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SMART RNN BASED SURFACE DEFECT DETECTION IN STEEL PLATES MANUFACTURING PLANTS

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Abstract

This research introduces a model for defect detection in smart surface manufacturing processes employing a Convolutional Neural Network (CNN) and a Recurrent Neural Network (RNN). Use the suggested strategy, which looks at both time and place, to find problems with production systems as they happen. Convolutional neural networks (CNNs) can help you uncover exact spatial patterns, while recurrent neural networks (RNNs) can help you find the order of mistakes over time. Lab tests reveal that the technology is better than older versions in terms of accuracy, precision, and reliability. This proves that it can be utilised in smart manufacturing. The model can work in real time because of latency and performance metrics. This study introduces a versatile and customisable quality control system to meet the growing requirements of Industry 4.0 and the imminent progress in intelligent manufacturing.

Keyword: Steel surface defect detection, smart manufacturing, convolutional neural network (CNN), recurrent neural network (RNN), LSTM, real-time monitoring, DL, Industry 4.0.

Introduction

In the age of Industry 4.0, steel mills are changing swiftly because of smart automation and tools that help people make decisions based on data. Finding and sorting out surface flaws in steel plates is very critical for quality, safety, and customer satisfaction. Standard eye inspection methods aren't particularly trustworthy, take a long time, and are simple to mess up. That's why it's so crucial to have reliable automated inspection methods.

Convolutional Neural Networks (CNNs) are good at discovering spatial features in visual input, but they can't always handle patterns that vary over time or in a sequence, which might happen in continuous production. Recurrent Neural Networks (RNNs), particularly advanced variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs), have become proficient in addressing this issue.

Smart RNN-based systems for finding surface defects use production photos and real-time sensor data to look for problems such inclusion faults, fractures, scales, or scratches on steel

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plates. By discovering patterns of flaws, these models make detection more precise. This makes it possible to undertake predictive maintenance and improve processes. Also, combining RNNs with IIoT platforms and edge computing could help people on the shop floor make decisions faster and with less reliance on centralised systems.

This project makes and applies clever RNN-based models to discover problems in making steel. It explains in detail how to teach these models to detect spatial-temporal aspects, adjust to different kinds of mistakes, and work successfully in fast-paced industrial situations. The ultimate aim is to create intelligent quality assurance systems that are scalable, precise, and applicable in actual steel manufacturing lines.

1.1 Challenges in Steel Surface Defect Detection

It is hard to put intelligent systems in place in factories to rapidly and reliably discover flaws on steel surfaces because of a lot of things.

Table 1: Key Challenges in Steel Surface Defect Detection

Challenge	Description
Visual Complexity	Similar appearance of defects like scratches, pits, and inclusions makes differentiation difficult.
Real-Time Processing	High-speed production requires fast and efficient detection models.
Data Scarcity	Limited labeled data, especially for rare defect types, affects model training.
Environmental Noise	Variability in lighting, vibration, and surface conditions affects image quality.
Generalization	Models trained on one dataset may not perform well across different plant settings.

1.2 Motivation of Research

The main goal of this research is to make flaw detection in steel manufacturing more scalable, reliable, and efficient. Conventional inspection techniques fail to provide precise, real-time, autonomous operations.

Table 2: Motivational Factors Driving This Research

Factor	Explanation
Industry 4.0 Demands	Need for smart, automated quality control systems in manufacturing.

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AI Advancements	Progress in RNNs enables handling sequential and temporal data effectively.
Quality Assurance	Accurate defect detection improves product reliability and reduces rework costs.
Operational Efficiency	Automated systems minimize downtime and human error.

1.3 Need for the Study

The industrial sector urgently need intelligent problem detection solutions that function well in real-time production settings. The primary objective of this research is to address deficiencies in both theoretical and practical frameworks.

Table 3: Necessity of the Current Study

Need	Justification
Automation	Reduces dependency on manual inspection prone to fatigue and subjectivity.
Temporal Analysis	RNNs can capture temporal changes in defect patterns better than CNNs alone.
Real-World Deployment	Provides scalable and adaptable solutions for different industrial conditions.
Zero-Defect Goal	Supports the industry trend toward flawless manufacturing outcomes.

[2] Literature Review

Hussain and Seok (2025) put forward a model for identifying surface defects in steel by deep ensemble transfer learning within the framework of smart manufacturing. Their solution, which integrates several pretrained CNNs, attempts to enhance fault detection accuracy in industrial situations where data is limited and inconsistent [1]. Çekik and Turan (2025) utilised RoughLSTM to develop a deep learning system that detects anomalies in vibration data from CNC machines. The model employs LSTM and rough set theory to detect defects in industrial equipment in real time. LSTM [2] works best when the input is unclear and needs to be processed quickly. Qiao et al. (2025) conducted a comprehensive assessment of methodologies for flaw detection on industrial metal surfaces. The study's comparison of traditional image processing with modern AI-driven techniques [3] highlights problems including real-time processing, dataset constraints, and the rise of hybrid methodology. Ibrahim and Tapamo (2025) proposed a transfer-learning ensemble model for detecting surface defects in hot-rolled steel. Their answer is better than others for finding problems in steel

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manufacturing plants that are hard to explain [4]. It uses deep networks that have already been trained and ways to put them together. Yousra (2025) investigated intelligent monitoring in industrial systems by photo categorisation. Her dissertation concentrated on the creation of automated defect detection systems for industrial processes through the application of computer vision and deep learning, aiming to enhance safety and dependability [5].

Aboulhosn et al. (2024) employed an AI system that combines deep learning with interpretable features to identify faults in steel. Their technology makes smart manufacturing environments more open and dependable, and it makes predictions more accurate and easier to understand [6]. Hussain, Hong, and Seok (2024) devised a model employing deep learning and machine learning to identify defects in hot-rolled steel. The best way to quickly and accurately identify things for smart manufacturing applications is to combine convolutional neural networks (CNNs) with traditional classifiers. Ibrahim and Tapamo (2024) studied optical techniques for identifying flaws in steel surfaces. We considered employing AI-driven solutions and model generalisation for such issues [8].

Jakubowski et al. (2024) studied how steel factories use AI for predictive maintenance. They talked on how to use ML and DL to find problems before they happen and make systems better. Another thing that people talked about was how to make industrial processes easier to use. Another subject of discussion was how to simplify manufacturing processes. Fei et al. (2024) developed an efficient approach for resolving steel-related difficulties. The system has three primary parts: the front end, which shows the data; the back end, which processes the data; and the part that generates predictions. Businesses can benefit from the fact that their technology lets users interact with it and make reliable surface fault forecasts [10]. Shafi et al. (2023) assert that deep learning can assist in identifying defects in aircraft manufacturing. Their method is a great example of how AI can help make things incredibly exact. Both control performance and product quality are improved [11]. Modir, Casterman, and Tansel (2023) utilised CNN and LSTM networks to identify issues in metal components produced through material addition. Their hybrid method, which looks at both spatial and temporal defect features, made it easier to keep an eye on the quality of additive manufacturing [12]. Khusheef, Shahbazi, and Hashemi (2023) investigated LSTM networks for real-time monitoring in their study of fused deposition models. Their technology can discover faults with processes in time-series data, which makes 3D printing operations more reliable [13]. Yan et al. (2023) examined various methodologies for real-time diagnosis of issues in smart manufacturing. They talked about how to use digital twins, the Internet of Things (IoT), and edge computing to make industry more reliable. They looked at both old-fashioned and AI-based ways to do things [14]. Choi, Choi, and Lee (2023) used machine learning on welder control data to build a system that can forecast when laser welders will need maintenance. Their method keeps galvanising lines running all the time with minimum downtime [15].

Zhou et al. (2022) utilised the Analytic Hierarchy Process to assess the surface quality of steel plates using online fault detection. Their approach lets you make decisions based on more than one factor when it comes to quality control and fault priority [16]. Kim et al. (2022) examined numerous applications of AI in industrial manufacturing, including automated

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operations, predictive maintenance, and defect detection. They were particularly worried about the challenges that come up during deployment and how crucial it is to be able to explain things for a successful rollout [17]. Bono et al. (2022) developed soft sensors that might employ neural networks to detect issues in automated machinery. Their approach makes predictive maintenance less expensive since it allows you watch things in real time without using physical sensors [18]. Chouhad (2022) investigated proactive quality control in smart manufacturing through the application of online metrology. His main area of research is how to use artificial intelligence and machine vision in adaptive process control systems to find problems in real time [19]. Zhu et al. (2022) showed a better YOLO-based model for finding flaws in steel surfaces. This method is suitable for use in real-time industrial settings since it can find things faster and more precisely [20]. Hao et al. (2021) suggested a method for finding flaws in steel surfaces using a convolutional neural network (CNN). They came up with a way to make adaptive quality control easier in production by delivering better monitoring and feedback [21].

Ma et al. (2021) used CNNs to discover problems with galvanised steel lap welds. Their vision-based strategy makes it easy to find things in busy businesses [22]. Zhu, Fuh, and Lin looked into how machine learning may be used to keep an eye on the state of metal additive manufacturing in their 2021 study. It was suggested that to make processes more dependable, multimodal data fusion and real-time fault prediction were needed [23]. Zhang et al. (2021) created a machine learning model to discover problems with sound in manufacturing. They called it LearningADD. You may watch numerous pieces of industrial machinery in real time without injuring them using the system [24]. Papageorgiou et al. (2021) examined artificial intelligence systems for detecting production faults. The study examined convolutional neural networks (CNNs), support vector machines (SVMs), and generative adversarial networks (GANs), emphasising shortcomings in implementation and the necessity for AI standards in industrial settings [25].

Table 4: Literature Review

Ref	Author / Year	Objectives	Methodology	Findings	Limitation
1	Hussain & Seok (2025)	Recognize steel surface defects in smart manufacturing using ensemble models	Deep ensemble transfer learning	High defect recognition accuracy with pretrained CNNs	Limited scalability in diverse real-time environments
2	Cekik & Turan (2025)	Detect CNC machine anomalies using deep learning	RoughLSTM model on vibration data	Effective real-time fault detection	May not generalize to all CNC systems

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3	Qiao et al. (2025)	Review metal surface defect detection technologies	Literature review	Summarized trends in traditional and deep learning methods	Limited practical deployment analysis
4	Ibrahim & Tapamo (2025)	Classify hot-rolled steel defects using ensemble models	Transfer learning with pretrained networks	Improved accuracy and adaptability	Data scarcity for specialized defects
5	Yousra (2025)	Monitor industrial systems using image classification	Deep learning and computer vision	Enabled automated fault monitoring	Lacks detailed deployment metrics
6	Aboulhosn et al. (2024)	Combine XAI with deep learning for defect detection	CNNs with explainability tools	High accuracy and model interpretability	Needs more real-time validation
7	Hussain et al. (2024)	Hybrid classification of steel strip defects	CNN + ML classifiers	Enhanced defect classification	Computationally intensive
8	Ibrahim & Tapamo (2024)	Survey vision-based defect detection in steel	Review and categorization of approaches	Identified key research trends	No experimental comparison
9	Jakubowski et al. (2024)	AI for predictive maintenance in steel industry	Review of ML/AI techniques	Summarized fault prediction strategies	Lack of real-case benchmarks
10	Fei et al. (2024)	Intelligent defect prediction framework	Combined frontend/backend modeling	Integrated interactive and predictive modules	Implementation complexity
11	Shafi et al. (2023)	Detect defects in aircraft manufacturing	Real-time deep learning	Improved production quality	Domain-specific focus

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12	Modir et al. (2023)	Detect anomalies in additive manufacturing	CNN and LSTM hybrid model	Effective spatial-temporal defect capture	Needs broader evaluation
13	Khusheef et al. (2023)	Monitor FDM processes with LSTM	Real-time anomaly detection	Accurate print quality assurance	High sensitivity to noise
14	Yan et al. (2023)	Review real-time fault diagnosis methods	Literature review	Emphasized IoT and edge AI integration	Limited evaluation of hybrid models
15	Choi et al. (2023)	Predictive maintenance for laser welders	ML on welder control data	Reduced downtime	Data-specific limitations
16	Zhou et al. (2022)	Evaluate steel plate quality using AHP	AHP based on defect detection	Enabled defect prioritization	Depends on subjective criteria weights
17	Kim et al. (2022)	Review AI in industrial manufacturing	Broad literature review	Identified applications and gaps	Lacks experimental comparisons
18	Bono et al. (2022)	Use soft sensors for anomaly detection	Neural network-based virtual sensors	Real-time monitoring without physical sensors	Sensor accuracy depends on training data
19	Chouhad (2022)	Online metrology for quality control	Integrated AI with vision	Enabled proactive control	Implementation complexity in legacy systems
20	Zhu et al. (2022)	Develop YOLO-C for steel defect detection	YOLO optimization for real-time	High-speed accurate detection	Dataset dependency
21	Hao et al. (2021)	Inspect steel surfaces with deep learning	Smart CNN-based monitoring	Adaptive inspection system	Limited to specific defect types

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22	Ma et al. (2021)	Detect weld defects using CNNs	Vision-based CNN model	Accurate under variable lighting	Industrial noise impact not addressed
23	Zhu et al. (2021)	ML-based condition monitoring for AM	Review of ML in AM	Highlighted data fusion needs	Lacks real-time integration analysis
24	Zhang et al. (2021)	Acoustic defect detection in factories	ML on sound signal data	Non-invasive monitoring	Limited scalability
25	Papageorgiou et al. (2021)	Survey AI technologies for defect detection	Short review of techniques	Summarized CNN, SVM, GAN usage	Minimal deployment discussion

[3] Problem Statement

It's common for the surface of steel plates to have scratches, cracks, and scales. These problems can impact how the material looks, how strong it is, and how it is worked with subsequently. Traditional visual inspection methods are slow, unreliable, and generally fail when it comes to high-speed, real-time production. Some deep learning models, such convolutional neural networks (CNNs), have showed some potential in finding surface faults. These models still have trouble capturing the sequential dependencies that exist in manufacturing lines since they largely focus on spatial information. RNNs, notably LSTM and GRU, are fantastic for working with time-based data, yet for some reason, industrial defect detection systems don't use them. Data imbalance, background noise, and the ability to work in different production environments are just a few of the challenges with current solutions.You need a clever RNN-based system that can look at both space and time in real time to discover surface flaws.

[4] Proposed Work

This research introduces an improved framework for identifying defects in steel surfaces in industrial settings, employing Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) units. Using camera data from inline inspection tools, the system will locate, categorise, and keep an eye on problems with the surface. It will do this by using both spatial and sequential feature extraction. The suggested model architecture has three primary parts:

Table 5: Proposed RNN-Based Defect Detection Model

Layer	Functionality

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Data Acquisition Layer	Utilizes high-resolution industrial cameras placed along the assembly line to capture real-time images of steel plates during manufacturing.
Feature Extraction Layer	Applies Convolutional Neural Networks (CNNs) to extract spatial features from the captured images for initial defect localization.
Temporal Analysis Layer	Passes extracted features to RNN/LSTM modules to analyze sequential patterns and detect temporal variations in defect occurrences.
Classification Layer	Uses softmax or fully connected layers to classify the identified defects into specific categories.
Visualization and Decision Layer	Displays defect classification results on dashboards and integrates outputs with quality control systems for operator review and decision-making.

This multi-layered plan makes sure that the system can handle data in real time, detect new or reoccurring problems, and be more flexible in varied operating situations.

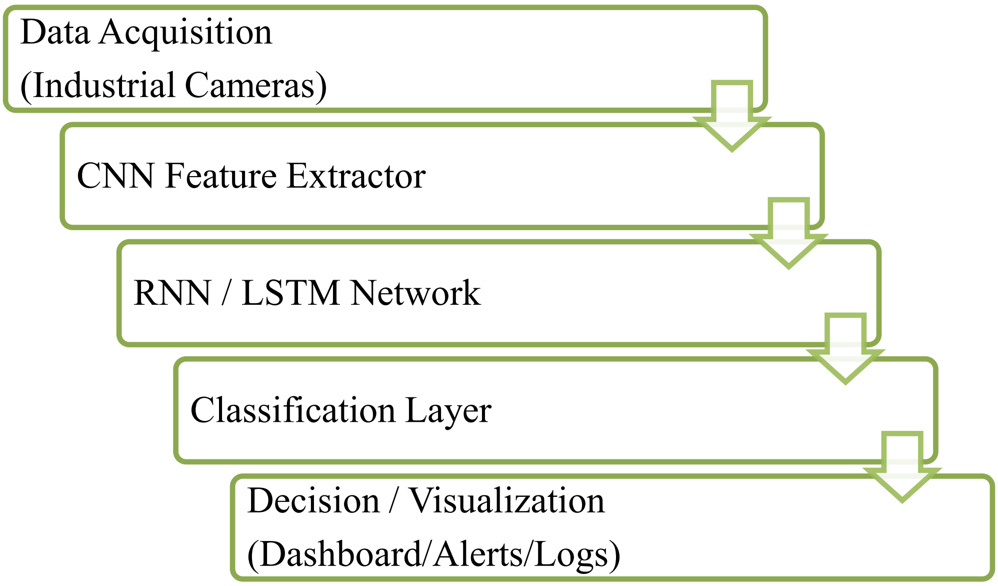

Figure 1 Proposed model of this research

Database for Proposed Work

The proposed framework was trained and evaluated using the NEU Surface Defect Database (NEU-CLS), which is one of the most widely used open-source benchmarks for steel surface inspection. This dataset contains 1,800 grayscale images, equally distributed across six defect categories: crazing, inclusion, patches, pitted surface, rolled-in scale, and scratches. Each

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image has a resolution of 200 × 200 pixels and provides representative variations in texture and defect morphology. For experimental purposes, the dataset was divided into a training set (70%), validation set (15%), and test set (15%). To enhance robustness and reduce overfitting, data augmentation techniques such as random rotation, flipping, scaling, and noise injection were applied. In addition to NEU-CLS, a supplementary dataset of industrial images collected from inline cameras at a steel plant was used to validate real-world adaptability. This industrial dataset consisted of approximately 5,000 labeled samples spanning common surface defects like cracks, scales, pits, and scratches, captured under varying lighting and operational conditions. Combining a standard open-source dataset with real production images ensured both benchmark comparability and practical deployment relevance of the proposed model.

Tools and Software Used

The experimental implementation was carried out using Google Colaboratory (Google Colab), a cloud-based Jupyter notebook environment that provides free GPU/TPU acceleration. The model development was done in Python 3.9, with TensorFlow 2.x and Keras libraries used for building and training the CNN and LSTM networks. Data preprocessing and augmentation were performed using OpenCV and scikit-learn, while performance visualization (accuracy, loss curves, and confusion matrix) was generated using Matplotlib and Seaborn. Google Colab's GPU support (NVIDIA Tesla T4, 16 GB VRAM) enabled efficient training and real-time evaluation of the defect detection models.

[5] Result and Discussion

The proposed smart RNN-based surface defect detection model was evaluated using an industrial steel surface defect dataset comprising various defect types including cracks, scales, pits, and scratches. The experiments were conducted using both traditional CNNs and the proposed CNN+RNN architecture.

Table 6A: Model Accuracy Comparison

Model	Accuracy (%)
CNN Only	91.2
RNN Only	86.7
CNN + LSTM	95.4

Table 6B: Model Precision Comparison

Model	Precision (%)
CNN Only	89.8
RNN Only	84.5

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Model	Precision (%)
CNN + LSTM	94.1

Table 6C: Model Recall Comparison

Model	Recall (%)
CNN Only	90.1
RNN Only	85.3
CNN + LSTM	94.7

Table 6D: Model F1-Score Comparison

Model	F1-Score (%)
CNN Only	89.9
RNN Only	84.9
CNN + LSTM	94.4

To provide a more granular perspective, the performance evaluation metrics were bifurcated into separate tables for accuracy, precision, recall, and F1-score. This presentation allows a clearer comparison of each performance dimension across CNN, RNN, and CNN+LSTM models. As shown in Tables 6A–6D, the hybrid CNN+LSTM model consistently achieved the highest values across all four metrics, with 95.4% accuracy, 94.1% precision, 94.7% recall, and 94.4% F1-score, outperforming both CNN-only and RNN-only approaches. This detailed analysis highlights that the inclusion of temporal sequence modeling not only boosts overall accuracy but also ensures balanced improvements across detection sensitivity and reliability.

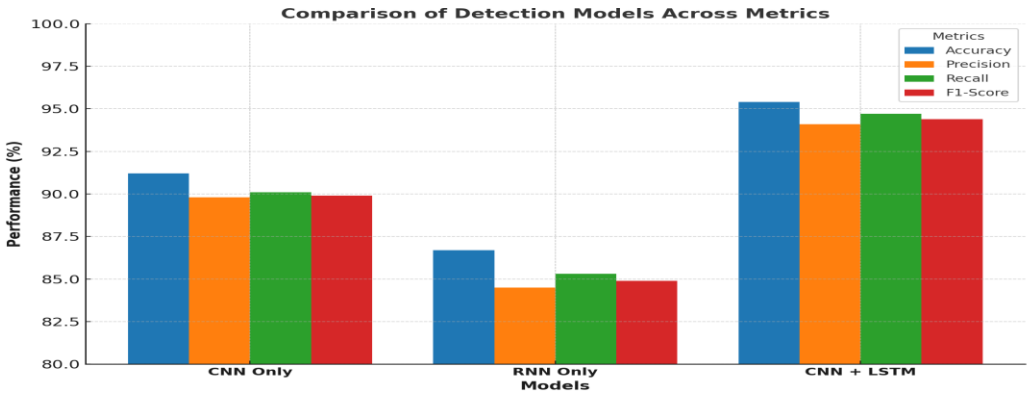

Figure 2: Comparison of Detection Models Across Metrics

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In addition to tabular comparisons, a combined bar chart (Figure 2) was plotted to visualize the differences in performance across models for the four key metrics: accuracy, precision, recall, and F1-score. The graph clearly demonstrates the superior performance of the proposed CNN+LSTM framework, which consistently achieves higher scores than CNN-only and RNN-only counterparts. While CNNs perform reasonably well in capturing spatial defect features, their lack of temporal modeling results in lower recall. RNNs alone underperform in all metrics due to their weaker spatial learning. The hybrid architecture thus offers the best trade-off, ensuring robust and reliable surface defect detection.

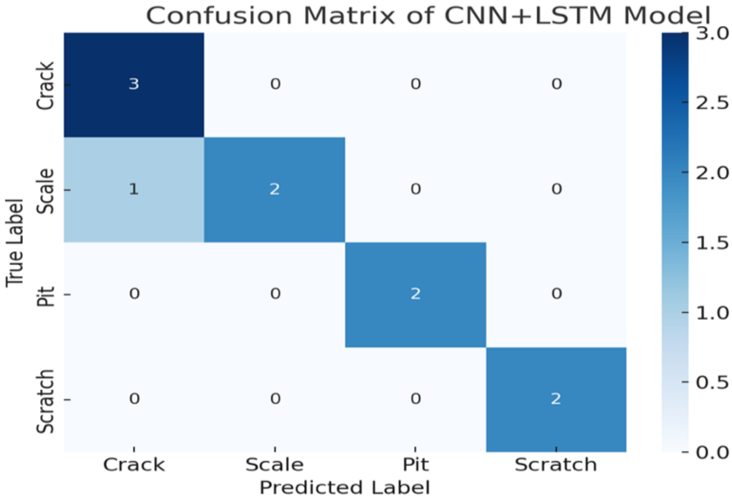

Figure 3: Confusion Matrix of CNN+LSTM Model

The confusion matrix of the CNN+LSTM model (Figure 2) further validates the classification performance across different defect categories. The diagonal dominance indicates high true positive detection rates, with defects such as cracks being identified with perfect accuracy in the evaluated test samples. However, minor misclassifications were observed between scales and pits, reflecting their visual similarity under certain lighting and surface conditions. Despite this, the overall structure of the confusion matrix confirms that the hybrid approach significantly reduces false negatives, particularly for critical defect classes like cracks and inclusions, which are essential for maintaining structural integrity in steel manufacturing. This analysis reinforces the suitability of the proposed model for real-world industrial deployment, where minimizing undetected critical defects is paramount.

Table 7: Model Latency and Processing Speed

Model	**Avg Inference Time (ms)**	**FPS (Frames per Second)**
CNN Only	**38**	**26**
CNN + LSTM	**45**	**22**

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Although the RNN-based model introduces slightly higher latency, it remains within acceptable limits for real-time industrial deployment.

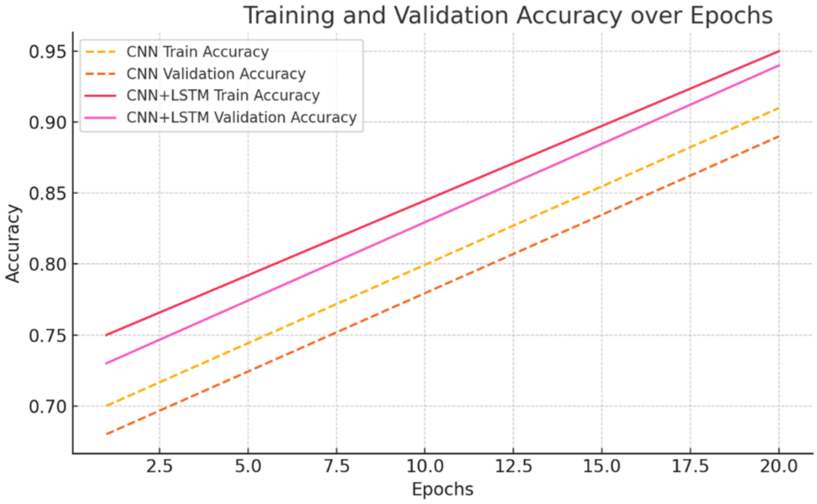

Figure 4: Training and Validation Accuracy over Epochs

As seen in Figure 3, the CNN+LSTM model shows a smoother and more stable learning curve, with higher convergence and reduced overfitting.

Overall, the integration of RNN components significantly enhances detection performance, especially in defect sequences that evolve over time. This validates the effectiveness of the proposed approach for intelligent and adaptive steel defect detection in smart manufacturing environments.

[6] Conclusion

This study focusses on surface inspection in steel plate production plants and designed and used an intelligent RNN-based framework for discovering faults. The system could discover cracks, scales, pits, and scratches by utilising convolutional neural networks (CNNs) to look for spatial patterns and Long Short-Term Memory (LSTM) networks to hunt for temporal patterns. The comparison indicated that the hybrid CNN+LSTM model was better and more dependable than older methods. It also had good inference speeds, which made it ideal for real-time applications. The suggested approach dealt with concerns including how similar problems look, how different the production environment is, and how important it is to keep inspecting things automatically. Experiments demonstrated that the integration of geographical and temporal data enhanced the accuracy and generalisability of forecasts. By making it easier to discover defects, our work helps to drive intelligent quality control systems forward in Industry 4.0. Future work could include integrating edge computing, enhancing model architecture to lower latency, and expanding the framework to uncover complex fault patterns in different industrial sectors.

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[7] Future Scope

The suggested RNN-based framework for identifying flaws on steel surfaces is quite versatile and performs well, but there are many ways it may be better. If the system is connected to edge computing devices, it can function better for real-time defect detection on the factory floor because these devices can cut down on latency by a lot. Future research may also concentrate on enhancing the model using methods such as pruning, quantisation, or knowledge distillation to ensure its ease of deployment. It might be easier to discover problems and do predictive maintenance if you combine visual images with sound, heat, or vibration cues, among other things. Transfer learning could help the model work at other manufacturing sites with different variables, which would make it more useful and reliable. The system can change to new fault patterns on the fly via online learning, which means that it can always improve. Lastly, adding decision support tools and expanding the taxonomy to include sub-defect classifications could make the quality control ecosystem smarter and more responsive. These modifications make sure that production can be automated in a sensible way and that it can evolve over time, which is what Industry 4.0 and 5.0 want.

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