

Automated Quality Control System for Manufacturing Defects using Image Processing and Machine Learning Classification

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ABSTRACT: Quality control plays a vital role in manufacturing industries to ensure product reliability, minimize defects, and maintain high levels of customer satisfaction. Traditional manual inspection techniques are often inefficient, time-consuming, and heavily dependent on human expertise, which may lead to inconsistent quality assessment and increased production costs. To address these challenges, this project titled Automated Quality Control System for Manufacturing Defects proposes an intelligent and automated defect detection framework using image processing and machine learning technologies. The proposed system captures high-resolution images of products directly from the manufacturing line using industrial cameras. These images are processed through multiple stages such as image preprocessing, noise reduction, contrast enhancement, segmentation, and feature extraction to improve defect visibility. Advanced machine learning and deep learning algorithms, including convolutional neural networks, are employed to accurately classify products as defective or non-defective. The system is capable of identifying various defect types such as surface cracks, missing components, misalignment, and structural abnormalities. Real-time defect detection enables early corrective actions, thereby reducing material wastage and production downtime. Experimental evaluation demonstrates improved accuracy, consistency, and faster inspection when compared to traditional manual inspection methods. The proposed system enhances operational efficiency, ensures consistent product quality, supports Industry 4.0 initiatives, and provides a reliable and scalable solution for modern automated manufacturing quality control systems.

KEYWORDS: Automated Quality Control, Manufacturing Defects, Machine Learning Models, Random Forest, SVM, Convolutional Neural Networks, Industry 4.0

I. INTRODUCTION

In the present era of industrial automation, manufacturing systems are increasingly adopting intelligent technologies to enhance product quality and ensure reliable production processes. Quality control has become a crucial component in manufacturing environments, as defects in products can lead to increased costs, reduced customer satisfaction, and potential safety concerns. However, traditional manual inspection techniques are often time-consuming, subjective, and prone to human errors, especially in high-speed and large-scale production lines. These limitations make manual quality inspection inefficient for modern manufacturing requirements [1,2]. As a result, defects may remain undetected until later stages of production, leading to material wastage and operational losses. With the advancement of computer vision and automation technologies, image-based inspection systems have emerged as an effective alternative to conventional quality control methods.

Image processing techniques enable the analysis of visual features such as texture, shape, and surface characteristics to identify defects in manufactured products. Unlike manual inspection, automated vision systems provide consistent and repeatable inspection results, thereby improving reliability and efficiency. However, traditional rule-based image processing methods lack adaptability and struggle to detect complex or previously unseen defect patterns under varying

environmental conditions [3]. To address these challenges, machine learning and deep learning techniques have been increasingly employed in automated quality control systems. Algorithms such as Support Vector Machines, Random Forests, and Convolutional Neural Networks have demonstrated superior performance in defect detection and classification tasks compared to traditional approaches. These learning-based methods improve precision and recall by automatically extracting discriminative features from image data and effectively distinguishing between defective and non-defective products [4–5].

By integrating image processing with intelligent learning models, automated systems can detect defects such as surface cracks, missing components, and structural irregularities in real time [6].

II. PROPOSED SYSTEM

2.1. Data Collection

High-resolution images of manufactured products are captured using industrial-grade cameras installed along the production line. Controlled lighting conditions are maintained to reduce shadows, reflections and image noise. Each image is manually examined and labeled as defective or non-defective based on predefined quality standards. The labeled dataset is used as supervised input for training and validating machine learning models.

2.2. Data Preprocessing

The data preprocessing is formed to enhance Image quality and improve defect visibility. Images are converted to grayscale to reduce computational complexity while retaining important details. Noise removal techniques such as gaussian and median filtering are applied to eliminate distortions. Edge detection and morphological operations highlight defect boundaries and surface irregularities.

2.3. Model Development

The meaningful features are extracted from images to represent defect characteristics. These features include texture descriptors, edge information, shape features, and intensity variations. The extracted feature vectors are then fed into various machine learning classifiers such as Random Forest, Gradient boosting, SVM, KNN, LSTM, DNN, Naïve Bayes, Decision Tree. Each model is trained to distinguish between defective and non-defective products. Hyperparameter tuning techniques such as grid search and cross-validation are applied to optimize model performance and prevent overfitting.

2.4. Model Evaluation

The trained models are evaluated using standard performance metrics including accuracy, precision, recall, and F1-score to measure classification effectiveness. Confusion matrices are analyzed to examine false positives and negatives, which are critical in quality control applications. Comparative analysis is performed to identify the most effective model for deployment.

2.5. Proposed Model

The proposed hybrid model integrates both traditional machine learning and deep learning classifiers to achieve robust defect detection. Ensemble-based models such as Random Forest and Gradient Boosting improve generalization and reduce false detection rates. While deep learning models like DNN and LSTM capture complex and non-linear defect patterns. This hybrid approach enhances accuracy, adaptability and scalability, making the system suitable for real time automated quality inspection in manufacturing environments.

III. METHODOLOGY

3.1. Random Forest Classifier

Random Forest is an ensemble learning technique that constructs multiple decision trees using random subsets of data and features. Each tree independently classifies the input image features and the final output is determined by majority voting. This approach reduces overfitting commonly observed in single decision trees. Random Forest efficiently handles high-dimensional feature spaces extracted from images and it captures complex and non-linear defect present in manufacturing data. The model is robust to noise and variations in defect appearance. Due to its stability and accuracy, it is well suited for automatically quality inspection systems.

3.2. Logistic Regression

Logistic Regression is used as a baseline binary classification model in this study. It predicts the probability of a product being defective or non-defective using a sigmoid function. The model establishes a linear relationship between extracted image features and output classes and is computationally efficient and easy to implement. It provides interpretable coefficients that indicate feature importance. Although limited in capturing non-linear patterns, it offers reliable initial performance. Its results serve as a benchmark for evaluating advanced classifiers.

3.3 Naive Bayes

Naive Bayes is a probabilistic classifier based on Baye's theorem with conditional independence assumptions. It computes class probabilities using extracted defect-related features from images and the model is computationally efficient and suitable for large datasets. Despite its simplicity, it performs well with noisy and high-dimensional data. Naive Bayes provides fast prediction, making it useful for real-time applications and it requires minimal training data to estimate parameters. The classifier complements complex models with the hybrid framework.

3.4. Gradient Boosting

Gradient Boosting is an ensemble technique that builds models sequentially to correct previous errors. Each new learner focuses on misclassified samples from earlier iterations, it reduces bias and improves overall classification accuracy. Hyperparameter tuning helps prevent overfitting and enhances generalization and gradient boosting performs well with imbalanced defect datasets. Its strong predictive capability makes it suitable for industrial quality control.

3.5. K-Nearest Neighbors

KNN algorithm is a non-parametric classification method that assigns class labels based on feature similarity between samples. In this approach, defect classification is performed by analyzing the majority class among the k closest neighbors in the feature space. Distance metrics such as Euclidean distance are commonly used to measure similarity between image feature vectors. KNN effectively identifies localized defect patterns by leveraging spatial proximity in high-dimensional feature space. The model does not require an explicit training phase, making it simple to implement. Despite this limitation, KNN performs well when defect classes are clearly separated.

3.6. Support Vector Machine

Support Vector Machine is a powerful supervised learning algorithm that classifies data by constructing an optimal hyperplane separating defect and non-defect classes. By maximizing the margin between classes, SVM ensures robust generalization and improved classification accuracy. Kernel functions such as linear, polynomial, and radial basis functions enable SVM to model non-linear defect patterns effectively. The algorithm performs well in high-dimensional feature spaces commonly produced by image processing techniques. SVM is particularly suitable for small to medium-sized datasets. Proper selection of kernel parameters significantly enhances model performance. Due to its reliability, SVM is widely used in industrial defect detection applications.

3.7. Decision Tree

Decision Tree classification utilizes a hierarchical tree structure where each node represents a decision based on a specific feature value. This approach enables straightforward interpretation of classification rules, making it highly transparent and easy to understand. Decision Trees effectively handle both numerical and categorical image features without requiring extensive preprocessing. They quickly identify the most significant features contributing to defect detection. Decision Trees are susceptible to overfitting when trained on complex or noisy datasets. Pruning techniques and depth control are commonly applied to mitigate this issue. To further improve performance, Decision Trees are often integrated into ensemble models.

3.8. Long Short-Term Memory

Long Short-Term Memory (LSTM) networks are advanced recurrent neural networks designed to capture long-term dependencies in sequential data. In manufacturing defect detection, LSTM models analyze temporal patterns within production and inspection sequences. Memory cells and gating mechanisms allow the network to retain relevant historical information while discarding irrelevant data. This capability makes LSTM particularly effective in identifying defects that evolve over time. Its adaptability makes it suitable for real-time manufacturing environments.

3.9. Deep Neural Networks

Deep Neural Networks consist of multiple hidden layers that enable hierarchical learning of complex feature representations. These networks automatically extract non-linear patterns from image-based features without manual feature engineering. Activation function such as sigmoid facilitate efficient learning and convergence. DNNs are trained using backpropagation and gradient descent optimization techniques. They achieve high accuracy in classifying defective and non-defective products. The model adapts well to variations in defect shape, size and appearance. Due to their scalability and robustness, DNNs are well suited for automated quality control systems.

IV. RESULTS

The proposed Automated Quality Control System was evaluated using a dataset of manufactured product images collected under controlled industrial conditions. The dataset consisted of both defective and non-defective product samples. Various machine learning and deep learning models were trained and tested to assess their effectiveness in detecting manufacturing defects.

4.1. Logistic-Regression

Logistic Regression correctly classified most benign and malicious activities, achieving 375 true negatives and 4231 true positives, with only 23 misclassifications [1,6].

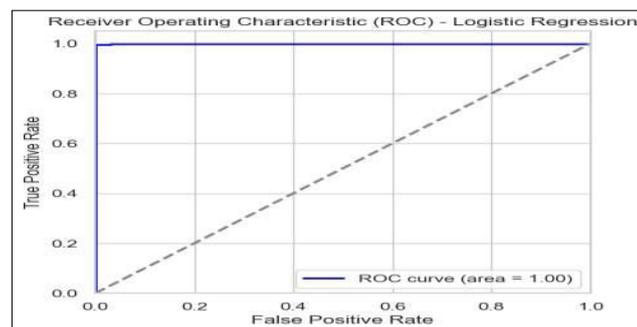


Figure: 4.1 Receiver operating characteristics for Logistic Regression

4.2 Long Short-Term Memory (LSTM)

The LSTM model achieved excellent classification performance by correctly identifying both defective and non-defective products with very high accuracy. Due to its ability to learn sequential and temporal patterns, LSTM effectively captured variations in defect appearance across production sequences.

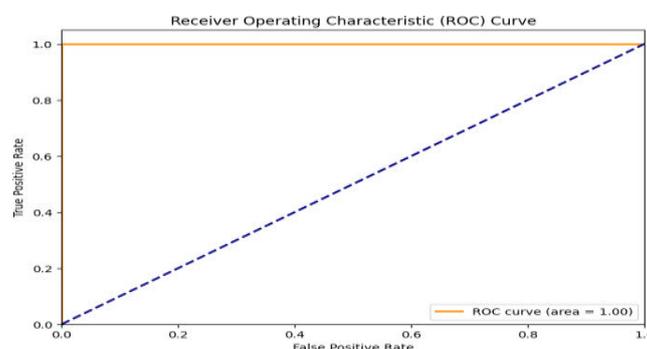


Figure: 4.2 Receiver operating characteristics for LST

4.3 Deep Neural Networks (DNN)

Deep Neural Networks were employed to model complex and non-linear relationships within manufacturing defect features. The multi-layer architecture enabled automatic learning of hierarchical representations from image data, leading to highly accurate defect classification.

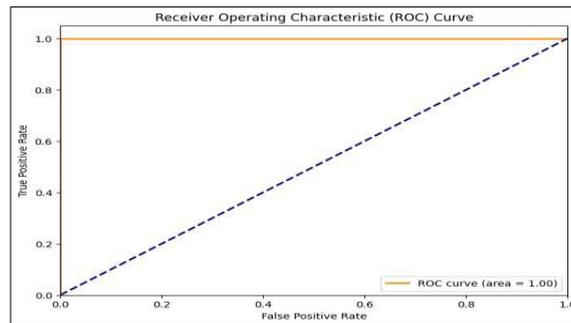


Figure: 4.3 Receiver operating characteristics for DNNs

4.4 Naïve Bayes

The Naïve Bayes classifier demonstrated efficient performance in defect detection by correctly classifying most product samples. Its probabilistic nature allowed it to handle noisy feature data effectively.

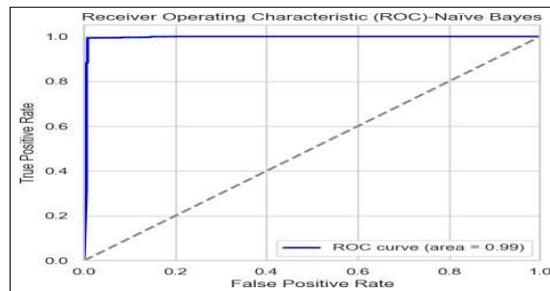


Figure: 4.4 Receiver operating characteristics for Naïve Bayes

4.5 K-Nearest Neighbors (KNN)

The KNN classifier achieved high accuracy by leveraging feature similarity between product samples. It effectively identified localized defect patterns by comparing new samples with nearby instances in the feature space.

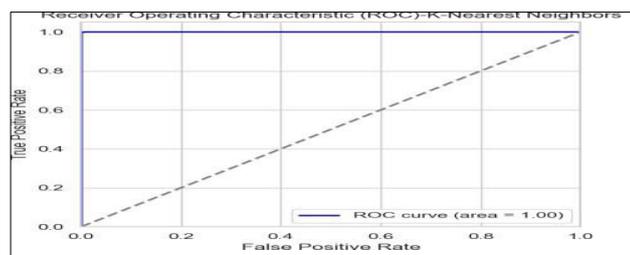


Figure: 4.5 Receiver operating characteristics for KNNs

4.6 Support Vector Machine (SVM)

Support Vector Machine demonstrated strong classification capability by constructing optimal decision boundaries between defective and non-defective products. Kernel functions enabled the model to detect complex defect patterns effectively.

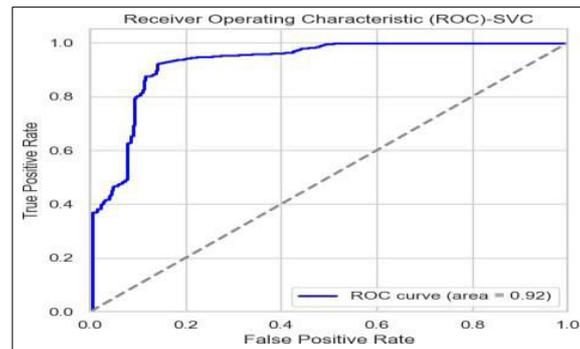


Figure: 4.6 Receiver operating characteristics for SVM

4.7 Random Forest Classifier

The Random Forest classifier achieved near-perfect classification results, accurately identifying all defective and non-defective products in the test dataset. Its ensemble structure enabled robust handling of feature variability and reduced overfitting.

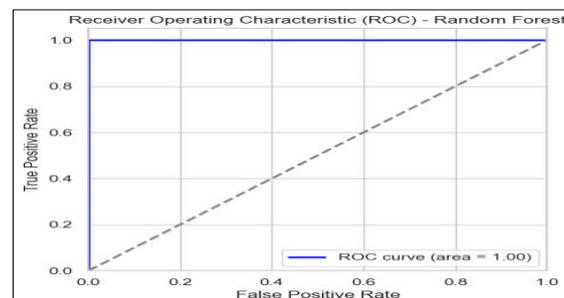


Figure: 4.7. Receiver operating characteristics for RFCs

4.8 Gradient Boosting

Gradient Boosting delivered outstanding classification performance by sequentially improving weak learners. The model successfully detected subtle manufacturing defects with zero false positives and false negatives.

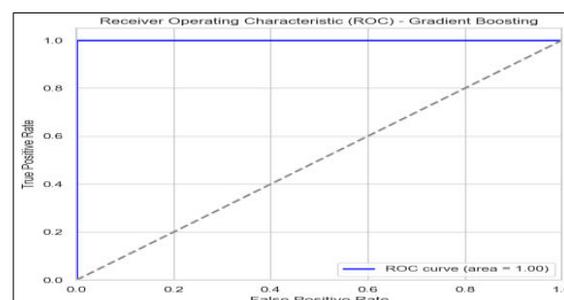


Figure: 4.8. Receiver operating characteristics for GBs

Volume 15, Issue 2, February 2026**|DOI: 10.15680/IJRSET.2026.1502086****V. CONCLUSION**

This project presented an Automated Quality Control System for Manufacturing Defects using image processing and machine learning techniques. The proposed system effectively addresses the limitations of traditional manual inspection methods by providing consistent, accurate, and real-time defect detection.

Experimental results demonstrate that ensemble learning models such as Random Forest and Gradient Boosting outperform individual classifiers in terms of accuracy and robustness. Deep learning models further enhance defect detection by learning complex feature representations and adapting to variations in defect shape, size, and appearance. The system successfully identifies multiple defect types, including surface cracks, misalignment, and structural irregularities.

By reducing human dependency, inspection time, and production errors, the proposed system improves operational efficiency and product quality. The developed framework supports Industry 4.0 initiatives and can be easily integrated into modern automated manufacturing environments. Future work may include real-time deployment, expansion to multi-class defect detection, and integration with explainable AI techniques to enhance transparency and decision-making.

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