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Research Article

Design of an Intelligent System Using RNNs to Detect Steel Plate Surface Defects

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Abstract:

For the steel manufacturing sector, steel defect diagnostics is crucial since it has a direct impact on both production efficiency and product quality. Although product quality control is less automated and unreliable in identifying steel imperfections in the surface, it suffers from a real-time diagnostic capacity. This paper introduces a Recurrent Neural Network (RNN) approach for detecting defects in steel plate manufacturing. The steel manufacturing plants may encounter a variety of flaws, including scratches, holes, crazing, and dirt. In the proposal, the first step is to take a different number of defective and non-defective images and then extract the feature using the wavelet transform. Prepare a feature matrix with 13 features for each image. The completed data set is fed into an RNN to assess the suggested algorithm's effectiveness during testing and training. The proposed method is evaluated using both online and industry data. Also feeding different numbers of images to determine the accuracy of suggested algorithms. The proposed approach is implemented using MATLAB software. The proposed strategies have an accuracy of 98.25% based on empirical data.

1. Introduction

Defect detection in the manufacturing field is a critical aspect of ensuring product quality, reducing waste, and maintaining customer satisfaction. In an era where precision and efficiency are paramount, manufacturers must employ advanced techniques and technologies to identify and rectify defects in real-time[1]. This comprehensive study delves into the intricacies of defect detection in the manufacturing industry, covering its importance. Various methods and technologies employed, challenges faced, and the future prospects of defect detection. Manufacturing is the backbone of many industries, ranging from automotive to electronics, pharmaceuticals to aerospace. The quality of products produced directly impacts on a company's reputation, customer satisfaction, and bottom line. Defects can lead to costly recalls, warranty claims, and legal issues, not to mention the damage to brand image[2]. Thus, effective defect detection is paramount for several reasons: Oxidation produces defect on the surface that can be removed by descaling processes. Longitudinal surface defects caused by improper rolling that can occur on the surface due to thermal stresses or mechanical forces. Mechanical damage to the surface from handling or processing. Overlapping layers of metal due to improper rolling. Non-metallic particles such as oxides, sulphides, or silicates trapped within the steel, affecting its mechanical properties. Non-uniform distribution of alloying elements, leading to localized variations in properties. Small voids caused by trapped gases during solidification, reducing the material's strength. Larger voids formed by gases during solidification[3]. Cracks that occur beneath the surface, often due to improper cooling or stress during solidification. Stresses remaining in the steel after processing, which can lead to warping or cracking. Localized areas of increased hardness due to uneven heat treatment. Localized areas of reduced hardness due to uneven cooling or heat treatment. As steel production processes get advanced, maintaining high quality and ensuring defect-free products have become progressively critical. Defects in steel products not only compromise structural integrity but can also lead to catastrophic failures, financial losses, and safety hazards. Consequently, the need for effective and efficient methods for detecting and diagnosing steel defects has never been greater[4]. Traditionally, steel defect detection has relied on a combination of visual inspection, ultrasonic testing, magnetic particle testing, and eddy current testing. While these techniques have been instrumental in identifying surface and subsurface defects, they often come with limitations. Visual inspection, for instance, is highly dependent on the skill and experience of the inspector and can be prone to human error. Ultrasonic and magnetic particle testing, is more reliable and are generally time-consuming and require specialized equipment and trained personnel[5]. The advancement of technologies and methodologies is therefore necessary to address these challenges and improve the accuracy and efficiency of defect detection in steel manufacturing. In recent years, the integration of artificial intelligence (AI) and machine learning (ML) has emerged as a transformative approach to defect detection across various industries. These technologies leverage data-driven techniques to enhance the accuracy and speed of inspections, offering significant improvements over traditional methods. Among many machine learning techniques, Recurrent Neural Networks (RNNs) have gained considerable attention due to their ability to model sequential data and capture temporal dependencies, which are crucial for tasks involving time-series data or sequences. RNNs are a class of neural networks designed to recognize patterns in sequences of data, making them well-suited for tasks where the order and context of data points are essential[6]. This characteristic is particularly advantageous in the context of steel defect detection, where the sequential nature of sensor readings or inspection data can provide valuable insights into the presence and nature of defects. By analysing sequences of data over time, RNNs can identify anomalies and patterns that may not be apparent through static inspection methods. Despite the promising potential of RNNs, their application to steel defect detection remains an area of active research and development[7]. This research article aims to explore the capabilities and limitations of RNN-based approaches in detecting defects in steel products. It will delve into the fundamental principles of RNNs, discuss their relevance to defect detection, and present a comprehensive analysis of their performance in comparison to traditional methods[8]. The paper begins with an overview of the current state of steel defect detection technologies. This is followed by a detailed examination of RNNs, including their architecture, training mechanisms, and advantages in processing sequential data[9]. The subsequent sections will focus on the specific application of RNNs to steel defect detection, discussing how these networks can be trained and optimized to enhance detection accuracy. To provide a thorough understanding of RNN-based defect detection, this article will also present case studies and experimental results from recent research[10]. These examples will illustrate how RNNs have been applied to real-world steel defect detection scenarios, showcasing their effectiveness and potential areas for improvement. Furthermore, the paper will address the challenges associated with implementing RNNs in industrial settings, including data acquisition, preprocessing, and model deployment. The ultimate goal of this research is to contribute to the development of more robust and efficient steel defect detection systems. By leveraging the strengths of RNNs and integrating them with existing inspection technologies, it is possible to achieve higher levels of accuracy and reliability in defect detection. This not only benefits the steel manufacturing industry by reducing defects and improving product quality but also has broader implications for safety and economic efficiency[11].

Robots equipped with advanced sensors and vision systems can conduct precise inspections on complex products, improving accuracy and speed. Blockchain can be used to create immutable records of product quality, ensuring transparency and traceability throughout the supply chain. AR and VR systems can assist human inspectors by overlaying digital information on the physical product, highlighting potential defects [12]. As 3D printing becomes more prevalent, specialized defect detection methods for additive manufacturing like multilevel neural network are emerging. Before discussing about the RNN, first clear the basic neural network analysis technique CNN. Convolutional Neural Networks (CNNs) are powerful tools for detecting steel defects[13]. High-resolution images of steel surfaces are captured using cameras or scanners during or after production. Defects in these images are annotated manually or using semi-automated tools to create a labelled dataset. Adjust the pixel values to a standard range (e.g., 0-1 or -1 to 1). Ensure all images are of uniform size suitable for the CNN architecture [14]. The transformations such as rotations, flips, and zooms are applied to increase dataset variability and improve model robustness except pre-processed images. The filters are applied to extract features such as edges, textures, and patterns. The dimensions of the defect images are reduced to attain the important features, typically through max pooling. The extracted features are combined to make predictions that provides the final classification (e.g., defect type) or detection (e.g., defect location) output. Typically, cross-entropy loss for classification or mean squared error for localization tasks. The optimizers like SGDM, ADAM and RMS Prop are used to minimize the loss function. The dataset is segmented into training, testing and validation to analyse the performance and ignore overfitting. The CNN classifies are used for each image to categorise the defect classes e.g., cracks, inclusions, scratches. Measure the proportion of correctly identified defects. Evaluate the balance between false positives and false negatives [15-17]. The model performance is analysed on the different types of defects. The trained CNN model into the production lines for real-time defect detection. The defective pieces are automatically detected to give an alarm to human inspectors. CNNs can achieve high accuracy by learning complex patterns in images. Once trained, CNNs can process images quickly, enabling real-time detection and reduces human error and acquire variability in defect detection. The defects are easily scalable and use high-quality, well-annotated data that is crucial for training effective models. For training CNNs requires significant computational power. The CNN makes decisions which can be challenging [18-20]. By leveraging CNNs, manufacturers can enhance the accuracy and efficiency of defect detection in steel production, leading to improved quality control and reduce the computation time.

2. Literature Review

This section will discuss the diverse study related to the concept of defect detection of metal sheets. Zhang et al. (2017) employed faster RCNN to detect surface defects on hot-rolled steel strips. They reported a high detection accuracy and emphasized the importance of fine-tuning the network for specific defect types. Automatic steel surface defects detection method based on deep learning. Two deep learning models for defect detection are evaluated. The experimental results show that the evaluated methods can detect steel surface defects. Yang et al. (2020) proposes a hybrid RNN-LSTM model to enhance the detection of metal surface defects. The RNN component processes sequential sensor data, while the LSTM component captures long-term dependencies and patterns. The combination allows for a more comprehensive analysis of defect progression over time. The hybrid model demonstrated superior accuracy compared to standalone RNN or LSTM models. It effectively identified both transient and persistent defects in metal surfaces. Li et al. (2021) integrates Convolutional Neural Networks (CNNs) with RNN-LSTM networks to detect defects in metal sheets. CNNs handle spatial feature extraction from defect images, while the RNN-LSTM model processes the temporal data to capture defect evolution. The CNN- RNN-LSTM model achieved high detection accuracy by leveraging both spatial and temporal features. The approach showed significant improvements in identifying complex defects that evolve over time. Experimental results show that our method is superior to existed methods in the detection accuracy for the internal defects of arc magnets, and the diagnosis time per a single arc magnet is controlled at the millisecond, making it appropriate for real-time applications. Zhang et al. (2019) explores the use of RNN-LSTM networks for real-time defect detection in rolling mills. The model processes time-series data from vibration sensors to detect anomalies and predict potential defects. The RNN-LSTM network successfully detected defects in real-time with high precision. The model was effective in identifying anomalies that could lead to defects in the rolling process. One- dimensional time-series vibration signals are first converted into two-dimensional images. Then, Gated Recurrent Unit (GRU) is introduced to exploit temporal information of time-series data and learn representative features from constructed images. A multilayer perceptron (MLP) is finally employed to implement fault recognition. Kim et al. (2020) investigates a hybrid approach combining RNN and LSTM networks for sequential defect detection in metal sheets. The RNN captures short-term dependencies, while the LSTM focuses on long-term patterns, enhancing the model's ability to detect defects over time. The hybrid RNN-LSTM model improved defect detection accuracy and robustness. It provided better insights into defect patterns and progression compared to traditional methods. Pan et al. (2022) shows the enhanced RNN-LSTM networks for defect detection by incorporating attention mechanisms. The attention mechanism helps the model focus on important features and temporal sequences, improving detection performance. The RNN-LSTM model with attention mechanisms achieved higher detection accuracy and reduced false positives. It demonstrated improved capability in handling complex and subtle defects. the results show that, compared with other deep learning models, DAN-DeepLabv3+ based on the Xception backbone exhibits the best segmentation performance under the mean intersection over union (IoU) of 89.95% and the frequency-weighted IoU of 97.34%. Besides, the F1-score for the three kinds of defects can reach 86.90%, 99.20%, and 92.81%. From the comparative study, it has been found that the adoption of the dual attention module and DeepLabv3+ contributes to boosting the segmentation performance. The significance of the proposed hybrid model lies in the enhancement in accurately detecting single or multiple steel defects, which has proven to outperform other classical methods. Xu et al. (2021) combines RNN and LSTM networks for predictive maintenance and defect detection in metal manufacturing. The model predicts potential defects based on historical data and time-series analysis. The RNN-LSTM model effectively predicted maintenance needs and detected defects early. It contributed to reducing downtime and improving operational efficiency. In this study, the author has developed a real-time laser welding data acquisition system to collect plasma density, laser intensity, and molten pool temperature data during the welding process. Additionally, we established a neural network based on a combination of LSTM and CNN models to rapidly detect laser welding defects. The experimental results demonstrate that this method can effectively identify welding defects with an average accuracy rate of 96%. Chen et al. (2020) presents a hybrid RNN-LSTM model for classifying defects in steel plates. The model combines the strengths of RNNs and LSTMs to process defect images and time-series data. The hybrid approach improved classification accuracy for various types of defects. It demonstrated robustness across different steel plate conditions and defect types. The Multilayer perceptron through NAS technology is used to classify defects with different depths. The Experiments have proved that the time-series temperature feature is very effective when used in the depth classification of defects, and the accuracy rate can reach 93% under the verification of traditional machine learning methods. The NAS technique used in this paper can search 100 multilayer perceptron's in a minimum of 121s and achieve 100% defect classification accuracy. Patel et al. (2022) proposes the periodical defect detection method based on a convolutional neural network (CNN) and long short-term memory (LSTM) is proposed to detect periodic defects, such as roll marks, according to the strong time-sequenced characteristics of such defects. Firstly, the features of the defect image are extracted through a CNN network, and then the extracted feature vectors are inputted into an LSTM network for defect recognition. The experiment shows that the detection rate of this method is 81.9%, which is 10.2% higher than a CNN method. In order to make more accurate use of the previous information, the method is improved with the attention mechanism. The improved method specifies the importance of inputted information at each previous moment, and gives the quantitative weight according to the importance. The experiment shows that the detection rate of the improved method is increased to 86.2%. Huang et al. (2023) This research combines RNN and LSTM networks with data augmentation techniques to enhance defect detection in metal sheets. Data augmentation helps the model generalize better across different defect scenarios. The combined RNN-LSTM model with data augmentation achieved high detection accuracy and generalization. It effectively handled diverse defect types and manufacturing conditions. Zixiang et al. (2021) focuses on optimizing RNN-LSTM networks for defect detection in high-speed metal processing environments. The study addresses challenges related to processing speed and data volume. the output accuracy and stability of digital model built by the network with two LSTM hidden layers are exceedingly better than that of traditional linear regression model. The average error of the LSTM digital regression model is only 1.4%, and the maximum error is only 6%. Li et al. (2018) used a combination of machine learning and image enhancement techniques to improve the detection of small and subtle defects in steel plates. Their approach demonstrated improved detection performance over traditional methods. the proposed approach achieves a near-perfect detection performance at 99.44% and 0.99 concerning the accuracy and F-1 score metric, respectively. The results are better than other shallow machine learning algorithms, i.e., support vector machine and logistic regression under the same validation technique. Zhu et al. (2018) implemented Mask RNN for detecting and segmenting multiple defect types on steel surfaces. The segmentation masks provided additional information about defect shapes and sizes, aiding in detailed analysis. The result shows that our model achieves 79.89% mAP on NEU-DET and 78.44% mAP on self-made detection dataset. Our model can detect at 23f/s when the input image size is 416 × 416 × 3. The detection performance of our model is significantly better than other models. The results show that the proposed method has better performance and can be used for real-time automatic detection of workpiece surface defects. Dong et al. (2019) proposed an enhanced faster RNN model incorporating multi-scale feature extraction to better handle varying defect sizes. This approach resulted in improved detection accuracy across different defect scales. we use deep learning CNN with Xception architecture to detect steel defects from images taken from high-frequency and high-resolution cameras. There are two techniques used, and both produce respectively 0.94% and 0.85% accuracy. The Xception architecture used in this case shows optimal and stable performance in the process and its results. Kang et al. (2019) integrated Faster RNN with a transfer learning approach, leveraging pre-trained models to reduce training time and enhance detection accuracy. This method proved effective for real-time defect detection in steel manufacturing lines. Our experimental findings on the Northeastern University dataset (NEU) proved our technique's efficacy, including six surface defects. The resulting classification accuracy was 99.44%, surpassing other existing methods. The success of our method can be attributed to the combination of a powerful feature extractor and a well-designed CNN classifier. Alaa et al. (2020) explored a hybrid approach combining Faster RNN with traditional image processing techniques for pre- processing and post-processing stages.

Texture is an important feature for defining the defects in steel. It is an efficient approach for differentiating the defects. The study [21] planned the general texture elaboration operator, which is known as general binary design. This operator has several advantages such as light, variance and insensitive behaviour in geometrical condition of the design. It is also used in several domains.

In real-world steel production lines, defect detection systems need to operate in real-time to prevent defective products from passing through the quality control process. CNN-based models such as YOLO and SSD (Single Shot Multibox Detector) are optimized for real-time performance by balancing accuracy with speed, ensuring that steel defects can be detected and flagged as early as possible[22]. Research into more sophisticated data augmentation techniques, including domain adaptation and synthetic data generation using GANs, is expected to continue to play a vital role in addressing data limitations. Since acquiring labelled data is expensive, unsupervised learning techniques are being investigated, where models detect anomalies or defects without prior labelled training data. Autoencoders and unsupervised clustering techniques have shown promise in this regard[23]. Transfer learning from models trained on different industries or similar manufacturing processes may provide useful insights into steel defect detection, allowing for faster model development without the need for large amounts of labelled steel data.

CNN and RNN models, with effective use of data, have proven to be powerful tools in steel defect detection. While CNNs excel in image-based tasks by extracting detailed spatial features, RNNs (particularly LSTMs) contribute significantly to time-series data analysis and hybrid models[24]. The combination of these models, along with data augmentation, transfer learning, and synthetic data, continues to advance the field toward more accurate and efficient defect detection in steel manufacturing. However, challenges related to data availability, imbalance, and real-time constraints remain areas for further research. With the help of this technique. The Production, production, and cost both can be improved drastically. As for the research has used the enhancement strategy, the enhancement strategies on data on various Levels Can be extracted from various input data so that it can be estimated. At what strength and what time. of life time the steel can get damaged or degraded this is used by the effect of CNN level in the processing[25]. And Resnet fif5ty network model is used to get the accuracy of ninety four percent approximately. This Research is carried out on the platform of center net as internet needs a very limited did input applications Resnet50 Yes Used to enhance these inputs and extract more significant. Frequent and which is as valuable trade, valuable traits while ignoring the unnecessary ones. This mechanism is capable to function one twenty-four frames per second with the efficiency of seventy five percent. There is a research area scared according to the deep learning baseball core. Ethan, which is approximately used in each and every steel. Industrial appliances affection. Manufacturing. It is using a data set which is namely termed as few shots NEU-DET [26]. The technique Here is dividing different types of flaws in a subcategory manner It is training the system in such a way to detect small faults in a small of time. But it is still a time consuming one. To effectively detect defects in metal sheets, it is crucial to understand the various types of defects that can occur during the manufacturing process or during service. The most common defects include.

- Surface Defects: Surface defects encompass scratches, dents, surface cracks, and corrosion. These defects can affect the aesthetics, corrosion resistance, and mechanical properties of the metal sheet.
- Subsurface Defects: Subsurface defects include laminations, inclusions, voids, and internal cracks. These defects may not be visible on the surface but can compromise the structural integrity of the metal sheet.
- Welding Defects: In welded metal sheets, defects like weld cracks, porosity, incomplete penetration, and heat-affected zone (HAZ) issues can occur, potentially leading to joint failures.
- Dimensional Deviations: Deviations in thickness, width, or length of metal sheets can also

be considered defects, affecting their suitability for specific applications

3. Challenges and Emerging Trends

While these advanced techniques have significantly improved defect detection in metal sheets, several challenges persist:

- Real-Time Processing: In industries with high-speed production lines, real-time defect detection is essential to catch defects as they occur. Achieving real-time processing remains a challenge [26].
- Data Quality: Machine-based systems rely on high-quality data. Dust, dirt, or poor lighting conditions can affect the accuracy of detection[27].
- False Positives and Negatives: Striking a balance between detecting genuine defects and avoiding false alarms remains a challenge, especially in complex industrial environments[28].
- Adaptability: Manufacturing processes are dynamic and may change frequently. Defect detection systems must be adaptable to new product designs and production methods[29].
- Cost: Implementing advanced defect detection systems can be expensive, particularly for smaller manufacturers[30].
- Training: Machine learning-based systems require extensive training datasets and ongoing maintenance to remain accurate[31].

Emerging trends in defect detection include:

- Artificial Intelligence (AI): AI and machine learning algorithms are becoming more sophisticated, improving defect detection accuracy and adaptability[32].
- Big Data Analytics: Manufacturers are leveraging big data analytics to collect and analyze vast amounts of production data, enhancing defect detection and process optimization[33].
- Internet of Things (IoT): IoT sensors provide real-time data from manufacturing equipment, enabling predictive maintenance and defect detection[34].
- Augmented Reality (AR): AR systems are being used to assist human inspectors by overlaying digital information on physical products, highlighting potential defects[35].

Blockchain Technology: Blockchain is being explored to create immutable records of product quality, ensuring transparency and traceability in the supply chain[36]. The RPN is a fully convolutional network that generates region proposals directly within the CNN architecture, eliminating the need for an external region proposal algorithm like Selective Search. RPN uses anchor boxes of different scales and aspect ratios to generate region proposals, which are then refined to propose bounding boxes that likely contain objects (or defects in the case of defect detection).

4. Proposed Methodology

The proposed methodology consists of following steps.

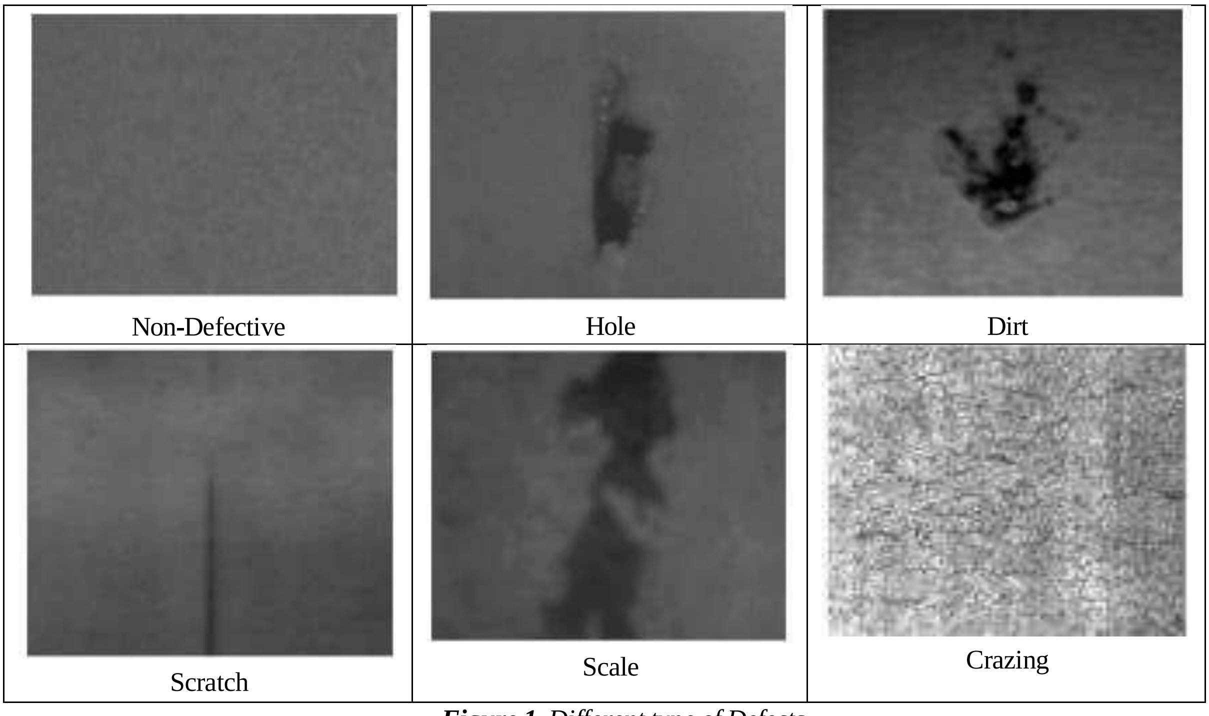

Figure 1. *Different type of Defects*

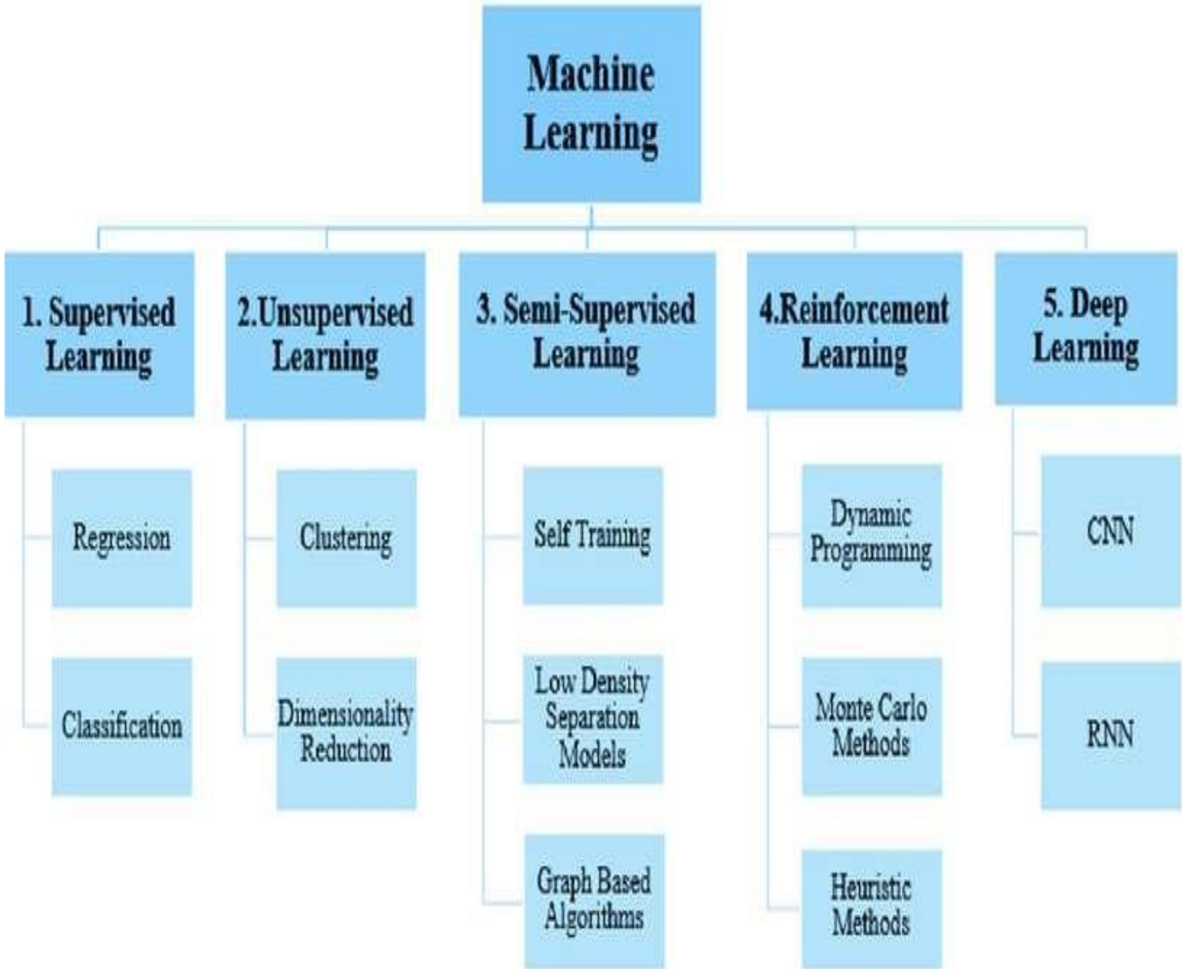

Figure 2. *Different structural presentation for types of machine learning*

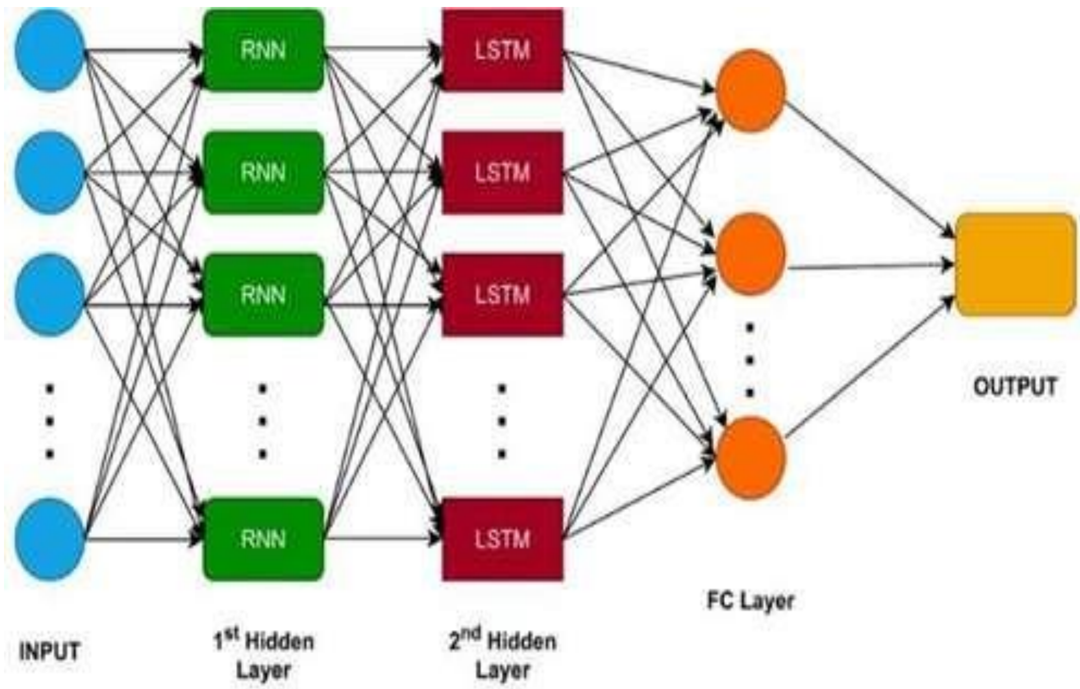

Figure 3. *The architecture of the region proposal network or RNN*

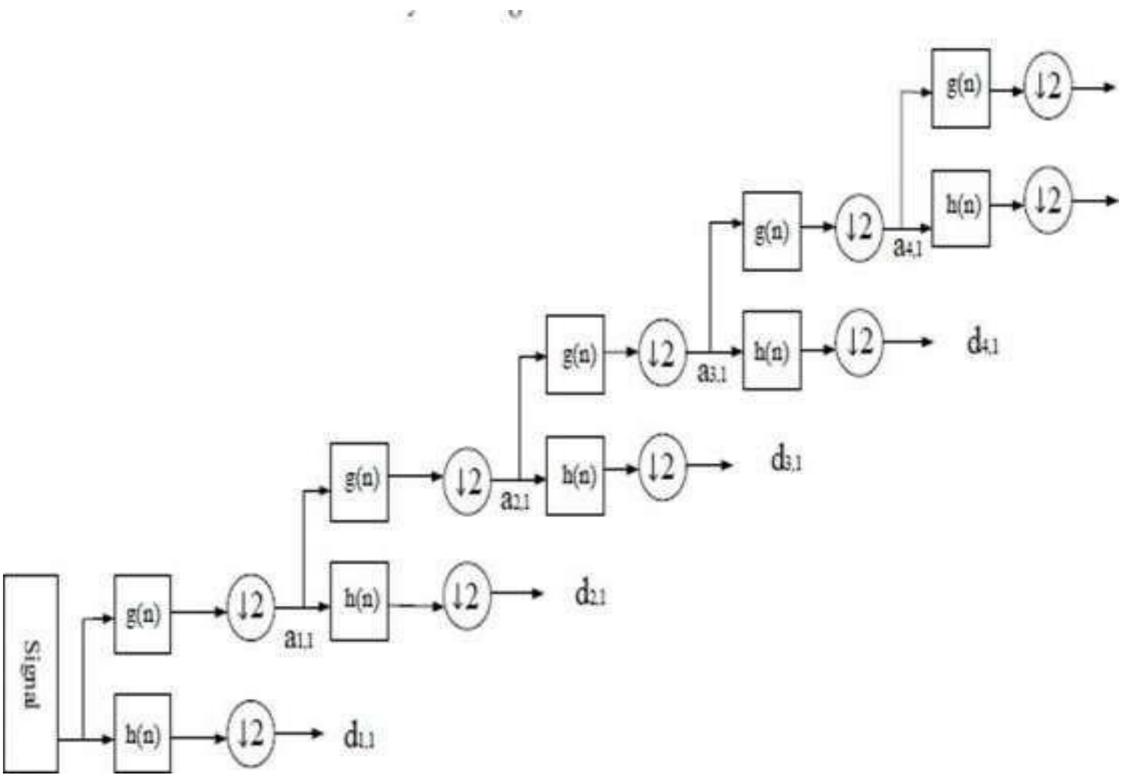

Figure 4. *The signal decomposition process using DWT; g(n) is the low-pass filter, h(n) is the high- pass filter [26]*

Table 1. *Accuracy of Industrial data (10 Features)*

No. of Images	Accuracy	Precision	Recall	F-Measure
500	90.25	92.14	86.32	89.1351
1000	92.65	93.56	88.14	90.7692
1500	94.56	95.86	89.96	92.8163
2000	96.28	97.25	90.87	93.9518

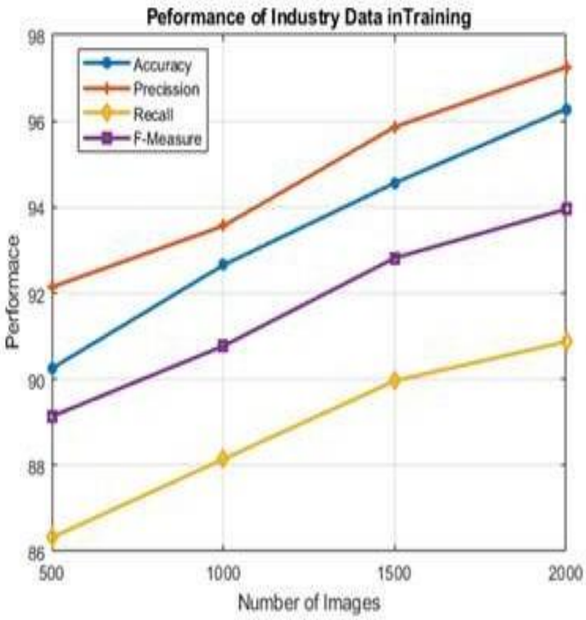

Figure 5. *Training performance parameter with Industrial Data set*

Table 2. *Testing Accuracy with Industry Dataset (10 Features)*

No. of Images	Accuracy	Precision	Recall	F-Measure
500	90.32	91.63	86.23	88.8480
1000	92.84	94.25	87.05	90.5070
1500	94.42	95.45	88.36	91.7683
2000	95.06	95.87	89.41	92.5274
3000	96.98	96.87	90.65	93.6568

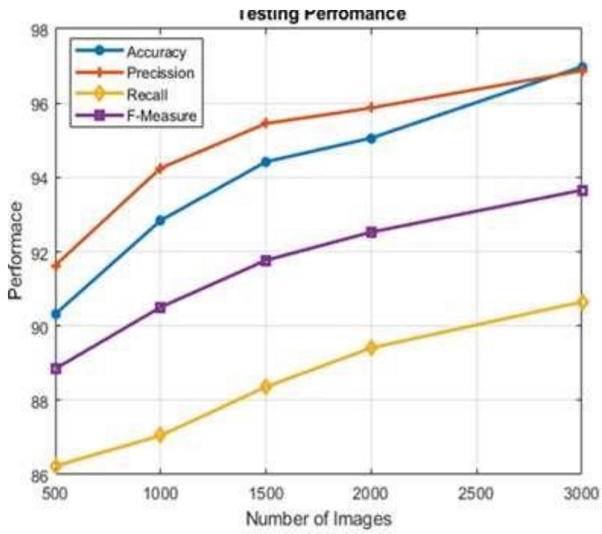

Figure 6. *Testing Accuracy of proposed with Industrial Data set*

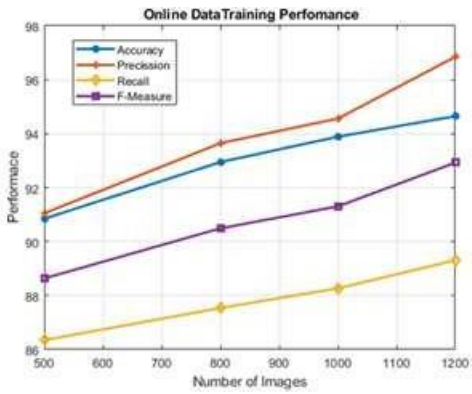

Figure 7. *Training Accuracy of Kaggle data set with proposed work*

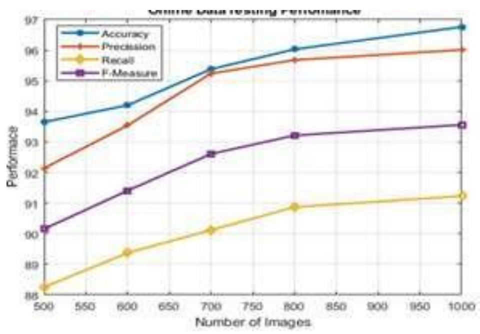

Figure. 8 *Testing Accuracy of Kaggle data set with proposed work*

Table 3. *Training Accuracy with Kaggle Dataset (10 Features)*

No. of Images	Accuracy	Precision	Recall	F-Measure
500	90.85	91.05	86.35	88.64
800	92.95	93.65	87.54	90.49
1000	93.89	94.56	88.27	91.31
1200	94.65	96.85	89.31	92.93

1. Preprocessing
2. Feature Extraction
3. Data Preparation
4. Training system
5. Testing System
6. Performance Parameter Calculation

Preprocessing – Images need to be pre-processed before we can be used for inference and model training. This covers alterations to the colour, size, and orientation, among other things. Pre-processing is done to improve the quality of the image so that we can analyse it more efficiently. Pre-processing enables us to enhance certain attributes that are crucial for the application we are working on and remove undesired distortions. These attributes may vary based on the intended use. Pre-processing an image is necessary for software to operate properly and yield the intended outcomes Pre-processing is required to get image data ready for input into the model. For example, the fully linked layers of convolutional neural networks required all the images to be in identically sized arrays.

Furthermore, model pre-processing could accelerate model inference and reduce model training time. Reducing the size of the input photographs will drastically cut down on the training time of the model without compromising its functionality, especially if the images are very large.

While pre-processing techniques include geometric image transformations (rotation, scaling, and translation), their main objective is to improve the image data by reducing inadvertent distortions or enhancing certain image features that are important for further processing

During fine-tuning, these weights and biases are adjusted based on the steel defect dataset using backpropagation: The loss function LLL (typically a combination of classification loss and bounding box regression loss) is minimized using gradient descent:

1. Loss Function LLL:
   - For classification, cross-entropy loss is commonly used.
   - For bounding box regression, smooth L1 loss is used.

$$L_{total} = L_{classification} + \lambda L_{regression}$$

2. Gradient Descent:
   - Update weights WWW and biases bbb:
   - $W \leftarrow W \leftarrow \eta \frac{\partial L}{\partial W}$
   - $b \leftarrow b \leftarrow \eta \frac{\partial L}{\partial W}$

The core of feature extraction in RCNN involves applying convolutional operations, activation functions, and pooling to extract meaningful features from input images. These operations are governed by the formulas for convolution, activation, and pooling. When using a pre-trained CNN, transfer learning and fine-tuning adjust the network parameters to optimize performance. Feature extraction is a step in the dimensionality reduction process that divides and reduces an initial collection of raw data to more manageable categories. As a result, processing will be simpler. The most crucial feature of these enormous data sets is the large number of variables. These variables need a significant amount of computational power to process. As a result, feature extraction aids in obtaining the best feature from large data sets by selecting and merging variables into features, effectively lowering the amount of data. These features are simple to process while accurately and uniquely describing the real data set. The classification model utilizes image and a textual dataset which are received at the input component of the model. The distinct datasets are preprocessed through the removal of noise and redundancy for the purpose of obtaining enhanced input. In case of the image dataset, the preprocessing and augmentation involve whitening of image samples, after their up sampling, its 32 by 32 crop size was selected [37]. While, the textual dataset during preprocessing were grouped into similar clusters [38], and conversion textual information into vectors or numeric values, and removal of infrequent classes using semantic and syntactic association of words by mean of natural language processing (NLP) [39].

Recurrent Neural Networks (RNNs) are a class of neural networks specifically designed to process sequences of data. Unlike traditional feedforward neural networks, RNNs have connections that form cycles, allowing information to persist across time steps. This makes them ideal for sequence data where the order of information is important, such as time-series data or any context where past inputs influence future outputs.

However, traditional RNNs suffer from the issue of vanishing gradients, making it difficult for them to retain long-term dependencies. This is particularly problematic when patterns or defects in data sequences span over long intervals[40]. To address this, Long Short-Term Memory (LSTM) networks were developed.

LSTMs are a specialized form of RNNs that solve the problem of vanishing gradients and improve the model's ability to learn from long-term dependencies. By using a memory cell and gate mechanisms (input, forget, and output gates), LSTMs can maintain and update relevant information over long sequences, making them highly effective for tasks involving time-series data or any data where temporal dependencies are critical. Steel surfaces can exhibit a variety of defects such as cracks, inclusions, or surface irregularities, which may not always be detectable from a single data point[41]. The sequential nature of sensor readings (e.g., acoustic emission sensors, thermal imaging, or sequential images) makes LSTMs an excellent choice for defect detection in steel. LSTM- based models, as a subset of RNNs, are well-suited for detecting steel defects where the input data is sequential or exhibits temporal dependencies. By leveraging the memory cell architecture and the ability to retain important information over long time intervals, LSTMs outperform traditional methods in identifying subtle, evolving defect patterns[42]. This makes LSTM a powerful tool for industrial quality control, ensuring early and accurate defect detection in steel manufacturing processes.

The process component undertakes feature extraction, feature selection and classification after training procedures. These are achieved with deep learning algorithms of LSTM-RNN situated within the process component of the model. The output component provides the results of the evaluation carried out by the distinct

deep classification models of LSTM-RNN using a test dataset, that is, a portion of the input dataset. The results are expressed in error rates and percentage of accuracy. Discrete Wavelet Transform is used for feature extraction is used. The most popular technique for time-frequency filtering is the discrete wavelet transform (DWT) [42]. Both the frequency and time domains have good resolution thanks to DWT's minimization of additive noise. The DWT approach splits the discrete signal x(n) into low- and high-frequency components, enabling multi- resolution analysis. An iterative Mallat algorithm can be used to calculate DWT [43]. Data is collected form one steel manufacturing unit and using Kaggle data also. All data is in the form of images. 5000 images collected form steel plant and 1000 images are downloaded from Kaggle website. Data is divided into two part one is defect and second one is non - defected. Recurrent Neural Network (RNN) is a class of powerful deep neural network using its internal memory with loops to deal with sequence data. The architecture of RNNs, which also is the basic structure of LSTMs. For a hidden layer in RNN, it receives an input vector, and generates the output vector. RNNs exhibit the superior capability of adapting themselves to predict nonlinear time series problems. Though, certain RNNs are bound to reach the vanishing with the Backpropagation coefficient learning, thereby making them unsuitable for long period lags learning nor accounting for long-term dependencies. These short-lived the widespread usage of RNNs, which gave rise to more improved approaches including the Long short-term memory (LSTM) and Gated Recurrent Unit (GRU) architectures. In recent applications, the LSTMs have shown promise on sequence-based computations with long-term dependencies. Through GRU is an abridged LSTM architecture, which is a relative innovation in machine translation tasks such as SemSeq4FD Recurrent neural network (RNN) is a class of neural network designed to handle sequential data. Unlike traditional feedforward neural network, RNNs have connections that form directed cycles, allowing them to maintain a form of memory. This makes them particularly useful for tasks where the order and context of inputs matter, such a time series prediction, natural language processing, and speech recognition.

An RNN processes sequences of input one elements at a time while maintaining a hidden state captures information about previous elements. This hidden state is updated at each time step based on the current input and the previous hidden state.

1. Hidden state update

At each time step t1 the hidden state ht is updated based on the previous hidden state ht-1 and the current input Xt. The update is given by

$$ht = \tanh(W_h\, ht{-}1 + U_h Xt + b_h)$$

where :

- Wh is the weight matrix for the hidden state from the previous time step
- Uh is the weight for the current input.
- Bh is the bias term
- tanh is the activation function, commonly used to introduce non-linearity. Output calculation

The output yt at time step t is computed from the hidden state ht using:

$$y_t = W_y h_t + b_y$$

where

- Wy is the weight matrix for the output layer.
- By is the bias term for the output layer.

Training an RNN involve adjusting its weight and basis to minimize the error in its predictions. This is done using a method called Backpropagation Through Time (BPTT), which us an extension of the standard backpropagation algorithm for Training feedforward network. Basic RNN suffer from the vanishing and exploding gradient problems, which make training difficult for long sequences. The vanishing gradient problem occurs when gradients become very small, making it hard to learn long-term dependencies. The exploding gradient problem occurs when gradients become excessively large, causing unstable training. Advanced RNN architectures. To address these issue, advanced architectures like long short-term memory (LSTM) network and gated recurrent units GRUs were developed. LSTM networks LSTMs include special units called gates that regulate the flow of information: For gate Gate:

$ft = \sigma(Wfht{-}1 + Uf\,Xt + bf)$

Input Gate:

$it = \sigma(Wihi{-}1 + UiXt + bi)$

$enew = \tanh(Wc\,ht{-}1 + UcXt + bc)$

Cell State Update:

$ct = ft\ \Theta\ ct + it\ \Theta\ cnew$

Output Gate:

$ot = \sigma(Wohi{-}1 + UoXt + bo)$ $ht = ot\ \Theta \tanh(ct)$

5. Results and Discussions

Main Algorithm in this work have been solved using MATLAB R2022. Additionally, MATLAB is installed on a laptop running Windows 10 with an Intel Core 2.5 GHz CPU and 8 GB of RAM. Two types of data sets are prepared to better test the suggested algorithm's performance. In the first type, ten features are selected for training and testing. In the second type dataset, all 13 features are used to train and test the suggested method. Images of steel plate surfaces are sourced from the industry and the Kaggle website. The results showing the accuracy of both two-type data set which is using to perform training and testing of proposed methodology. To analyses the proposed system different number of images are used for training and testing. In this section, only ten features are used to train the proposed algorithm, as well as to test it. The table below shows the accuracy when various numbers of photos are used to train the proposed system. This type of system analysis takes into account industry-specific data.

To determine the performance of the proposed technique, many parameters have been determined, including precision, recall, and F-Measure. These characteristics also indicate the performance and dependability of the proposed system. The F-measure is based on precision and recall levels.

Precision = TP/ (TP + FP) (1)

Recall = TP/ (TP + FN) (2)

F-measure = 2 x [(Precision x Recall) / (Precision + Recall)] (3)

When testing of this sort of dataset is completed, the accuracy for each number of images is displayed in Figure 6. Table 2 shows the correctness of the suggested system's testing results. It is apparent that the accuracy of output data values increases as the number of images increases. The exceptionally high F-measure value additionally indicates the proposed system's dependability and effectiveness. In this section total number are features are used for both training testing process. Also, comparison of both data sets accuracy is showing under it.Tables V and VI point out the accuracy results for both the training and testing processes using two types of datasets. Fig.9 and 10 displays the training accuracy for both industrial and online datasets. It is obvious from the figure that when industrial data sets are used to train the suggested system, greater accuracy values are produced. However, online datasets are less accurate than industrial datasets. This is due to the fact that industrial datasets are more precise and lucid than those found online. The testing procedure also yields the same results. When evaluating the suggested algorithm on an industrial dataset, accuracy is more important. The number of pictures and the type of dataset also have an impact on accuracy values. If both the number of input images and the image quality are good, the accuracy of any advanced algorithm will be quite high.The proposed system parameters are calculated in all of the following tables to determine their robustness and dependability. The precision, recall, and F-Measure scores are used to calculate the robustness of the training and testing processes. Precision and recall values are used to calculate the F-measure. The proposed algorithm exhibits a higher F-measure, suggesting that the proposed technique is more accurate in distinguishing between images that are defective and those that are not.The performance of the proposed method employing thirteen features and industrial data is displayed in figures 9 and 10 below. Thirteen features make up the feature matrix, which is subsequently input into the classification network. Figure 11 depicts the comparative curve between the proposed classification technique's testing accuracy when trained on industrial and online data, respectively. When industrial data is utilized to train the suggested methodology, the accuracy is quite high, at 98.25. The quantity of images in the online data set is lower than that in the industrial data set, but the accuracy is 96.28 percent. Based on the information that is accessible, it is obvious that the proposed approach is far more reliable and precise in classifying defective and non-defective steel plates in steel producing plants.

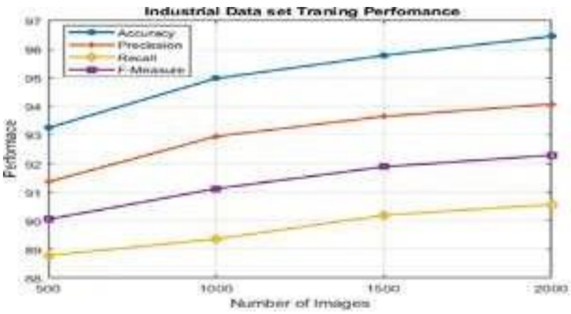

Figure 9. *Performance Parameter of industrial dataset with 13 Features*

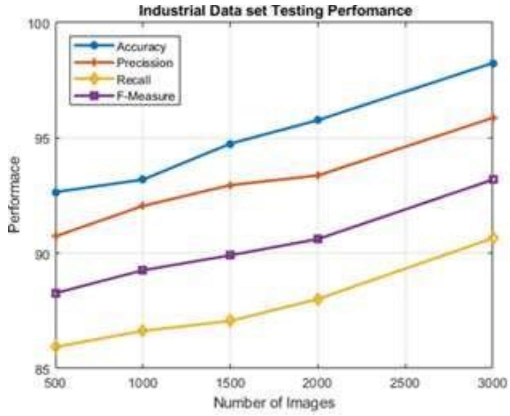

Figure 10. *Testing Accuracy industrial dataset with 13 features*

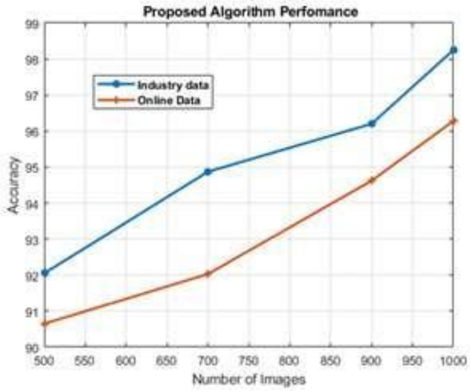

Figure 11. *Comparative Analysis of Testing Accuracy between industrial and online dataset*

***Table 4**. Testing Accuracy with Kaggle Dataset (10 Features)*

No of images	Accuracy	Precision	Recall	F-Measure
500	93.65	92.14	88.25	90.15
600	94.20	93.54	89.37	91.41
700	95.38	95.24	90.12	92.61
800	96.03	95.68	90.87	93.21
1000	96.76	96.01	91.23	93.56

Table 5. *Training Accuracy of Industrial Dataset (13 Features)*

No. of Images	Accuracy	Precision	Recall	F-Measure
500	93.25	91.36	88.78	90.05
1000	94.98	92.95	89.36	91.12
1500	95.78	93.65	90.19	91.89
2000	96.45	94.08	90.57	92.29

Table 6. *Testing Accuracy of Industrial Dataset (13 Features)*

No. of Images	Accuracy	Precision	Recall	F-Measure
500	92.65	90.73	85.93	88.8480
1000	93.19	92.05	86.63	90.5070
1500	94.75	92.95	87.06	91.7683
2000	95.77	93.37	88.01	92.5274
3000	98.25	95.87	90.65	93.6568

Table 7. *Testing Accuracy Comparison (13 Features)*

No. of Images	Industrial Dataset Accuracy	Online Dataset Accuracy
500	92.05	90.65
700	94.87	92.03
900	96.20	94.62
1000	98.25	96.28

6. Conclusions

- In this study, we provide a unique technique for classifying defective and non-defective defect detection in steel manufacturing plants. In the proposed RNN technique, features are extracted from distinct data sets and classified as defective or non-defective images.
- The dataset consists of both defective and non-defective photos of steel plates. All data are taken from a steel manufacturing factory. Then it will use a feature extraction approach based on wavelet transformations. Following that, a feature matrix for the entire dataset is created, which is fed into the suggested RNN algorithm.
- The proposed work has been split into two parts. In the first part, only 10 features are considered for feature extraction and preparing the feature matrix, however in the second part, 13 features are taken from each image of the dataset to generate the feature matrix.
- The accuracy of both training and testing is calculated and displayed in tables as the number of images taken changes during the training and testing processes. According to performance statistics, the outcomes with 13 features outperform the other technique, which only includes 10 features for training.
- The section's accuracy is lower than when 13 features are evaluated. When 13 features are used to generate a feature matrix for the training of the proposed approach. The results are more accurate and consistent. Precision, Recall and F-Measure values are also showing results of proposed system for considering 10 features and 13 features respectively. Experimental results are showing accuracy, precision and recall of proposed RNN technique. The suggested technique achieves an overall accuracy of 98.25%, indicating robust performance of the algorithm in classifying and providing more precise findings.
- An approach based on region-based fault identification has been suggested to improve its performance. Because a single unit of steel plate can withstand multiple types of defeats. Thus, if region-based algorithms are employed in the future for various forms of defect identification. Accuracy will then improve.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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