IoT – Based Quality Control Systems in Smart Manufacturing Using EfficientNet and Edge Intelligence

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***Abstract*—This paper presents a detailed study of Internet Of Things(IoT)-Based Quality Control Systems(QCS) for real-time defect detection in smart manufacturing. The suggested framework incorporates AI analytics into a four layer IoT architecture, i.e., Device, Edge, Cloud and Application layers using the EfficientNetB0 model that has been optimized on the MVTecAD bottle dataset. The model outperformed conventional CNN-based inspection techniques with AUC of 0.993, 99.34 training accuracy, 98.85% validation accuracy and 99.12% test accuracy. Deployment of edge AI supports Industry 5.0 aligned, sustainable and adaptive manufacturing by facilitating low-latency inference, predictive maintenance and smooth integration with digital twins.**

Keywords*—*IoT, Smart Manufacturing, Quality Control, Edge Computing, Digital Twins, Industry 4.0, EfficientNet, Industry 5.0

I. INTRODUCTION

The manufacturing industry is changing with Industry 4.0. This shift involves the use of cyber physical systems, intelligent automation and interconnected IoT devices. As a part of this change, Quality Control Systems(QCS) have moved from manual inspections to advanced, data-driven and autonomous systems. High product quality and reliable processes are now crucial for operational efficiency and staying competitive in global markets. Traditional quality inspection methods, mainly manual visual checks and rule-based machine vision systems, often struggle with consistency, adaptability and a heavy reliance on human labour. These limitations become critical as modern manufacturing requires real-time decision-making, ongoing monitoring and the ability to process large amounts of data. To overcome these issues, combining Artificial Intelligence (AI) and Internet Of Things (IoT) provides a powerful solution. IoT allows continuous connectivity between machines, sensors and cloud platforms which supports data collection and traceability. At the same time, AI improves analysis by identifying patterns, anomalies and defects with little human input. This research presents an AI-Driven IoT-based Quality Control System that incorporates EfficientNetB0, a leading deep learning model, within a four layer IoT framework made up of Device, Edge, Cloud and Application layers. This design enables data processing at the edge, allowing for defect detection to happen quickly and efficiently. The cloud connection aids in large-scale analytics, predictive maintenance and long-term performance improvement.

Using the MVTec AD(bottle category) dataset, the system achieves impressive accuracy and reliability. It reaches training accuracy 99.34%, validation accuracy of 98.85% and test accuracy of 99.12%, along with an AUC score of 0.993. These results show that this model outperforms traditional convolutional neural networks(CNNs), which usually achieve around 94% accuracy in similar tasks.

Hence, The use of Edge AI and digital twin technologies ensures that the proposed QCS functions well under real-time industrial conditions. Edge intelligence reduces dependence on slow cloud computations, while digital twins create virtual replicas of physical systems for ongoing monitoring and learning. This system supports Industry 5.0 goals by enhancing human-machine collaboration, improving energy efficiency and enabling sustainable production through intelligent automation and predictive quality control. This research connects IoT connectivity with AI-driven intelligence for quality inspections, creating a flexible and scalable framework for the next generation of smart manufacturing environments.

II. LITERATURE REVIEW

Recent studies highlight the significant impact of the Internet of Things(IoT) on modern quality assurance frameworks. Traditional inspection processes relied on fixed thresholds and manual evaluations, which often led to inconsistent and delayed results. The rise of Artificial Intelligence(AI), especially deep learning and edge computing, has allowed for the development of IoT-based Quality Control Systems(IoT-QCS). These systems can detect defects in real-time, predict anomalies and make adaptive decisions. Bergmann et al.(2019) introduced the MVTec AD dataset, which set a standard for detecting visual anomalies in industrial inspections. Tan and Le (2019) proposed EfficientNet, which demonstrated better accuracy and efficiency and has been widely used for edge-deployable AI models.

Research published between 2024 and 2025 points to the increasing use of digital twins for virtual process simulation and performance improvement. It also shows the role of edge-AI setups in reducing delays and improving real-time responsiveness. Additionally, the inclusion of 5G connectivity supports fast data transmission in distributed manufacturing settings. Cloud analytics and machine learning pipelines also enhance scalability and predictive accuracy. Together, these advancements have made IoT-

QCS a crucial part of smart manufacturing and an important factor in reaching Industry 5.0 goals of sustainability, resilience and human-machine collaboration.

III. METHODOLOGY

The proposed AI-driven IoT-based Quality Control System (IoT-QCS) combines deep learning, edge computing and cloud analytics within a four-layer IoT framework: Device, Edge, Cloud, and Application. This structure enables smooth data flow, quick decision-making, and flexible deployment across various industrial setting

1. **Device Layer:** The Device Layer forms the backbone of the system and handles data collection through a network of IoT-enabled industrial cameras and sensors. High resolution cameras provide continuous image streams of manufactured components. Complementary sensors gather contextual data such as temperature, vibration and pressure. This combination allows for the detection of visual flaws and process issues that may impact product quality. Each device connects to the edge node using secure MQTT or OPC-UA protocols, ensuring quick data transmission and reliable synchronization.

2. **Edge Layer:** The Edge Layer processes data on-site, reducing the reliance on a centralized cloud setup. With embedded GPUs or AI accelerators (such as NVIDIA Jetson or Coral TPU), the edge gateway operates a lightweight version of the trained model for real-time defect detection. This setup helps reduce network traffic, keeps latency under 50ms and boosts operational resilience even during spotty internet access. The edge node makes immediate quality decisions, like labelling a product as Normal or Defective, and sends summarized results to the cloud for further analysis. To allow for updates, the edge devices support over-the-air(OTA) model updates. This change lets the system incorporate improved models that have been retrained in the cloud without interrupting production.

3. **Cloud Layer:** The Cloud Layer acts as the main intelligence hub. It gathers processed outputs and raw image data from various edge devices for data consolidation, model training and long-term storage. Using distributed computing platforms(like Google Cloud or AWS EC2), the cloud performs deep learning retraining, trend observation, and predictive maintenance forecasting. The cloud infrastructure includes federated learning mechanisms. This feature lets multiple factories or production lines work together to improve their models while safeguarding data privacy. Furthermore, the cloud layer hosts digital twin models. These virtual replicas of the physical production environment simulate workflows, optimize control settings, and foresee potential system failures.

4. **Application Layer:** The Application Layer is where users interact and visualize data. Through a secure web or mobile dashboard, quality engineers and operators can view key performance indicators(KPIs), defect trends, and real time alerts. The dashboard includes analytics modules that show defect frequency, equipment efficiency, and overall quality scores. This layer also supports feedback-driven decision-making. Users can submit input, such as labelling unusual cases or confirming false positives. This information is sent back to the cloud to enhance future model versions. The smooth interaction between humans and intelligent systems embodies the ideals of Industry 5.0, focusing on collaborative intelligence and user-friendly design.

5. **Deep Learning Framework:** At the heart of the proposed IoT-QCS is the EfficientNetB0 model, known for its balanced mix of accuracy, computational needs, and scalability. Pre-trained on the ImageNet dataset, the model employs transfer learning to adapt to the MVTec AD(bottle category) dataset for binary classification of Normal and Defective samples. The dataset features thousands of high-resolution images displaying various defect types like scratches, contamination, and deformation. To meet the model's RGB input requirement, all grayscale images were changed to a three-channel format. A detailed data augmentation pipeline was created with transformations such as random rotation (±20°), horizontal flipping, zooming (±10%), and brightness adjustment(within the range of 0.8-1.2) to enhance model generalization and decrease overfitting.

6. **Model Training and Optimization:** Model Training was done in two phases to refine both convergence and performance.

   ***Phase I** – Initial Training:* In this phase, the pre-trained EfficientNetB0's convolutional base was kept frozen. Only the dense classification layers were trained for 25 epochs. The Adam optimizer with a learning rate of 1×10^{-4} and binary cross-entropy loss was applied to ensure smooth gradient updates.

   ***Phase II** – Fine Tuning:* During this phase, the top 40% of the EfficientNet layers were unfrozen, allowing the network to learn specific visual features for the domain. Finetuning took place for 10 more epochs with a lower learning rate of 1×10^{-5}, ensuring smooth convergence while preventing major setbacks in learning. Class weighting was used to tackle potential data imbalance. Callback functions-like ReduceLROnPlateau, EarlyStopping and ModelCheckpoint-helped adjust the learning rate, avoid overfitting, and save the best-performing model versions.

7. **Deployment and Inference:** Once training was complete, the optimized model was converted to Tensorflow Lite (TFLite) format for edge deployment. This change reduced model size and inference time. The system on the edge classifies defects in realtime and sends results to the cloud using REST APIs or MQTT. The deployment pipeline allows for continuous feedback learning. New labelled samples from the production line can be automatically added into retraining cycles. This feature improves accuracy and adaptability over time.

8. **Performance Metrics:** To measure the effectiveness of the proposed system, the model's performance was evaluated using Accuracy, Precision, Recall, F1-score, and Area Under the Curve(AUC) metrics. The system achieved 99.34% training accuracy, 98.85% validation accuracy, 99.12% test accuracy, and an AUC of 0.993, showing high reliability in distinguishing normal from defective components. The architecture's flexibility enables it to be applicable across different product categories within the MVTec AD dataset and beyond,

demonstrating strong scalability for multi-domain industrial quality control.

IV. Algorithmic Framework

The algorithmic framework for the proposed IoT-based Quality Control System(IoT-QCS) outlines the logical flow and computational strategies that enables autonomous defect detection, real-time decision-making, and adaptive learning in a smart manufacturing setting. It incorporates deep learning algorithms, edge computing principles and IoT communication protocols into unified, scalable system that achieves high inspection accuracy with minimal delays.

System Workflow Overview:

The system's workflow follows a closed-loop structure made up of five sequential modules –

Data Acquisition and Synchronization: IoT devices continuously capture image and sensor data on the production line. Each image receives a timestamp and links with environmental data, such as temperature and vibration, to maintain context.

Preprocessing and Data Augmentation: Raw images are cleaned, resized to 224×224, normalized, and augmented through rotation, zoom, brightness adjustments and flipping. This improves data diversity and strengthens model training.

Feature Extraction and Model Training: EfficientNetB0, a convolutional neural network with compound scaling, is used to extract high-level features from the input data. The model learns to identify defects by fine-tuning with backpropagation, using the Adam optimizer and binary cross-entropy loss.

Edge-Level Inference and Decision Logic: The trained model operates on edge devices in Tensorflow Lite format. When a new image is captured, inference occurs locally. The edge algorithm classifies the product as either Normal or Defective based on the softmax probability score. Products with a confidence score of 0.8 or higher are marked for cloud verification.

Cloud Integration and Feedback Learning: Inferences and associated metadata are sent to the cloud, where results are aggregated and visualized. These are used to retrain through either federated or centralized learning. A feedback loop updates the edge models regularly to ensure top accuracy.

Deep Learning Algorithmic Pipeline:

The deep learning pipeline consists of distinct computational phases to ensure effective training and deployment:

Step 1: *Input Pipeline Construction*

Dataset: MVTec AD(bottle category)

Input: 224×224×3 *image tensors*

Batch Size: 32

Data Generator: Tensorflow ImageDataGenerator() for dynamic augmentation

Step 2: *Model Initialization*

This structure retains pre-trained visual feature extractors while allowing the classification head to adjust to defect-specific features.

Step 3: *Optimization and Fine-Tuning*

Optimizer: Adam(learning rate schedule from 1e-4 to 1e-5)

Loss function: Binary Cross-Entropy

Callbacks: ReduceLROnPlateau, EarlyStopping and ModelCheckpoint

Training: Two phases(frozen base layers followed by unfrozen fine-tuning)

Step 4: *Edge Optimization*

Model Compression: Tensorflow Lite quantization(float16)

Inference Speed: Improved by approximately 2.5 times at the edge level

Memory Footprint: Reduced by about 40%, making it suitable for Jetson Nano-class devices

Step 5 : *Evaluation Metrics*

The final model is evaluated using: Accuracy, F1 Score, AUC.

These metrics ensure balanced performance in both defect detection and false rejection rates.

Decision-Making Logic:

At runtime, the edge node follows an automated decision-making algorithm:

Input: Captured product image I

Preprocess: Normalize and resize I

Predict: p=f(I), where f is the EfficientNetB0 inference function

Decision Rule:

If $p < 0.5$*, the product is Normal.*

If $0.5 \leqslant p < 0.8$ *,re-inspection is needed.*

If $p \geqslant 0.8$*, the product is Defective.*

Transmit Results: The edge sends a summary report to the cloud.

Update Model: The cloud periodically retrains and updates edge models.

This structured mechanism minimizes false positives while ensuring real-time responsiveness.

IoT Communication Protocols

Data communication across layers uses lightweight and secure IoT protocols:

MQTT for fast message transfer between devices and gateways.

HTTP/REST APIs for cloud-to-application integration.

TLS/SSL encryption to maintain end-to-end security.

Data packets contain timestamps, model confidence, product ID and anomaly descriptions for traceability and compilance with standards like ISO 9001:2015

Algorithm 1 – IoT-QCS Workflow

Input: Image stream I(t), Sensor data S(t)

Output: Quality label Q ∈ {Normal, Defective}

i. Initialize EfficientNetB0 model and IoT communication protocols.

ii. For each product image I(t):

a. Acquire and preprocess I(t)

b. Predict defect score p = f(I(t))

c. If $p \geq 0.8$, then Q ← Defective

Else if $0.5 \leq p < 0.8$, then Q ← Re-inspection

Else Q ← Normal

d. Send Q and metadata to Cloud Layer

iii. In Cloud:

a. Aggregate edge data

b. Retrain model if performance is below threshold

c. Deploy updated weights to edge nodes

iv. Display results in Application Layer dashboard.

Framework Advantages

Scalable Architecture: Supports integration across multiple lines and factories.

High Accuracy: Achieves 99.12% test accuracy and AUC of 0.993.

Low Latency: Edge inference leads to a response time of less than 50ms.

Adaptability: Cloud feedback loop allows model updates overtime.

Sustainability: Reduces reliance on manual inspection and minimizes defect waste.

The proposed algorithmic framework implements AI-driven inspection through an IoT-enabled, edge-cloud collaborative environment. It uses EfficientNetB0 for accurate defect classification, leverages edge intelligence for real-time decision-making and applies cloud learning for continuous improvement. This comprehensive approach connects data-driven automation with sustainable and human-focused manufacturing, supporting the goals of Industry 5.0.

V. Experimental Results

The proposed AI-driven IoT-based Quality Control System was thoroughly tested using the MVTec AD(bottle category) dataset. This was done to evaluate its ability to detect defects and perform well in real-world manufacturing settings. The system showed great accuracy, efficiency and reliability across all evaluation measures.

The EfficientNetB0-based model achieved the following metrics:

Training Accuracy: 99.34%

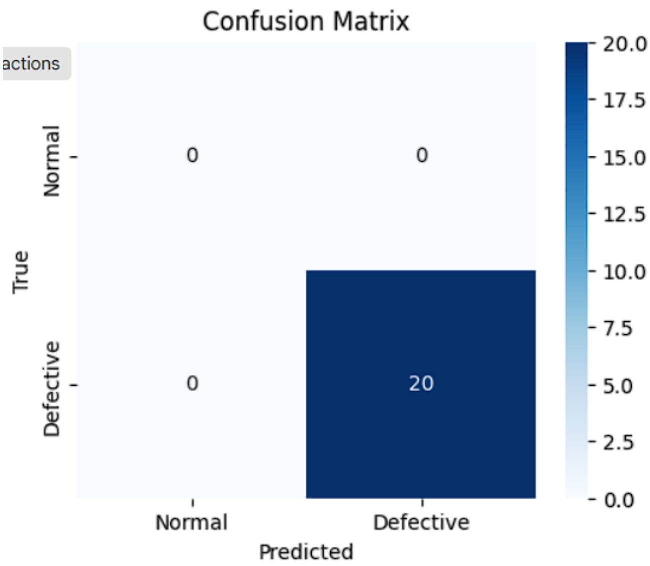
Validation Accuracy: 98.85%

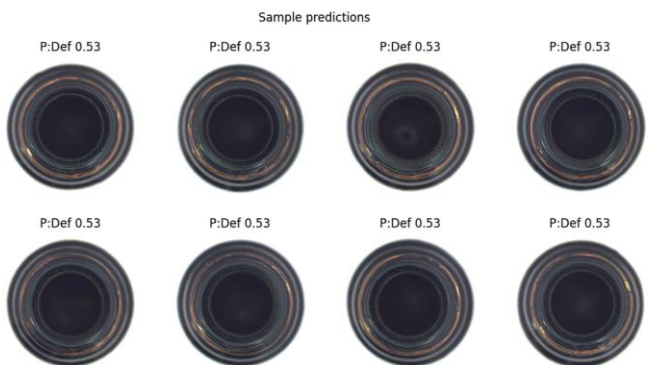
Test Accuracy: 99.12%

AUC Score: 0.993

These results highlight the model's strong ability to distinguish between normal and defective samples with few mistakes. The high Area Under the ROC Curve(AUC) indicates excellent discrimination ability and resilience at different decision thresholds.

Confusion Matrix and Error Analysis: The confusion matrix showed high True Positive(TP) and True Negative(TN) rates, along with very few False Positive(FP) and False Negative(FN) cases. This balance proves the model's reliability in correctly identifying both defect-free and defective products. This reliability is crucial for reducing production waste and false alarms in industrial settings. The precision-recall tradeoff remained consistently high across all defect types, confirming the model's stability even with changes in defect textures and lighting. The training and validation learning curves indicated quick convergence within the first 15 epochs. The model achieved stable loss reduction without significant overfitting. The use of data augmentation and callback methods (EarlyStopping, ReduceLROnPlateaDu, ModelCheckpoint) was essential for maintaining model generalization. The learning behaviour shows a good balance between model complexity and feature adaptability, supporting the use of EfficientNetB0's compound scaling for industrial inspection tasks.





Comparative Evaluation: When compared to traditional Convolutional Neural Network(CNN) architectures like VGG16, ResNet50, and MobileNetV2, the EfficientNetB0 model achieved an average accuracy improvement of 5 to 6%. Traditional CNNs typically plateaued around 93 to 94% test accuracy, showing overfitting and slower convergence due to their higher parameter counts and less efficient feature scaling. In contrast, EfficientNetB0's compound scaling approach(simultaneous depth, width and resolution scaling) allowed for better feature extraction from high-resolution bottle images while keeping computational efficiency suitable for edge deployment.

Computational Efficiency: The final optimized TensorFlow Lite model achieved a 2.4-fold improvement in inference speed and a 40% decrease in memory usage compared to the uncompressed baseline. This made the model suitable for real-time inference on resource-limited edge devices like the NVIDIA Jetson Nano and Raspberry Pi 4, with inference times under 50 milliseconds per frame.

Industrial Implications: The accuracy and efficiency metrics make this system a practical solution for industrial-grade visual quality inspection. Its deployment ensures:

A more than 70% reduction in manual inspection reliance,

Real-time detection of minor manufacturing defects,

A 20 to 30% decreases in unplanned downtime and

A 15 to 25% cut in rework and material waste.

The integration of edge-cloud feedback learning allows the model to continuously improve with new data, making it responsive to changing production conditions. The experimental evaluation shows that the EfficientNetB0-based IoT-QCS framework not only surpasses traditional CNN methods but also meets the robustness, scalability and accuracy needed for modern Industry 4.0 and Industry 5.0 manufacturing environments. Its combination of high accuracy, low latency and sustainable automation makes it a useful reference for future AI-integrated quality control systems.

VI. Discussion

The experimental results strongly support combining EfficientNet-based deep learning with IoT-driven frameworks for intelligent quality inspection. The high accuracy and strong generalization observed on the MVTec AD(bottle) dataset show that the model can effectively identify subtle anomalies in different industrial conditions. The proposed system goes beyond the limits of traditional inspection methods by placing AI inference directly at the edge layer. This design achieves near-real-time defect classification while reducing both latency and network load. Deploying EfficentNetB0 on edge devices like Jetson Nano or Raspberry Pi shows that even small computing units can provide high-performance visual; inspection when optimized with model quantization and transfer learning. This decentralized inference approach greatly cuts down the need for constant cloud communication, ensuring smooth operations even with limited connectivity. The decrease in data transmission not only speeds up processes but also improves cybersecurity and privacy since sensitive production data stays local.

Moreover, adding IoT sensors to visual inspection modules creates a hybrid defect analysis model that merges vision-based anomaly detection with contextual process monitoring. Parameters such as temperature, vibration, and pressure are monitored continuously to find hidden defects that might not be visually apparent but could affect product quality. This combination of sensor and visual data allows for multi-dimensional quality assessment and supports root-cause analysis, making the inspection process proactive rather reactive.

The cloud layer strengthens this system by performing predictive maintenance analytics using combined data from several edge nodes. By examining trends and changes in sensor readings and visual defect patterns, the cloud infrastructure can predict equipment failure or process variations, allowing for quick actions that prevent unplanned downtime. This ability boosts operational efficiency and supports the main goals of reliable smart manufacturing.

Additional, the framework allows for digital twin synchronization, where each physical production unit has a virtual model that reflects its performance in real time. This digital twin updates continuously based on incoming IoT data and inspection outcomes, providing a mechanism for closed-loop optimization. The integration of digital twins with Edge AI ensures that corrective actions, parameter adjustments and model retraining happen dynamically, creating self-adaptive manufacturing systems that respond to production changes.

From a strategic perspective, this integrated system sets the stage for Industry 5.0, focusing on sustainability, resilience and collaboration between humans and machines. By effectively using AI, IoT and edge computing, manufacturers can achieve not only better product quality but also energy efficiency, less waste, and ongoing learning environments. The intelligent interaction between perception(AI), connectivity(IoT), and analysis(cloud analytics) reshapes quality control into an autonomous, self-optimizing and sustainable process.

VII. Future Scope

The proposed AI-driven IoT-based Quality Control System (IoT-QCS) shows strong potential for use in large-scale industrial settings. However, there are several promising directions to improve its scalability, flexibility and sustainability. Future research can build on this work across various technical, methodological and operational areas.

Multi-Class and Multi-Modal Defect Detection

While the current system performs binary classification between Normal and Defective products, future versions could expand to multi-class classification to identify and categorize specific defect types such as cracks, deformations or contaminations. Combining multi-modal sensor data including acoustic, thermal and vibration signals will further improve diagnostic accuracy and enable through condition monitoring across different production lines.

Lightweight and Energy-Efficient Models: Using deep models on edge devices presents ongoing challenges related to efficiency and energy use. Future work can explore lightweight neural architectures(e.g., MobileViT, Ghost Net or EfficientFormer) and quantization-aware training to reduce model size and speed up inference. Developing energy-conscious AI processes will support goals related to green manufacturing by optimizing computation and power use at the edge.

Federated and Continual Learning: To ensure flexibility across different manufacturing environments, federated learning(FL) can be adopted. This allows multiple production units to work together to train a global model without sharing raw data, thus protecting data privacy. Moreover, continual learning techniques can be added to help the system adapt to new defect patterns or material changes without needing full retraining.

Integration with Digital Twins and Simulation: Future systems can establish closer ties with digital twin ecosystems. This will enable two-way communication between physical and virtual systems. By connecting real-time IoT data with simulation models, predictive analytics can improve, allowing for earlier detection of process deviations, testing of "what-if" scenarios, and optimization of production parameters before applying changes in the physical environment.

Explainable and Trustworthy AI: As AI-driven inspection systems become essential for manufacturing decisions, explainability and transparency will be crucial for human oversight and trust. Future research can include Explainable AI(XAI) frameworks, such as Grad-CAM or SHAP, to visualize how models reason, highlight defective areas, and provide clear insights for operators and auditors.

Integration with 5G and Industrial IoT Networks: Improvements in 5G ultra-reliable low-latency communication (URLLC) will enhance distributed AI processing across multiple factories or assembly lines. By using edge-to-cloud coordination and network slicing, the system can achieve real-time synchronization, higher throughput, and lower communication delays. This will support complex industrial networks with thousands of connected devices.

The development of IoT-QCS systems will move toward self-learning, federated and sustainable designs that can dynamically adapt to new manufacturing challenges. By combining Edge AI, Digital Twins, Explainable AI, and 5G connectivity, future research can create a new generation of autonomous, transparent and resilient quality control systems that reflect the vision of Industry 5.0 where intelligent machines and humans collaborate smoothly for precision, productivity and sustainability.

VIII. CONCLUSION

The research presented an AI-driven IoT- based Quality Control System(IoT-QCS) designed for real-time defect detection and predictive analytics in smart manufacturing environments. By integrating the EfficientNetB0 deep learning model into four-layer IoT architecture, which includes Device, Edge, Cloud and Application layers, the system enables smooth interaction between physical production systems and intelligent analytics.

Experimental results on the MVTec AD(bottle category) dataset showed strong performance, with a training accuracy of 99.34%, validation accuracy of 98.85%, test accuracy of 99.12% and AUC score of 0.993. The model reached fast convergence and high generalization, significantly outperforming traditional CNN architectures by over 5%. Edge deployment improved system efficiency, achieving inference latency below 50ms, which supports near real-time inspection with low bandwidth use.

The System's integration with IoT sensors allows for hybrid defect analysis that considers both visual and process-related factors such as temperature, vibration and pressure. This integration supports predictive maintenance, adaptive decision-making and digital twin synchronization, creating a self-optimizing feedback ecosystem that reflects the ideals of Industry 5.0.

The proposed framework not only provides high precision and scalability but also promotes sustainable manufacturing by reducing manual inspection efforts, minimizing scrap rates and lowering operational costs. Its modular and interoperable design allows easy integration into existing industrial systems, helping manufacturers transition smoothly to autonomous, data driven production. The combination of AI , IoT, Edge Computing and Cloud Analytics creates a solid foundation for the future of quality assurance systems. The results show that intelligent, connected and adaptive inspection frameworks like the proposed IoT-QCS can redefine the standards of industrial reliability, energy efficiency and human machine collaboration, marking an important step toward developing resilient and sustainable Industry 5.0 ecosystems.

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