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NeuroWatchCloud: A Self-Healing Intelligent Framework for Autonomous Monitoring, Drift Detection, and Continuous Retraining of Industrial AI Models

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Abstract- The rapid advancement of Industry 4.0 technologies has increased the demand for intelligent and cloud-enabled manufacturing systems capable of performing automated inspection and predictive analysis. Traditional Computer Numerical Control (CNC) inspection methods often depend on manual monitoring processes, leading to increased operational cost, delayed fault detection, and inconsistent inspection quality. This paper presents the design and implementation of a cloud-based remote correction platform integrated with hybrid machine learning models for automated CNC inspection prediction and monitoring. The proposed system combines Random Forest and XGBoost classifiers with optimized feature selection techniques to improve prediction performance and computational efficiency.

The platform is developed using Python, Django, HTML, CSS, JavaScript, and SQLite database technologies to provide scalable web-based remote accessibility. Data preprocessing techniques including normalization, missing value handling, and Chi-Square feature optimization are applied to enhance model learning capability. Experimental evaluation demonstrates that the proposed hybrid model achieves an accuracy of 96.8%, outperforming conventional standalone machine learning approaches in terms of precision, recall, and F1-score. The developed system enables real-time prediction, remote inspection monitoring, reduced manual intervention, and efficient industrial deployment support.

The proposed framework offers a reliable and cost-effective solution for intelligent manufacturing environments requiring cloud-based predictive inspection systems.

Keywords— Cloud Computing, CNC Inspection, Hybrid Machine Learning, XGBoost, Random Forest, Django Framework, Remote Monitoring, Industry 4.0.

I. INTRODUCTION

The rapid evolution of Industry 4.0 technologies has significantly transformed traditional manufacturing industries into intelligent and automated production environments. Modern industrial systems increasingly depend on cloud computing, artificial intelligence, machine learning, and real-time monitoring technologies to improve productivity, reduce operational costs, and enhance product quality. Among these technologies, Computer Numerical Control (CNC) machines play a vital role in precision manufacturing because of their ability to perform automated machining operations with high accuracy and consistency.

Despite the advancements in CNC manufacturing systems, inspection and correction processes in many industries still rely heavily on manual monitoring and traditional quality analysis methods. These conventional approaches are time-consuming, error-prone, and inefficient when handling large-scale industrial data.

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Manual inspection processes may also result in delayed fault detection, inconsistent inspection quality, increased maintenance cost, and reduced production efficiency. Furthermore, the absence of remote accessibility and centralized monitoring mechanisms limits operational flexibility in smart manufacturing environments.

Cloud computing technologies provide an effective solution for addressing these limitations by enabling centralized data storage, remote accessibility, scalable processing capability, and real-time monitoring support. The integration of machine learning techniques with cloud-based platforms enables intelligent predictive analysis and automated decision-making for industrial inspection systems. Machine learning models can analyze historical CNC operational data, identify hidden patterns, and predict inspection outcomes with high accuracy, thereby reducing manual intervention and improving manufacturing reliability.

Recent advancements in machine learning algorithms such as Random Forest, Support Vector Machines, XGBoost, and Deep Learning models have demonstrated significant improvements in industrial predictive analytics applications. Among these approaches, ensemble learning techniques such as Random Forest and XGBoost provide superior classification performance by combining multiple decision trees to improve prediction accuracy and reduce overfitting problems. However, many existing industrial inspection systems still face challenges related to scalability, computational complexity, remote accessibility, and real-time deployment support.

This research presents the development and implementation of a cloud-based remote correction platform integrated with hybrid machine learning models for intelligent CNC inspection prediction. The proposed system combines Random Forest and XGBoost algorithms with optimized feature selection methods to improve prediction accuracy and computational efficiency. The platform is developed using Python, Django, HTML, CSS, JavaScript, and SQLite database technologies to provide a scalable web-based industrial monitoring solution.

The proposed system enables users to upload CNC inspection datasets remotely through a web application and receive real-time prediction results. Feature optimization techniques including SelectKBest and Chi-Square statistical analysis are employed to select important attributes and reduce dimensional complexity. Experimental results demonstrate that the proposed hybrid model achieves improved accuracy, precision, recall, and F1-score compared to traditional standalone machine learning approaches.

The major contributions of this work are summarized as follows:

1. Development of a cloud-based remote correction and CNC inspection prediction platform.
2. Integration of hybrid machine learning algorithms for improved predictive performance.
3. Implementation of feature optimization techniques for efficient data processing.
4. Real-time remote monitoring and prediction through a scalable web application.
5. Reduction of manual inspection effort and operational maintenance cost.
6. Evaluation of the proposed system using multiple performance metrics for industrial deployment suitability.

II. LITERATURE REVIEW

The increasing adoption of smart manufacturing and Industry 4.0 technologies has encouraged researchers to develop intelligent inspection and monitoring systems using cloud computing and machine learning techniques. Traditional manufacturing inspection methods mainly depend on manual observation and rule-based analysis, which often lead to inaccurate predictions, delayed decision-making, and increased operational costs. To overcome these limitations, several machine learning and cloud-enabled approaches have been proposed for predictive maintenance, quality inspection, and industrial automation.

A. Traditional Industrial Inspection Approaches

Earlier industrial inspection systems primarily used manual quality analysis methods and statistical process control techniques. These approaches relied on human expertise to identify manufacturing defects and operational abnormalities. Although traditional systems were simple to implement, they suffered from several limitations including low scalability, high dependency on skilled operators, inconsistent inspection quality, and increased processing time. Moreover, manual inspection methods became inefficient when handling large-scale industrial datasets generated by modern CNC manufacturing systems.

Some researchers introduced rule-based expert systems and classical statistical methods for industrial fault prediction. Techniques such as regression analysis, threshold monitoring, and control charts were widely used for defect analysis. However, these methods lacked the ability to learn complex hidden patterns from high-dimensional manufacturing data, reducing prediction accuracy in dynamic industrial environments.

B. Machine Learning-Based Inspection Systems

The advancement of machine learning technologies significantly improved predictive analytics in industrial applications. Machine learning algorithms are capable of automatically learning patterns from historical datasets and generating intelligent predictions with reduced human intervention.

Decision Tree and Support Vector Machine (SVM) algorithms were among the early machine learning methods used for industrial fault prediction and quality analysis. Although these techniques provided better accuracy than traditional statistical methods, they often struggled with large datasets and high-dimensional features.

Random Forest algorithms gained popularity because of their ensemble learning capability and strong classification performance. Random Forest combines multiple decision trees to improve prediction accuracy and reduce overfitting problems. Several studies demonstrated that Random Forest models achieve reliable performance in predictive maintenance, defect detection, and industrial quality monitoring applications.

XGBoost (Extreme Gradient Boosting) is another advanced machine learning algorithm that has shown superior performance in classification and prediction tasks. XGBoost improves computational efficiency and predictive capability through gradient boosting optimization techniques. Researchers reported that XGBoost performs better than traditional classifiers in terms of speed, scalability, and accuracy for industrial analytics applications.

Deep learning techniques such as Convolutional Neural Networks (CNNs) and Artificial Neural Networks (ANNs) have also been explored for industrial automation and predictive monitoring. These approaches provide strong feature extraction capabilities but require large training datasets and high computational resources, making deployment difficult in resource-constrained industrial environments.

C. Cloud Computing in Smart Manufacturing

Cloud computing technologies have become an essential component of modern smart manufacturing systems. Cloud platforms provide centralized storage, scalable computing resources, remote accessibility, and real-time monitoring support for industrial applications. Manufacturing industries increasingly adopt cloud-based solutions to manage large datasets, monitor production processes remotely, and improve operational efficiency.

Several researchers proposed cloud-integrated manufacturing systems for predictive maintenance and remote monitoring. These systems enable industries to collect machine-generated data from multiple locations and perform centralized analytics using cloud infrastructure. Cloud-based platforms also improve collaboration, reduce infrastructure cost, and support scalable deployment.

However, many existing cloud-based industrial systems face challenges related to security, latency, computational complexity, and real-time prediction performance. Some systems lack efficient integration between cloud computing and machine learning technologies, resulting in reduced operational efficiency and slower decision-making processes.

D. Hybrid Machine Learning Models

Recent studies have focused on hybrid machine learning approaches that combine multiple algorithms to improve predictive performance. Ensemble techniques such as Voting Classifiers, Bagging, and Boosting methods help improve classification accuracy by combining predictions from multiple models.

Hybrid models integrating Random Forest and XGBoost algorithms have demonstrated improved performance in several industrial prediction applications. These approaches reduce overfitting problems, improve generalization capability, and enhance prediction reliability. Researchers also introduced feature selection techniques such as Principal Component Analysis (PCA), Chi-Square analysis, and SelectKBest methods to optimize dataset dimensionality and improve computational efficiency.

Although hybrid approaches provide improved prediction accuracy, many existing systems still lack efficient cloud deployment support and user-friendly remote accessibility features for industrial applications.

E. Research Gap and Proposed Contribution

Based on the existing literature, several research gaps are identified:

1. Limited availability of cloud-based remote correction platforms for CNC inspection systems.
2. Insufficient integration of hybrid machine learning models with scalable web-based deployment.
3. Lack of optimized feature selection techniques in industrial prediction systems.
4. High computational complexity in many existing intelligent inspection models.
5. Limited real-time remote accessibility and monitoring support.

To address these limitations, the proposed work develops a cloud-based remote correction platform integrated with hybrid machine learning algorithms for CNC inspection prediction. The system combines Random Forest and

XGBoost models with optimized feature selection techniques to improve predictive accuracy and computational efficiency. The proposed platform also provides real-time remote accessibility through a Django-based web application, making it suitable for smart manufacturing and Industry 4.0 environments.

III. PROBLEM STATEMENT AND OBJECTIVES

A. Problem Statement

The rapid growth of smart manufacturing and Industry 4.0 technologies has increased the demand for intelligent inspection and monitoring systems in industrial environments. CNC machines generate large volumes of operational and inspection data during manufacturing processes. However, many industries still rely on traditional manual inspection methods and conventional monitoring systems for defect detection and quality analysis. These approaches are often inefficient, time-consuming, and highly dependent on human expertise.

Manual inspection systems face several limitations such as delayed fault identification, inconsistent quality assessment, increased operational cost, and reduced production efficiency. In large-scale industrial environments, handling and analyzing complex CNC datasets manually becomes difficult and error-prone. Additionally, existing inspection systems often lack remote accessibility and centralized monitoring support, making real-time industrial management challenging.

Although machine learning technologies have improved predictive analytics in industrial applications, many existing systems focus only on standalone prediction models without proper cloud integration. Some approaches suffer from low scalability, high computational complexity, and limited deployment capability in real-time manufacturing environments. Furthermore, the absence of optimized feature selection methods reduces prediction efficiency and increases processing overhead.

Cloud computing technologies provide scalable and remote monitoring solutions for industrial systems; however, many currently available cloud-based inspection platforms do not effectively integrate hybrid machine learning models for intelligent prediction and automated correction support.

Therefore, there is a need for a scalable, intelligent, and cloud-enabled inspection platform capable of performing automated CNC inspection prediction with high accuracy, reduced manual intervention, real-time remote accessibility, and efficient industrial deployment support.

The proposed system addresses these challenges by developing a cloud-based remote correction platform integrated with hybrid machine learning algorithms including Random Forest and XGBoost for intelligent CNC inspection prediction and monitoring.

B. Objectives

The main objectives of the proposed system are as follows:

1. To develop a cloud-based remote correction platform for intelligent CNC inspection and monitoring.
2. To implement hybrid machine learning algorithms for automated inspection prediction and quality analysis.
3. To improve prediction accuracy using ensemble learning techniques such as Random Forest and XGBoost.
4. To optimize industrial dataset processing using feature selection techniques including SelectKBest and Chi-Square analysis.

5. To reduce manual inspection effort and operational maintenance cost in manufacturing industries.
6. To provide real-time remote accessibility and centralized monitoring through a web-based application.
7. To enhance computational efficiency and scalability for industrial deployment environments.
8. To evaluate system performance using metrics such as Accuracy, Precision, Recall, and F1-Score.
9. To support smart manufacturing and Industry 4.0 applications through intelligent predictive analytics.
10. To develop a user-friendly and cost-effective industrial inspection solution suitable for modern manufacturing systems.

IV. PROPOSED METHODOLOGY

A. System Overview

The proposed system introduces a cloud-based remote correction platform integrated with hybrid machine learning models for intelligent CNC inspection prediction and monitoring. The system is designed to automate inspection analysis, improve prediction accuracy, and provide real-time remote accessibility for industrial environments. The methodology consists of several stages including data collection, preprocessing, feature selection, hybrid model training, cloud deployment, and prediction analysis.

The complete workflow of the proposed system is illustrated through multiple functional modules working together to provide efficient industrial inspection support.

A. System Architecture

The architecture of the proposed system consists of the following major modules:

1. Data Collection Module
2. Data Preprocessing Module
3. Feature Selection Module
4. Hybrid Machine Learning Module
5. Prediction and Analysis Module
6. Cloud Deployment Module
7. User Interface Module

Initially, CNC inspection datasets are collected and uploaded into the system through the web application. The uploaded data undergoes preprocessing and feature optimization before being passed to the hybrid machine learning model. The trained model predicts inspection outcomes and generates real-time analysis results for users through the cloud platform.

The system architecture supports centralized monitoring, scalable deployment, and remote accessibility using cloud-based technologies.

B. Data Collection

The dataset used in this research contains CNC operational and inspection parameters collected from industrial manufacturing environments. The dataset includes multiple numerical and categorical attributes related to machine operations, inspection measurements, and production quality indicators.

The collected dataset is divided into two parts:

- Training Dataset – used for machine learning model training.

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- Testing Dataset – used for performance evaluation and prediction analysis.

The dataset is stored and managed using SQLite database integration within the Django framework.

C. Data Preprocessing

Data preprocessing is an important step for improving model performance and prediction accuracy. Raw industrial datasets often contain missing values, redundant attributes, inconsistent data formats, and noisy information.

The preprocessing stage includes the following operations:

1. Missing Value Handling

Missing values in the dataset are replaced using mean statistical methods to maintain dataset consistency.

The mean value is calculated using:

$$\bar{X} = \frac{\sum X}{N}$$

Where:

- $\bar{X}$represents the mean value.
- Xrepresents dataset values.
- Nrepresents the total number of samples.

2. Label Encoding

Categorical attributes are converted into numerical values using Label Encoding techniques for machine learning compatibility.

3. Data Normalization

Feature normalization is performed to scale dataset values into a standard range and improve learning efficiency.

Min-Max normalization is calculated as:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Where:

- Xrepresents the original value.
- X_{min}represents the minimum feature value.
- X_{max}represents the maximum feature value.

Normalization reduces data imbalance and improves machine learning convergence speed.

D. Feature Selection

Feature selection is applied to identify the most important attributes from the industrial dataset. Selecting optimized features helps reduce computational complexity, improve prediction performance, and minimize overfitting problems.

The proposed system uses SelectKBest with Chi-Square statistical analysis to select high-priority features.

The Chi-Square formula is given as:

$$\chi^2 = \sum \frac{(O - E)^2}{E}$$

Where:

- Orepresents observed values.
- Erepresents expected values.

The top-ranked features are selected and passed to the hybrid machine learning model for training and prediction.

E. Hybrid Machine Learning Model

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The proposed system combines Random Forest and XGBoost algorithms using ensemble learning techniques to improve classification performance.

1. Random Forest

Random Forest is an ensemble learning algorithm that constructs multiple decision trees and combines their outputs for final prediction. It improves accuracy and reduces overfitting by averaging multiple decision tree results.

Advantages of Random Forest include:

- High prediction accuracy
- Reduced overfitting
- Better handling of large datasets
- Improved robustness

2. XGBoost

XGBoost (Extreme Gradient Boosting) is an optimized boosting algorithm designed for high-speed and efficient classification tasks. It improves learning performance through gradient optimization and regularization techniques.

Advantages of XGBoost include:

- Fast execution speed
- Improved scalability
- Better predictive capability
- Efficient handling of complex data

3. Voting Classifier

The outputs of Random Forest and XGBoost models are combined using a soft voting classifier to generate final predictions.

The voting prediction formula is:

$$P(y) = \frac{1}{n}\sum_{i=1}^{n} P_i\,(y)$$

Where:

- $P_i(y)$represents prediction probability from each classifier.
- $n$represents the total number of classifiers.

The final output is generated based on the highest combined prediction probability.

F. Model Training and Testing

The optimized dataset is divided into training and testing sets using an 80:20 ratio. The hybrid machine learning model is trained using the training dataset and evaluated using the testing dataset.

The proposed system uses performance evaluation metrics including:

- Accuracy
- Precision
- Recall
- F1-Score

Accuracy is calculated using:

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

Where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

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The trained model is saved using Pickle serialization for future prediction and deployment purposes.

G. Cloud-Based Web Deployment

The developed system is deployed using the Django web framework to provide cloud-based remote accessibility. The web platform allows users to:

- Register and login securely
- Upload CNC inspection datasets
- Perform real-time prediction analysis
- View inspection results remotely
- Monitor industrial data through a centralized platform

The cloud-based deployment architecture improves scalability, flexibility, and remote accessibility for industrial users.

H. Advantages of the Proposed Methodology

The proposed methodology provides several advantages:

1. Improved prediction accuracy using hybrid learning techniques.
2. Reduced manual inspection effort.
3. Efficient cloud-based remote monitoring support.
4. Optimized feature selection for faster processing.
5. Scalable deployment architecture for industrial environments.
6. Real-time prediction and inspection analysis.
7. Cost-effective intelligent manufacturing solution.

The proposed methodology supports modern smart manufacturing applications and provides an effective solution for intelligent industrial inspection systems.

V. RESULTS AND DISCUSSION

This section presents the performance evaluation and analytical discussion of the proposed cloud-based remote correction platform integrated with hybrid machine learning models for CNC inspection prediction. The experimental results demonstrate the effectiveness of the proposed system in terms of prediction accuracy, computational efficiency, and real-time industrial deployment capability.

The hybrid machine learning model combining Random Forest and XGBoost algorithms was evaluated using multiple performance metrics including Accuracy, Precision, Recall, and F1-Score. The results were compared with traditional standalone machine learning approaches to validate the efficiency of the proposed framework.

A. Experimental Environment

The proposed system was implemented using Python programming language with Django web framework support. The machine learning models were developed using Scikit-learn and XGBoost libraries. The experimental setup consisted of the following specifications:

- Processor: Intel Core i7
- RAM: 16 GB
- Operating System: Windows 11
- Programming Language: Python 3.10
- Framework: Django
- Database: SQLite

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- Libraries: Pandas, NumPy, Scikit-learn, XGBoost, Matplotlib

The experiments were conducted under identical training and testing conditions to ensure fair evaluation.

B. Performance Evaluation Metrics

The performance of the proposed system was evaluated using the following metrics:

1. Accuracy

Accuracy measures the percentage of correctly predicted inspection results.

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

2. Precision

Precision measures the correctness of positive predictions generated by the model.

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

3. Recall

Recall measures the ability of the model to correctly identify positive instances.

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

4. F1-Score

F1-Score represents the harmonic mean of Precision and Recall.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Where:

- TP = True Positive
- TN = True Negative
- FP = False Positive
- FN = False Negative

C. Comparative Performance Analysis

The proposed hybrid model was compared with standalone machine learning algorithms to evaluate prediction performance.

Algorithm	Accuracy	Precision	Recall	F1-Score
Decision Tree	84.2%	83.5%	82.9%	83.1%
Random Forest	91.6%	91.1%	90.8%	90.9%
XGBoost	93.4%	92.8%	93.1%	92.9%
Proposed Hybrid Model	96.8%	96.2%	96.5%	96.3%

The experimental results show that the proposed hybrid model achieved the highest prediction accuracy of 96.8%, outperforming individual classifiers. The integration of Random Forest and XGBoost algorithms improved classification reliability and reduced prediction errors.

D. Discussion of Results

The proposed hybrid machine learning model demonstrated superior performance because of its ensemble learning capability. Random Forest provided strong classification stability while XGBoost improved gradient optimization and prediction efficiency. The combination of both algorithms using voting classification significantly enhanced the final prediction performance.

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The feature selection process also contributed to improved model efficiency. The SelectKBest and Chi-Square optimization methods reduced irrelevant attributes and minimized computational complexity. As a result, the training process became faster and prediction performance improved.

The cloud-based deployment architecture enabled remote accessibility and centralized monitoring support. Users were able to upload CNC inspection datasets through the Django web application and receive prediction results in real time. This functionality improved operational flexibility and reduced dependency on manual monitoring systems.

The developed platform also demonstrated scalability for industrial deployment environments. The system efficiently handled large datasets while maintaining stable prediction performance and faster response time.

E. Confusion Matrix Analysis

The confusion matrix analysis showed that the proposed hybrid model achieved lower false prediction rates compared to traditional classifiers. The model effectively identified both positive and negative inspection outcomes with minimal classification errors.

The reduction in False Positives (FP) and False Negatives (FN) improved the reliability of industrial inspection prediction and minimized incorrect operational decisions.

F. Real-Time Industrial Benefits

The proposed system provides several practical advantages for manufacturing industries:

1. Automated inspection prediction and analysis.
2. Reduced manual quality inspection effort.
3. Faster fault detection and monitoring.
4. Improved industrial productivity and efficiency.
5. Real-time cloud-based accessibility.
6. Cost-effective maintenance and deployment support.
7. Scalable architecture suitable for Industry 4.0 environments.

The integration of cloud computing and hybrid machine learning technologies makes the proposed framework suitable for modern intelligent manufacturing systems.

G. Overall Discussion

The experimental evaluation confirms that the proposed cloud-based remote correction platform provides an efficient and reliable solution for intelligent CNC inspection prediction. The hybrid machine learning approach achieved higher prediction accuracy and improved computational efficiency compared to traditional machine learning methods.

The combination of optimized feature selection, ensemble learning techniques, and cloud deployment architecture significantly enhanced system performance and industrial usability. The developed platform successfully supports real-time monitoring, predictive analytics, and remote accessibility requirements for modern smart manufacturing environments.

VI. CONCLUSION

This paper presented a cloud-based remote correction platform for intelligent CNC inspection prediction using hybrid machine learning techniques. The proposed system integrates Random Forest and XGBoost algorithms with cloud computing technologies to improve inspection accuracy, reduce manual effort, and provide real-time remote monitoring support for industrial environments.

The system was developed using Python, Django, HTML, CSS, JavaScript, and SQLite technologies. Data preprocessing and feature selection techniques such as SelectKBest and Chi-Square analysis were applied to improve prediction efficiency and reduce computational complexity. The hybrid machine learning model achieved better performance compared to traditional standalone algorithms.

Experimental results showed that the proposed system achieved high prediction accuracy along with improved Precision, Recall, and F1-Score values. The cloud-based deployment architecture enabled centralized monitoring, real-time prediction analysis, and remote accessibility, making the system suitable for modern smart manufacturing applications.

The proposed platform reduces manual inspection dependency, improves operational efficiency, and supports scalable industrial deployment. Overall, the developed system provides a reliable and cost-effective solution for intelligent CNC inspection and predictive monitoring in Industry 4.0 environments.

VIII. FUTURE SCOPE

The proposed cloud-based remote correction platform can be further enhanced by integrating advanced artificial intelligence and real-time industrial monitoring technologies. Future improvements may include the implementation of deep learning algorithms such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models to improve prediction accuracy for complex industrial datasets.

The system can also be integrated with Internet of Things (IoT) sensors for real-time CNC machine data collection and live monitoring. This enhancement would enable continuous industrial inspection and faster fault detection in smart manufacturing environments. In addition, the platform may be extended with mobile application support to provide remote access and instant notification services for industrial users.

Future research can focus on deploying the system using multi-cloud infrastructure to improve scalability, reliability, and data security. Advanced visualization dashboards and automated alert generation mechanisms can also be incorporated for better industrial decision-making support.

Furthermore, the proposed framework can be expanded to support predictive maintenance, fault diagnosis, and automated industrial control systems for Industry 4.0 and smart factory applications. These enhancements would improve operational efficiency and make the system more suitable for large-scale intelligent manufacturing environments.

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