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Automatic Sorting System in a Production Line using Machine Learning

Md Forhatul Hasan Tamim[1], Md. Khairul Hasan Limon[1], Dr. Shahajada Mahmudul Hasan[1]
[1]Department of Mechanical Engineering, Rajshahi University of Engineering & Technology, Rajshahi-6204, Bangladesh
E-mail: 1802143@student.ruet.ac.bd , 1802131@student.ruet.ac.bd , hasansuclab@gmail.com

Abstract

Quality control is critical for modern manufacturing, driving both customer satisfaction and business success. This study presents a system that uses machine learning to automatically identify and sort faulty products on a production line. The system incorporates a VGA camera, servo motors, and Arduino Uno R3, providing a cost-effective solution to enhance productivity. The underlying model uses YOLOv8, a leading object detection algorithm known for its accuracy and speed. Trained on a dataset of 600 images, this model achieves an 86% success rate in categorizing products as "Faulty" or "Not Faulty", with a confidence level of 0.869. The YOLOv8 architecture, favored for its single-stage design, ensures rapid and efficient processing, making it suitable for real-time applications and deployment in resource-constrained environments. This research demonstrates the potential of machine learning to transform quality control in industrial settings. It offers a robust tool for improving operational efficiency, reducing production errors, and increasing customer satisfaction.

Keywords: Quality Control, Machine Learning, Industrial Automation.

1. Introduction

Industry 4.0 technologies like machine learning and robotics are revolutionizing product sorting and quality control in modern factories [1]. Traditional manual sorting methods are inefficient, time-consuming, and prone to human error. Automated robotic sorting systems promise increased speed, accuracy, and cost savings by leveraging advanced machine vision and intelligent fault detection algorithms. [2]

This study explores the application of machine learning techniques to enhance fault detection capabilities and optimize sorting tasks in industrial robotic systems. Accurate fault identification is crucial for precisely separating defective products and ensuring high-quality output. However, existing methods may struggle with complex or evolving fault patterns, large training data requirements, and a lack of model interpretability. [3]

Recent studies by several researchers focused on developing automated systems for object sorting and quality assurance using machine learning, computer vision, and robotics technologies. The studies highlight the successful implementation of these techniques in various domains, including industrial automation, agricultural product sorting, fault detection, and visual quality assurance in manufacturing. For instance, Vandana et al. (2021) developed a color-based object sorting system using a programmable logic controller and electromagnetic actuators, demonstrating high accuracy and parallel processing capabilities [4]. Adiguna et al. (2023) designed a 5-DoF robot arm that successfully manipulated and sorted objects based on color and size with 91.5% accuracy [5]. However, many of these approaches focus on specific use cases or product types, limiting their scalability and adaptability to diverse manufacturing environments. Yashas et al. (2020) proposed an automated sorting robot using machine learning but acknowledged the need for further optimization and improvements. [6]

In the agricultural domain, machine learning models have been employed for classifying and grading apples based on visual cues, effectively identifying high-quality specimens, and automating the sorting process. Similarly, in the tea industry, a combination of deep learning algorithms and robotic arms has been utilized for efficient online sorting of machine-picked fresh tea leaves, achieving impressive identification accuracy. [7]

The research also emphasizes the importance of computer vision and deep learning techniques in fault detection and visual quality assurance. Convolutional neural networks (CNNs) and transfer learning have shown promising results in detecting faults across various engineering domains, such as photovoltaic solar panels, manufacturing, and electrical systems. [8] [9]

While AI and CNNs have been widely adopted for defect detection, a systematic literature review highlights the need for increased integration of explainable artificial intelligence (XAI) methodologies in visual quality assurance. This would enhance model transparency, foster trust in AI systems, and enable broader applications beyond visual quality control, including process optimization and root cause analysis. [10]

Overall, the studies demonstrate the significant potential of integrating machine learning, computer vision, and robotics technologies for automating sorting, quality assurance, and fault detection processes across diverse industries. However, further research and development are suggested to address limitations, improve accuracy, and explore the integration of XAI methodologies for enhanced transparency and trust in AI-driven quality assurance systems.

By addressing these limitations, this research aims to contribute to a general and cost-effective fault detection and sorting system that can be easily integrated into existing production lines across multiple industries. The system's design emphasizes simplicity, modularity, and affordability, enabling widespread adoption and implementation.

The following sections will present the system architecture, experimental setup, methodology, and results obtained from evaluating the proposed fault detection and sorting system's performance. The discussion will highlight the strengths, limitations, and potential areas for further improvement, ultimately underscoring the significance of integrating advanced technologies to enhance quality control and operational efficiency in industrial settings.

2. Methodology

2.1 System Architecture

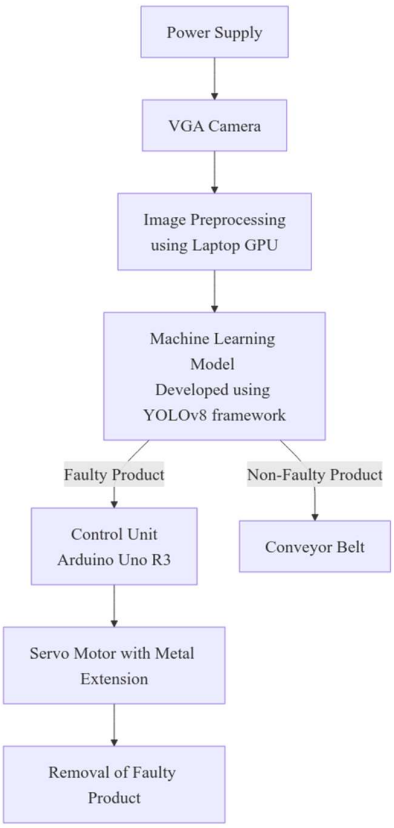


Fig 1: System Architecture of the Fault Detection and Sorting System using Machine Learning

The fault detection and sorting system developed in this research efficiently identifies and removes defective products from a production line while allowing non-defective items to pass smoothly. As shown in Fig. 1, a camera captures images of each item on the conveyor belt, and these images are preprocessed to enhance quality and reduce noise.

A machine learning model trained on 600 images (100 images of the correct product and 500 of faulty products) utilizes the YOLOv8 architecture for object detection and analysis. Visual Studio Code (VS Code) was used for system development, supporting YOLOv8 integration with tools like syntax highlighting and debugging.

The model classifies items as "faulty" or "non-faulty." Upon detecting a fault, it sends a signal to an Arduino Uno R3, which controls a servo motor to direct faulty items onto a separate conveyor belt, maintaining an uninterrupted flow of quality items on the main line. Constant system operation enables real-time fault detection and sorting, enhancing quality control and operational efficiency across the production line.

2.2 System Specification

The fault detection and sorting system utilizes a VGA camera to capture images of every product passing through the production line or conveyor belt. These images undergo preprocessing to enhance quality and remove noise. A machine learning model, trained on a dataset of 600 images including correct products (king chess pieces) and faulty products (other chess pieces), analyzes the preprocessed images to identify defective items.

When a defective product is detected, the machine learning model triggers a signal to the control unit. This control unit, implemented using an Arduino Uno R3 as the processing unit, initiates the removal process. A Tower Pro MG995 metal gear servo with a metal extension is then actuated to physically remove the identified defective item from the production line.

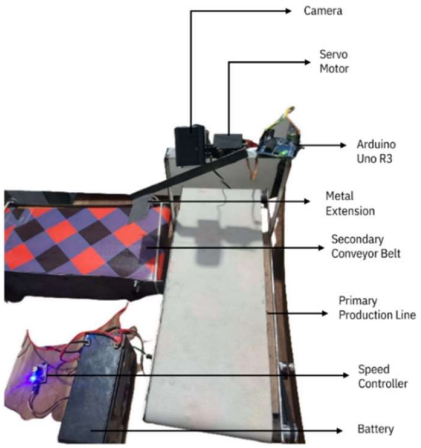


Fig 2: Complete Setup of the Developed System

Non-defective products, identified by the machine learning model, proceed uninterrupted along the conveyor belt system, which is driven by motors. The system is powered by a 12V 2.5A battery, with a laptop containing a dedicated GPU handling computationally intensive image processing and model inference tasks. Male-to-male jumper wires interconnect the components, with additional wiring for power distribution. Figure 2 illustrates the complete setup of the developed automated sorting system, detailing each component and its integration within the conveyor-based design. Overall, the integration of the image acquisition system, preprocessing, machine learning model, control unit, servo actuation mechanism, and conveyor belt enables efficient automated fault detection and sorting, thereby enhancing quality control while maintaining smooth operational flow on the production line.

2.3 Data Collection

The system was evaluated under three different conditions: normal, misaligned, and low light. By testing these varied conditions, the robustness and versatility of the system could be assessed, accounting for potential real-world scenarios where lighting or product positioning may not be ideal. The collected data shown in Table 1.

Table 1: System Performance Data

Obs No.	**Product**	**Condition**	**Correctly Detected?**	**Confidence Level**						
01	King	Normal	Yes	.91		04	Pawn	Normal	Yes	.90
02	King	Normal	Yes	.94		05	Pawn	Normal	Yes	.89
03	Bishop	Normal	No			06	Rook	Normal	Yes	.91

07	Knight	Normal	Yes	.95		26	Bishop	Misaligned	Yes	.72
08	Bishop	Normal	Yes	.94		27	Bishop	Misaligned	Yes	.82
09	Knight	Normal	No			28	Bishop	Misaligned	Yes	.55
10	Rook	Normal	Yes	.90		29	Pawn	Misaligned	Yes	.88
11	Knight	Normal	Yes	.92		30	Pawn	Misaligned	Yes	.88
12	Pawn	Normal	Yes	.93		31	Pawn	Misaligned	Yes	.89
13	King	Normal	Yes	.92		32	Knight	Misaligned	Yes	.93
14	Rook	Normal	Yes	.94		33	Knight	Misaligned	No	
15	Bishop	Normal	Yes	.93		34	Knight	Misaligned	Yes	.9
16	King	Normal	Yes	.89		35	King	Misaligned	Yes	.88
17	Pawn	Normal	Yes	.90		36	King	Misaligned	Yes	.79
18	Rook	Normal	Yes	.89		37	King	Misaligned	Yes	.92
19	Knight	Normal	No			38	Rook	Misaligned	Yes	.74
20	Knight	Normal	Yes	.92		39	Rook	Misaligned	Yes	.85
21	King	Normal	Yes	.91		40	Rook	Misaligned	Yes	.85
22	Pawn	Normal	Yes	.94		41	Knight	Low light	Yes	.76
23	Bishop	Normal	Yes	.90		42	Knight	Low light	Yes	.8
24	Rook	Normal	No			43	Bishop	Low light	Yes	.82
25	Rook	Normal	Yes	.93		44	Bishop	Low light	Yes	.79
						45	King	Low light	No	
41	King	Normal	Yes	.91		46	Rook	Low light	Yes	.71
42	Pawn	Normal	Yes	.94		47	King	Low light	Yes	.84
43	Bishop	Low light	Yes	.82		48	Pawn	Low light	Yes	.78
44	Bishop	Low light	Yes	.79		49	Pawn	Low light	No	
45	King	Low light	No			50	Rook	Low light	Yes	.81

The graph in Fig 3 illustrates the consistency ratios for correctly detecting faulty and non-faulty products under three conditions: Normal, Misaligned, and Low Light. In the Normal condition, the system demonstrated better performance in identifying faulty products. However, in the Misaligned condition, the consistency ratio for detecting faulty products decreased. In contrast, in the Low Light condition, the consistency ratio for faulty products decreased to the lowest point among the three conditions, indicating the lowest performance. Overall, the system exhibited better accuracy in detecting faulty products across all conditions.

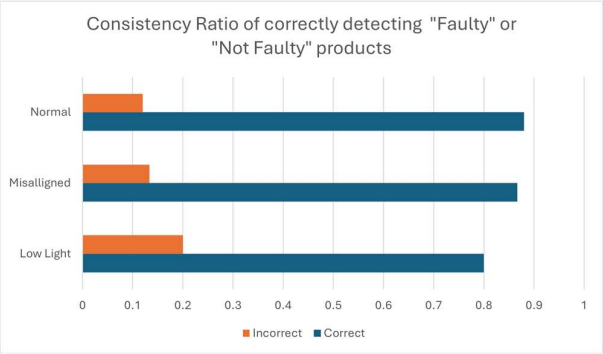


Fig 3: Consistency ratio of the system

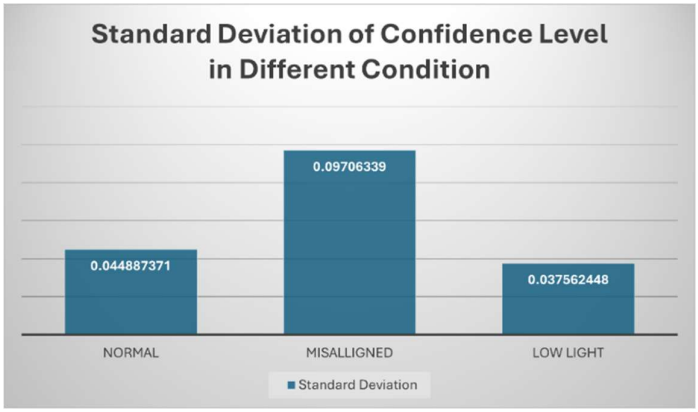


Fig 4: Standard Deviation of Confidence Level

The graph in Fig 4 displays the standard deviation of confidence levels assigned by the system when detecting faulty and non-faulty products across three conditions: Normal, Misaligned, and Low Light. In the Normal condition, with a standard deviation of around 0.04, confidence levels remained consistently low, indicating little variation. Conversely, in the Misaligned condition, the higher standard deviation of approximately 0.10 implies greater variability in confidence levels, indicating less consistency compared to the Normal condition. The Low Light condition, with a standard deviation of approximately 0.03, exhibited the least variability, suggesting consistent confidence levels despite challenging lighting conditions. It's important to note that a lower standard deviation generally indicates more consistent performance, as the confidence levels assigned by the system are clustered closer to the mean value.

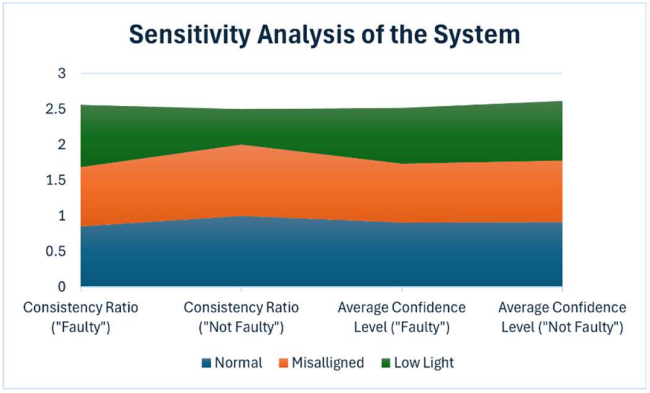


Fig 5: Sensitivity analysis of the system

The graph in Fig 5 highlights that the Misaligned condition exhibits the best performance in terms of consistency ratio for faulty products and average confidence level for faulty products. The Low Light condition appears to be the most challenging for the system, with lower consistency ratios and average confidence levels for both faulty and non-faulty products.

3. Result and Discussion

Out of 50 attempts to find the “Faulty” or “Not Faulty” product, 43 were successful and 7 were unsuccessful. The success rate of the fault detection system is.

$$\text{Success Rate} = \frac{43}{50} * 100\% = 86\%$$

$$\text{Average Confidence Level} = \frac{\sum Confidence\ Level}{Unit} = \frac{37.17}{43} = 0.869$$

The prototype system demonstrated an 86% accuracy rate, as illustrated in Figure 6, correctly identifying faults in 43 out of 50 trials, with the aim of categorizing products as "Faulty" or "Not Faulty." This result was further bolstered by an observed confidence level of 0.869, indicating a high degree of certainty in the system's

predictions and highlighting its potential for effective defect identification. However, it is crucial to note that seven misclassifications occurred, underscoring areas where the system could benefit from further refinement and optimization of its machine-learning model and image-processing techniques. Despite these positive initial results, the presence of misclassifications emphasizes the necessity for continuous improvement efforts. Major challenges that must be addressed include handling the complexities of real-world production environments, such as varying lighting conditions, product orientations, and conveyor speeds, as well as ensuring the system's resilience and adaptability across different product types, sizes, shapes, and surface properties in various manufacturing settings. In comparison to traditional rule-based systems, the machine-learning approach excels in adaptability and efficiency. Rule-based systems, while effective for repetitive and uniform tasks, often require substantial recalibration when defect characteristics change. In contrast, the machine-learning model adapts to new defect types without manual intervention. For instance, the system demonstrated a consistent performance across diverse conditions that typically hinder rule-based methods, such as low-light scenarios where rule-based systems may fail to detect subtle defects accurately.

4. Conclusion

The outcomes of this work yielded precise inferences showcasing the system's promising capabilities. By leveraging machine learning algorithms and image processing techniques, the system exhibited proficiency in accurately distinguishing between "Faulty" and "Not Faulty" products. The image processing component played a crucial role in analyzing visual data captured by the VGA camera and extracting relevant features. Subsequently, the machine learning algorithms leveraged these features to identify patterns and make predictions about whether the products passing through the production line were faulty or not. The integration of YOLOv8 into the image processing pipeline streamlined the quality control process, offering a reliable and automated approach for detecting manufacturing defects. Beyond basic fault detection, Machine Learning offers crucial advantages such as continuous adaptation to new defect patterns, detection of subtle and complex defects that traditional systems might miss, significant reduction in false positives/negatives, easy scalability across different product lines without major system redesign, and predictive capabilities for identifying potential process issues before they become critical. These advanced capabilities, combined with reduced long-term operational costs, provide strong justification for implementing ML over conventional sorting systems in modern manufacturing environments.

5. References

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