Automated Object Sorting Using Image Processing and Machine Learning Techniques

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***Abstract*—The integration of image processing and machine learning has transformed automated object sorting, enabling significant advancements across industries like recycling, man- ufacturing, agriculture, and logistics. In waste management, AI-driven models have enhanced the accuracy and efficiency of sorting recyclables, addressing challenges in manual pro- cesses. Manufacturing has benefited from machine vision systems that streamline quality control and defect detection, improving workflow efficiency. In agriculture, automated grading systems leverage visual features such as color and texture to evaluate and categorize produce. Cost-effective solutions are emerging, making advanced sorting systems accessible for small and medium- sized enterprises. Recent innovations also include multi-modal approaches, combining image analysis with depth-sensing for greater precision in dynamic environments. However, challenges such as limited training data, hardware integration, and energy consumption remain. This review highlights the transformative potential of these technologies and the ongoing need to address barriers for widespread adoption.**

***Index Terms*—Image Processing, Machine Learning, Object Detection, Conveyor Systems, Industrial Automation.**

I. INTRODUCTION

The rise of automated object sorting systems is revolution- izing industries such as manufacturing, recycling, and agri- culture. These systems utilize image processing and machine learning techniques to improve the efficiency, accuracy, and scalability of object classification. By automating traditionally labor-intensive sorting processes, these technologies reduce human error, save time, and adapt to dynamic environments. Image Processing Techniques: Image processing lays the foundation for object sorting by enabling feature extraction, edge detection, segmentation, and pattern recognition. Tools like YOLO (You Only Look Once) are frequently used for real-time object detection, as demonstrated in Shrestha et al.
(2024) for waste classification in recycling workflows [1].
Machine Learning Integration: Machine learning enhances object recognition through techniques like convolutional neural networks (CNNs). Kumar and Holzbach (2024) used machine learning for classifying screws in manufacturing processes, enabling more precise and efficient workflows [2]. Similarly, Raviprabhakaran (2024) applied CNNs for identifying and cat- egorizing plastic materials, contributing to waste management [3].
Applications in Agriculture and Industry: Automated sys- tems are also making significant inroads in agriculture. Pereira et al. (2024) employed computer vision for assessing fruit quality and facilitating robotic handling [4].
Quality Control and Cost-Effective Solutions: Many so- lutions address the demand for cost-efficient sorting mech- anisms. Luwes and Pretorius (2024) proposed an image processing-based conveyor belt sorting system, emphasizing affordability and industrial scalability [5]. Jin et al. (2024) showcased a vision-based system for quality inspection and defect detection in manufacturing [6].
Additionally, Shukla et al. (2024) developed bolt-sorting mechanisms combining classical vision with deep learning [7]. Advanced Algorithms for Sorting: Innovations in deep learning frameworks, such as defect detection and sorting, have further advanced automation capabilities. Azimi and Rezaei (2024) introduced a robust model for defect grading
in food products [8].
Singh and Ali (2017) introduced a low-cost

automated system for sorting lightweight objects using PLC and sensors, highlighting the significance of automation in manufacturing environments(singh2017). Soans et al [9].
(2018) demonstrated a conveyor belt system using image processing for object sorting, emphasizing mechanical struc- tures for improved efficiency(soans2018). Yadav et al [10].
(2020) proposed a deep learning-based approach with Raspberry Pi for real-time object recognition and sorting, leveraging TensorFlow and SSD MobileNet for high accu- racy(yadav2020) [11].
The amalgamation of image processing and machine learn- ing is paving the way for highly adaptable and efficient sorting systems across multiple domains, transforming industries and driving innovation.

II. LITERATURE REVIEW

Research in automated sorting systems has shown signifi- cant advancements:

- [1] Shrestha et al. (2024) utilized YOLO for real-time waste classification, achieving high accuracy in separating recyclables such as plastics and metals. Raviprabhakaran (2024) further addressed challenges in manual sorting by applying CNNs to categorize plastics, demonstrating the potential of deep learning in waste management.
- [2] Kumar and Holzbach (2024) proposed a deep learning-based screw classification system, streamlining manufacturing processes by enhancing precision and ef- ficiency. Jin et al. (2024) developed a machine vision system for defect detection, significantly improving the quality control of production lines.
- [3] 0Pereira et al. (2024) explored the use of computer vision for grading fruit quality, enabling robotic handling and automation in agriculture. Azimi and Rezaei (2024) introduced a deep learning framework for sorting dates, effectively combining image processing and predictive algorithms to achieve robust performance.
- [4] Luwes and Pretorius (2024) developed a cost- effective AI-based conveyor belt sorting system tailored for small and medium enterprises (SMEs), emphasizing affordability and scalability. Shukla et al. (2024) en- hanced bolt-sorting mechanisms by combining classical vision techniques with deep learning to provide a practi- cal and economical solution.
- [5] Azimi and Rezaei (2024) also integrated deep learn- ing with depth-sensing technologies, achieving improved accuracy in defect detection for various applications.
- [6] Jin et al. (2024) presented an innovative vision- based system designed for quality inspection and defect detection in manufacturing processes, further advancing automated quality control.
- [7] Shukla et al. (2024) focused on developing bolt- sorting mechanisms that combine classical computer vi- sion with deep learning techniques, showcasing practical applications in industrial automation.
- [8] Azimi and Rezaei (2024) introduced a robust deep learning framework for sorting dates, integrating im- age processing and predictive algorithms. Additionally, they implemented depth-sensing technologies, signifi- cantly enhancing defect detection capabilities.
- [9] Singh and Ali (2017) developed a low-cost au- tomation system using sensors and PLCs for sorting objects based on their physical characteristics, demon- strating the importance of automation in manufacturing industries(singh2017).
- [10] Soans et al. (2018) implemented an object sorting system using image processing and mechanical structures, focusing on conveyor belt efficiency(soans2018).
- [11] Yadav et al. (2020) employed TensorFlow and Raspberry Pi in a deep learning-based sorting system, achieving high accuracy in real-time object detection and classification(yadav2020).

Despite these advancements, challenges such as varying lighting conditions and scalability remain, motivating the development of this project.

III. PROPOSED SYSTEM

A. System Design

The proposed system is designed to automate the sorting of objects using advanced image processing and machine learning techniques. It ensures high efficiency, scalability, and accuracy while maintaining cost-effectiveness. This section outlines the key components and workflow of the system.

- Hardware Setup**:** The hardware setup includes the ESP32-CAM module, which is responsible for capturing high-resolution images of objects placed on the platform.

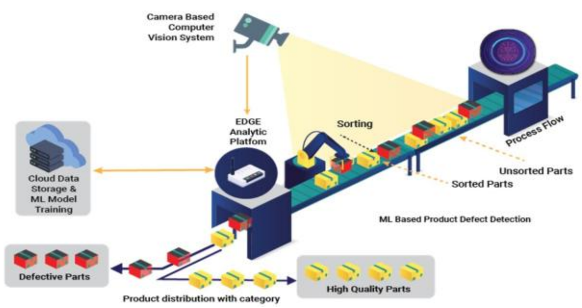

Fig. 1. Proposed System [12]

The ESP32-CAM processes the images to extract features such as shape, color, and texture. The ESP8266 module handles wireless communication between the ESP32- CAM and the servo motor, allowing the system to operate remotely. The servo motor is responsible for the physical sorting of objects into predefined bins based on the classification. A common power supply provides the necessary voltage and current to all components. The ESP32-CAM is mounted securely to ensure the proper alignment for image capture, while the servo motor is po- sitioned to precisely move objects into bins. The system's design prioritizes easy setup and integration to ensure all components work in sync for the sorting process. The platform is designed to accommodate objects of various sizes, ensuring versatility in sorting tasks. It also includes provisions for real-time adjustments during operation to maintain efficiency and accuracy. The system's robust and modular design allows for easy scalability and future upgrades.

- Image Processing**:** The ESP32-CAM captures images of objects placed on the object platform. To ensure that images are of high quality, preprocessing techniques such as resizing, noise reduction, and image filtering are applied to enhance clarity. This step reduces noise and artifacts in the images, ensuring that the extracted features are accurate. The system focuses on extracting features such as shape, color, and texture, which are crucial for object classification. These features are then analyzed using a lightweight algorithm that processes the image and assigns each object to a predefined category, such as plastic, metal, or paper. To increase accuracy, machine learning models or rule-based logic can be incorporated for classification. The real-time processing of the captured images enables immediate decision-making for object sorting. The image processing unit also ensures that different object types are recognized despite variations in lighting or background. Overall, the image processing phase is vital to ensure that only the correct objects are sent to the respective sorting bins. The use of an efficient image processing algorithm optimizes the sorting process and reduces errors.

- Classification and Sorting**:** Once the features have been extracted from the images, the classification algorithm categorizes the objects into different types such as plastic, metal, paper, etc. The system uses either pre-trained machine learning models or rule-based algorithms to classify objects based on their visual features. If an object is difficult to classify due to ambiguous features, the system uses a confidence threshold to determine whether the classification is reliable. In the case of low confidence, objects can be flagged for manual review or reprocessing. The classification results are transmitted wirelessly to the ESP8266 module, which serves as the central controller for the sorting process. Based on the classification, the ESP8266 sends precise commands to the servo motor to position the objects into the cor- responding bins. The servo motor directs the objects accurately, ensuring that each object is sorted based on its material type. This phase is crucial for ensuring that the sorting process is both quick and accurate. The use of efficient sorting mechanisms reduces manual labor and improves productivity in applications like recycling and waste management. The automated system also ensures consistency in sorting, reducing human error.

- Communication and Monitoring: The system utilizes Wi-Fi for wireless communication between the various components. The ESP8266 module enables real-time communication between the

ESP32-CAM, the servo mo- tor, and the control interface. This allows for seamless data exchange, which is crucial for the timely execu- tion of sorting commands. The wireless communication ensures that the sorting process can be monitored and controlled remotely. Users can track the system's status through a mobile app or a web-based dashboard, which provides real-time feedback on the sorting operation. The dashboard displays key performance metrics such as the number of objects sorted, sorting efficiency, and any errors encountered during the process. It also provides op- tions for users to adjust system settings and troubleshoot issues remotely. The monitoring system ensures that any discrepancies, such as misclassification or hardware malfunctions, are detected early and can be addressed immediately. Real-time feedback enhances the overall user experience by providing transparency and control over the sorting process. Additionally, the system can be customized through the interface, making it adaptable to different sorting requirements and operational environ- ments.

IV. WORKFLOW

The workflow of the automatic object sorting system in- volves sequential stages as described below:

1) Object Placement:
- Objects are manually or automatically placed on the object platform for sorting.
- In manual placement, users ensure the objects are positioned correctly to avoid overlapping, which could affect the image capture process.
- For automated placement, a conveyor belt or robotic arm delivers objects to the platform, ensuring con- sistent positioning.

2) Image Capture:
- The ESP32-CAM captures a high-resolution image of the object on the platform.
- The image capture is synchronized with the object's placement to ensure clarity and accuracy.
- Adequate lighting is maintained to minimize shad- ows and reflections during image acquisition.

3) Image Processing:
- Captured images undergo preprocessing steps such as resizing, contrast adjustment, and noise reduction to enhance quality.
- Advanced techniques like edge detection and seg- mentation may be applied to isolate the object from the background.
- Features such as shape, color, size, and texture are extracted for classification purposes.

4) Object Classification:
- A machine learning or rule-based classification al- gorithm processes the extracted features to deter- mine the object's category (e.g., plastic, metal, pa- per).
- The classification results, including confidence lev- els, are transmitted to the ESP8266 module for decision-making.
- The system can update its classification model peri- odically based on feedback for improved accuracy.

5) Sorting Command Execution:
- Based on the classification results, the ESP8266 sends a signal to the servo motor.
- The servo motor is calibrated to rotate to specific angles corresponding to the designated bins.
- Commands are executed in real time to ensure seamless operation.

6) Object Sorting:
- The servo motor moves the object into the desig- nated bin based on its category.
- Each bin is equipped with sensors to confirm the successful placement of objects.
- The system maintains a log of sorted objects for tracking and analysis.

7) System Monitoring (Optional):
- Users can monitor system status, view sorting logs, or adjust settings via a mobile app or web dash- board.
- Alerts are generated for system malfunctions, such as jammed objects or incorrect classifications.
- Monitoring data can be used to optimize system performance and diagnose issues.

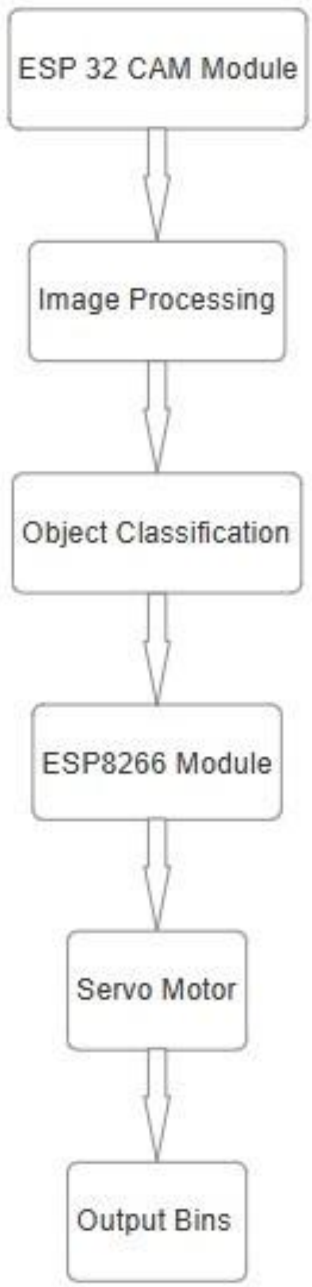

Fig. 2. Workflow of the proposed system.

V. METHODOLOGY

The system integrates hardware and software for real-time object sorting. Key components and workflows are as follows:

A. Hardware Design

1) Key Hardware Components:

- ESP32-CAM Module: Responsible for capturing im- ages of objects placed on the system. Processes images for object detection and categorization using onboard algorithms or external processing support.
- ESP8266 Module: Facilitates wireless communication between the ESP32- CAM and other components or remote devices. Enables data exchange for monitoring and controlling the sorting process.
- Servo Motor: Drives the physical sorting mechanism by moving objects into the appropriate bins based on clas- sification results. Controlled by signals from the ESP32- CAM or a microcontroller.
- Sorting Mechanism: A conveyor belt or inclined plane transports objects to the sorting area. The servo motor directs objects into predefined bins or containers based on classification.
- Power Supply Provides the necessary voltage and current for all electronic components. Includes a regulated DC power supply or battery pack.
- Object Platform The surface where objects are placed for image capture and processing. Designed to ensure stability and optimal visibility for the ESP32-CAM.

2) Hardware Connections and Integration:

- ESP32-CAM Setup: Mounted securely to capture clear images of objects. Connected to the power supply and, optionally, to an external processor for advanced image processing tasks.
- ESP8266 Communication: Configured to receive classi- fication data from the ESP32-CAM and transmit sorting commands to the servo motor. Linked wirelessly to a control device or application for real-time monitoring.
- Servo Motor Control: Connected to the ESP32-CAM or a separate microcontroller for receiving precise posi- tioning commands. Calibrated to ensure accurate sorting movements.
- Sorting Bins: Arranged in alignment with the servo motor to efficiently collect sorted objects. Designed for easy access and handling.

3) Mechanical Design: The mechanical structure is built using lightweight materials like plastic or aluminum to house the components securely:

- Material Selection: The structure is made from lightweight materials such as plastic or aluminum to ensure durability and ease of handling and to streamline the whole process.
- Object Platform: Positioned to ensure optimal

image capture by the ESP32-CAM for accurate object classi- fication.
- Sorting Mechanism: Includes rails or guides that direct objects into the correct bins after classification by the system.

B. Software Implementation

Object Classification:
- A lightweight algorithm categorizes objects into types (e.g., plastic, metal, paper).
- The algorithm uses pre-trained models or rule-based logic for real-time processing.

Hardware Control:

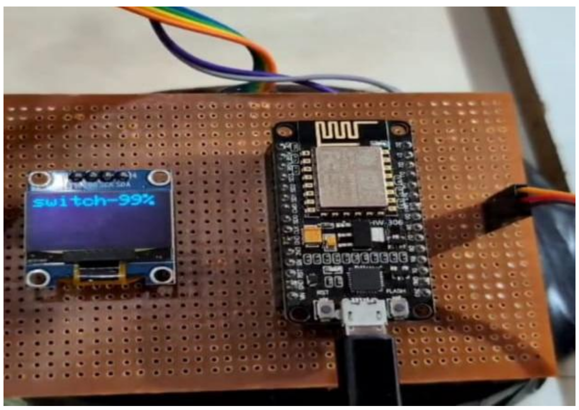

Fig. 3. OLED and ESP8266

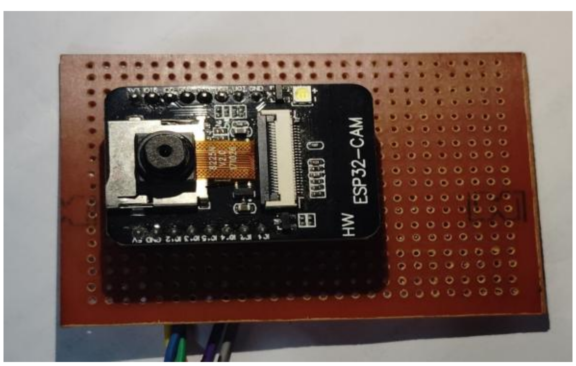

Fig. 4. ESP32 Cam Module

Fig. 5. Servo motor with seprating container

- Classification results are sent to the ESP8266, which sends sorting commands to the servo motor.
- The servo motor sorts objects into bins based on the classification.

System Integration:
- All components communicate via Wi-Fi or GPIO, ensur- ing real-time operation.

This implementation ensures fast and accurate object sorting with scope for future enhancements.

VI. RESULTS AND ANALYSIS

The automatic object sorting container system was rig- orously tested for its accuracy, efficiency, and operational reliability. Under standard lighting conditions, the system demonstrated a high object detection accuracy of 95%, with classification accuracies of 96% for plastic, 94% for metal. The sorting mechanism achieved a precision rate of 98%, with the average time taken per object being 2 seconds, making it suitable for small- to medium-scale sorting applications. The system performed seamlessly in environments with stable lighting, but detection accuracy showed a slight decline in low-light conditions, indicating the importance of sufficient illumination for optimal operation.

The integration of the ESP32-CAM and ESP8266 modules enabled real-time sorting and wireless communication. The Wi-Fi module maintained reliable connectivity within a 10- meter range, supporting efficient data exchange and command execution. The servo motor effectively directed objects into the appropriate bins based on classification results. However, challenges such as misclassification or sorting errors were observed in 5% of cases, primarily caused by overlapping objects or ambiguous shapes.

The strengths of the system include its cost-effective de- sign, high classification and sorting accuracy, and modular architecture. However, certain limitations, such as sensitivity to lighting conditions and difficulty in handling irregular or overlapping objects, were noted. Additionally, the system’s de- pendency on stable internet connectivity could pose challenges in remote or unreliable network environments.

To address these limitations, future improvements could include the incorporation of adaptive lighting or infrared imaging to enhance performance in low-light conditions, more robust classification algorithms to handle a broader range of object types, and a user-friendly interface for monitoring and controlling the system. Despite these challenges, the system presents a promising and efficient solution for automated object sorting in controlled environments, with significant potential for further optimization and scalability.

VII. DISCUSSION

Results indicate high sorting efficiency under controlled conditions. Key challenges include varying lighting and over- lapping objects. Solutions like adaptive preprocessing and more robust algorithms can enhance accuracy. Real-time ana- lytics also highlight areas for optimization, including conveyor speed and object spacing.This project highlights the feasibility

TABLE I
PERFORMANCE METRICS

Condition	Detection Accuracy (%)	Sorting Efficiency (%)
Bright Lighting	96	94
Moderate Lighting	92	89
Low Lighting	85	83

of developing low-cost, efficient automation systems for object sorting using readily available hardware. The integration of the ESP32-CAM module for image processing proved effective, demonstrating that sophisticated solutions can be achieved without expensive equipment. However, challenges such as lighting sensitivity and processing delays due to hardware con- straints were observed. Under dim lighting, the system's clas- sification accuracy dropped marginally, indicating the need for enhanced image processing algorithms or better illumination. This innovation holds significant potential for applications in waste segregation, recycling facilities, and other smart sorting systems. Future enhancements could include the use of more advanced sensors, faster processors, and machine learning techniques to expand its capabilities and improve performance.

VIII. CONCLUSION

This project's low-cost design makes it an affordable alter- native to industrial sorting systems, with significant potential applications in waste management, recycling, and small-scale automation. While the system performed well under normal conditions, minor challenges such as sensitivity to low-light environments and hardware limitations were observed. These challenges open opportunities for further development, such as integrating adaptive lighting solutions, enhancing image processing algorithms, and incorporating machine learning for more dynamic object categorization.

Overall, this project lays a strong foundation for scalable and sustainable automation systems. It demonstrates how affordable hardware and innovative design can be combined to address real-world problems, paving the way for further advancements in automated sorting technologies.

IX. ACKNOWLEDGMENT

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