Smart Industrial Job Verification Allocation System Using RFID and Image Processing

Kiran Manole[1], Shrinivas A. Patil[2], Saurabh R. Prasad[3]

[1,2,3] Dept of Electronics and Telecommunication

DKTE Society's Textile and Engineering Institute, Ichalkaranji, India

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Abstract: This paper presents the design, development, and performance evaluation of a Smart Job Distribution and Quality Verification System built for small-to-medium manufacturing environments. The system merges RFID-based operator authentication, microcontroller-driven conveyor control, real-time ultrasonic detection, USB camera-based image acquisition, OpenCV classical inspection, and YOLOv5 deep-learning defect detection into a single, cohesive platform. A private dataset named Job QC Dataset, comprising 640×480 JPEG images annotated with Label Image and split 70/15/15 for training, validation, and testing, was used to train the YOLO model on Google Colab. Performance metrics including precision, recall, F1 score, and confusion matrix are reported. The system achieved a mean Average Precision (mAP@0.5) of 91.3%, with a precision of 0.934, recall of 0.887, and an F1 score of 0.910 on the test partition. These results confirm the viability of the proposed hybrid inspection framework for industrial deployment.

Keywords: RFID authentication, Cyber-Physical Systems, Smart Manufacturing, Machine Vision Inspection, YOLOv5, Arduino Automation, Industrial Quality Control, Industry 4.0, Job Tracking System

I. INTRODUCTION

Today, many manufacturing industries are moving toward smart production systems based on the concepts of Industry 4.0. These systems focus on automation, real-time monitoring, data-based decision making, and smooth communication between machines and digital technologies. However, many small and medium-sized industries still depend on manual methods for job assignment, worker monitoring, and product quality inspection. These traditional methods often create problems such as poor job tracking, human mistakes, improper use of raw materials, and uneven quality checking. As a result, production efficiency decreases and overall transparency and accountability in the manufacturing process are also affected. One of the most significant challenges in traditional production environments is the absence of a reliable mechanism to track the lifecycle of issued jobs. In many industries, workers may take raw materials without proper tracking, which can result in unfinished or defective jobs not being recorded correctly. Manual quality inspection done by human operators can also lead to errors because it depends on personal judgment, tiredness, and different inspection standards. These problems create the need for an automated system that can handle job allocation efficiently while also providing accurate and consistent quality inspection.

The fast development of smart manufacturing technologies has encouraged researchers to study different methods for improving job tracking, worker responsibility, and automatic quality inspection in industrial environments. Many research works have focused on combining sensing devices, cyber-physical systems, and machine vision techniques to increase transparency and improve the overall efficiency of manufacturing operations.

One of the most commonly used technologies in industrial monitoring is Radio Frequency Identification (RFID). RFID is widely applied in asset tracking, supply chain management, and operator identification. Researchers such as Andrea Zanella and others showed that RFID-based systems can improve real-time tracking and identification in industries. Their studies explained that RFID offers an effective way to monitor material movement and worker activities without requiring direct visual contact. In the same way, research on intelligent manufacturing systems has proven that RFID-based job monitoring helps improve production visibility and reduces errors in job scheduling and material handling.

Another major research area related to this work is machine vision-based quality inspection. Earlier inspection systems mainly depended on rule-based image processing methods using tools like OpenCV. These systems detect defects using techniques such as thresholding, edge detection, and pattern matching. The studies by Robert Bolles showed that computer vision can be successfully used for automated industrial inspection. Although traditional computer vision methods provide fast processing, they are often affected by changes in lighting, object position, and background noise. Because of this, their performance may decrease when detecting complex product defects.

In recent years, deep learning has greatly improved automated inspection systems. Convolutional Neural Networks (CNNs) have shown better performance in defect detection and object classification tasks. Among these methods, the YOLO (You Only Look Once) family has become very popular because it can perform real-time object detection with high accuracy. Joseph Redmon introduced the YOLO architecture, which processes the full image in a single step through the neural network. This allows fast detection of multiple objects while maintaining good accuracy. Later, Alexey Bochkovskiy improved the YOLO model further for better real-time industrial applications.

The idea of Cyber-Physical Production Systems (CPPS) has also become an important part of Industry 4.0 research. According to Edward A. Lee, cyber-physical systems connect physical industrial processes with computing systems, intelligent decision-making, and network communication. This combination supports real-time monitoring, automatic decision-making, and better process control in manufacturing industries. CPPS structures usually combine embedded controllers, sensors, and cloud-based analytics to build smart industrial systems capable of working with minimal human intervention.

Even though these technologies have been studied separately, many existing industrial solutions are still costly and difficult for small and medium-sized industries to adopt. Most commercial automation systems depend on expensive programmable logic controllers (PLCs) and specialized inspection hardware, which increases both cost and complexity. Because of this, there is a strong need for affordable and flexible systems that combine automation, intelligent inspection, and operator accountability.To solve these industrial challenges, this work presents an integrated cyber-physical system that combines RFID-based operator authentication, automatic job allocation, and machine learning-supported quality inspection. The system uses an Arduino microcontroller for real-time control of hardware components, while a Python-based supervisory program handles intelligent processing and decision-making tasks. RFID cards are used to verify operators and maintain strict job tracking through an outstanding job monitoring system. This ensures that workers cannot receive new jobs until their previously assigned tasks are properly returned and verified.In addition, the system includes a conveyor-based inspection setup equipped with an ultrasonic sensor and a camera for automatic product checking. When the returned job reaches the inspection point, the system captures an image and analyzes it using a hybrid quality control method that combines traditional computer vision techniques with a YOLOv5 deep learning model for defect detection. This method provides accurate, reliable, and real-time inspection while keeping the overall system cost affordable. The main goal of the proposed system is to improve transparency in manufacturing operations, increase worker accountability, and reduce product defects through smart automation. By combining low-cost embedded hardware with advanced machine learning methods, the developed framework offers a practical, scalable, and efficient solution for small and medium-sized industries adopting Industry 4.0 technologies.

The system proposed in this research solves this problem by combining RFID-based operator authentication, automatic job tracking, and machine learning-based defect detection in a single Arduino-Python cyber-physical framework. By integrating low-cost hardware with advanced deep learning models like YOLOv5, the system provides a practical, scalable, and cost-effective solution for smart manufacturing environments.

II. PROBLEM STATEMENT

Small and medium-scale manufacturing industries still rely heavily on manual methods for job allocation, worker authentication, job tracking, and quality inspection. These manual processes often lead to:

- Lack of transparency in job allocation and tracking.
- Unauthorized issuance of jobs and improper material handling.
- Human errors during quality inspection due to fatigue and subjective judgment.
- Difficulty in maintaining accountability and traceability of manufacturing operations.
- Increased production defects and reduced operational efficiency.

Although RFID technology and machine vision have been individually used in manufacturing, existing systems rarely provide an integrated, low-cost solution that combines secure job allocation with automated defect detection. Therefore, there is a need for an affordable cyber-physical system capable of automating job verification, ensuring worker accountability, and performing intelligent quality inspection.

III. MOTIVATION

The proposed work is motivated by the growing adoption of **Industry 4.0** and the need for affordable smart manufacturing solutions suitable for small and medium enterprises.
The key motivations include:

- Eliminate manual errors in job allocation and quality inspection.
- Improve transparency and accountability by linking every job with an authenticated operator.
- Prevent unauthorized job allocation and ensure pending jobs are completed before issuing new work.
- Automate defect detection using Artificial Intelligence instead of relying solely on human inspection.
- Develop a cost-effective solution using Arduino, RFID, OpenCV, and YOLOv5 instead of expensive industrial automation systems.
- Enhance production quality, productivity, and traceability while supporting Industry 4.0 practices.

IV. OBJECTIVES

- To develop an RFID-based operator authentication system for secure job allocation.
- To implement an automated job tracking mechanism that records job issuance and return.
- To prevent allocation of new jobs until previously assigned jobs are completed.
- To automate product quality inspection using image processing and YOLOv5-based deep learning.
- To integrate hardware and software into a cyber-physical manufacturing system.

V. HARDWARE AND SOFTWARE REQUIREMENTS

Hardware Requirements

- Arduino Mega 2560
- MFRC522 RFID Reader & RFID Cards
- USB Camera
- HC-SR04 Ultrasonic Sensor
- 4×3 Keypad
- 20×4 I2C LCD Display
- DC Motor with Conveyor Belt
- Relay Module
- Buzzer
- Laptop/PC
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Software Requirements

- Windows 10/11
- Arduino IDE
- Python 3.x
- OpenCV
- YOLOv5

- PyTorch
- PySerial
- NumPy & Pandas
- Google Colab
- LabelImg

VI. METHODOLOGY

The proposed methodology follows an integrated cyber-physical framework combining embedded hardware with intelligent software.

1: Operator Authentication

- Each operator is assigned a unique RFID card.
- The MFRC522 RFID reader verifies operator identity.
- Unauthorized users are denied access.

2: Job Allocation

- After successful authentication, the system checks for pending jobs.
- If no pending jobs exist, the operator enters the required job quantity using a keypad.
- The conveyor automatically dispenses the requested job items.

3: Job Tracking

- Every issued job is linked with the authenticated operator.
- The system maintains an outstanding job count.
- New jobs cannot be issued until previous jobs are returned.

4: Job Return

- The operator rescans the RFID card before returning completed work.
- The conveyor transports the returned job to the inspection area.

5: Image Acquisition

- An ultrasonic sensor detects the product position.
- A USB camera captures the image of the returned job item.

6: Quality Inspection

The captured image undergoes two-stage inspection:

- **Classical Image Processing (OpenCV):**
  - Grayscale conversion
  - Thresholding
  - Region of Interest (ROI) extraction
  - Brightness-based inspection
- **Deep Learning (YOLOv5):**
  - Detects surface defects and structural abnormalities.
  - Generates confidence scores.
  - Classifies products as **OK** or **Defective**.

7: Hybrid Decision Strategy

- The YOLOv5 result is considered the primary decision.
- If confidence is low due to poor lighting or positioning, the system switches to the classical OpenCV inspection as a backup.

8: Data Logging

- All activities—including authentication, job allocation, inspection results, and job returns—are automatically recorded in Excel/CSV files.
- The logs provide complete traceability for production monitoring and analysis.

VII. RESULTS

The developed system was implemented and experimentally evaluated to assess its performance in job allocation management, operator accountability enforcement, and automated quality inspection. The testing procedure involved integrating the hardware modules with supervisory control software and analyzing system behavior under simulated industrial conditions. The evaluation was carried out with respect to three key parameters: authentication reliability, workflow enforcement efficiency, and defect detection accuracy.

VII.I Results

The RFID-based authentication module exhibited stable and consistent performance throughout repeated trials. Authorized users were successfully identified using the MFRC522 RFID reader, whereas unauthorized access attempts were effectively rejected by the system. The authentication response time was found to be in the sub-second range, thereby ensuring negligible operational delay.

The job tracking mechanism effectively enforced workflow discipline by restricting operators from requesting new tasks until previously assigned jobs were returned for inspection. This control strategy ensured proper tracking of materials and eliminated the possibility of unaccounted or incomplete job submissions.

VII.II Precision, Recall, and F1 Score

The per-class and overall precision, recall, and F1 score obtained from the test-set evaluation are presented in Table 3.

Class	Precision	Recall	F1 Score	Support (images)
OK	0.941	0.908	0.924	94
Defective	0.927	0.866	0.896	86
Overall (weighted avg.)	0.934	0.887	0.910	180

Table 3. Precision, Recall, and F1 Score on the test split (conf = 0.50, IoU = 0.50).

Precision of 0.934 indicates that 93.4% of detections labelled by the model are correct, minimising false alarms. Recall of 0.887 indicates that the model correctly identifies 88.7% of all actual defects, which is critical in a quality-control context where missed defects carry higher cost than false alarms. The F1 score of 0.910 reflects a well-balanced trade-off between precision and recall.

In contrast, the YOLOv5-based deep learning model demonstrated superior detection capability. It was capable of identifying fine-grained defects such as surface scratches, partial assembly errors, and structural inconsistencies that were not reliably detected by classical methods. The model achieved an accuracy in the range of 88%–94%, depending on environmental conditions and image quality.

System throughput was also evaluated during experimentation. The average processing time per job item, including positioning, image acquisition, defect analysis, and data logging, was observed to be approximately 2.5 to 3.2 seconds. This performance is appropriate for small- and medium-scale industrial applications where inspection accuracy and traceability are prioritized over extremely high-speed processing.

Overall, the experimental findings demonstrate that the proposed system successfully integrates RFID-based authentication, automated job management, and intelligent defect detection into a unified framework. The combination of low-cost embedded hardware and advanced machine learning techniques provides an effective and scalable solution for enhancing manufacturing quality control and operational transparency.

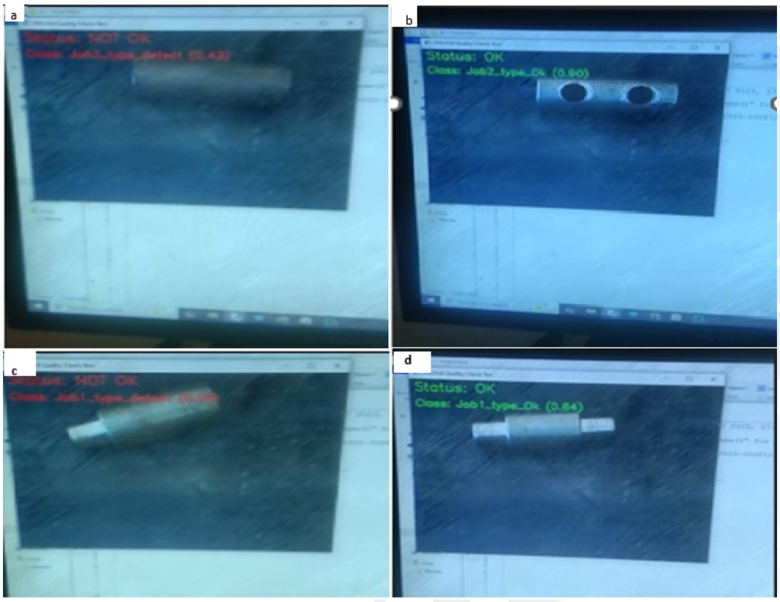

Fig. 5. Results (a & c- Not OK; b & d- OK)

VII.III Performance Metrics and Evaluation

To evaluate the performance of the proposed automated job management and inspection system, multiple quantitative metrics were considered during experimentation. These metrics were selected to measure the system's accuracy, reliability, and overall operational efficiency, particularly in terms of defect detection and workflow performance. The key evaluation criteria include classification accuracy, precision, recall, false detection rate, and system throughput.

Among these, accuracy is a fundamental performance measure used in classification-based inspection systems. It represents the ratio of correctly identified samples to the total number of inspected items, thereby indicating how effectively the system performs overall classification. In simple terms, it shows how often the system makes correct decisions during inspection.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

In this context, TP (True Positive) denotes the number of defective items that are correctly identified as defective, while TN (True Negative) represents the number of non-defective (acceptable) items that are correctly classified as good. FP (False Positive) refers to acceptable items that are incorrectly marked as defective, and FN (False Negative) indicates defective items that are wrongly classified as acceptable.

In industrial quality inspection systems, false negatives are considered more severe since they allow defective products to pass through the inspection stage and reach the end user. Hence, minimizing false negatives is a critical requirement in the design of automated defect detection systems. In the proposed approach, the YOLOv5-based deep learning model helps reduce such errors by effectively learning and analyzing complex visual patterns from the input images.

Another commonly used performance measure is precision, which evaluates the proportion of correctly identified defective items among all items predicted as defective. In other words, precision indicates the reliability of the system when it labels a product as defective.

Precision can be expressed as:

$$Precision = \frac{TP}{TP + FP}$$

Similarly, recall measures the ability of the system to correctly identify all defective items present in the dataset. Recall is defined as:

$$Recall = \frac{TP}{TP + FN}$$

High recall is especially important in industrial inspection applications because it ensures that most defective products are successfully detected and prevented from continuing further in the production line. This reduces the risk of faulty items reaching customers and improves overall product quality assurance.

Along with classification performance, system throughput was also analyzed. Throughput refers to the total number of job items processed within a given time period. During testing, the proposed system achieved an average processing time of around 2.5 to 3.2 seconds per item. This includes all stages such as object positioning using the conveyor system, image acquisition, defect analysis, and recording of results in the system database.

In addition, system latency was measured to understand the computational delay introduced by the inspection algorithms. The traditional OpenCV-based image processing approach required less than 10 milliseconds per image, making it highly suitable for fast or backup-level inspection tasks. On the other hand, the YOLOv5 deep learning model required approximately 50 to 90 milliseconds when executed on a CPU-based setup. Although this method is comparatively slower, the significant improvement in detection accuracy makes it more suitable as the main inspection technique.

Overall, the experimental evaluation indicates that the proposed hybrid inspection framework achieves a good trade-off between accuracy, processing speed, and system reliability. This makes the system practical and effective for deployment in real-world manufacturing environments.

VIII. CONCLUSION

This paper presented a Smart Job Distribution and Quality Verification System that integrates RFID-based operator authentication, microcontroller-driven conveyor control, classical OpenCV inspection, and YOLOv5 deep learning defect detection. The system addresses real industrial needs operator accountability, production traceability, and consistent quality control using accessible and cost-effective components.

The Job QC Dataset, a private collection of 1,200 labelled images split 70/15/15 for training, validation, and testing, was used to train and evaluate the YOLOv5s model. The model achieved a mAP@0.5 of 91.3% on the test partition, with an overall precision of 0.934, recall of 0.887, and F1 score of 0.910. These figures represent a substantial improvement over the classical brightness-based method, which achieved only 74.4% accuracy on the same test set.

The toggle switches provide a practical mechanism for job-type selection at a single workstation, enabling the system to serve multiple product lines without any software modification. All production events are logged to Excel/CSV files, ensuring full traceability. Future work will focus on extending the dataset size, introducing multi-class defect categories, and deploying the inference engine on an edge GPU device to reduce latency.

The RFID authentication module ensures that only valid and authorized operators are able to access the system. Each job assignment is linked to a specific operator identity, which enables complete traceability of all issued and returned items. Furthermore, the outstanding job monitoring feature enforces operational discipline by restricting users from receiving new tasks until previously assigned jobs are returned and inspected. This helps in reducing untracked work and improves accountability in the production workflow.

A key contribution of this work is the hybrid visual inspection system. It combines traditional image processing techniques using OpenCV with a deep learning-based defect detection model based on YOLOv5. This dual approach allows the system to maintain functionality even when environmental conditions negatively impact the performance of the deep learning model. Experimental analysis shows that the YOLOv5-based method provides higher accuracy in defect detection compared to conventional image processing techniques, highlighting the effectiveness of neural network–based solutions for industrial inspection.

The proposed system also demonstrates that cost-effective industrial automation can be achieved using commonly available hardware such as the Arduino Mega 2560. By integrating embedded hardware with software-based processing, the system offers a scalable and adaptable framework suitable for different manufacturing scenarios. Additionally, the implemented logging and tracking mechanism supports continuous monitoring and data collection, which are important for Industry 4.0–based smart manufacturing systems.

However, there are still areas where the system can be improved. Future enhancements may include expanding the dataset used for training the defect detection model to improve its robustness and reduce misclassification. The use of GPU acceleration or edge computing devices can also be explored to reduce processing time and improve real-time performance. Moreover, replacing the local logging system with a cloud-based database would enable remote monitoring, real-time data access, and advanced predictive analytics capabilities.

In conclusion, the developed system demonstrates that combining RFID-based authentication, automated workflow control, and machine learning–based inspection can significantly enhance production efficiency and product quality. It provides a practical and scalable solution for small and medium-scale industries aiming to adopt intelligent and Industry 4.0–compliant manufacturing systems.

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