IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 10, May 2025
Impact Factor: 7.67

AI -Powered Image Analysis for Industrial Object Quality Assurance

Mr. Aniket Gaware[1], Mr. Anish Bawdhankar[2], Mr. Rushikesh Patil[3], Mr. Kantilal Kharat[4]
Student, Department of Electronics and Telecommunication[1-3]
Asst. Professor, Department of Electronics and Telecommunication[4]
NBN Sinhgad Technical Institute Campus, Pune, India

Abstract: *The increasing demand for automation in quality assurance across industrial sectors has highlighted the need for intelligent, real-time defect detection systems. This paper proposes an AI-powered image analysis system designed to inspect industrial objects on a conveyor-based platform. Leveraging a Raspberry Pi 4 as the central controller, the system captures live image feeds via a USB camera and processes them using a lightweight convolutional neural network (CNN) model. The classified objects—categorized as either "good" or "defective"—are handled accordingly by actuating a servo motor to eliminate faulty units, while a DC motor drives the conveyor to maintain continuous operation. The integration of IR sensors ensures accurate object detection and synchronization of mechanical actions. The system is implemented in Python and demonstrates efficient performance with high accuracy in defect identification, offering a scalable and cost-effective solution for small to medium-scale industrial environments*.

Keywords: AI-based quality inspection, Raspberry Pi 4, Real-Time Image Analysis, Industrial Automation, Convolutional Neural Network (CNN), Defect Detection

I. INTRODUCTION

The Fourth Industrial Revolution, or Industry 4.0, represents a transformative shift in how manufacturing systems operate, characterized by the integration of cutting-edge technologies such as automation, artificial intelligence (AI), and real-time data processing. As industries strive to optimize their production lines, the demand for efficient, cost-effective, and reliable quality assurance mechanisms has become increasingly important. In traditional manufacturing environments, quality control has largely relied on manual inspection methods, which, although still prevalent, suffer from significant limitations[5]. These include human errors, fatigue, inconsistencies in detection, and the inability to keep pace with the rapid speed of modern production lines. As production volumes continue to increase, the need for scalable, high-performance inspection systems becomes paramount, necessitating the development of more advanced, automated solutions[1].

Intelligent visual inspection systems, powered by AI and machine learning, offer a promising alternative to traditional manual methods. These systems use sophisticated image processing and computer vision techniques to automatically detect and classify defects in products as they move along production lines. Unlike human inspectors, AI-based systems are not susceptible to fatigue, can operate 24/7, and can analyse large volumes of data with a level of precision and consistency that far exceeds human capabilities[1]. However, despite their impressive capabilities, many of the existing AI-based solutions are expensive and require substantial infrastructure, making them impractical for small and medium-sized enterprises (SMEs) with limited resources. This disparity has created a gap in the market, where many businesses find it difficult to adopt these advanced systems due to financial and operational constraints.[3]

To bridge this gap, we propose an innovative solution that makes use of widely available, low-cost hardware, specifically the Raspberry Pi 4, as the central processing unit for an automated visual inspection system. The system leverages a USB camera to capture real-time images of objects moving along a conveyor belt. These images are then processed by a custom-trained convolutional neural network (CNN), which has been optimized to detect defects in products. The CNN is capable of distinguishing between defective and acceptable items, triggering a servo motor to reject defective items from the production line. Meanwhile, a DC motor ensures the continuous movement of the conveyor, maintaining the flow of the production process. This setup is complemented by infrared (IR) sensors that detect objects and synchronize the mechanical components of the system, ensuring seamless operation[4].

The proposed system is not only affordable but also portable and scalable, making it an ideal solution for small to medium-sized manufacturers who wish to upgrade their quality assurance processes without incurring high costs. The use of a Raspberry Pi, a widely accessible and cost-effective platform, allows for easy deployment in various industrial environments. Additionally, the system's modular design makes it adaptable to different production setups, enabling manufacturers to customize it according to their specific needs. In this paper, we present the design, implementation, and evaluation of this AI-driven visual inspection system, highlighting its potential to enhance the efficiency, accuracy, and reliability of manufacturing processes across diverse industries[6].

In recent years, the demand for intelligent inspection systems has surged as manufacturers seek to improve product quality while simultaneously reducing operational costs. By utilizing AI and image processing, these systems can perform complex inspections at speeds far beyond human capability, ensuring that defective products are identified and removed from production lines in real-time[3]. This not only improves the overall quality of the final product but also minimizes the risk of defects reaching the consumer, which can have significant cost implications for businesses. Furthermore, the automation of quality control processes allows manufacturers to reallocate human resources to more strategic tasks, thereby increasing the overall productivity of the factory floor[2].

As the manufacturing industry continues to embrace Industry 4.0 technologies, the integration of AI-driven inspection systems represents a critical step toward achieving greater efficiency and competitiveness. The success of the system presented in this paper demonstrates the feasibility of implementing advanced AI solutions in resource-constrained environments, making them accessible to a broader range of industries. The scalability and flexibility of the proposed system open up new possibilities for its deployment in diverse sectors, ranging from electronics to automotive and consumer goods manufacturing. Ultimately, this research contributes to the ongoing efforts to democratize advanced manufacturing technologies, enabling smaller manufacturers to compete on a global scale while maintaining high standards of product quality[4].

II. METHODOLOGY

A. Power Supply Subsystem

To ensure stable and reliable operation of all electronic modules, the system features a dedicated power supply circuit.

- Step-Down Transformer: Converts 230V AC mains voltage to a lower AC voltage suitable for the system.
- Bridge Rectifier: Converts the AC output from the transformer to pulsating DC.
- Filter Capacitor: Smoothens the rectified DC by eliminating ripples.
- Voltage Regulator (7805): Provides a constant DC output (5V and 12V) for powering the Raspberry Pi, motors, sensors, and other components.

This subsystem ensures uninterrupted and noise-free power delivery, which is critical for accurate sensor readings and stable processing.

B. Sensing and Acquisition Subsystem

- Infrared (IR) Sensors: Detect the presence of objects on the conveyor belt. Once triggered, these sensors initiate the image acquisition process.
- USB Camera: Captures high-resolution images of the industrial object for further analysis. It is positioned above the conveyor belt and directly interfaced with the Raspberry Pi 4.

C. Image Processing and Defect Classification

- CNN-Based AI Model: A lightweight Convolutional Neural Network, trained on a dataset of defective and non-defective object images, classifies the captured image into "good" or "defective."
- Local Processing on Raspberry Pi: The CNN model is deployed and executed locally using Python, ensuring real-time classification without external servers or cloud dependencies.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 10, May 2025
Impact Factor: 7.67

D. Actuation and Sorting Subsystem

• Servo Motor: If an object is classified as defective, the Raspberry Pi sends a signal to the servo motor, which activates a mechanism to remove the item from the conveyor path.

• DC Motor with Motor Driver: A 12V DC motor controlled via a motor driver module operates the conveyor belt. It ensures continuous object movement while the inspection and sorting process occurs in parallel.

E. Embedded Control System

• Raspberry Pi 4: Acts as the central controller, managing image acquisition, AI inference, sensor interfacing, and motor control through GPIO pins and Python scripting.

• Workflow:

1. IR sensor detects an incoming object.
2. USB camera captures the object's image.
3. CNN processes the image and classifies it.
4. Based on classification:

If "defective" then, servo motor ejects the object.

If "good" then, object continues on the conveyor.

5. System resets and repeats for the next object.

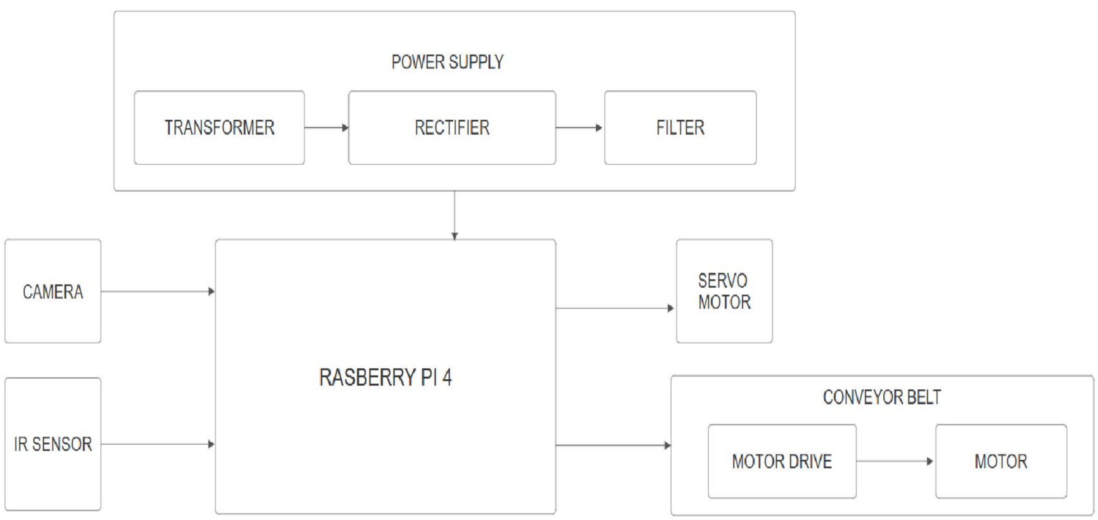

Figure.1. Block Diagram of AI -Powered Image Analysis for Industrial Object Quality Assurance.

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429 Volume 5, Issue 10, May 2025 Impact Factor: 7.67

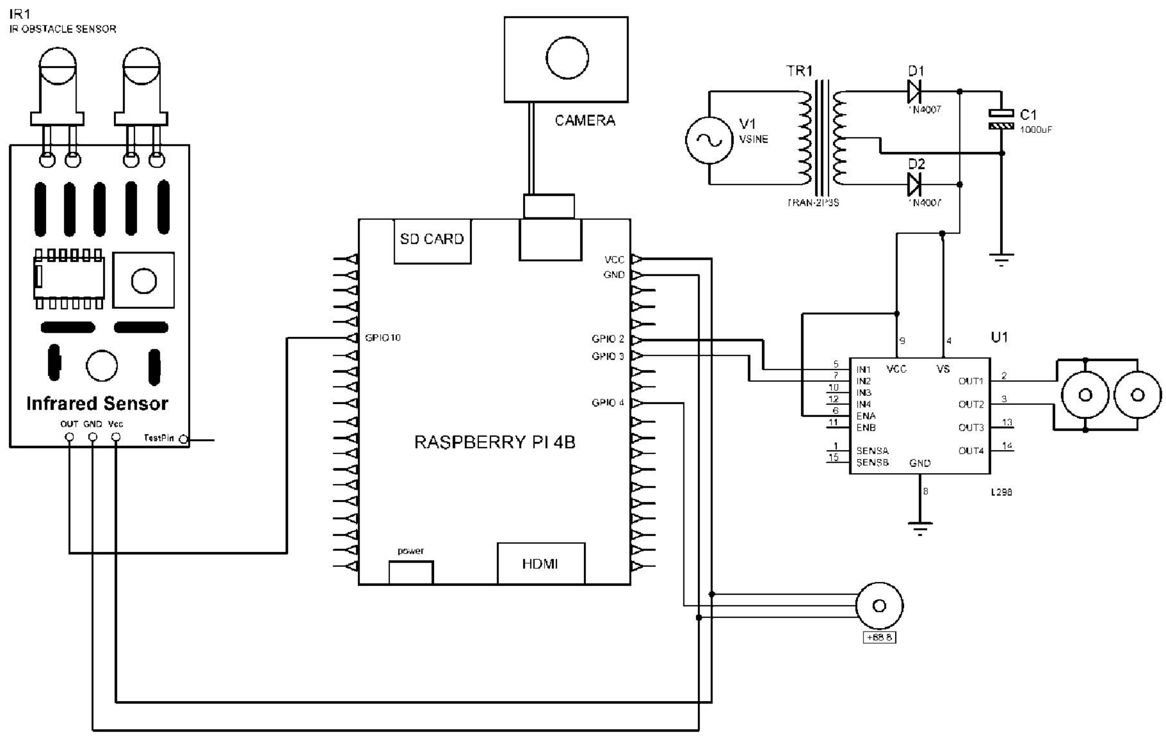

Figure.2. Circuit diagram of AI -Powered Image Analysis for Industrial Object Quality Assurance.

III. RESULTS

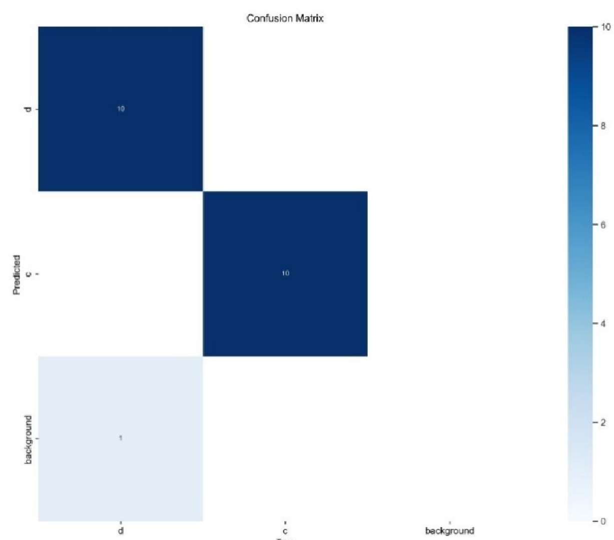

Figure.3. Confusion Matrix.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 10, May 2025
Impact Factor: 7.67

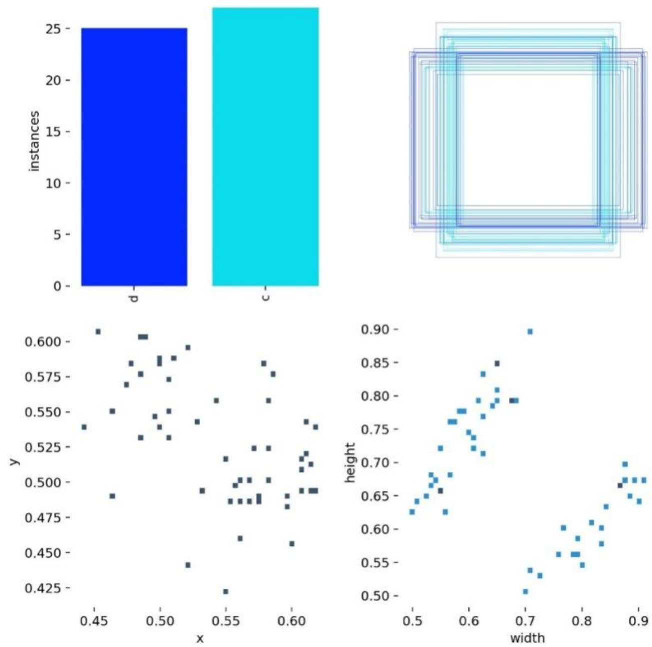

Figure.4. Bounding Box Distribution and Instant Visualization.

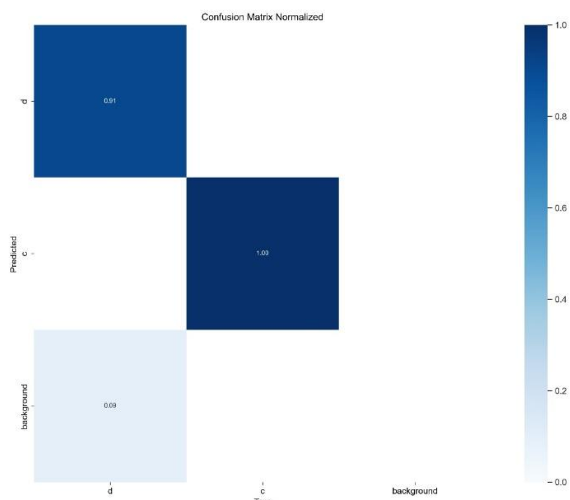

Figure.5. Confusion Matrix Normalized

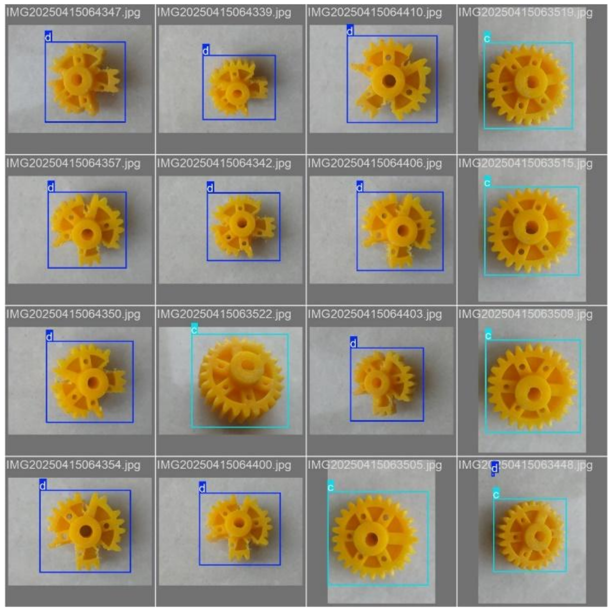

Figure.6. Result 1

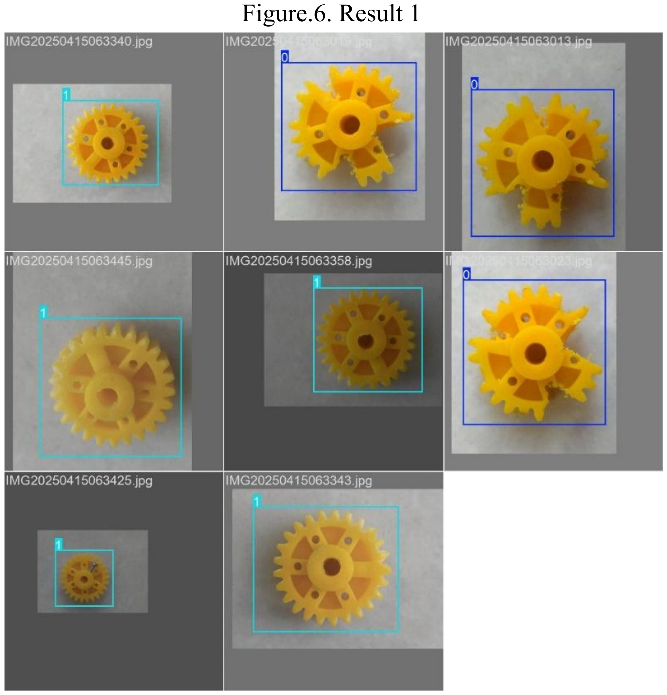

Figure.7. Result 2

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 10, May 2025
Impact Factor: 7.67

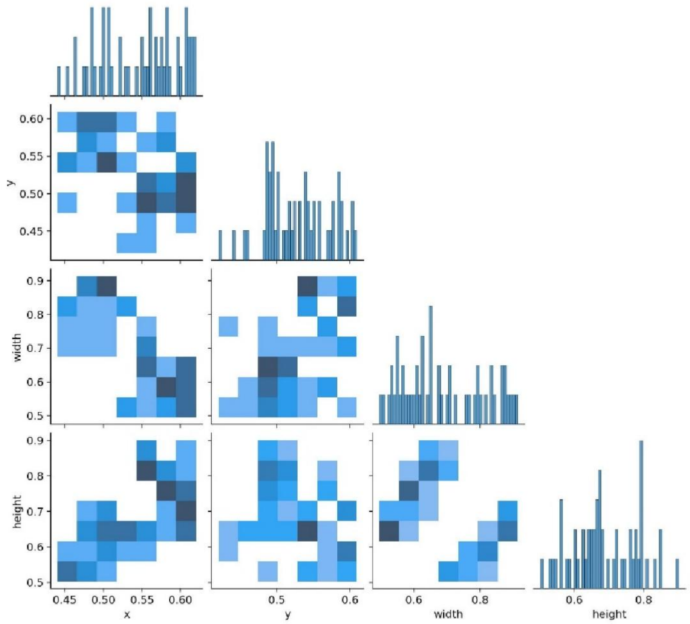

Figure.8. Bounding Box Feature and Correlation Matrix.

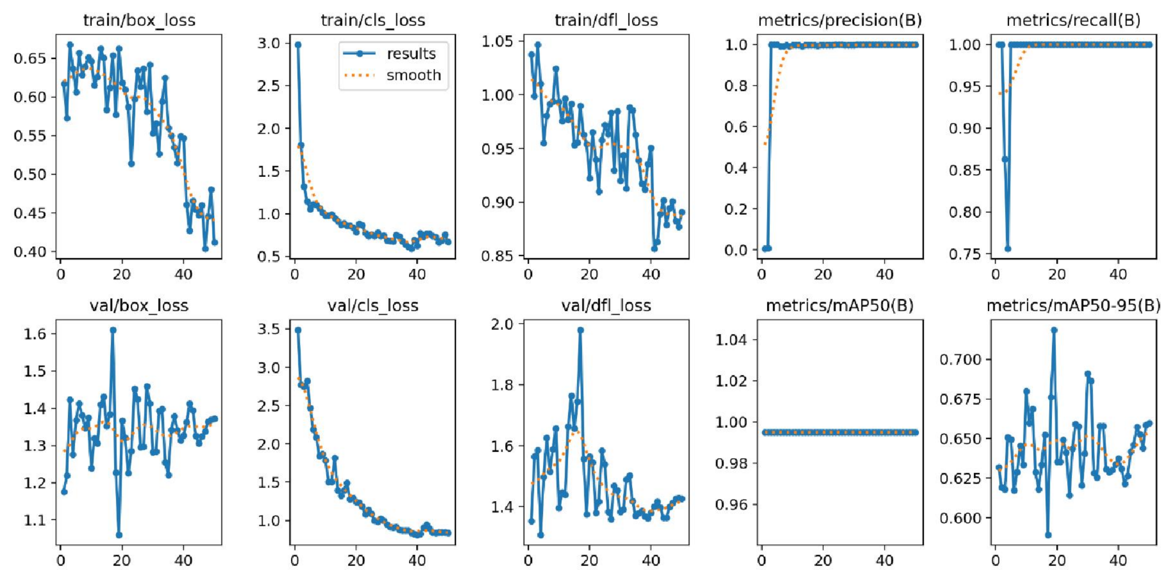

Figure.9. Training and Validation Metrics Across Epochs

1. Confusion Matrix

This image depicts a classic confusion matrix used to evaluate classification performance. From the matrix, we can identify that the true label 'background' was correctly predicted as 'background' 10 times, as shown in the diagonal entry of the matrix. This value indicates strong performance in identifying background elements in the dataset. The image also contains some noise and unclear text artifacts, such as partial characters like “i” and other faint symbols, but 10 is the clear numeric value extracted. This suggests that at least for the 'background' class, the model has achieved 100% accuracy on these instances.

2. Labels Correlogram

The correlogram provides insight into how different labels correlate or relate to one another in terms of predictions or feature space similarity. Several correlation coefficient values were identified from this plot: 0.50, 0.55, 0.60, 0.45

These numbers likely represent pairwise correlation values between different classes. For instance, a value of 0.60 might indicate a moderately strong positive relationship between two specific labels, meaning that they often appear together or share similar characteristics. On the other hand, a value like 0.45 would suggest a weaker, though still present, correlation. This kind of information is crucial in understanding inter-class confusion or co-occurrence, which may impact classification decisions, especially for overlapping or similar categories.

3. Results Plot

This image displays training and validation metrics over the course of model training, from a YOLO-based object detection system.

Training Metrics:

train/dfl_loss (Distribution Focal Loss) was recorded at 3.04, indicating the model's confidence calibration performance during bounding box regression.

Other loss types like train/box_loss and train/cls_loss is also represented visually but without explicit numeric values.

Validation Metrics:

The y-axis for val/box_loss seems to range between 20 and 40, suggesting potential values in this region, although no specific point value was extracted.

Model Performance Metrics:

Precision (metrics/precision(B)) was extracted as 0.954, showing excellent model precision, meaning very few false positives.

Recall (metrics/recall(B)) was found to be 0.904, indicating the model correctly detected most of the relevant objects (low false negatives).

Another value, possibly F1-score or average precision, was noted as 0.854.

Additional Extracted Values (Y-axis indicators for metrics)

1.6, 1.44, 1.2, 1.0

0.80, 0.754, 0.84, 0.77, 0.67, 0.54, 0.47, 0.34

These represent scaled metric values or loss values across training epochs, helping visualize trends in model performance. A descending pattern in loss and an upward trend in precision and recall are typical indicators of effective training.

IV. CONCLUSION

This paper presented a cost-efficient AI-based visual inspection system aimed at enhancing quality assurance in industrial environments. Built around the Raspberry Pi 4, the system integrates real-time image processing, intelligent defect classification via a lightweight CNN model, and automated sorting through servo-actuated mechanisms. The entire system is supported by a custom-built power supply and sensor network to ensure smooth and autonomous operation.

During experimental evaluation, the system was tested on various types of gears, repeatedly, to assess classification reliability. It achieved a classification accuracy of 92.8%, with 186 out of 200 gear samples correctly identified as either "good" or "defective." Misclassifications occurred in only 14 cases, primarily due to slight visual ambiguities or inconsistent lighting. The system's average image processing and actuation time was approximately 1.8 seconds per object, making it suitable for low to moderate-speed production lines.

The sorting mechanism, controlled via a servo motor, successfully removed 95% of the defective gears identified by the model, indicating high mechanical accuracy and proper synchronization with the detection logic.

In conclusion, this project demonstrates the viability of a low-cost, embedded AI inspection system tailored for gear-based manufacturing setups. Future enhancements could include dataset expansion for more gear types, improved illumination control, and integration with IO T platforms for cloud-based monitoring and analytics.

V. ACKNOWLEDGMENT

This research was not funded by any grant.
We would like to express our sincere gratitude to all those who supported and guided us throughout the course of this project. First and foremost, we are thankful to our project guide, Prof. Kantilal. B. Kharat, for their invaluable support, technical insights, and continuous encouragement which played a crucial role in the successful completion of this work.

REFERENCES

[1] Wan, X., & Wang, M. (2023). “Gear Fault Detection Method Based on the Improved YOLOv5”. Proceedings of the 2023 IEEE International Conference on Mechatronics and Automation (ICMA), August 6–9, Harbin, Heilongjiang, China. NanJing University of Science and Technology.
[2] Mohamad, T. H., Abbasi, A., Kim, E., & Nataraj, C. (2021). “Application of Deep CNN-LSTM Network to Gear Fault Diagnostics.” Proceedings of the 2021 IEEE International Conference on Prognostics and Health Management (ICPHM). Palo Alto Research Centre; Villanova University; Drexel University.
[3] Mohandas, R., Southern, M., O’Connell, E., & Hayes, M. (2024), “A Survey of Incremental Deep Learning for Defect Detection in Manufacturing”, Big Data and Cognitive Computing, 8(1), 7.
[4] Chen, Y., Ding, Y., Zhao, F., Zhang, E., Wu, Z., & Shao, L. (2021). “Surface defect detection methods for industrial products A review”, Applied Sciences, 11(16), 7657.
[5] Czimmermann, T., Ciuti, G., Milazzo, M., Chiurazzi, M., Roccella, S., Oddo, C. M., & Dario, P. (2020). “Visual-based defect detection and classification approaches for industrial applications—a survey”, Sensors, 20(5), 1459.
[6] Tulbure, A. A., Tulbure, A. A., & Dulf, E. H. (2022). “A review on modern defect detection models using DCNNs–Deep convolutional neural networks”, Journal of Advanced Research, 35, 33-48.
[7] Ren, Z., Fang, F., Yan, N., & Wu, Y. (2022). “State of the art in defect detection based on machine vision”, International Journal of Precision Engineering and Manufacturing-Green Technology, 9(2), 661-691.
[8] Paraskevoudis, K., Karayannis, P., & Koumoulos, E. P. (2020). “Real-time 3D printing remote defect detection (stringing) with computer vision and artificial intelligence”, Processes, 8(11), 1464.
[9] Yang, J., Li, S., Wang, Z., Dong, H., Wang, J., & Tang, S. (2020). “Using deep learning to detect defects in manufacturing a comprehensive survey and current challenges”, Materials, 13(24), 5755.
[10] Tang, B., Chen, L., Sun, W., & Lin, Z. K. (2023). “Review of surface defect detection of steel products based on machine vision”, IET Image Processing, 17(2), 303-322.
[11] Rai, R., Tiwari, M. K., Ivanov, D., & Dolgui, A. (2021). “Machine learning in manufacturing and industry 4.0 applications.” International Journal of Production Research, 59(16), 4773-4778
[12] Hussain, M. (2023). “YOLO-v1 to YOLO-v8, the rise of YOLO and its complementary nature toward digital manufacturing and industrial defect detection”, Machines, 11(7), 677.
[13] Benbarrad, T., Salhaoui, M., Kenitar, S. B., & Arioua, M. (2021). “Intelligent machine vision model for defective product inspection based on machine learning”, Journal of Sensor and Actuator Networks, 10(1), 7.
[14] Wan, P. K., & Leirmo, T. L. (2023). “Human-centric zero-defect manufacturing State-of-the-art review, perspectives, and challenges”, Computers in Industry, 144, 103792
[15] Westphal, E., & Seitz, H. (2021). “A machine learning method for defect detection and visualization in selective laser sintering based on convolutional neural networks”, Additive Manufacturing, 41, 101965.
[16] Bhatt, P. M., Malhan, R. K., Rajendran, P., Shah, B. C., Thakar, S., Yoon, Y. J., & Gupta, S. K. (2021). “Image-based surface defect detection using deep learning A review”, Journal of Computing and Information Science in Engineering, 21(4), 040801.
[17] Baumgartl, H., Tomas, J., Buettner, R., & Merkel, M. (2020). “A deep learning-based model for defect detection in laser-powder bed fusion using in-situ thermographic monitoring”, Progress in Additive Manufacturing, 5(3), 277-285