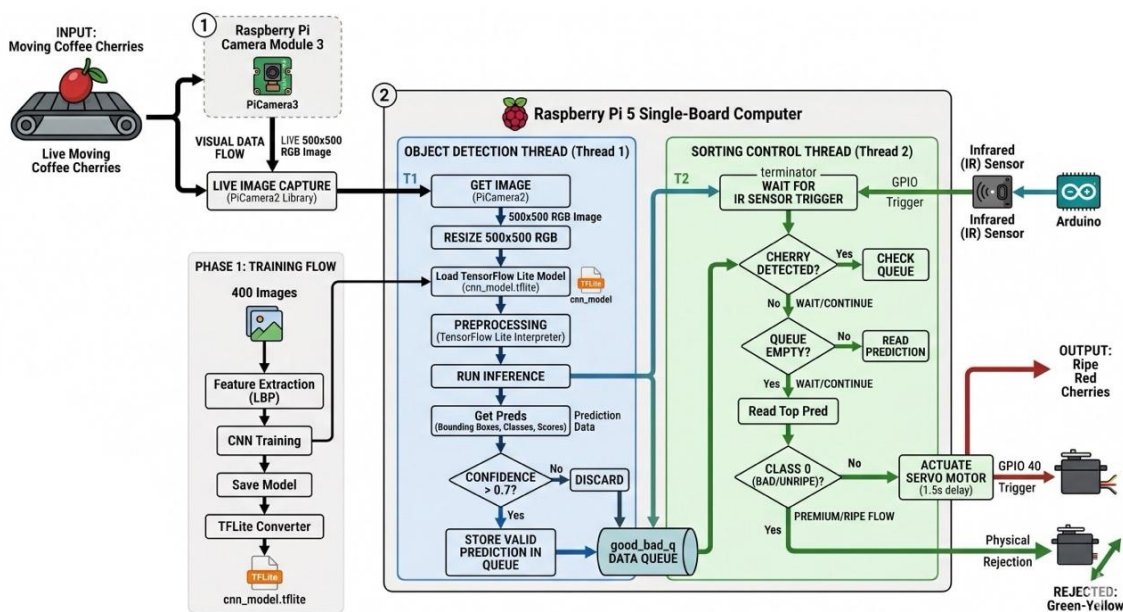


Figure 3. System architecture and data flow of the automated coffee cherry sorting prototype. The flowchart illustrates the multi-threading integration of the TensorFlow Lite object detection model (Thread 1) and the electro-mechanical sorting logic (Thread 2) controlled by the Raspberry Pi 5.

The performance of the sorting line system was evaluated based on the mean average precision (mAP) of the object detector and the overall system's processing speed. All statistical analyses were determined at a 95% confidence level ($p < 0.05$)

Results

The findings of this study are presented in two distinct stages. First, the preliminary classification accuracy and processing speed of four machine learning models (SVM, KNN, ANN, and CNN) are compared across multiple image resolutions and feature representations (Section 3.1). Second, the real-world operational performance of the prototype coffee cherry sorting line, which utilizes the best-performing model from the first stage, is evaluated (Section 3.2).

3.1 Classification Model Comparison (Static Images - Dataset A)

To determine the most effective algorithm for classifying coffee cherry images, the four machine learning models were trained and tested on the preliminary dataset (Dataset A) of 400 static images. Images were evaluated at three dimensions (64×64, 128×128, and 256×256 pixels) using various color spaces and feature descriptors (Grayscale, RGB, HSV, HOG, and LBP). Model performance was evaluated based on peak classification accuracy and average inference runtime per image.

The comprehensive performance metrics for the tested configurations of each model are detailed in Table 1. The empirical data reveal a distinct accuracy-speed trade-off. The Convolutional Neural Network (CNN) consistently achieved the highest classification accuracy.

Specifically, at a 64×64-pixel resolution in the RGB color space, the CNN achieved a preliminary peak accuracy of 94.00%. This substantially outperformed models relying on single-feature extractions, such as SVM (84.00%), KNN (78.10%), and ANN (76.25%).

However, this superior accuracy requires a higher computational cost. The CNN model required an average of 0.532 seconds per image, whereas simpler algorithms like KNN and SVM processed images in just 0.015 and 0.040 seconds, respectively. Because the prototype sorting line strictly prioritizes accuracy to ensure premium-grade coffee quality, and since a processing time of ~0.5 seconds is still viable for small-scale operations, the CNN architecture was selected for deployment on the physical prototype.

3.2 Prototype Sorting Line Performance (Dynamic Operation - Dataset B)

Building on the preliminary findings, the optimal CNN model was quantized into a TensorFlow Lite format and deployed onto the Raspberry Pi 5. The full physical prototype system includes a cleaning unit, a specific gravity separation unit, and the optical object detection unit. For this operational stage, the model was tasked with real-time object detection on a moving conveyor belt.

System performance was evaluated using mean Average Precision (mAP) at an IoU threshold range of 0.5 to 0.95, which effectively measures the model's ability to accurately place bounding boxes around moving cherries. As shown in Table 2, the CNN-based model achieved an mAP of 84.53% for Class 1 (Premium Cherries) and 78.92% for Class 0 (Substandard Cherries). The higher mAP for Class 1 is attributed to the highly distinctive red coloration, which provides

Table 1. Performance Comparison of Machine Learning Models for Preliminary Coffee Cherry Classification (Dataset A).

Model Architecture	Image Dimension (pixels)	Image Representation / Feature Descriptor	Maximum Accuracy (%)	Average Inference Runtime (s/image)
CNN	64 × 64	RGB (Color Space)	94.00 ^a	0.532 ^c
CNN	64 × 64	Grayscale (Intensity Representation)	85.50 ^a	0.412 ^c
CNN	128 × 128	RGB/HSV (Color Space)	88.00 ^a	1.800 ^c
CNN	256 × 256	RGB/HSV (Color Space)	87.50 ^a	8.000 ^c
ANN	64 × 64	RGB (Color Space)	76.25 ^c	0.230 ^a
ANN	64 × 64	Grayscale (Intensity Representation)	82.10 ^b	0.210 ^a
ANN	128 × 128	RGB (Color Space)	81.50 ^b	0.085 ^a
SVM	64 × 64	RGB (Color Space)	84.00 ^b	0.040 ^a
SVM	64 × 64	Grayscale (Intensity Representation)	78.10 ^c	0.015 ^a
SVM	64 × 64	HOG (Gradient-based Shape)	75.60 ^c	0.052 ^a
SVM	128 × 128	HOG (Gradient-based Shape)	73.40 ^c	0.022 ^a
KNN	64 × 64	Grayscale (Intensity Representation)	78.10 ^c	0.015 ^a
KNN	64 × 64	RGB (Color Space)	74.00 ^c	0.510 ^b
KNN	64 × 64	LBP (Texture Descriptor)	71.10 ^c	0.185 ^b

Note: Different superscript letters (a,b,c) within the same column indicate statistically significant differences between the machine learning models at the 95% confidence level ($p < 0.05$) according to One-Way ANOVA and post-hoc comparison tests. For Maximum Accuracy, higher values are superior (group 'a' is the highest). For Average Inference Runtime, lower values are superior (group 'a' is the fastest).

Table 2. Mean Average Precision (mAP) Values for Real-Time Object Detection on the Prototype Sorting Line (Dataset B)

Target Class Name	Average mAP @0.5–0.95 (%)	Qualitative Performance Evaluation
Class 0: Substandard Cherries (Unripe & Defective)	78.92%	Good
Class 1: Premium Cherries (Fully Ripe)	84.53%	Very Good

a stronger signal compared to the green-yellow hues of Class 0 that occasionally blend with the conveyor belt background.

At the system level, combining the object detection software with the electro-mechanical rejection hardware, the integrated prototype achieved an overall practical sorting accuracy of 81.73% during continuous operation. The system successfully processed approximately 120 cherries per minute, equating to a throughput capacity of roughly 2 kg per hour. While modest compared to large industrial machines, this capacity aligns well with the processing volumes of small-to medium-sized specialty coffee community enterprises in Thailand.

Discussion

This study set out to develop and evaluate a working prototype of an automated sorting line for Thai Arabica coffee cherries, and the results show that the goal was largely achieved. In the first stage, a comparative analysis of classification models revealed that the CNN stood out clearly, reaching 94.00% accuracy on 64×64 pixel RGB images, a result that left traditional approaches like SVM, KNN, and ANN well behind. While the CNN did take slightly longer per inference, its ability to learn deep visual features made it the right choice for a task that demands the precision specialty coffee grading requires.

Building on that foundation, the second stage brought the quantized CNN into a physical sorting line, complete with cleaning and specific-gravity separation units. Running continuously on a moving conveyor belt, the full system sorted cherries at around 120 per minute (roughly 2 kg

per hour) with a practical accuracy of 81.73%, reliably separating premium, fully ripe cherries (Class 1) from unripe and defective ones (Class 0). These numbers suggest the prototype is a genuinely viable tool for small-to-medium specialty coffee enterprises in Thailand.

That said, the system is not without its shortcomings. The current single-camera, top-down scanning setup leaves a real blind spot: defects on the underside of a cherry can go undetected, and the system remains sensitive to changes in ambient lighting. These are not minor issues, and they are worth addressing directly before any broader deployment is considered.

Future work should therefore focus on designing a light-controlled enclosure to stabilize imaging conditions and integrating a 360-degree dual-camera setup to eliminate visual gaps. Thorough field testing in real farm environments will also be essential to understand how the system performs in practice before taking any steps toward full commercialization.

Acknowledgements

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