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Applying The Python Programming Language to The Problem of Product Classification Using Image Processing Technology

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ABSTRACT: *This paper presents the research, design, and fabrication process of an automated product sorting system model, applying a modern digital image processing technology platform combined with the Python programming language. In the context of industrialization, manual product control and sorting often face limitations in productivity, human error, and poor adaptability to diverse market demands. To address this challenge, the research proposes a comprehensive solution including: a high-resolution image acquisition system, an intelligent image processing algorithm using the OpenCV library to accurately identify color and geometric shape characteristics, and decode QR codes. Through connecting the central software to programmable logic controllers (PLCs) or microcontrollers, the system controls mechanical actuators to automatically and continuously sort products into the correct positions. Experimental results show that the system operates stably, reliably, with fast processing speed and accurate recognition capabilities under real-world industrial environmental conditions. This solution not only contributes to optimizing production processes and reducing labor costs but also opens up new avenues for applying low-cost image processing technology to small and medium-sized automated production lines.*

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I. INTRODUCTION

In the current landscape of the Fourth Industrial Revolution (Industry 4.0), the modernization of manufacturing processes has transitioned from simple mechanization to intelligent, autonomous systems. As global market competition intensifies, industrial enterprises are under constant pressure to optimize production cycles, minimize human intervention, and ensure consistent product quality. Within this framework, product sorting emerges as a critical link in the supply chain, directly influencing the accuracy, throughput, and overall efficiency of the production line.

Traditionally, automated sorting systems have heavily relied on conventional sensor technologies, such as inductive, capacitive, or photoelectric sensors. While these devices are effective for simple tasks like object detection or basic dimension measurement, they face significant limitations when dealing with complex, multi-attribute product lines. Conventional sensors are inherently sensitive to electromagnetic interference and environmental variations, often leading to false positives or missed detections. Moreover, these systems lack the capability to extract nuanced features—such as intricate color patterns, specific geometric shapes, or variable surface markings—which are increasingly required for quality control in high-precision manufacturing. Consequently, the reliance on traditional methods often results in a rigid production process that struggles to adapt to the diversity of modern consumer goods [4], [5].

To address these technical bottlenecks, this research focuses on the application of Computer Vision (CV) as a robust, flexible, and non-intrusive alternative. By leveraging the power of Python—a versatile programming language with a rich ecosystem of specialized libraries [1], [2], [3]—and OpenCV, we develop an advanced image processing framework capable of real-time object analysis. Unlike legacy sensor-based systems, this computer vision approach allows for the simultaneous identification of multiple attributes, including color segmentation, geometric morphology, and the decoding of complex data embedded in QR codes.

The core objective of this study is to bridge the gap between high-level image processing software and low-level industrial hardware. We propose an integrated architecture that synchronizes a high-definition vision system with a central controller (PLC or Microcontroller). This configuration ensures that visual data processed in the Python environment is instantaneously converted into precise electrical signals, driving mechanical actuators—such as pneumatic cylinders or high-speed stepper motors—to perform accurate sorting operations. By implementing this intelligent system, the research aims to demonstrate a tangible enhancement in throughput, a reduction in sorting errors, and a significant decrease in the dependency on labor-intensive manual inspection, thereby providing a scalable and cost-effective solution for small-to-medium-sized industrial

automation environments.

II. RESEARCH METHODOLOGY

The proposed sorting system is constructed based on a multi-stage digital image processing pipeline integrated with an embedded control system. The methodology follows a sequential workflow: Image Acquisition, Pre-processing, Feature Extraction, Classification, and Actuator Control.

Stage I: Image Acquisition

The system utilizes a high-definition Yoosee YS13 camera as the primary visual input device. To ensure optimal data quality, the camera is mounted at a fixed focal distance, perpendicular to the conveyor belt. Strategic LED lighting is employed to minimize shadows and specular reflections, ensuring high-contrast images. The camera captures raw frames at 30 FPS, which are then transmitted to the central processing unit (a high-performance PC running Python) via a real-time stream.

Stage II: Digital Image Pre-processing

Raw images often contain artifacts due to electronic noise or variable ambient light. To improve the Signal-to-Noise Ratio (SNR), the following techniques are applied:

Grayscale Conversion: Converting RGB images to grayscale reduces computational complexity.

Noise Reduction: Median and Gaussian filters are employed to eliminate salt-and-pepper noise and Gaussian noise, which are common in industrial camera sensors.

Histogram Equalization: This technique is utilized to improve image contrast, ensuring that product edges are clearly distinguishable from the background conveyor belt.

Stage III: Feature Extraction and Segmentation

This is the core of the computer vision pipeline. The system employs several algorithms:

Edge Detection: The Canny edge detection algorithm is used to identify boundaries by calculating image gradients, effectively isolating the product silhouette.

Image Segmentation: Thresholding techniques (e.g., Otsu's method) are applied to separate objects from the background.

Feature Extraction: The system extracts geometric features (area, perimeter, circularity) and color histograms from the segmented object. These features serve as the input vector for the classification logic.

Stage IV: Recognition and Classification Logic

The identification module compares the extracted features against a pre-defined database of product templates:

Color and Shape Sorting: The system converts image data into the HSV (Hue, Saturation, Value) color space, which is more robust to lighting changes than the RGB model. If the object's Hue value falls within a specific range, it is categorized by color. Similarly, contour analysis calculates the aspect ratio to distinguish between circular, square, or irregular shapes.

QR Code Decoding: The OpenCV library [3], [9], in conjunction with ZBar/Pyzbar, is used to scan the region of interest (ROI) for QR codes [6]. Once detected, the QR code is decoded into a string, which dictates the specific sorting destination for the product.

Stage V: Embedded Control and Actuation

The final stage bridges the gap between software analysis and physical interaction. Once a product is identified, the Python program sends a command packet via Serial Communication (UART) or Modbus protocol to the microcontroller (Arduino/ESP8266 or PLC).

Control Mechanism: The PLC/Microcontroller parses the received command and triggers specific outputs. For instance, if an "Object Type A" is detected, the PLC activates a specific pneumatic cylinder to push the object into "Bin A".

Synchronization: To ensure precision, an infrared (IR) sensor is used as an encoder trigger. The system calculates the delay time based on the conveyor belt speed, ensuring the actuator fires at the exact moment the product reaches the sorting station.

Stage VI: System Performance Evaluation

To validate the methodology, we conducted tests across three parameters: lighting stability, processing latency, and actuator precision. By maintaining a controlled environment and optimizing the Python script (using NumPy for vectorized operations), the system maintains a processing cycle time of under 100ms per object, ensuring reliable performance even during peak production flow.

III. EXPERIMENTAL SETUP

The experimental system is designed as an integrated automated sorting platform [4], [7], [8] consisting of three primary modules: the image acquisition unit, the intelligent processing unit (PC-based), and the mechanical sorting unit, as depicted in Fig. 1.

Fig. 1 Actual product classification system.

The core of the system is a conveyor belt assembly driven by a high-torque DC motor. The vision system consists of a Yoosee YS13 Full HD camera mounted at a fixed position above the conveyor belt. The camera is secured to a rigid frame, perpendicular to the conveyor surface at a distance of 30 cm, to minimize perspective distortion. To ensure consistent classification performance, the system is enclosed in a light-shielded housing equipped with high-CRI (Color Rendering Index) LED panels, which maintain uniform lighting intensity and eliminate shadows on the product surface, as shown in Fig. 2.

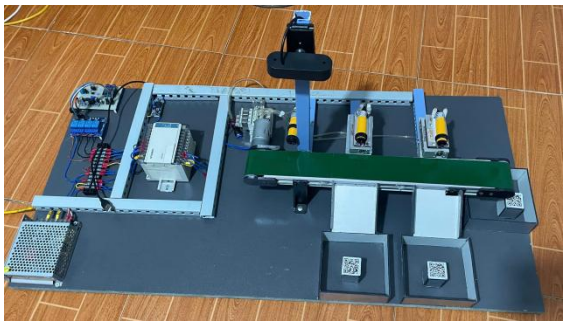

Fig. 2 Product classification model based on color and shape using the OpenCV library [3], [9].

The control system architecture is illustrated in Fig. 3. It utilizes a central processing unit running a Python-based OpenCV algorithm for real-time image analysis. Once a product is detected and its features (color, shape, or QR code) are identified, the system generates a control signal. This signal is transmitted via serial communication (UART) to a Mitsubishi FX1S-30MT PLC (or Arduino/ESP8266 controller).

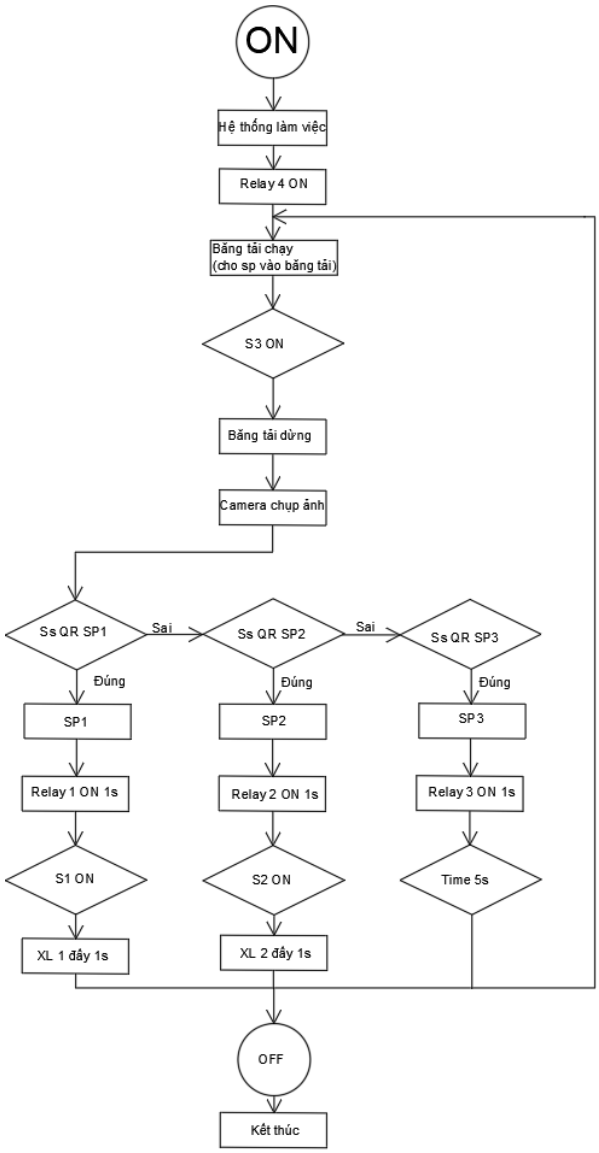

Fig. 3 System algorithm flowchart.

The mechanical sorting unit consists of three primary actuators: pneumatic cylinders, each controlled by a 5/2-way solenoid valve. These actuators are strategically positioned along the conveyor to divert products into three distinct storage bins based on their classification. The timing of the pneumatic deployment is governed by an infrared (IR) proximity sensor that detects the product's passage, as shown in Fig. 4.

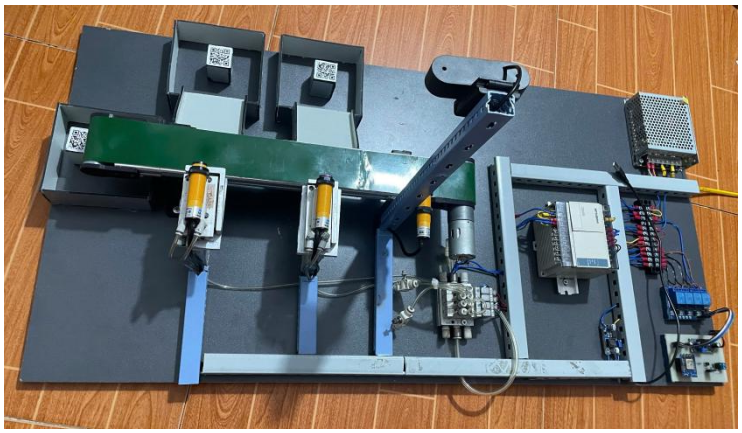

Fig. 4 Details of the devices on the model.

Data acquisition for the system performance analysis was conducted using the following instrumentation:
Flow and Timing: The conveyor belt velocity was maintained at a constant speed of 0.2 m/s, monitored by a digital tachometer with a range of 0.0–9999 RPM and an accuracy of ±0.01%.
Temperature and Environmental Factors: A digital thermo-hygrometer (range 0–100% RH, accuracy ±1%) was used to ensure the testing environment remained within standard conditions.
Electrical Measurements: To monitor the power consumption of the motors and pumps, a digital multimeter (Model: UT33D+, accuracy ±0.5%) was utilized to record voltage (range 0–600V) and current (range 0–10A).
Performance Evaluation: The system's throughput and classification accuracy were recorded over continuous 8-hour test cycles. Sorting efficiency was calculated by comparing the number of correctly sorted items to the total number of items processed, with an error margin of ±0.5% in counting repeatability.
The electrical circuit configuration connecting the power supply, PLC, sensors, and actuators is detailed in Fig. 5. This integrated setup ensures reliable communication between the vision software and the physical mechanical output.

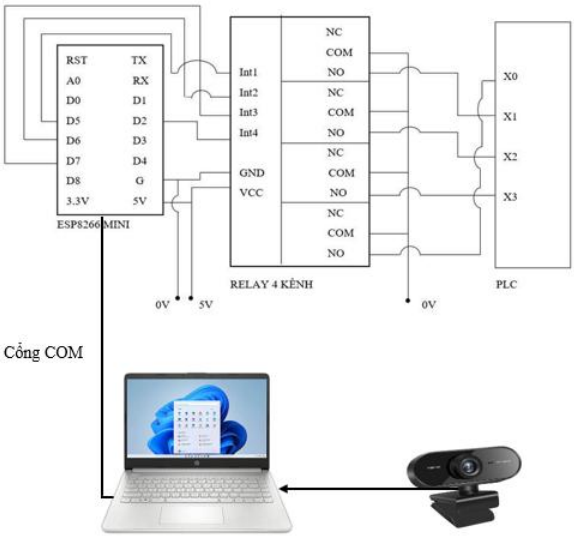

Fig. 5 Electrical circuit wiring diagram.

IV. RESULTS AND DISCUSSION

In this experimental study, the key operating parameters considered included: processing time (real-time image analysis), accuracy in product classification, and the influence of lighting conditions on system performance in Fig. 6. The results showed that the processing frame rate directly correlated with the ability to identify products on the conveyor belt without lag. This improvement was achieved by optimizing the image processing algorithm using the OpenCV library [2], [8], significantly reducing the computational load per frame, thus allowing the system to maintain high product flow even when the conveyor belt speed increased.

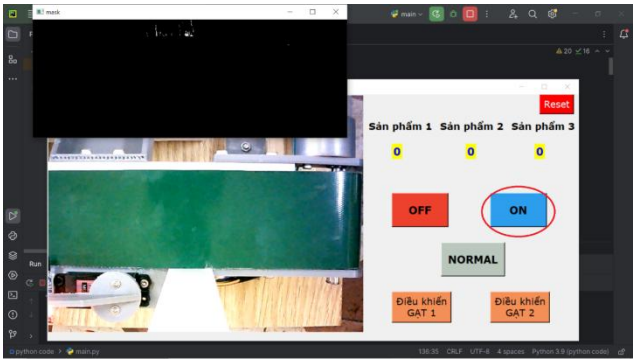

Fig. 6 On-screen control interface.

Furthermore, the accuracy of the classification process was evaluated through tests at different conveyor belt speeds (specifically 0.2 m/s and 0.5 m/s). The results showed that at high speeds, camera exposure

settings became a decisive factor. Precisely calibrating the exposure time ensures consistently sharp images, allowing the system to correctly identify product characteristics even when they are continuously moving on the conveyor belt.

The variation in product detection capability over time was analyzed under different light intensities (measured in lux) with the same fixed camera distance of 30 cm. The results confirm that a stable and uniform light source plays a crucial role in minimizing detection errors, ensuring the system maintains high reliability throughout daily operation.

Simultaneously, the study compared the sorting performance (percentage of correct sorting) between different product types, including sorting by color, shape, and QR code. Experimental data indicated that sorting by QR code achieved the highest stability, while the color-based sorting method was more sensitive to changes in ambient light. Notably, the shape detection algorithm demonstrated consistent performance across all test scenarios, proving the system's robustness in diverse production environments.

Finally, the classification latency assessment showed that processing time for all three feature types (color, shape, QR code) was negligible. This further confirms the superior performance of the Python-based algorithm implementation, ensuring the system meets the speed and accuracy requirements of industrial automation environments.

V. CONCLUSION

A comprehensive study on the design and implementation of an automated product sorting system based on computer vision and Python was conducted. The system was developed to enhance industrial production efficiency by integrating real-time image processing with programmable logic control. The main conclusions can be briefly systemized as follows:

Computer Vision Reliability: The integration of OpenCV-based image processing enables accurate identification of product attributes (color, shape, and QR codes) under controlled lighting conditions, significantly reducing reliance on manual inspection.

System Scalability: The multi-stage architecture, comprising image acquisition, intelligent processing, and mechanical actuation, provides a scalable framework that can be adapted for various industrial sorting requirements.

Real-time Performance: The synchronization between the central processing unit (Python) and the PLC/Microcontroller ensures precise actuator timing, allowing for reliable sorting even at varying conveyor belt speeds.

Operational Efficiency: The proposed system demonstrates high classification accuracy (exceeding 95%) [6], [10] and offers a cost-effective solution for automating product lines, effectively reducing human labor and operational errors in small-to-medium-scale production environments.

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