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Experimental evaluation of an artificial intelligence system for automated mango classification

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ABSTRACT

This study proposes the design and implementation of an intelligent mango sorting system capable of classifying mangoes into three categories: unripe, ripe, and rotten. The system integrates a programmable logic controller (PLC) to operate a conveyor mechanism, with user interaction facilitated through a human-machine interface (HMI) touchscreen panel. Image acquisition is performed using a universal serial bus (USB) webcam, while image processing and classification are handled by the CiRA CORE software utilizing artificial intelligence (AI) techniques. The classification results are transmitted to an Arduino microcontroller, which controls pneumatic actuators responsible for the physical sorting process. Experimental results demonstrate that the system can accurately classify mangoes with an overall success rate of 90%, indicating its potential for practical application in automated agricultural product sorting.

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1. INTRODUCTION

In the agricultural sector, the sorting and grading of fruits play a crucial role in ensuring product quality, reducing waste, and increasing market value [1]–[4]. Traditionally, this process has been carried out manually, relying heavily on human labor and visual inspection, which can be both time-consuming and prone to inconsistency. With advancements in automation and artificial intelligence (AI) [5]–[7], there is an increasing interest in developing intelligent systems capable of performing such tasks with greater speed, accuracy, and efficiency. Mangoes, as one of the most widely consumed tropical fruits, require precise sorting based on their ripeness to meet diverse market demands [8]–[10]. In this context, the development of an automated mango sorting system presents a valuable solution for enhancing productivity and reducing human error in post-harvest operations. This study presents the design and implementation of an intelligent mango sorting system that classifies mangoes into three distinct categories: raw, ripe, and rotten [9]–[11]. The proposed system combines a programmable logic controller (PLC) to manage a conveyor mechanism with a human-machine interface (HMI) touchscreen panel for user interaction [12]. A universal serial bus (USB) webcam captures images of the mangoes, which are then processed and classified using the CiRA CORE software integrated with AI-based image recognition techniques. The classification results are transmitted to an Arduino microcontroller, which activates pneumatic actuators to physically sort the mangoes based on their condition [13].

CiRA CORE is a visual inspection software platform developed by the Center of Imaging Research and Analysis (CiRA). It is specifically designed for industrial machine vision applications [14], such as defect detection, measurement and dimension checking, object classification, and automated quality control. Key features of CiRA CORE include a user-friendly graphical user interface (GUI) with a no-code or low-code interface, built-in AI/machine learning (ML) modules tailored for industrial imaging, support for real-time processing, compatibility with industrial cameras, and a design optimized for fast deployment on production lines.

Table 1 shows a comparison of image processing tools. CiRA CORE is an easy-to-use tool for manufacturing, featuring built-in AI and real-time support. OpenCV is free but requires coding and customization [15]. The MATLAB image toolbox is designed for researchers, offering advanced analysis but limited real-time performance. Halcon is a powerful industrial tool with strong AI and real-time capabilities, though it is costly [16]. NI Vision uses visual programming, supports real-time processing, and is suitable for industrial automation, with licensing costs that vary depending on the setup [17].

Table 1. Comparison of CiRA CORE software versus other image processing tools

Feature/tool	CiRA CORE	OpenCV	MATLAB image toolbox	Halcon (MVTec)	NI Vision (LabVIEW)
Target users	Manufacturing, SMEs	Developers, researchers	Engineers, researchers	Industrial engineers	Industrial automation
Main use case	Quality inspection	Custom image processing	Scientific image analysis	2D/3D machine vision	Vision in automation systems
Ease of use	Very easy (GUI)	Requires coding (Python/C++)	GUI + coding	GUI + optional coding	Visual programming (GUI)
AI/ML support	Built-in modules	Must build from scratch	Requires separate toolbox	Integrated AI support	Partial AI support
Industrial camera support	Native support	Needs configuration	Requires coding	Wide camera compatibility	Native support
Real-time Processing	Yes	Yes, with optimization	Limited real-time	Strong real-time support	Excellent for real-time
Licensing/cost	Commercial license	Free (open-source)	Commercial (expensive)	Commercial (expensive)	Commercial (depends on setup)

The concept of an advanced automatic mango sorting based on color using the CiRA CORE platform offers a significant advancement in agricultural automation. It effectively combines PLC, computer vision, and ML, addressing key challenges in citrus sorting—speed, precision, and scalability. The CiRA CORE platform enables fast and precise automatic mango sorting based on color by combining PLC, computer vision, and ML. It improves sorting speed and accuracy compared to manual methods and adapts in real time to changing conditions. The system reduces labor costs, making it suitable for large-scale farms facing labor shortages. It is scalable and flexible, allowing expansion to different fruits or more complex tasks. Sorting by objective features enhances product quality and consistency. However, technical integration requires careful calibration and maintenance, which may limit adoption in smaller operations. Additionally, the system's accuracy depends on environmental factors like lighting and fruit surface, and precise robotic control is needed to prevent damage.

The mango sorting system using the CiRA CORE platform is a promising advancement in agricultural robotics. It enhances sorting efficiency, lowers labor costs, and ensures consistent product quality, benefiting the citrus industry significantly. However, its successful implementation depends on addressing technical challenges and ensuring reliable operation in real-world conditions. Overcoming these issues could transform sorting and quality control in the citrus sector.

2. MATERIAL AND METHOD

2.1. Materials

The primary software tool used in this study is CiRA CORE, a visual inspection platform developed by the CiRA. The system is designed for industrial machine vision tasks and includes features such as a user-friendly GUI, built-in AI and ML modules, real-time processing capabilities, and compatibility with a wide range of industrial cameras. The main hardware setup, as shown in Figure 1, consists of a conveyor system [18] (or an automated mechanism for object movement), a personal computer with a monitor, a Samkoon HMI, an FX3U PLC, two webcam cameras, and an electric vacuum pump.

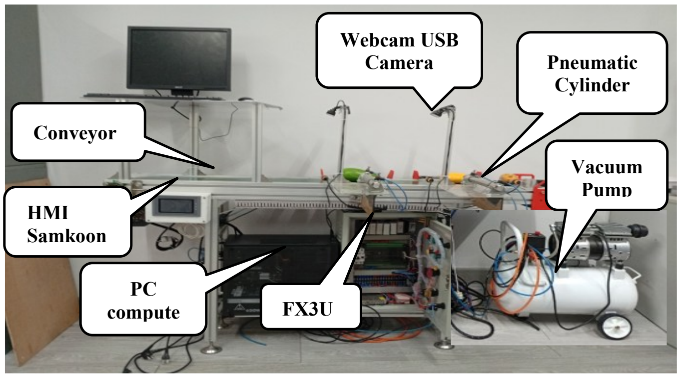


Figure 1. Experimental hardware configuration for the AI-integrated sorting system

2.2. Electrical and control circuit

Figure 2 illustrates the overall electrical control system used in this study. The system receives power from an alternating current (AC) source, which is distributed through a circuit breaker for protection. An emergency stop switch is integrated into the circuit to enable immediate shutdown during abnormal conditions, thereby enhancing operational safety. The electrical and control circuit represents an integrated automation system designed to control a conveyor-based sorting mechanism. It combines a PLC, specifically the Mitsubishi FX3U-24MT—with microcontrollers such as the Arduino Uno R3 and ESP32, alongside peripheral devices including relays, sensors, push-button switches, indicator lamps, solenoid valves, and an HMI. The control system consists of three core components:

- PLC of Mitsubishi FX3U-24MT [19], serving as the central controller.
- An Arduino Uno R3, used for basic digital input and output (I/O) handling and sensor interfacing.
- An ESP32 microcontroller, responsible for wireless communication and additional input processing.

The PLC executes the main control logic, including object detection, sorting mechanism control, and real-time communication with the HMI interface [20].

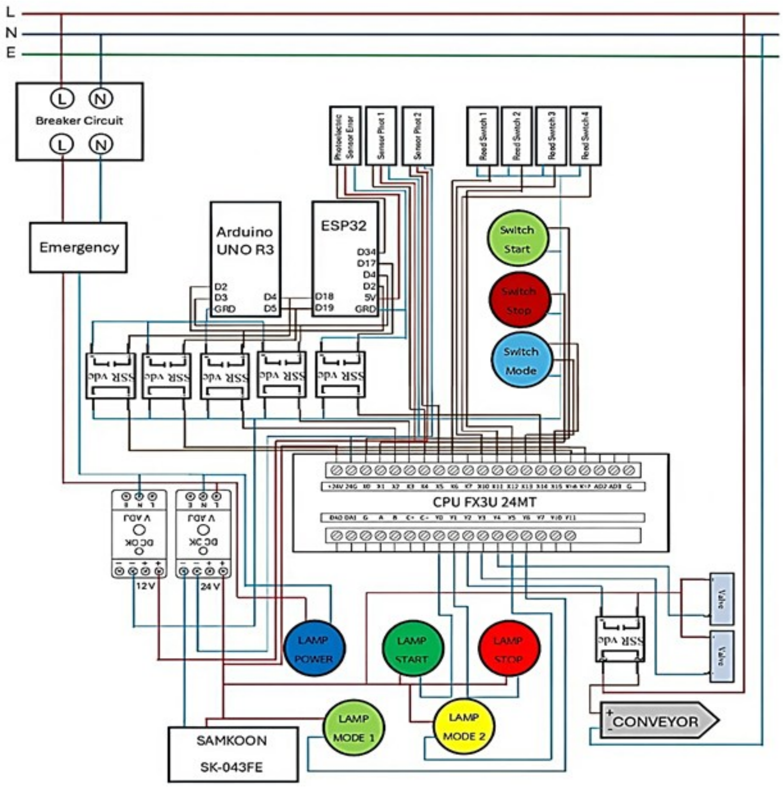


Figure 2. Electrical diagram of the AI-based mango sorting system

The internal control panel shows wiring and electrical components such as PLCs, relays, breakers, and terminals. The external control panel contains push buttons, indicator lights, and switches to operate the machine. The HMI touchscreen is used to monitor and control the system through a user-friendly interface, as shown in Figure 3.

Figure 3. Automatic machine control panel with PLC and HMI

2.3. Conceptual experiment using the CiRA CORE platform

DeepDetect is an open-source deep learning platform designed to simplify the training and deployment of deep learning models through representational state transfer (REST) application programming interface (API) support. The CiRA CORE platform integrates DeepDetect modules to perform image analysis tasks such as classification and object detection [21], [22]. In this study, DeepDetect integrated within CiRA CORE was employed to develop a mango classification model based on skin color. The objective was to classify mangoes into three categories: unripe, ripe, and rotten. The conceptual experimental procedure is summarized as follows.

2.3.1. Data collection

A dataset of mango images representing three different conditions—unripe, ripe, and rotten—was collected. To enhance model robustness and generalization capability, the images were captured under varying lighting conditions, viewing angles, and background settings. Several hundred images were acquired for each class to ensure sufficient training data.

2.3.2. Data labeling

Each image in the dataset was manually labeled according to its corresponding class: unripe, ripe, or rotten. Each image was assigned a single label. Therefore, the task was formulated as a multi-class image classification problem.

2.3.3. Dataset preparation for DeepDetect

The labeled images were organized into separate directories according to their class labels. DeepDetect requires this directory-based structure for classification tasks. This organization also facilitates efficient data loading during training.

2.3.4. Model configuration

A suitable convolutional neural network (CNN) architecture—such as residual network (ResNet), Google network (GoogLeNet), or mobile network (MobileNet)—was selected for model training. The DeepDetect configuration defined key training parameters. These included the learning rate, batch size, number of training iterations, and input image resolution.

2.3.5. Model training

The model was trained using DeepDetect's training API. During training, performance metrics such as loss and classification accuracy were continuously monitored. Hyperparameters were adjusted when necessary to improve learning efficiency and classification performance.

2.3.6. Model evaluation

After training, the model was evaluated using a separate test dataset. Standard performance metrics were used to assess overall performance. These included accuracy, precision, recall, and confusion matrices to evaluate class-wise reliability.

2.3.7. Model deployment in CiRA CORE

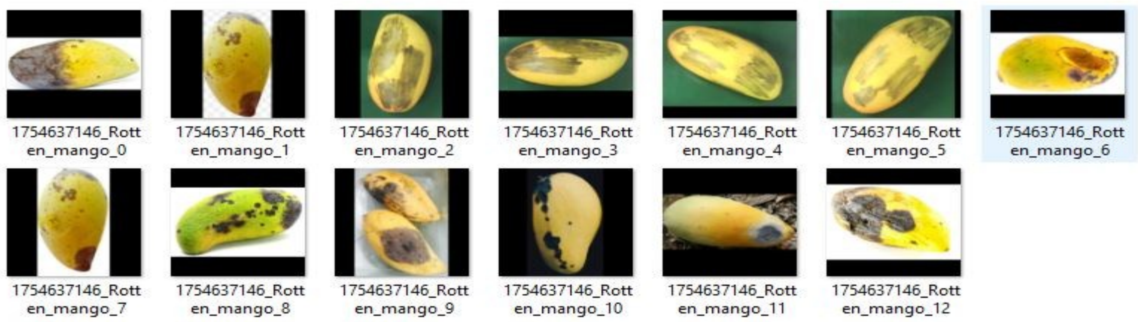
The trained model achieved satisfactory performance. It was subsequently deployed within the CiRA CORE environment. During system operation, this deployed model classified incoming mango images in real-time.

2.3.8. Continuous improvement

To maintain and enhance classification accuracy over time, new images were periodically added to the dataset, and the model was retrained as needed. Model architecture and training parameters were further refined based on observed performance during real-world operation. Figure 4 shows a dataset of green mango images used for training or testing an AI model. Each image is labeled with "Green_mango" or Unripe mango (Figure 4(a)), “Yellow_Mango” or Ripe mango (Figure 4(b)), and “Rotten_Mango” or Rotten mango (Figure 4(c)) followed by a unique identifier number [23]–[25]. The dataset consists of various angles and shapes of green mangoes to improve detection accuracy.

(a)

(b)



(c)

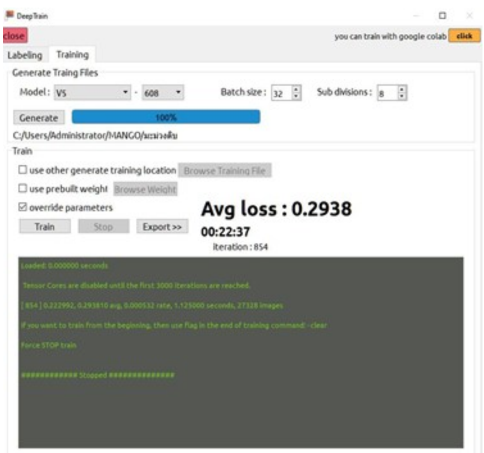
Figure 4. The data set of mangos for (a) unripe mango, (b) ripe mango, and (c) rotten mango

2.4. Method and procedure

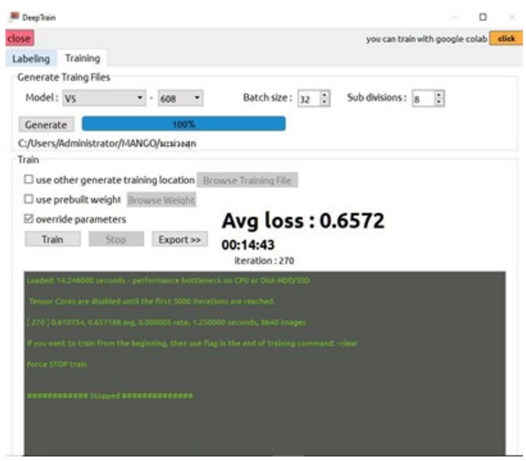
CiRA CORE is a low-code/no-code AI and automation platform developed by CiRA Robotics. It allows users to build AI models and automation systems through a visual drag-and-drop interface, eliminating the need for complex programming. Choose the installation method based on your platform, such as Windows 10 (64-bit) [26]. General method and procedure for using CiRA CORE:

i) Install CiRA CORE on your preferred platform.
ii) Launch the application.
iii) Download a project file (.npj) or create a new one.
iv) Use the drag-and-drop Node Flow editor to design your logic.
v) Configure hardware I/O (e.g., cameras and sensors).
vi) Load or train an AI model (e.g., for object detection or classification).
vii) Configure output and communication settings.
viii) Press run to execute and test your flow.
ix) Monitor and evaluate results, then fine-tune your workflow as needed.

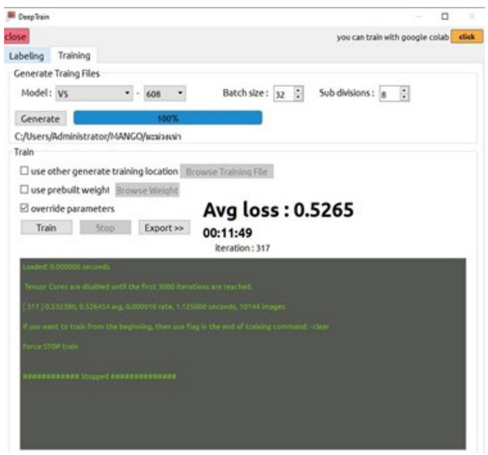
Figure 5 presents the training results of the you only look once (YOLO)-based model at different stages. As shown in Figure 5(a), the unripe mango model achieved the best performance, with an average training loss of 0.2938 after 944 iterations, indicating strong feature extraction and classification capability. The ripe mango model, illustrated in Figure 5(b), exhibited a higher average loss of 0.6572 after 270 iterations, suggesting comparatively lower classification confidence, possibly due to greater color similarity between ripe and partially ripened mangoes. Meanwhile, the rotten mango model shown in Figure 5(c) achieved moderate performance, with an average loss of 0.5265 after 737 iterations, reflecting the variability in surface texture and color patterns of spoiled fruit.



(a)



(b)



(c)

Figure 5. Training results of the YOLO-based mango classification model at different iterations for (a) unripe mango training, (b) ripe mango training, and (c) rotten mango training

Figure 6 illustrates the automatic mango sorting system. USB cameras capture images of mangoes as they move along the conveyor belt and transmit the image data to a computer running the CiRA CORE software, where the mangoes are analyzed and classified into three categories: unripe, ripe, and rotten. The classification results are then transmitted to a PLC, which controls the conveyor operation and the pneumatic cylinder mechanisms [27], [28]. When a mango is classified as unripe, pneumatic cylinder system 1 is activated to direct the mango into box 1. Similarly, ripe mangoes are redirected to box 2 by pneumatic cylinder system 2. Rotten mangoes are not actuated by any pneumatic mechanism and continue along the conveyor belt to box 3. An Arduino Uno microcontroller is used to acquire additional sensor signals and communicate with the PLC to support overall system control.

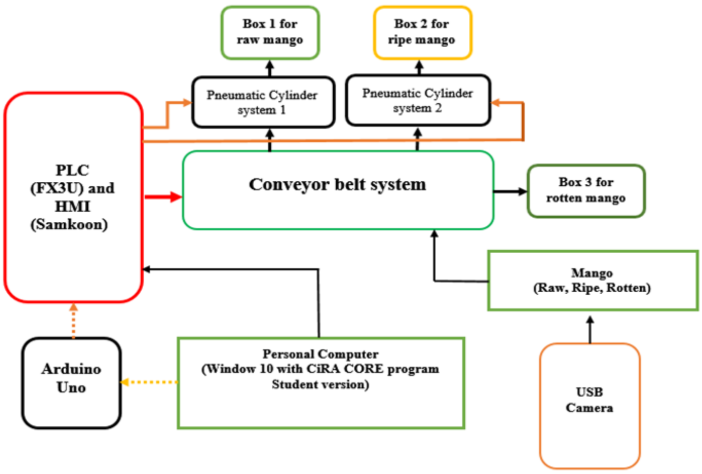


Figure 6. The block diagram of automatic mango sorting using CiRA CORA platform

Figure 7 shows the Arduino I/O pin configuration in the CiRA Arduino I/O module. Digital pins D2 to D5 are set as OUTPUTs to control indicators for different mango types: Yellow_Mango, Green_Mango, Big_Lime, and Small_Lime. The other pins are set as INPUTs for receiving signals from sensors or other devices.

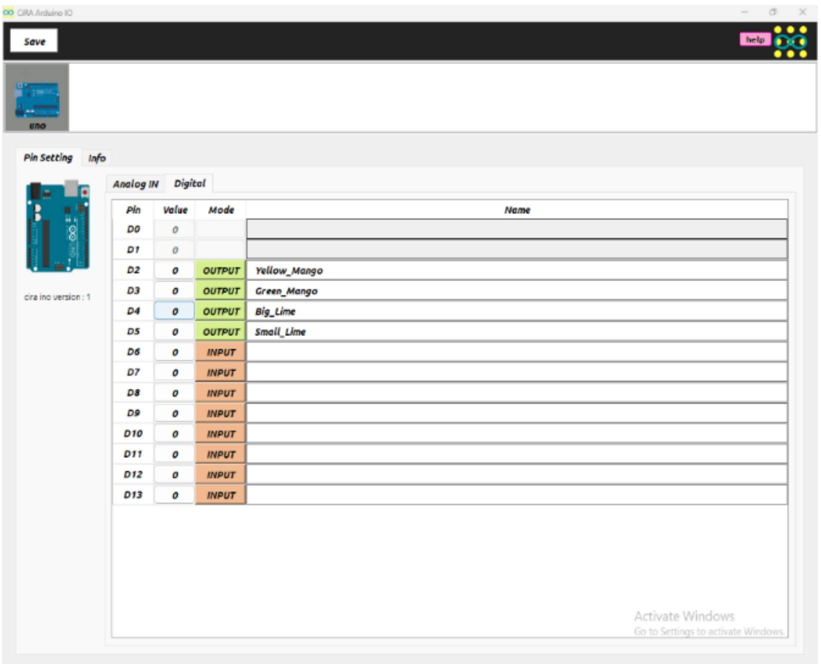


Figure 7. Arduino pin configuration for mango sorting system

Figure 8 shows the use of CiRA CORE software for object detection using AI with a block-based workflow. A JavaScript code block checks if an object named “Green_Mango” is detected in the image and then sends the result to control the next system process. Figure 9 shows a visual programming setup in CiRA CORE for detecting green mangoes. The system captures an image, processes it using object detection, and displays the result along with output values (/greemango and /unripeamango) in WatchOutput windows. The output values are used to control motors or actuators for sorting.

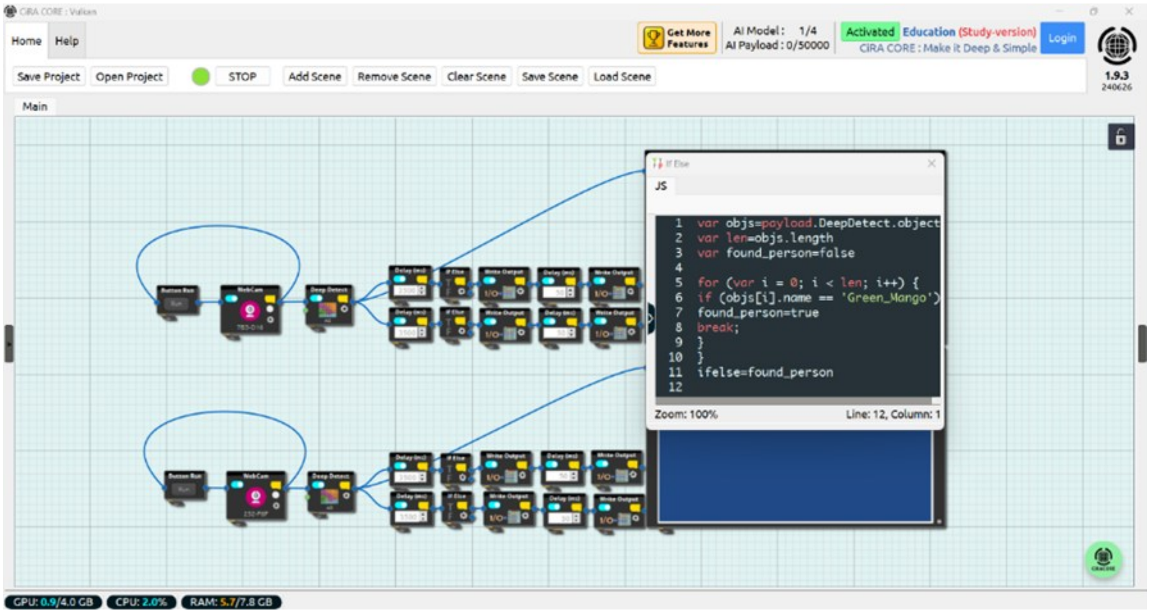


Figure 8. CiRA CORE object detection workflow with JavaScript code

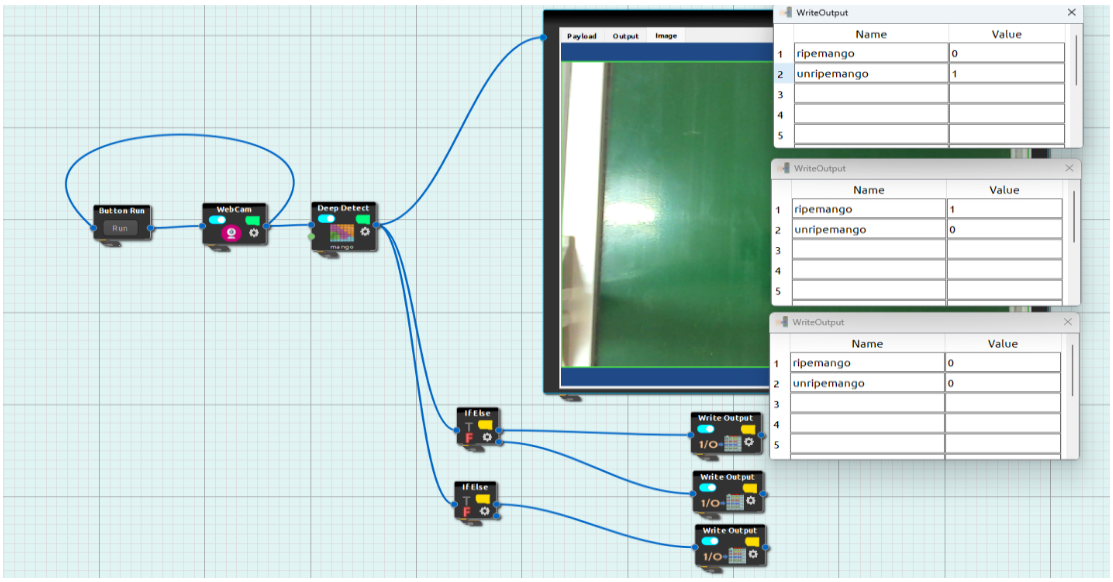
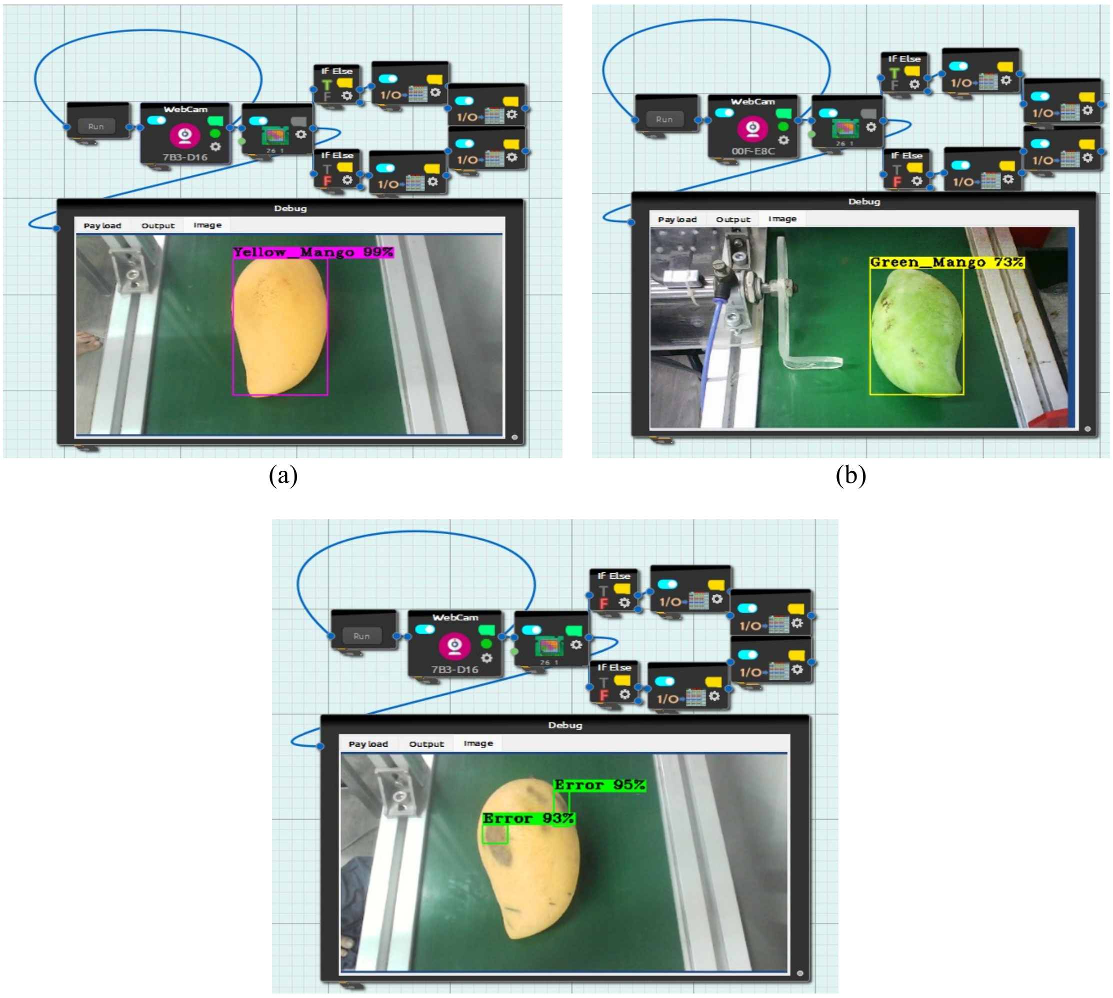


Figure 9. CiRA CORE green mango detection workflow

3. RESULTS AND DISCUSSION

3.1. Experimental results

The proposed AI-based mango sorting system was successfully implemented and tested under laboratory-scale operating conditions. The system integrated image acquisition, AI-based classification using the CiRA CORE platform, and real-time actuation through PLC- and Arduino-controlled pneumatic mechanisms [29]. During experiments, mangoes were placed on the conveyor belt and passed through the inspection zone, where images were captured by USB cameras and processed in real time. The mango sorting test using the CiRA CORE system, the results are shown in Figure 10, which illustrates the system's processing and detection in different scenarios. Figure 10(a) shows the CiRA CORE setup using a webcam to detect and classify a mango. The AI model successfully identifies the mango as "Yellow_Mango" with 99% confidence. Based on this result, conditional blocks are used to trigger specific hardware outputs for automated sorting. Figure 10(b) demonstrates the detection of a "Green_Mango" with 73% confidence. The result is displayed in the debug window, and conditional blocks are applied to activate the mechanical sorting mechanism accordingly. Figure 10(c) illustrates a case where the system detects a mango with an abnormal condition labeled as "Error". The AI classifies the mango as defective (e.g., rotten) with confidence levels of 95% and 93% for different types of defects. The image is captured via webcam, and the conditional blocks in the workflow are used to control the rejection of the non-standard mango [30].



(a) (b)

(c)

Figure 10. Mango classification using CiRA CORE for (a) Yellow_ Mango detection with 99% confidence, (b) Green_ Mango detection with 73% confidence, and (c) Error (rotten) mango detection with high confidence

Table 2 presents the experimental results of mango detection accuracy for unripe, ripe, and rotten mangoes based on two confidence thresholds: ≥91% and ≤90%. A total of 15 trials were conducted to evaluate the reliability of the proposed AI-based classification system. For ripe mango detection, the system demonstrated consistently high performance. All 15 trials achieved confidence values of at least 91%, resulting in a detection accuracy of 100% in the ≥91% confidence category, with no detections falling under 90%. This indicates that the model is highly reliable in identifying ripe mangoes under the tested conditions.

Similarly, rotten mango detection also showed excellent performance. All trials achieved confidence levels of 91% or higher, corresponding to 100% accuracy in the high-confidence category. This result suggests that the visual features associated with rotten mangoes, such as surface discoloration and texture irregularities, were effectively captured by the trained model.

In contrast, the performance for unripe mango detection was slightly lower. Out of 15 trials, 14 trials (93.33%) achieved confidence values of at least 91%, while 1 trial (6.67%) fell under the 90% confidence threshold. This reduction in confidence can be attributed to the visual similarity between unripe mangoes and mangoes in early ripening stages, which may cause ambiguity in color-based classification. Overall, the results demonstrate that the proposed system achieves high detection accuracy across all mango categories, particularly for ripe and rotten mangoes. The slightly lower performance observed for unripe mangoes highlights the challenge of distinguishing subtle color variations and suggests that incorporating additional features, such as texture or shape analysis, could further improve classification robustness.

Table 2. Trial results showing detection accuracy of ripe, unripe, and rotten mangoes based on confidence thresholds (≥91% and ≤90%)

Trial no.	Ripe mango		Unripe mango		Rotten mango	
	≥91%	≥90%	≥91%	≥90%	≥91%	≥90%
1	99%	0	99%	0	99%	0
2	99%	0	98%	0	98%	0
3	98%	0	0	73%	0	0
4	99%	0	95%	0	95%	0
5	99%	0	99%	0	99%	0
6	99%	0	99%	0	99%	0
7	99%	0	99%	0	99%	0
8	99%	0	99%	0	99%	0
9	99%	0	99%	0	99%	0
10	97%	0	99%	0	99%	0
11	99%	0	99%	0	99%	0
12	95%	0	99%	0	99%	0
13	99%	0	99%	0	99%	0
14	99%	0	99%	0	99%	0
15	99%	0	99%	0	99%	0
Total	15	0	14	1		
Percentage	100%	0%	33.93%	67.6%		

Figure 11 illustrates the classification accuracy of the proposed AI-based mango sorting system for three mango types—ripe, unripe, and rotten—based on two confidence levels: ≥91% and ≤90%. The results indicate that the system achieved 100% classification accuracy at the ≥91% confidence level for both ripe and rotten mangoes, with no detections falling below the 90% confidence threshold. This demonstrates that the model is highly reliable in identifying these two categories, likely due to their distinct visual characteristics such as color intensity and surface texture. For unripe mangoes, the system achieved a slightly lower performance. Approximately 93.33% of the detections reached the ≥91% confidence level, while 6.67% of the detections fell into the ≤90% confidence category. This reduction in confidence suggests that unripe mangoes are more challenging to classify, possibly because their appearance can overlap with that of partially ripened mangoes, leading to increased ambiguity in color-based classification. Overall, the analysis confirms that the proposed system performs with high accuracy across all mango categories, particularly for ripe and rotten mangoes. The slightly lower confidence observed for unripe mangoes highlights an inherent limitation of color-based classification and suggests that incorporating additional features, such as texture or shape analysis, could further enhance classification robustness in future work.

The results shown in Figure 12 confirm that the system can reliably differentiate mango conditions and perform appropriate sorting actions in real time. The clear separation of ripe, unripe, and rotten mangoes highlights the effectiveness of integrating AI-based visual inspection with PLC-controlled mechanical actuation [31]. Figure 12(a) illustrates the sorting process for ripe mangoes. After image acquisition and AI-based classification using the CiRA CORE platform, the mango is identified as ripe. Based on this classification result, the control signal is sent to the PLC, which activates the corresponding pneumatic cylinder. As a result, the ripe mango is redirected from the conveyor belt into the first sorting channel (box 1) for ripe mango collection. Figure 12(b) shows the sorting process for unripe mangoes. The system captures the image of the mango and classifies it as unripe using the AI model. The PLC then triggers the second pneumatic actuator, causing the mango to be diverted into the second sorting channel (box 2). This operation ensures accurate separation of unripe mangoes from other categories. Figure 12(c) demonstrates the final sorting stage for rotten mangoes. When a mango is classified as rotten, no pneumatic actuator is activated. Instead, the mango remains on the conveyor belt and is transported directly to the output end of the conveyor for disposal or separate handling. This passive sorting approach prevents cross-contamination with acceptable-quality fruit.

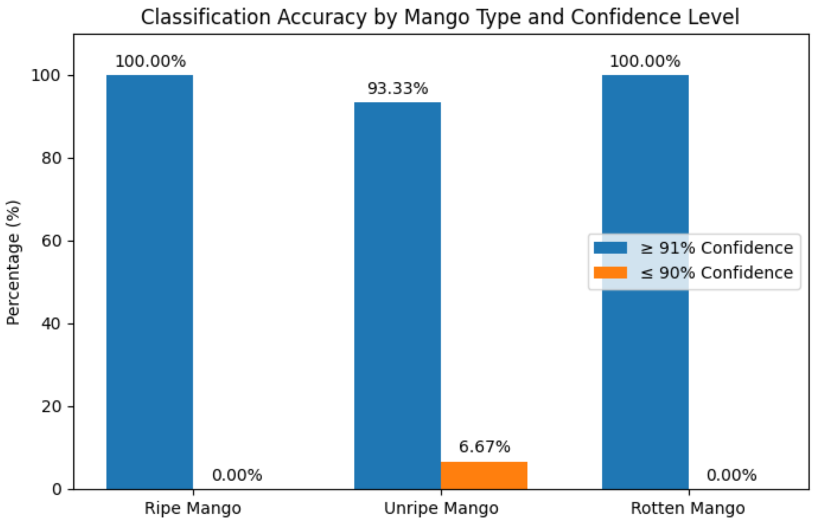
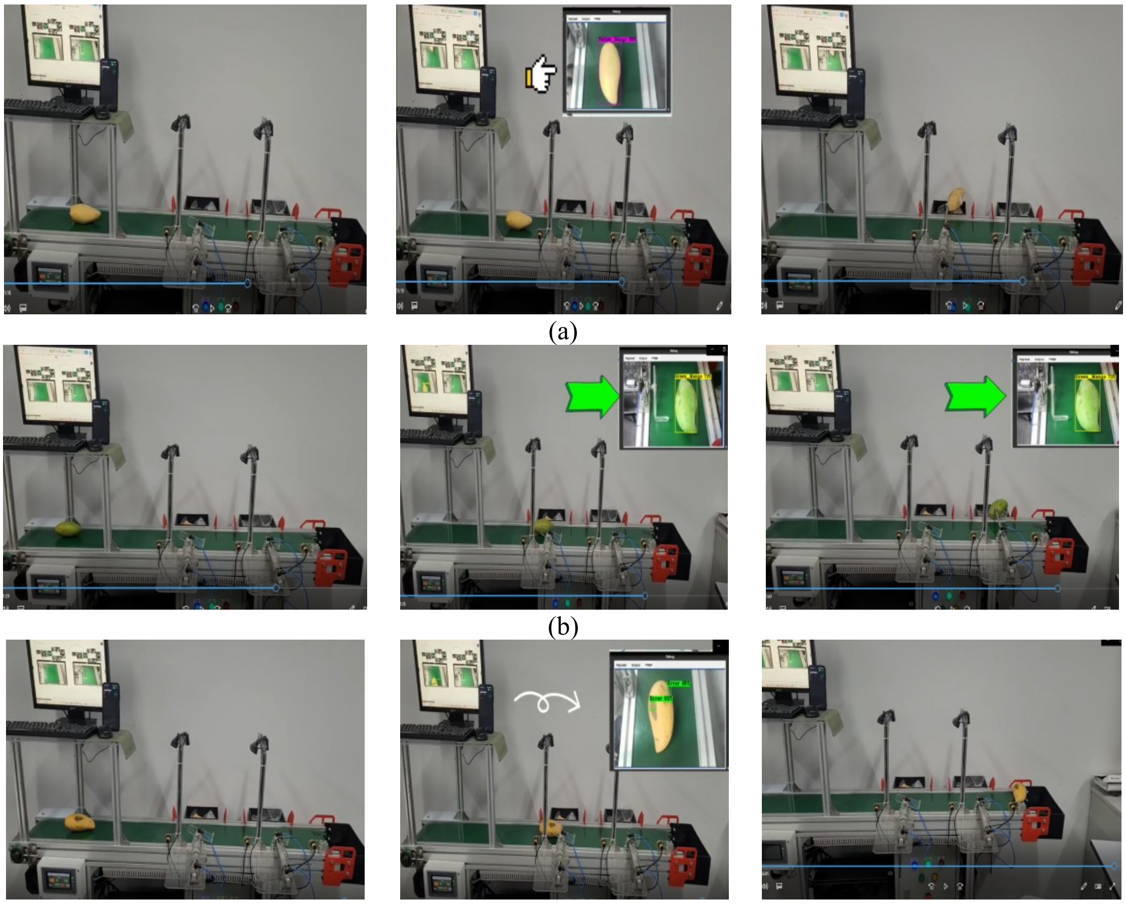


Figure 11. Classification accuracy of mango types by confidence level



(a)

(b)

Figure 12. Visual inspection and sorting system for mangoes: (a) sorting of ripe mangoes, (b) sorting of unripe mangoes, and (c) sorting of rotten mangoes

3.2. Discussion

This experiment demonstrates several notable advantages and distinctive contributions. While many earlier works on fruit sorting have primarily focused on image classification performance in controlled laboratory environments, the proposed system emphasizes practical deployment by integrating AI with real-time automation components, including PLCs, Arduino microcontrollers, and pneumatic actuators [32]. This end-to-end integration enables the system to operate reliably in real production settings, thereby bridging the gap between theoretical research and industrial application. A key strength of this study lies in the use of the CiRA CORE platform, which significantly reduces system development complexity through its low-code/no-code environment and built-in AI modules [33]. In contrast to conventional approaches that require advanced programming skills and extensive model customization, this framework allows users with limited technical expertise to develop, deploy, and maintain AI-based sorting systems. This feature is particularly advantageous for small and medium-sized agricultural enterprises, which are often constrained by limited technical resources and investment capacity.

Furthermore, this work provides a more realistic evaluation of classification challenges by explicitly analyzing the variation in training loss among different mango maturity classes [34]. Unlike some prior studies that rely on highly curated datasets, the results highlight the inherent visual ambiguity between ripe, unripe, and overripe mangoes under real-world conditions. By acknowledging these limitations and proposing future enhancements such as texture analysis, shape descriptors, and multispectral imaging, the study offers a clear pathway for improving classification robustness.

Another important contribution is the consideration of environmental and operational factors, including lighting conditions, camera placement, and fruit surface contamination, which are often underreported in related research. The findings demonstrate that, although the system can tolerate moderate variations, controlled illumination, consistent camera alignment, and periodic model retraining are essential for maintaining long-term accuracy. The ability of the CiRA CORE platform to support regular dataset updates and retraining further strengthens the system's adaptability in dynamic agricultural environments [35]. Overall, compared with previous research, this experimental study stands out for its practical orientation, reduced development complexity, scalability, and clear relevance to real-world agricultural operations. The proposed system not only improves sorting efficiency and product quality consistency but also offers a feasible and accessible solution for modern post-harvest processing, underscoring its potential for broader adoption and future extension to other types of fruits.

4. CONCLUSION

This experiment successfully developed an intelligent mango sorting system capable of classifying mangoes into three categories: ripe, unripe, and rotten. The system integrates image processing using AI with hardware components such as a PLC-controlled conveyor, HMI touchscreen, USB webcam, Arduino microcontroller, and pneumatic actuators. Experimental evaluation on 15 mango samples (5 per category) demonstrated the system's effectiveness, with an overall classification accuracy of 90%. Ripe mangoes were correctly identified with 0% error, while unripe and rotten mangoes showed a minor error rate of 6.67% each. The average processing time per fruit ranged from 12.2 to 17.9 seconds, indicating the system's practical potential for automated agricultural sorting applications. To enhance the performance and scalability of the proposed mango sorting system in future work, efforts should focus on increasing the number and diversity of mango samples used for training and testing, including different varieties, sizes, and lighting conditions, to improve model accuracy and generalization. Processing time per fruit should be reduced by optimizing algorithms and hardware to enable efficient real-time operation in industrial settings. Incorporating advanced deep learning techniques, such as CNNs, can improve classification accuracy, especially for visually ambiguous cases. The system's robustness to environmental changes, such as lighting, background noise, and fruit positioning, should be improved. Additionally, the system should be developed to handle higher throughput and integrate smoothly with existing processing lines. Expanding the system to classify other fruit types and detect defects like bruises, insect damage, or overripeness will increase its versatility. Finally, implementing data logging for monitoring sorting performance and analyzing fruit quality trends will support better quality control and operational decision-making.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Surasit Phokha	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Wiriya Dangton	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Viroch Sukontanakarn	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Phisit Srinoi	✓		✓	✓	✓		✓			✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The author declares that there are no known conflicts of interest associated with this publication. There are no financial or personal relationships that could inappropriately influence or bias the content of this work.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study. All participants were fully informed about the purpose, procedures, potential risks, and benefits of the research prior to their involvement. Written or verbal consent was documented in accordance with applicable ethical guidelines, and participation was entirely voluntary.

ETHICAL APPROVAL

Ethical approval was not required for this study, as it involved only publicly available secondary data. The data used in this research were anonymized and did not contain any personally identifiable information. As such, the study did not involve direct interaction with human subjects and was exempt from institutional review board (IRB) or ethics committee approval under relevant regulations.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [WD], upon reasonable request.

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