Federation Learning for Vision Based Product Quality Inspection

Nischitha T S[1], Harshitha N[2], Harshitha N G[3], Manoj T[4], Rohith D M[5]

[1]Nischitha T S Information Science and Engineering & RR Institute of Technology

[2]Harshitha N Information Science and Engineering & RR Institute of Technology

[3]Harshitha N G Information Science and Engineering & RR Institute of Technology

[4]Manoj T Information Science and Engineering & RR Institute of Technology

[5]Rohith D M Information Science and Engineering & RR Institute of Technology

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Abstract - In modern manufacturing industries, maintaining consistent product quality is a major challenge. Vision-based product quality inspection systems help in identifying defects by analyzing images of products. However, traditional machine learning approaches require collecting data from all production units at one place, which can raise concerns related to data privacy, security, and high communication cost. To overcome these limitations, this project adopts a federated learning approach for vision-based product quality inspection. In the proposed system, image data is processed locally at different inspection units, and only the learned model parameters are shared with a central server instead of raw images. This ensures data privacy while allowing the system to learn from multiple sources. The trained federated model is capable of detecting defects such as surface irregularities, shape deviations, and visual inconsistencies with improved accuracy. By combining computer vision techniques with federated learning, the system achieves efficient defect detection while reducing data transfer and protecting sensitive manufacturing information. This approach proves to be a reliable, scalable, and secure solution for automated product quality inspection in industrial environments. The integration of AI-driven inspection with IoT-based actuation establishes a closed-loop quality control system that significantly minimizes human error, reduces inspection time, and enhances overall manufacturing throughput. By employing techniques such as image preprocessing, feature extraction, and model optimization, the system achieves high detection accuracy even in varying lighting and background conditions. The proposed solution not only enhances consistency and reliability in quality assurance but also enables scalability across diverse product lines with minimal hardware or algorithmic adjustments. Ultimately, this project demonstrates how the fusion of machine learning and IoT can revolutionize industrial inspection processes, transforming traditional manual quality checks into intelligent, automated, and data-driven operations. The results affirm that the ML-IoT integrated inspection system substantially improves productivity, consistency, and precision in Wheels assembly operations.

***Key Words*:** Fault detection in the product, Federation Learning, Vision Based Inspection System, Voice Feedback.

1. INTRODUCTION

This Quality inspection is essential in today's smart manufacturing settings to guarantee that every product satisfies necessary requirements before being delivered to consumers. Conventional visual inspection systems often rely on centralized machine learning algorithms which necessitate all a single server for the collection and storage of image data. This restricts scalability across several factories, raises privacy issues, and increases network demand. This research presents a Federated Learning-based Vision Inspection System to get over these restrictions. Federated learning makes it possible for several production facilities or devices to work together to train a machine learning model without sharing unprocessed data. Rather, only the learnt A central server receives model updates by each node, which trains the model locally on its own dataset.

In order to create a global model that ensures increased accuracy while Protecting Data privacy, the server collects these updates. The federated learning paradigm is employed in this project to confirm whether a product is placed correctly. or not on a conveyor surface or manufacturing wheel. Real-time photos of the product arrangement are taken by a camera and processed by the vision model. The technology instantly marks a product as defective if it is misaligned, missing, or positioned wrongly. The system has verbal feedback to improve usability. When a problem is discovered, a speaker will say something like "Defective on the wheel." Even if they are not always observing the system physically, this speech output aids employees in promptly identifying issues. This clever fusion of computer vision, voice feedback, and federated learning improves product quality, boosts dependability, and permits privacy-preserving model enhancements across several production units.

2. Body of Paper

The federation learning for vision based product quality inspection inspect weather a product is arranged properly or not if not then it will be giving us a voice message By these we can improve our product it help us to give a good product to the customer.

Section 1 presents the motivation and objectives of the proposed system

Figure 1 illustrate the role of microcontroller board acts as a bridge between the vision-based federated learning system and the hardware components.

It receives the inspection result and controls the LED and voice alert to indicate whether the product is good or defective.

System Requirements

Section 2 describes the functional and non-functional requirements of the proposed system. In Sec. 2.1, requirement modelling is discussed, focusing on system inputs, outputs, and constraints. Table 1 lists the functional requirements, while Table 2 presents the non-functional requirements such as scalability and reliability. Section 2.3 details the hardware requirements, including the Arduino uno Microcontroller board, USB Cable, LED light, Camera Modules, Jumper Wires.

System Design

Section 3 describes The proposed system consists of three major components: image acquisition, federated learning-based model training, and hardware-based feedback generation. A camera captures images of products placed on the inspection platform. These images are processed locally on edge devices, where a deep learning model evaluates the arrangement and quality of the product.
Instead of transmitting raw images to a central server, only model updates are shared with a global server using federated learning. The server aggregates these updates to improve the global model, which is then redistributed to the participating devices. This approach ensures data privacy, reduces network load, and improves scalability. The final decision is communicated to the hardware module, which triggers LED indicators and voice alerts to notify whether the product is defective or acceptable.

Implementation

Section 4 The software implementation is carried out using Python with machine learning libraries for image processing and model training. The federated learning framework manages distributed training and model aggregation. OpenCV is used for image preprocessing, including resizing, normalization, and noise reduction.
On the hardware side, an Arduino Uno board is interfaced with LEDs and a buzzer module. Serial communication is established between the processing unit and the microcontroller to transmit inspection results. This integration enables seamless coordination between software intelligence and physical feedback mechanisms.

Testing

Section 5 describes Testing ensures that the vision-based federated learning system correctly identifies properly arranged and defective products under different conditions. It also verifies reliable communication between the software model and the microcontroller for accurate LED and voice alerts.

Results

Section 6 describes The system successfully identifies correctly arranged and defective products with reliable accuracy using the federated learning–based vision model. Real-time LED and voice alerts provide immediate and clear feedback, demonstrating effective integration of software and hardware components.

Table -1: Hardware and Software Configuration

Hardware Component	Description	Function
Camera Module / USB Camera	High-resolution camera used For image capture	Capture images for quality inspection
Arduino Uno	ATmega328P based microcontroller board	Controls LED, buzzer, and output actions
LED Indicator	Light-emitting diode	Indicates whether the product is good or defective
Buzzer / Voice Module	Audio output	Gives voice or beep alert based on inspection result
Jumper Wires	Connecting wires	Connects all hardware components
USB Cable	5V regulated power source	Supplies power to Arduino and peripherals
Laptop / PC	Computing system	Runs vision model

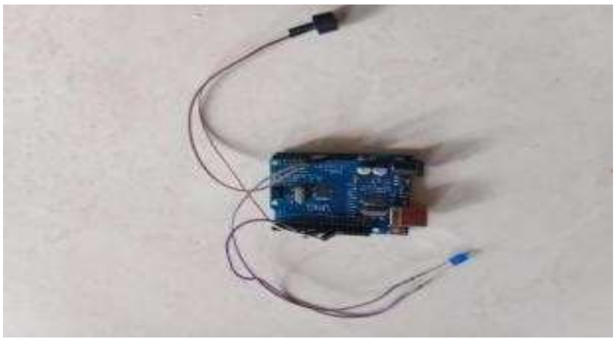

Fig -1: **Arduino Uno**

Fig-2 USB Cable

Fig -3 Jumper Wire

3. CONCLUSIONS

In order to achieve effective, dependable, and user-friendly industrial quality control, the federated learning-based vision product quality inspection system created in this project effectively demonstrates the integration of cutting-edge artificial intelligence techniques with realistic hardware implementation. By integrating hardware elements like the Arduino Uno, blue LED, buzzer, and speech output module with a federated learning-enabled vision model, the system offers precise and instantaneous feedback on product placement, guaranteeing that flaws are quickly found and fixed. The system can evaluate product photos locally on several devices thanks to federated learning, which preserves data privacy while continuously enhancing the inspection model's accuracy. This method not only increases the system's intelligence but also makes it scalable and adaptable to various production scenarios, where it could be necessary to run several inspection points concurrently without sacrificing security or performance. Throughout the project, thorough testing of the hardware and software components verified that the system functions dependably in a range of scenarios, such as variations in lighting, product orientation, and minor flaws. The speech module, buzzer, and LED outputs were all coordinated in real time with little latency by the Arduino microcontroller, which turned out to be an efficient central unit. By providing operators with clear, understandable, and useful multisensory feedback, the possibility of human error was decreased and total productivity was increased. The system's resilience and appropriateness for industrial deployment are further demonstrated by its capacity to maintain continuous operation without hardware or software faults. Additionally, the mix of visual, aural, and verbal signals guarantees usability and accessibility across various operator skill levels, resulting in a quicker, more accurate inspection process that requires less constant human supervision. 2025-26 74 DEPT OF ISE, RRIT Federation Learning For Vision Based Product Quality Inspection The implementation's outcomes show how well AI-driven inspection can be combined with useful hardware feedback methods. The hardware outputs responded consistently, giving operators instant feedback, and the system was able to accurately identify both well organized and damaged objects. By drastically lowering the possibility that faulty goods would advance along the production line, this integration minimizes possible losses and upholds high standards of quality. Furthermore, the system's humanized design, which includes voice output and simply understood LED and buzzer signals, guarantees that the technology is not only useful but also practical and easy for industrial personnel to utilize. In conclusion, by showing how federated learning and vision-based AI can be successfully integrated with responsive hardware to produce an intelligent, dependable, and scalable solution, this study establishes a solid foundation for contemporary quality inspection systems. By lowering human error, increasing operational efficiency, and offering real-time defect identification, the technology satisfies important industrial needs. It is a workable solution for deployment in manufacturing environments because to its strong performance, high accuracy, and user-friendly feedback mechanism. This opens the door for future improvements including multi-stage inspection, automated reporting, and increased scalability across bigger production Overall, the project sets the foundation for upcoming developments in intelligent industrial automation and demonstrates the potential of AI-driven, human-centric hardware systems to transform product quality assessment.

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BIOGRAPHIES

Author 1 : Prof. Nishchitha T S
Professor, Department of Information Science and Engineering, RR Instution of Technology.

Author 2: Harshitha N
Student, Department of Information Science and Engineering, RR Instution of Technology.

Author 3: Harshitha N G
Student, Department of Information Science and Engineering, RR Instution of Technology.

Author 4: Manoj T
Student, Department of Information Science and Engineering, RR Instution of Technology.

Author 5: Rohith DM
Student, Department of Information Science and Engineering, RR Instution of Technology.