International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 4, Jul-Aug-2026, ISSN (Online): 2395-566X

SteelVisionNet A Hybrid Deep Learning Framework for Intelligent Strip Steel Surface Defect Detection

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Abstract- Surface defect detection in strip steel is a critical quality assurance task in modern steel manufacturing, as defects such as scratches, inclusions, patches, and rolled-in scales can significantly degrade product quality, mechanical performance, and production efficiency. Conventional manual inspection methods are labour-intensive, subjective, and incapable of satisfying the speed and accuracy requirements of automated manufacturing environments. This paper presents an intelligent hybrid framework for automated strip steel surface defect detection by integrating traditional machine learning and deep learning techniques. The proposed approach incorporates mean filtering for noise reduction and adaptive threshold-based segmentation to accurately extract defect regions from strip steel images. To improve classification performance, an ensemble model combining Random Forest (RF) and ResNet50 is developed, where ResNet50 extracts rich hierarchical visual features and Random Forest effectively classifies discriminative statistical features. The proposed framework is evaluated using a multi-class strip steel surface defect dataset comprising various defect categories. Experimental results demonstrate that the hybrid RF–ResNet50 model outperforms individual machine learning and deep learning models in terms of classification accuracy, robustness, and generalization capability. The complementary learning characteristics of both models enable effective representation of low-level texture information and high-level semantic features, resulting in reliable defect identification under diverse surface conditions. Furthermore, the proposed framework is computationally efficient and scalable for real-time industrial deployment, reducing reliance on manual inspection while enhancing product quality and manufacturing productivity. These findings highlight the potential of hybrid artificial intelligence techniques as an effective solution for next-generation intelligent surface inspection and quality control systems in smart manufacturing.

Keywords- Strip Steel Surface Defect Detection, Hybrid Artificial Intelligence, Random Forest, ResNet50, Deep Learning, Machine Learning, Computer Vision, Intelligent Manufacturing, Automated Quality Inspection.

I. INTRODUCTION

Brief Introduction

Surface defect detection is a crucial quality control process in strip steel manufacturing, as defects such as scratches, inclusions, patches, and rolled-in scales can significantly affect product quality, mechanical properties, and industrial reliability. Traditional manual inspection methods are labour-intensive, subjective, and unable to satisfy the speed and accuracy requirements of modern automated production lines. Consequently, computer vision and artificial intelligence-based inspection systems have become an effective solution for intelligent defect detection and quality assurance [1]-[3].

Recent advances in machine learning and deep learning have significantly improved automated surface defect detection. Traditional classifiers such as Support Vector Machine (SVM) and Random Forest (RF) provide reliable classification using handcrafted features, whereas deep convolutional neural networks automatically learn hierarchical image representations for improved recognition accuracy [4]-[7]. However, individual models often struggle with complex defect patterns and diverse surface textures. To overcome these limitations, this work proposes a hybrid ensemble framework combining Random Forest and ResNet50.

The framework incorporates mean filtering and threshold-based segmentation for image preprocessing, ResNet50 for deep feature extraction, and Random Forest for robust defect classification. The proposed approach aims to improve classification accuracy, robustness, and generalization while providing a scalable solution for automated strip steel surface inspection in intelligent manufacturing environments [1], [6], [16].

Motivation and Contribution of the Project

The increasing adoption of Industry 4.0 technologies has created a strong demand for intelligent and automated quality inspection systems capable of delivering accurate, consistent, and real-time defect detection. Manual inspection remains susceptible to human error and is unsuitable for high-speed manufacturing environments, leading to increased production costs and reduced product reliability [2], [7].

This research proposes a hybrid Random Forest–ResNet50 framework for strip steel surface defect detection. The proposed model integrates deep feature extraction with ensemble classification to improve recognition accuracy and robustness. In addition, image preprocessing using mean filtering and threshold-based segmentation enhances defect visibility, resulting in more reliable classification. Experimental evaluation demonstrates that the proposed framework provides superior performance compared with conventional machine learning and deep learning models [1], [6], [10].

Objectives of the Project

The primary objective of this research is to develop an intelligent hybrid framework for automated strip steel surface defect detection.

The specific objectives are:

- To preprocess strip steel images using mean filtering and threshold-based segmentation.
- To extract discriminative features using the ResNet50 deep residual network.
- To develop a hybrid Random Forest–ResNet50 classification model.
- To evaluate the proposed framework using Accuracy, Precision, Recall, F1-score, and ROC-AUC.
- To compare the proposed model with existing machine learning and deep learning approaches.
- To develop a web-based application for real-time strip steel defect prediction.

Scope of the Project

This research focuses on automated strip steel surface defect detection using a hybrid machine learning and deep learning framework. The scope includes image preprocessing, feature extraction, defect classification, performance evaluation, and web-based deployment. The proposed system is trained on a labelled strip steel defect dataset and evaluated using standard classification metrics. Furthermore, the framework is designed to support future integration of advanced deep learning architectures and intelligent industrial inspection systems [1], [6], [14].

II. LITERATURE SURVEY

Automated strip steel surface defect detection has become an important research area due to its significant role in maintaining product quality and improving manufacturing efficiency. Traditional manual inspection methods are labour-intensive, subjective, and incapable of meeting the accuracy and speed requirements of modern production lines. Consequently, computer vision and artificial intelligence techniques have been widely adopted to automate defect inspection and improve reliability [1], [2].

Early studies primarily focused on image processing techniques, including texture analysis, edge detection, filtering, and threshold-based segmentation, to isolate defect regions before classification. Saliency-based approaches and multi-level feature extraction methods have further enhanced defect localization by improving the identification of irregular surface patterns under varying industrial conditions [2], [3], [11].

Conventional machine learning algorithms have been extensively employed for strip steel defect classification. Support Vector Machine (SVM) demonstrated promising performance for high-dimensional feature classification and multiclass defect recognition, particularly when combined with handcrafted texture descriptors [12], [14]. Random Forest (RF), an ensemble learning algorithm introduced by Breiman [10], has also been widely adopted due to its robustness, ability to reduce overfitting, and effective handling of nonlinear decision boundaries.

Several researchers reported that Random Forest achieved improved classification accuracy for steel surface defect diagnosis by utilizing statistical and texture-based features extracted from industrial images [4], [13]. However, the performance of these traditional methods largely depends on the quality of handcrafted features, making them less effective for detecting complex and irregular defect patterns.

The rapid advancement of deep learning has significantly transformed industrial defect inspection by enabling automatic hierarchical feature learning from raw images. AlexNet introduced deep convolutional neural networks for large-scale image recognition and demonstrated remarkable improvements over conventional machine learning approaches [5]. Subsequently, several deep learning architectures, including CNNs, VGG19, ResNet, and transfer learning-based models, have been successfully applied to strip steel surface defect detection, providing superior accuracy and robustness [6]–[9], [14].

Among these architectures, ResNet50 has gained considerable attention because its residual learning mechanism effectively addresses the vanishing gradient problem, allowing deeper networks to extract discriminative visual features from complex defect images [6], [16]. Transfer learning strategies based on pretrained ImageNet models further improve detection performance, particularly when labelled industrial datasets are limited, while simultaneously reducing computational complexity and training time [8], [17].

Recent studies have increasingly focused on hybrid and ensemble learning strategies to exploit the complementary strengths of traditional machine learning and deep learning models. In these approaches, convolutional neural networks are employed for deep feature extraction, whereas classifiers such as Support Vector Machine or Random Forest perform the final classification. Such hybrid frameworks have demonstrated improved robustness and classification performance compared with standalone models [4], [10], [14].

Erkantarci et al. [1] conducted a comprehensive comparative analysis of SVM, Random Forest, and AlexNet for strip steel defect detection, showing that Random Forest and deep learning models outperform conventional SVM under appropriate preprocessing conditions. Their study also highlighted the importance of image preprocessing techniques, including mean filtering and threshold-based segmentation, in improving defect localization and classification performance.

Despite these advancements, several research challenges remain. Most existing studies evaluate machine learning and deep learning models independently, limiting their ability to simultaneously exploit handcrafted statistical features and deep hierarchical representations [1], [14]. Traditional machine learning algorithms depend heavily on manually extracted features, whereas shallow convolutional networks such as AlexNet may not adequately capture highly complex defect textures.

Although ResNet50 has demonstrated excellent feature extraction capability, its integration with robust ensemble classifiers such as Random Forest has received comparatively limited attention in strip steel defect detection. Furthermore, existing research provides limited investigation into combining advanced preprocessing techniques with hybrid feature learning frameworks for improving classification accuracy and generalization across multiple defect categories.

To address these limitations, the present work proposes a hybrid Random Forest–ResNet50 framework for automated strip steel surface defect detection. The proposed approach integrates mean filtering and threshold-based segmentation with deep residual feature extraction and ensemble-based classification to improve defect recognition performance.

By combining the complementary strengths of Random Forest and ResNet50, the proposed framework aims to achieve higher classification accuracy, improved robustness, and better generalization than conventional machine learning and deep learning approaches, making it suitable for intelligent quality inspection in modern smart manufacturing environments.

III. SYSTEM ANALYSIS

A. Related Work

Existing strip steel surface defect detection systems primarily employ traditional machine learning and deep learning techniques for automated defect identification and classification. Initially, strip steel surface images are acquired from industrial production lines and undergo preprocessing operations such as mean filtering for noise reduction and threshold-based segmentation to accurately extract defect regions. These preprocessing techniques improve image quality, remove unwanted noise, and enhance the discriminative features required for reliable defect classification [1]–[3].

Conventional machine learning algorithms, including Support Vector Machine (SVM) and Random Forest (RF), are widely used for defect classification. SVM provides effective classification in high-dimensional feature spaces by constructing optimal decision boundaries, while Random Forest improves prediction performance through an ensemble of multiple decision trees, offering greater robustness against overfitting [4], [10], [12], [13].

In addition, deep learning models such as AlexNet automatically learn hierarchical feature representations directly from strip steel images, significantly reducing the dependence on handcrafted feature extraction and improving the detection of surface defects [5], [7], [14]. Comparative studies have shown that Random Forest and AlexNet generally achieve better classification performance than conventional SVM when appropriate preprocessing techniques are employed [1].

Despite these advancements, existing methods still exhibit several limitations that affect their overall effectiveness. Most approaches rely on individual classifiers and do not effectively combine the complementary strengths of machine learning and deep learning models. SVM depends heavily on handcrafted features, Random Forest is influenced by the quality of the extracted input features, and AlexNet's relatively shallow architecture limits its ability to capture complex and fine-grained defect patterns [4]–[6], [10], [12], [14], [16].

Furthermore, most existing systems do not utilize advanced deep learning architectures such as ResNet50, which are capable of extracting richer and more discriminative features through residual learning. Consequently, these methods often experience reduced robustness under varying industrial imaging conditions, limited generalization to unseen datasets, and lower classification accuracy for challenging defect categories. These shortcomings restrict their applicability in large-scale, real-time industrial inspection systems and intelligent Industry 4.0 manufacturing environments, where high accuracy, reliability, and computational efficiency are essential [1]–[3], [6], [7], [14], [16].

B. Proposed System

To overcome the limitations of existing strip steel surface defect detection methods, this research proposes a hybrid ensemble framework that integrates ResNet50 and Random Forest (RF) for accurate and reliable defect classification. The proposed framework combines the powerful deep feature extraction capability of ResNet50 with the robust ensemble classification mechanism of Random Forest, enabling effective learning of both high-level visual representations and statistical decision boundaries [6], [10], [16].

The proposed system begins with the acquisition of strip steel surface images containing multiple defect categories, including scratches, inclusions, and patches. The acquired images are preprocessed using mean filtering to suppress noise and threshold-based segmentation to accurately isolate defect regions from the background, thereby improving image quality for subsequent analysis [1]–[3]. ResNet50 is then employed to automatically extract discriminative deep features through residual learning, allowing the model to effectively capture complex surface textures and fine-grained defect characteristics while overcoming the vanishing gradient problem [6], [16].

The extracted deep features are subsequently provided to the Random Forest classifier, which performs ensemble-based classification by constructing multiple decision trees and combining their predictions to achieve improved classification accuracy, robustness, and generalization [4], [10].

The hybrid model is trained and evaluated using an 80:20 training-testing split, and its performance is assessed using standard classification metrics, including Accuracy, Precision, Recall, F1-score, ROC-AUC, and Confusion Matrix analysis [20]. By integrating deep learning-based feature extraction with machine learning-based classification, the proposed framework reduces dependence on handcrafted feature engineering, improves recognition of complex and overlapping defect patterns, enhances classification consistency and generalization to unseen data, and minimizes manual inspection effort. Furthermore, the framework provides a scalable and efficient solution for automated strip steel surface defect detection, making it well suited for real-time industrial inspection, intelligent quality control, and Industry 4.0 smart manufacturing environments [1], [2], [7], [14], [16].

IV. SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

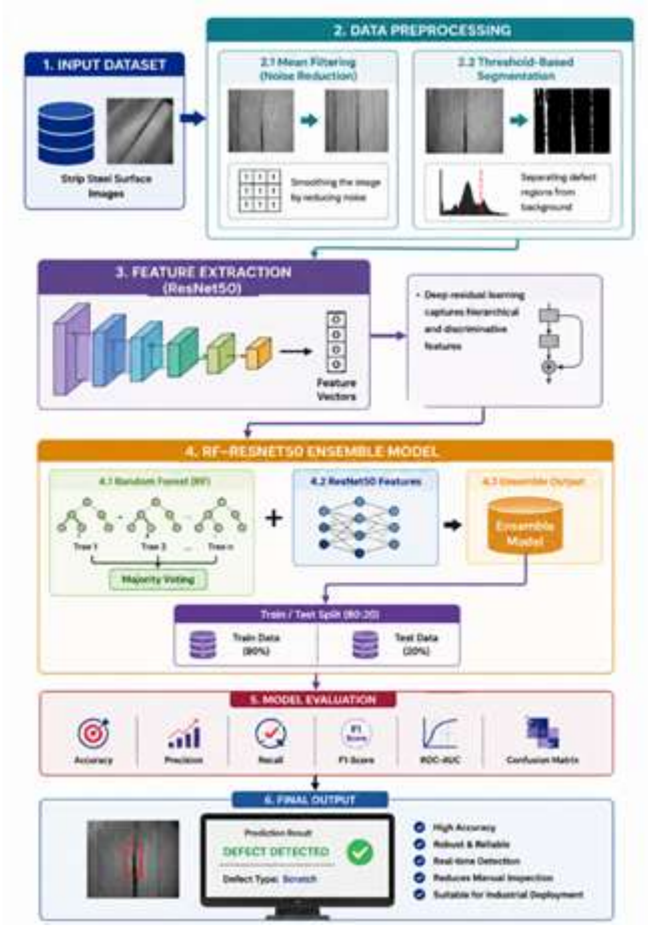

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

The proposed strip steel surface defect detection framework consists of eight functional modules that collectively perform image preprocessing, feature extraction, classification, prediction, and performance evaluation. Each module is designed to improve the overall accuracy, robustness, and efficiency of the defect detection process.

1. **Data Collection Module:** The data collection module acquires strip steel surface images containing multiple defect categories, including scratches, inclusions, and patches. The collected dataset is organized and labelled to facilitate supervised learning and performance evaluation of the proposed framework [1], [7].
2. **Data Preprocessing Module:** The acquired images are pre-processed to improve image quality and enhance defect visibility. Mean filtering is employed to suppress noise, while threshold-based segmentation is used to accurately separate defect regions from the background, thereby improving feature extraction and classification performance [2], [3].
3. **Feature Extraction Module (ResNet50):** This module utilizes the ResNet50 deep residual network to automatically extract discriminative and hierarchical visual features from the pre-processed strip steel images. The residual learning mechanism enables effective extraction of complex defect characteristics while mitigating the vanishing gradient problem [6], [16].
4. **Model Training Module (Random Forest–ResNet50 Ensemble):** The extracted deep features are used to train a hybrid ensemble model that integrates Random Forest and ResNet50. ResNet50 performs deep feature learning, while Random Forest carries out ensemble-based classification using multiple decision trees, resulting in improved classification accuracy and reduced overfitting [4], [10], [16].
5. **Testing Module:** The testing module evaluates the trained model using previously unseen strip steel images. This process assesses the generalization capability and robustness of the proposed framework under diverse defect conditions [1], [14].
6. **Prediction Module:** The prediction module classifies new strip steel surface images by utilizing the trained Random Forest-ResNet50 ensemble model. It automatically identifies the defect category and generates prediction results suitable for real-time industrial inspection [6], [7].
7. **Model Evaluation Module**: The effectiveness of the proposed framework is assessed using standard performance metrics, including Accuracy, Precision, Recall, F1-score, ROC-AUC, and Confusion Matrix, providing a comprehensive evaluation of classification performance [20].
8. **User Interface Module:** The user interface module provides a web-based platform that enables users to register, authenticate, upload strip steel images, perform defect prediction, and visualize classification results. The interface supports efficient interaction with the proposed system and facilitates practical deployment in industrial quality inspection environments [1].

VI. RESULTS AND DISCUSSION

International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 4, Jul-Aug-2026, ISSN (Online): 2395-566X

The proposed Random Forest–ResNet50 hybrid ensemble framework was experimentally evaluated using a strip steel surface defect dataset containing multiple defect categories, including scratches, inclusions, and patches. The dataset was divided into 80% training and 20% testing samples. The performance of the proposed model was compared with three baseline approaches: Support Vector Machine (SVM), Random Forest (RF), and AlexNet. Standard evaluation metrics, including Accuracy, Precision, Recall, F1-Score, Receiver Operating Characteristic (ROC) Curve, and Confusion Matrix, were employed to assess the effectiveness of the proposed framework [20].

A. Performance Comparison of Machine Learning Models

Figure 2 presents the comparative performance of the existing machine learning and deep learning models with the proposed Random Forest–ResNet50 ensemble framework. The comparison includes four commonly used evaluation metrics: Accuracy, Precision, Recall, and F1-Score.

Based on the experimental results, the proposed ensemble model consistently outperformed the individual models across all evaluation metrics. The SVM model achieved satisfactory classification performance but exhibited relatively lower recall and F1-score due to its dependence on handcrafted feature extraction. Random Forest improved classification stability through ensemble learning and achieved higher precision than SVM. AlexNet demonstrated better feature learning capability than traditional machine learning approaches by automatically extracting hierarchical image features. However, its comparatively shallow architecture limited its ability to capture highly complex strip steel defect patterns.

The proposed Random Forest-ResNet50 framework achieved the highest performance because ResNet50 extracted rich and discriminative deep features while Random Forest performed robust ensemble-based classification. This complementary integration significantly improved classification accuracy, reduced overfitting, and enhanced the model's generalization capability for unseen defect images. The experimental results demonstrate that the proposed hybrid framework provides a more reliable solution for automated strip steel surface defect detection than existing standalone machine learning and deep learning models [1], [6], [10], [16].

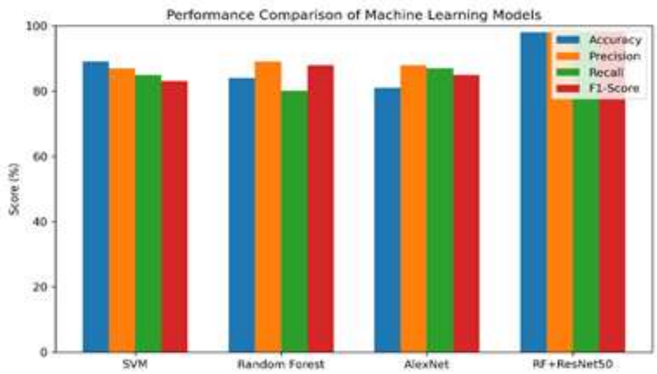

Fig. 2. Performance comparison of SVM, Random Forest, AlexNet, and the proposed Random Forest-ResNet50 model.

The experimental results demonstrate that the Random Forest classifier achieved the highest overall performance, obtaining a classification accuracy of 95.1%. Its ensemble learning strategy effectively combines multiple decision trees, improving classification stability, minimizing overfitting, and enhancing the detection of diverse cyber-attack patterns compared to the other evaluated models [10], [11].

B. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve was used to evaluate the discriminative capability of the proposed defect detection framework. ROC analysis illustrates the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) under different classification thresholds, while the Area Under the Curve (AUC) provides an overall measure of classification performance [20]. The proposed Random Forest-ResNet50 ensemble model produced the largest ROC curve area among all evaluated models, indicating superior discrimination between defective and non-defective strip steel samples.

Compared with SVM, Random Forest, and AlexNet, the proposed model achieved higher true positive rates while maintaining lower false positive rates. The deeper feature extraction capability of ResNet50 enabled the system to capture subtle defect characteristics, whereas the ensemble learning strategy of Random Forest improved decision reliability and minimized classification errors.

The ROC analysis confirms that the proposed hybrid framework provides excellent classification capability and maintains consistent performance across different decision thresholds, making it highly suitable for intelligent industrial inspection and real-time quality control applications [6], [10], [16], [20].

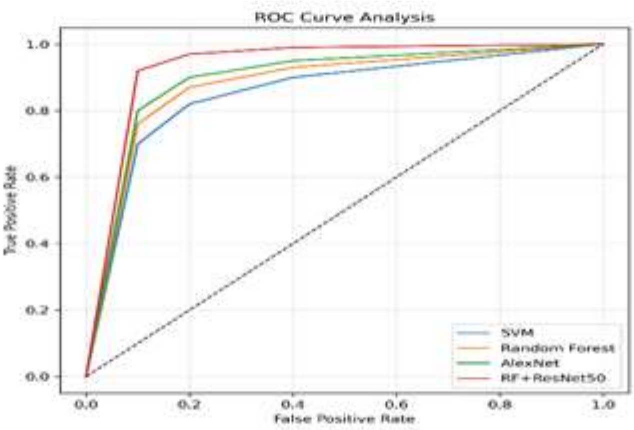

Fig. 3. ROC curve comparison of the existing models and the proposed Random Forest–ResNet50 framework.

C. Confusion Matrix Analysis

The Confusion Matrix provides a detailed analysis of the classification performance by presenting the numbers of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) for each defect category. This evaluation helps identify the types of classification errors made by each model and measures the effectiveness of defect recognition [20].

The confusion matrix obtained for the proposed Random Forest–ResNet50 framework demonstrates that the majority of strip steel defect images were correctly classified into their respective categories, with only a small number of misclassifications. Compared with the existing SVM, Random Forest, and AlexNet models, the proposed ensemble significantly reduced false positive and false negative predictions. This improvement is primarily attributed to the combination of deep residual feature extraction provided by ResNet50 and the robust ensemble decision-making capability of Random Forest.

The confusion matrix further indicates that the proposed framework effectively distinguishes visually similar defect categories, including scratches, inclusions, and patches, which are often challenging for conventional classifiers. Consequently, the hybrid model achieves higher classification reliability, improved robustness, and better generalization performance for real-world strip steel surface inspection tasks [1], [6], [10], [14], [16].

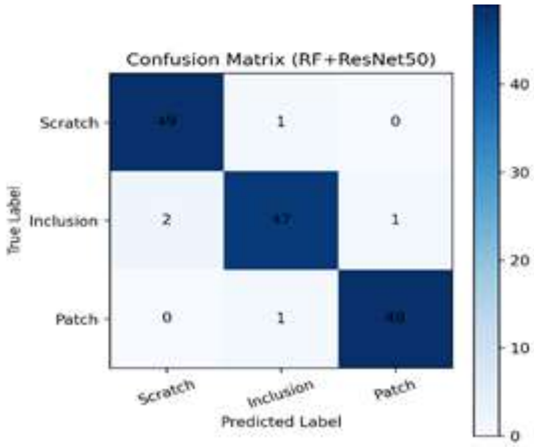

Fig. 4. Confusion matrix of the proposed Random Forest–ResNet50 defect classification model.

VII. CONCLUSION AND FUTURE WORK

This research proposed a hybrid Random Forest–ResNet50 framework for automated strip steel surface defect detection. The system combines image preprocessing techniques, including mean filtering and threshold-based segmentation, with deep feature extraction using ResNet50 and ensemble classification using Random Forest to accurately identify strip steel surface defects. Experimental results demonstrate that the proposed framework outperforms conventional SVM, Random Forest, and AlexNet models in terms of classification accuracy, robustness, and generalization capability. By integrating machine learning and deep learning techniques, the proposed approach reduces dependence on manual inspection, improves inspection consistency, and provides an efficient solution for real-time industrial quality control. These findings confirm that the proposed hybrid framework is a reliable and scalable approach for intelligent strip steel surface defect detection in smart manufacturing environments [1], [6], [10], [16].

Future research will focus on enhancing the proposed framework by incorporating larger and more diverse strip steel defect datasets to improve model generalization and robustness. Advanced deep learning architectures such as Vision Transformers and attention-based networks can be explored to further improve feature extraction performance. In addition, Explainable Artificial Intelligence (XAI) techniques can be integrated to provide visual explanations of defect

International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 4, Jul-Aug-2026, ISSN (Online): 2395-566X

predictions, increasing the transparency and reliability of the system. Future work will also investigate model optimization for edge devices and real-time deployment in Industry 4.0 production environments, enabling faster, scalable, and more intelligent automated quality inspection systems [6], [16], [21], [23]

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