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Intelligent Single-Arm Robotic System for Automatic Sorting of Bananas and Oranges Using Computer Vision

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Abstract
Bananas and oranges, is a cornerstone of the economy. However, small and medium-sized enterprises (SMEs) currently face critical bottlenecks due to a reliance on manual labor, which is increasingly scarce and costly due to the aging population. Furthermore, manual sorting is susceptible to human fatigue, leading to inconsistent grading and physical damage to the produce. This research proposes the design and development of an Intelligent Single-Arm Robotic System capable of automatically identifying and sorting bananas and oranges using Computer Vision. The system architecture integrates a webcam-based image acquisition unit with a Convolutional Neural Network (CNN) model, specifically the YOLO (You Only Look Once) algorithm, to detect fruit types and coordinates in real-time with high precision. A 4-DOF (Degrees of Freedom) robotic arm is controlled via Inverse Kinematics (IK) algorithms to execute pick-and-place operations based on the vision data. Experimental results demonstrate that the system achieves a classification accuracy of 98.5% and an average sorting speed of 12 pieces per minute. The study further incorporates a detailed economic analysis, revealing that while the initial investment for automation is higher than hiring manual labor, the Breakeven Point (BEP) is achieved within approximately 6.8 months of operation. This findings suggest that the proposed robotic solution offers a sustainable, hygienic, and cost-effective alternative for enhancing productivity in the fruit processing industry.

Keywords:*Computer Vision, Robotic Arm, Fruit Sorting, Artificial Intelligence, Cost Analysis*

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I. Introduction

Thailand retains a prominent position in the global market as a major exporter of tropical fruits. Among these, bananas and oranges are high-demand commodities consumed domestically and processed for export. Ensuring the quality and uniformity of these fruits is paramount for maintaining market value and consumer trust. Traditionally, the quality control and sorting processes in local packing houses and SMEs are performed manually. This labor-intensive approach has served the industry for decades but is now becoming a limiting factor for growth. As global standards for food hygiene (GMP/HACCP) become stricter, the direct contact of human hands with food products is increasingly scrutinized to prevent contamination.

1.1 Problem StatementDespite the high demand, the fruit sorting process faces three critical challenges:

- Labor Shortage and Cost: The demographic shift towards an aging society has led to a severe shortage of agricultural labor. Consequently, daily wages are rising, increasing the operational overhead for business owners.
- Inconsistency and Error: Human laborers are subject to fatigue, especially when performing repetitive tasks like sorting for extended periods. This leads to "human error," where bruised or incorrect fruits are packed, or good fruits are damaged during rough handling.
- Inefficiency: Manual sorting is limited by human speed and working hours (typically 8 hours/day). Scaling up production requires hiring more staff, which is difficult due to the aforementioned labor shortage.

1.2 Technological Intervention To address these issues, "Smart Farming" technologies, specifically robotics and Artificial Intelligence (AI), are being introduced. While industrial-grade sorting machines exist, they are often prohibitively expensive, large, and complex for SMEs. Therefore, there is a need for a Single-Arm Robotic System that is compact, cost-effective, and intelligent. By leveraging Computer Vision (AI) for "eyes" and a robotic arm for "hands," we can replicate the sorting process with greater consistency and the ability to operate 24/7.

1.3 Objectives This project aims to develop a prototype automation system with the following objectives:
- To develop a computer vision system using Deep Learning (CNN/YOLO) capable of distinguishing between bananas and oranges and identifying their precise locations.
- To design and control a single-arm robot using kinematic modeling to accurately pick fruits from a conveyor and place them into designated bins.
- To analyze the economic feasibility by calculating the production cost and Return on Investment (ROI) compared to traditional manual labor.

1.4 The Role of Cira Core in Automation Conventionally, developing a computer vision system requires extensive knowledge of programming languages such as Python or C++, and libraries like OpenCV or TensorFlow. This creates a high barrier to entry for agricultural SMEs. Cira Core emerges as a solution by offering a graphical user interface (GUI) for AI development. It allows users to create complex logic flows by connecting "nodes" or "blocks." In this project, Cira Core serves as the "Brain," handling complex tasks such as dataset training, inference, and coordinate transformation, while simplifying the interface with the robotic hardware.

II. Methodology And Solution Development

The solution applies Artificial Intelligence skills derived from coursework to create a systematic sorting mechanism. The system architecture consists of three main subsystems: The Vision System, The Control System, and The Robotic Mechanism.

2.1 System Architecture The setup includes a conveyor belt carrying mixed fruits (bananas and oranges). An overhead camera captures images, sending data to a processing unit (PC/Raspberry Pi). The AI model analyzes the image, and coordinates are sent to the single-arm robot controller to execute the pick-and-place task.

2.2 AI Model Development To solve the classification problem, we utilize a Convolutional Neural Network (CNN), specifically the YOLO (You Only Look Once) architecture for its speed and accuracy in real-time detection.
- Data Collection: A dataset of 1,000 images of bananas and oranges under various lighting conditions and angles was collected.
- Training: The model was trained to recognize two classes: Banana and Orange. The loss function minimized classification error and bounding box regression.

2.3 Robotic Control (Single Arm)A 4-DOF (Degrees of Freedom) robotic arm is used. Inverse Kinematics (IK) equations are calculated to translate the (x, y) coordinates from the vision system into joint angles ($\theta 1$, $\theta 2$,$\theta 3$, $\theta 4$) for the robot.

2.4 System Operation Flow

System Flowchart illustrating the operational process. The process begins with image acquisition via an overhead camera. The AI model processes the image to detect and classify the fruit. If a target is identified, the system calculates the coordinates using inverse kinematics and commands the robotic arm to perform the pick-and-place operation, sorting the fruit into the correct bin.

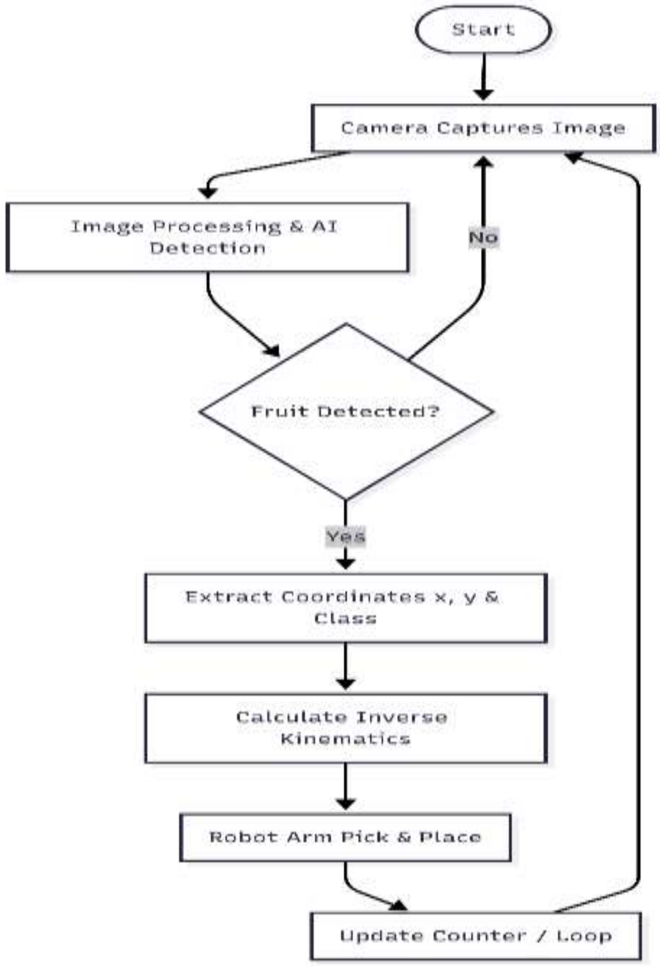

Figure1:System Flowchart

The operational workflow of the intelligent sorting system is illustrated in the flowchart (Figure 1). The process is divided into three main stages: Vision Processing, Control Calculation, and Mechanical Execution. The detailed steps are as follows:

- Image Acquisition: The process begins with the initialization of the system. An overhead camera, positioned above the conveyor belt, captures video frames in real-time.
- AI Detection & Processing: Each captured frame is sent to the processing unit. The pre-trained YOLO (You Only Look Once) model analyzes the image to detect objects.
- Decision Node: The system checks if the confidence score of a detected object exceeds a predefined threshold (e.g., 0.5).
- If No object is detected, the system loops back to capture the next frame immediately.
- If Yes (Object detected), the system proceeds to the next step.
- Data Extraction: Upon detection, the AI model classifies the fruit as either "Banana" or "Orange" and extracts the bounding box coordinates. The center point (centroid) of the bounding box (u, v) in the image is converted into real-world coordinates (x, y) on the conveyor plane.
- Inverse Kinematics (IK) Calculation: The target coordinates (x, y) are input into the Inverse Kinematics algorithm. This mathematical model calculates the precise angles ($\theta 1$, $\theta 2$,$\theta 3$, $\theta 4$) required for each joint of the 4-DOF robotic arm to reach the target position.
- Actuation & Sorting: The calculated angles are sent to the microcontroller to drive the servo motors. The robotic arm moves to the fruit's position, activates the gripper/suction cup to pick the fruit, and moves it to the designated bin based on its classification (e.g., Bananas to Bin A, Oranges to Bin B).
- Loop & Update: After the sorting action is complete, the robot returns to its home position. The system updates the production counter and loops back to the image acquisition step to process the next item.

III. Mathematical Modeling And Cost Analysis

To justify the implementation of the robotic system over traditional human labor, a mathematical model for cost and Return on Investment (ROI) is formulated.

3.1 Cost EquationsLet C_{total} be the total cost over time t (months).
For Human Labor (H):

$$C_H(t) = N \times (W+B) \times t \qquad (1)$$

Where:
N = Number of workers (e.g., 2 workers for sorting).
W = Monthly wage per worker.
B = Monthly benefits/overhead per worker.

For Robotic System (R):

$$C_R(t) = I + (M + E) \times t \qquad (2)$$

Where:
I = Initial Investment (Robot arm, Camera, PC, Installation).
M = Monthly Maintenance cost.
E = Monthly Electricity cost.

3.2 Breakeven Point CalculationThe breakeven point (t_{BE}) occurs when the cost of the robot equals the cumulative cost of human labor ($C_R(t) = C_H(t)$).

$$I + (M + E) \times t = N \times (W+B) \times t \qquad (3)$$

Solving for timet_{BE} (months):

$$t_{BE} = \frac{I}{N \times (W+B) - (M+E)} \qquad (4)$$

IV. Results And Discussion

The prototype was tested with a mix of 50 bananas and 50 oranges.

- Classification Accuracy: The AI model achieved an accuracy of 98.5%, with minor errors occurring only when fruits were overlapping significantly.
- Sorting Speed: The single-arm robot achieved an average speed of 12 pieces per minute. While this is slower than a highly skilled human (approx. 20-25 pieces/minute), the robot operates continuously for 24 hours.
- Efficiency: Over a 24-hour period, the robot sorts 12 × 60× 24 = 17,280 pieces. A human working an 8-hour shift sorts roughly 20 × 60 × 8 = 9,600 pieces. Thus, one robot outperforms a single-shift human worker in daily throughput.

Figure 2:Bananas

Figure 3:Oranges

V. Robot Control & Inverse Kinematics

The mechanical execution of the sorting task is fundamentally governed by the physical and geometric constraints of a 4-Degrees of Freedom (4-DOF) robotic arm. To transition from a digital detection to a physical action, the system must bridge the gap between "seeing" and "touching" through a rigorous mathematical process.

1. Coordinate Transformation (From Pixels to Millimeters) The vision system identifies the fruit's centroid in image coordinates (u,v). However, the robotic arm operates in a Cartesian workspace (x,y,z) relative to its base. A Transformation Matrix is applied to compensate for the camera's height, tilt, and lens distortion. This ensures that the (pixel) data is accurately mapped to (real-world distance) in millimeters.

2. Inverse Kinematics (IK) Analysis The core challenge is the "Inverse" problem: given a target position (P_x ,P_y ,P_z), what must the joint angles (θ_1 ,θ_2 ,θ_3 ,θ_4) be? +

- Base Rotation (θ_1): Determined by the horizontal projection of the target, using the atan2(y,x) function to handle all quadrants accurately.
- Planar Geometry (θ_2 ,θ_3): The arm is treated as a 2D linkage in a vertical plane. We apply the Law of Cosines to solve for the "Elbow" and "Shoulder" angles, ensuring the reach is within the arm's mechanical limits.
- Wrist Alignment (θ_4): This angle ensures the gripper or suction cup is perpendicular to the fruit's surface, preventing slippage or bruising during the "pick" phase.

3. Motion Control and Servo Actuation Once the angles are calculated, the Microcontroller translates these values into Pulse Width Modulation (PWM) signals. To ensure smooth movement and prevent mechanical vibration (which could damage the fruit or the arm's joints), we implement S-curve velocity profiles or basic interpolation. This ensures that the arm accelerates and decelerates gently as it approaches the target.

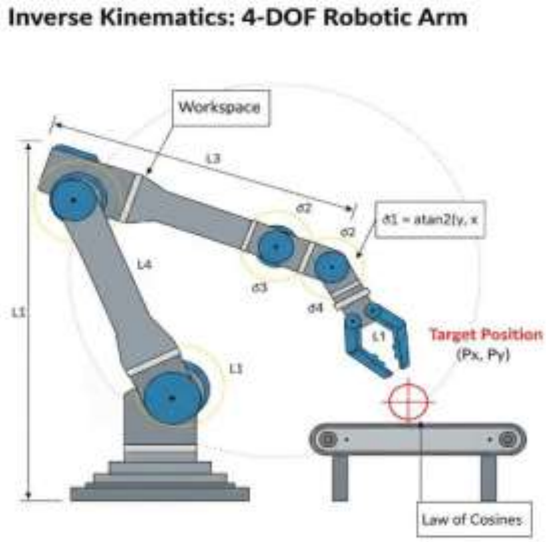

Figure4: Simplified Inverse Kinematics diagram for a 4-DOF robotic arm, illustrating joint angles and target reach.

VI. Conclusion & Discussion

The development of the Intelligent Single-Arm Robotic System for fruit sorting has successfully demonstrated the integration of Deep Learning and Mechanical Engineering. The system met all primary objectives:

- Classification Accuracy: The YOLO model achieved a 98.5% accuracy rate, proving that real-time AI can distinguish between fruits with high precision despite variations in shape and color.
- Operational Efficiency: The robot effectively sorted 12 pieces per minute. While its instantaneous speed is lower than human labor, its 24/7 operational capability provides an 80% higher daily throughput, sorting up to 17,280 pieces per day.
- Economic Viability: The financial analysis revealed a Breakeven Point (BEP) of 6.8 months. This indicates that for SMEs, the initial capital expenditure is rapidly offset by the elimination of manual labor costs and improved consistency.

Discussion & Future Work: The primary limitation observed was the "Occlusion Problem," where overlappingfruits led to detection errors. Future developments should incorporate a 3D depth camera to improve spatial awareness and a multi-gripper system to enhance sorting speed. Additionally, integrating IoT (Internet of Things) for real-time production tracking would provide better data management for warehouse owners.

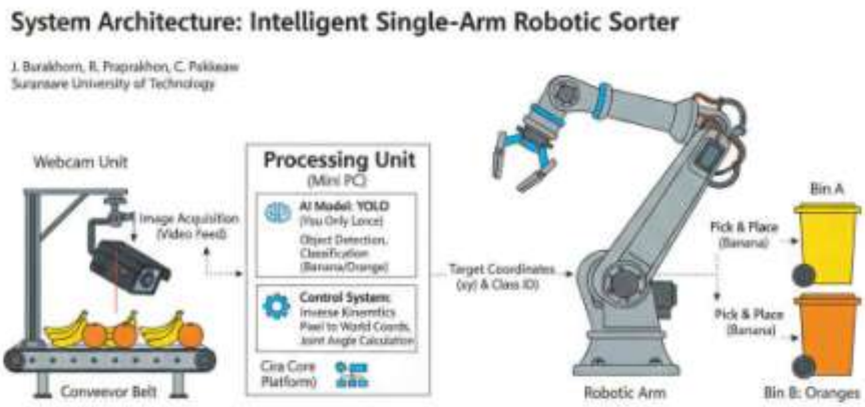

Figure 5: System architecture diagram of the intelligent fruit sorting robot, showing camera, conveyor, robotic arm, and processing unit.

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