Journal of Information Systems Engineering and Management
2025, 10(32s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Multi-Scale Defect Detection Using Modified Faster R-CNN for Plates with Complex Surfaces

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ARTICLE INFO

Received: 29 Dec 2024

Revised: 15 Feb 2025

Accepted: 24 Feb 2025

ABSTRACT

Defect recognition plays a crucial role in investigating a panel. Mostly the recent manual investigating methods are time consuming and high expense. The fast recurrent neural network is enhanced and is less time consuming. The faster R-CNN has been proposed in the research work. A feature pyramid network associated with ResNet-50 has been efficiently able to detect the defects in a precise manner. In this manuscript for localization of defects we have used Region of Interest Align in place of pooling ROI. Then an enhanced feature network has been used to precisely detect the defects. Therefore, the k-means clustering algorithm is used to cluster the defects so that the defects can be easily detected. In this paper the data set has been taken and the algorithms are compared with the existing algorithm to check the accuracy and efficiency of the proposed system. The detection accuracy has been converted and detected properly and validated in the paper.

Keywords: faster R-CNN, ROI, ResNet-50, clustering algorithm.

INTRODUCTION

In Recent, by 2020 reports the China's current furnishing industry is going to an extent. The market of China is booming because of the reason that nowadays people are very concerned about the environmental conditions and design and concept of the home. Nowadays to customize furniture increases the market up to twenty percent and is also experiencing to attain the marketplace around 2500 trillion till 2025. As the demand of attraction enterprises or increase in day by day so the raw material used in the plate manufacturing is also increasing gradually. To meet the market requirements there are different types of automated plate manufacturing types that are introduced like pet manufacturing, manmade surfaces and high-definition surfaces wooden panels and many more. The production stage of the polished prototype from raw, pits, bumps, dents and several other kinds of defects arise at the finalized end. The quality of the surface of the steel plates made by man has a certain kind of defect in the manufacturing process. The defect and affect the quality of the finished product so to terminate or ignore the defects we need to detect the defects caused due to manmade or domestic manufacturing. So, it is required to have the cluster of investigation approaches for different detection. Machine vision is a good kind of defect detection approach due to high accuracy and fast detection. In this method the image is firstly attained, and the preprocessing is being performed the features are extracted and based on that features the defect is classified. The features are in the form of shape and size. In the literature several different detection approaches are available. The decision tree approach is proposed to detect the defect based on the artificial board. The CART algorithm is used to detect the cost complexity and then the synthetic surface defect detection. In the existing review, defect lumber detection an approach with NIR spectrum and inverse NN is used for the process. Another method for defect detection is the binary method and the binary differential method is used for histogram defect analysis. The artificial board detection methods include random forest, region screening detection methods and clustering and there are also ensemble machine learning methods for defect detection. The training, testing and validation are the three phases of detection. The feature selection is also an important parameter for the whole process. In steel production, defects such as cracks, scratches, inclusions, dents, and holes can occur due to various reasons including material defects, processing errors, or external damage. Identifying these defects early is essential to avoid costly downstream issues and to maintain product standards. Traditional machine vision techniques for defect detection often rely on handcrafted features and threshold-based methods, which may fail in complex or noisy environments. The development of deep learning-based approaches has shifted the paradigm by allowing models to automatically learn relevant features from raw image data, thus improving robustness and accuracy. The "hole" defect on steel sheet surfaces often originates from microstructural issues during processes like shearing or punching. In high-strength steel sheets, hole-related defects, such as micro-ductile cracks, are prone to occur at shear edges where tensile stresses create cleavage fractures, making the steel susceptible to crack propagation. These defects can be managed by adjusting tool clearances, which reduces stress and prevents crack initiation. Recent research indicates that microstructural examination and simulation models help in predicting and controlling these defects for improved steel quality https://doi.org/10.2355/isijinternational.ISIJINT-2019-326.“Dirt" defects on steel sheet surfaces are often caused by external particulate contamination or chemical residue left during manufacturing processes, especially in casting or rolling phases. These defects manifest as small, embedded particles or dark spots on the steel surface, impacting its appearance and quality. Typically, dirt defects originate from the incorporation of non-metallic inclusions, dust particles, or chemical residues, often introduced during cooling, handling, or surface treatments. Research indicates that such contaminants can be minimized by improving the cleanliness of the processing environment and using controlled filtration systems. Studies also suggest that automated detection systems based on machine vision and deep learning are increasingly effective for real-time identification and categorization of these surface impurities, allowing for faster response and corrective actions in production settings. For an in-depth look, recent analyses on the generation mechanisms of such defects, and their detection, are discussed in journals like Tetsu to Hagane and MDPI’s Steel Surface Defect Recognition Survey from 2023. A "scratch" defect on a steel sheet surface is typically a narrow, linear imperfection caused by friction, mechanical handling, or contact with other materials or equipment during manufacturing or transport. These scratches, if not addressed, can compromise the steel’s strength, reduce its fatigue resistance, and impact visual quality, which is crucial in industries such as automotive and appliance manufacturing. Scratches tend to run along the rolling direction of the steel, making them distinctive but often challenging to detect due to their narrow profile. Recent advances in defect detection technology are increasingly focusing on the automation of scratch detection. Studies have applied convolutional neural networks (CNNs) and deep learning techniques for real-time, high-accuracy identification. For example, the modified YOLO-v5 network offers enhanced detection capabilities by incorporating multi-scale detection and spatial attention mechanisms, which help in distinguishing fine, narrow scratches from other surface textures. This approach aims to improve detection speed and accuracy to meet industrial production demands (Ma et al., 2023). Another recent study used a unique U-Net-based model that combines down sampling with a spatial-depth module to improve the localization of small scratches, which are otherwise difficult to capture due to image resolution limitations (Liu et al., 2024). These developments highlight the importance of real-time, precise scratch identification in quality control, enabling manufacturers to minimize defects and optimize production efficiency by reducing reliance on manual inspection methods. For more details, refer to research by Ma et al. (2023) and Liu et al. (2024) in Processes and Electronics journals, respectively. The "scale" defect in steel sheet surfaces, often referred to as "rolled-in scale," originates during the hot rolling process, where iron oxides formed on the surface become pressed into the steel due to high temperature and pressure. These oxides, primarily consisting of magnetite and hematite, can lead to irregular surface textures and, if not removed, significantly impact the steel’s mechanical properties and surface aesthetics. This defect poses challenges in downstream processes like coating or painting, where a smooth surface is essential for adhesion and durability. Recent studies in defect detection have focused on automated, real-time methods to address scale defects using deep learning techniques. For instance, improved multi-scale models, such as an enhanced YOLO-v5, integrate spatial attention mechanisms that help localize and identify scale defects across varying image resolutions with high accuracy and speed. This approach is particularly effective in distinguishing scale from other defects, offering improvements in precision over manual inspection methods. This advancement not only supports quality control but also optimizes production by allowing for consistent, non-destructive testing throughout manufacturing lines. For a deeper understanding of these detection methods, refer to works by Ma et al. (2023) on real-time detection advancements and a comprehensive review by Wen et al. (2023).

The "crazing" defect on steel sheet surfaces appears as fine, irregular cracks, often caused by stress in the material during cooling or forming processes. These cracks are usually superficial but can significantly impact both the aesthetic quality and structural performance of the steel, especially in applications requiring high surface integrity. Current research leverages deep learning-based models to detect crazing and other microdefects in real-time, with methods like multi-scale YOLO networks achieving high accuracy and efficiency in distinguishing complex defect patterns on steel surfaces, critical for quality assurance in production lines. For more details, see recent advancements in steel defect detection systems (MDPI, 2023). Object detection has evolved significantly with the introduction of deep learning techniques. Among the pivotal advancements in this domain is the R-CNN (Regions with Convolutional Neural Networks) framework, which has set new standards for accuracy and efficiency in detecting objects within images. Object detection is a critical task in computer vision that involves identifying and localizing objects within images. Traditional methods relied heavily on hand-crafted features and classifiers. However, the rise of deep learning has revolutionized this field, with R-CNN being one of the first to leverage Convolutional Neural Networks (CNNs) for this purpose. Introduced by Girshick et al. in 2014, R-CNN combined selective search for region proposal with deep learning for classification and localization, achieving remarkable performance on benchmark datasets. Defect detection in industrial applications is critical for ensuring product quality and operational efficiency. In manufacturing environments, components such as metal plates with complex surface textures often present significant challenges for defect detection due to their non-uniformity and variability in defect appearance. Traditional methods rely heavily on manual inspection or conventional image processing techniques, which are labour-intensive, time-consuming, and prone to human error. To address these limitations, automated defect detection using advanced deep learning techniques has emerged as a promising solution. Among deep learning approaches, Faster R-CNN (Region-based Convolutional Neural Network) is a widely adopted object detection model due to its robustness and ability to handle diverse object scales and categories. However, when applied to plates with complex surface patterns, standard Faster R-CNN may struggle to detect multi-scale defects effectively. The variability in defect sizes, shapes, and contrast levels relative to the background necessitates modifications to enhance the model's feature extraction and region proposal capabilities. This study introduces a Modified Faster R-CNN framework designed to improve defect detection performance on complex surfaces. The proposed approach integrates multi-scale feature extraction techniques, enhanced region proposal strategies, and domain-specific preprocessing to better accommodate the challenges posed by irregular surfaces. By leveraging these modifications, the model achieves superior accuracy and robustness in identifying various types of defects. The significance of this research lies in its potential to revolutionize quality control processes in industries such as metal fabrication, electronics, and automotive manufacturing. The proposed method not only automates defect detection but also provides a scalable and efficient solution adaptable to diverse industrial settings. In the following sections, the paper delves into the methodology, implementation, and evaluation of the Modified Faster R-CNN model, showcasing its effectiveness in handling multi-scale defect detection for complex surface scenarios. Steel plates are critical components in numerous industries, including construction, automotive, and shipbuilding. Ensuring the quality of these plates is essential to maintain product integrity and safety. Surface defects such as scratches, dents, inclusions, and cracks can significantly impact the functionality and aesthetics of steel products. Traditionally, defect detection has relied on manual inspection or rule-based image processing techniques, which are often time-consuming, labour-intensive, and prone to human error. With advancements in machine learning (ML) and artificial intelligence (AI), automated steel plate surface defect detection has become more accurate, efficient, and scalable. Modern approaches leverage machine learning models such as Support Vector Machines (SVM) and deep learning architectures like Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks. These techniques use advanced algorithms for feature extraction and classification to identify and categorize defects effectively. Feature extraction is the foundation of any machine learning model. In the context of steel plate defect detection, texture, color, shape, and edge patterns are some key features. Traditional methods rely on handcrafted features using techniques like Histogram of Gradients (HOG) and Local Binary Patterns (LBP). Deep learning, however, enables automatic feature extraction, allowing models to learn hierarchical representations of defects directly from raw image data. SVM is widely used for binary and multi-class classification. It works by finding an optimal hyperplane that separates classes with the largest margin. In defect detection, SVM can classify extracted features into defect or non-defect categories and is particularly effective in scenarios with small datasets. CNNs have revolutionized image-based defect detection due to their ability to capture spatial hierarchies in data. A CNN-based model can automatically learn and extract complex features from steel plate surface images, outperforming traditional methods in defect identification and localization. Although RNNs and LSTMs are primarily designed for sequential data, they are valuable in defect detection when combined with spatial-temporal data or sequential images. They help in analysing patterns over time, such as evolving surface changes during manufacturing. AI-driven frameworks combine the strengths of these machine learning models with techniques like ensemble learning, data augmentation, and optimization algorithms. These systems adapt dynamically to different environments and defect patterns, achieving high accuracy and robustness in real-world scenarios. the fusion of machine learning techniques like SVM, CNN, RNN, and LSTM with advanced AI frameworks offers a transformative approach to steel plate surface defect detection. These technologies enable manufacturers to ensure higher product quality, reduce wastage, and improve operational efficiency. As research in this field continues to advance, more sophisticated and generalized models are expected to emerge, addressing diverse challenges in defect detection with unparalleled precision.

The R-CNN framework consists of several key components:

1. Region Proposal: R-CNN uses an external algorithm called selective search to generate about 2,000 region proposals from an image. These regions likely contain objects and serve as candidates for further analysis.

2. Feature Extraction: Each proposed region is warped into a fixed size and fed into a pre-trained CNN (typically Alex Net) to extract feature vectors. This step is computationally intensive but critical for capturing the spatial hierarchies of the images.

3. Classification and Bounding Box Regression: The extracted features are then fed into a set of SVM classifiers to determine the object classes. Additionally, a linear regression model is used to refine the bounding box coordinates, improving localization accuracy.

Post-processing: Finally, non-max suppression is applied to eliminate duplicate detections and ensure that each object is represented by a single bounding box.

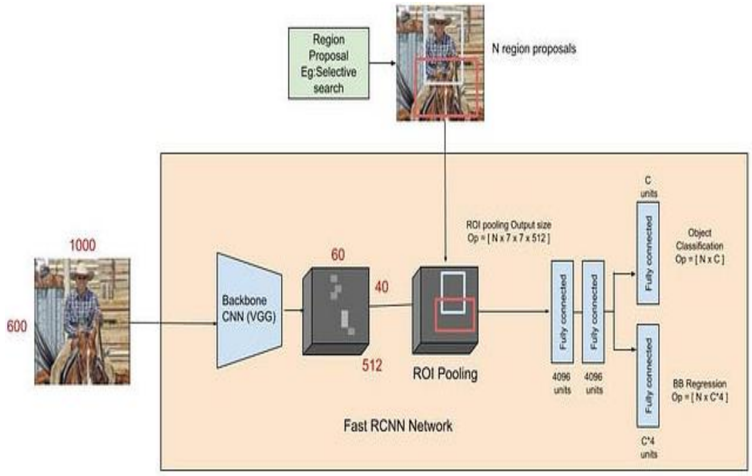

Fig.1. RCNN Architecture

High Accuracy: R-CNN significantly improves object detection accuracy by utilizing deep learning for feature extraction.

Flexibility: The framework can be adapted to various CNN architectures, enhancing its applicability across different tasks.

Computationally Intensive: The need to extract features for each proposed region makes R-CNN slow, rendering it impractical for real-time applications.

Storage Requirements: The model requires considerable storage due to the necessity of storing CNN features for each region proposal.

Evolution and Successors

Following R-CNN, several variants emerged to address its limitations:

Fast R-CNN: Introduced a unified architecture that shares convolutional features across proposals, significantly speeding up the process.

Faster R-CNN: Integrated a Region Proposal Network (RPN) that generates proposals more efficiently, further reducing computational overhead.

Mask R-CNN: Extended Faster R-CNN to perform instance segmentation, allowing for pixel-level predictions in addition to bounding box detection.

R-CNN has played a foundational role in the advancement of object detection using deep learning. Its innovative approach to combining region proposals with CNNs has paved the way for more efficient and accurate models. Despite its limitations, the principles established by R-CNN continue to influence modern object detection techniques. Future research may focus on further enhancing efficiency and accuracy, especially in real-time applications and resource-constrained environments.

Layers in architecture

Input Layer: The input to a CNN is usually a 3D array (height, width, depth) representing an image. For example, a color image might be represented as a 224x224x3 array, where 3 corresponds to the RGB color channels.

Convolutional Layers: These layers perform the core operation of a CNN. They apply convolution operations to the input data using small filters (kernels). Each filter slides (convolves) over the input image, computing dot products to create a feature map that highlights specific patterns, such as edges or textures.

Activation Function: After each convolution, an activation function (often ReLU - Rectified Linear Unit) is applied to introduce non-linearity into the model. This helps the network learn complex patterns.

Pooling Layers: Pooling (typically max pooling) is applied after some convolutional layers to reduce the spatial dimensions (height and width) of the feature maps. This down-sampling helps to decrease computational load and makes the representation more invariant to small translations.

Fully Connected Layers: After several convolutional and pooling layers, the high-level reasoning in the CNN is done through fully connected layers. Here, the feature maps are flattened into a one-dimensional vector and passed through one or more dense layers, leading to the final output.

Output Layer: The final layer provides the network's predictions, such as class probabilities for classification tasks.

R-CNN (Regions with Convolutional Neural Networks) is an innovative framework for object detection that builds on the principles of CNNs but introduces additional steps to address the specific challenges of detecting and localizing objects within images. Here's a breakdown of how R-CNN functions and how it differs from standard CNNs.

Functioning of R-CNN

Input Image: R-CNN starts with an input image, just like a CNN.

Region Proposal:

Instead of processing the entire image at once, R-CNN uses a method called selective search to generate approximately 2,000 region proposals. These proposals are candidate bounding boxes that are likely to contain objects.

Classification:

The extracted feature vectors are then input into a set of SVM (Support Vector Machine) classifiers. Each SVM is trained to identify specific object classes (e.g., cars, dogs).

The classifiers output probabilities for each class, determining the presence of objects in each region.

Bounding Box Regression:

Alongside classification, a linear regression model is applied to refine the bounding box coordinates of each proposed region. This step improves the accuracy of object localization.

Post-processing:

Non-maximum suppression (NMS) is applied to eliminate duplicate detections. This process ensures that each object is represented by a single bounding box in the final output.

Key Differences Between R-CNN and CNN

While R-CNN builds on CNN architecture, there are several fundamental differences:

Purpose:

CNN: Primarily used for tasks like image classification, where the goal is to assign a single label to the entire image.

R-CNN: Designed specifically for object detection, requiring both classification (which objects are present) and localization (where they are located).

Region Proposal Mechanism:

CNN: Processes the entire image without distinguishing regions; the whole image is fed into the network for classification.

R-CNN: Uses selective search to generate region proposals, allowing the model to focus only on parts of the image that may contain objects.

Feature Extraction:

CNN: A single forward pass through the network extracts features for the entire image.

R-CNN: Multiple forward passes are required—one for each region proposal—resulting in a feature vector for each candidate region.

Post-Processing Steps:

CNN: Generally, does not require additional processing steps after classification.

R-CNN: Involves additional steps like bounding box regression and non-maximum suppression to refine the results and eliminate redundancies.

II. LITERATURE REVIEW

Faster R-CNN, introduced by Ren et al. (2015), is a state-of-the-art object detection framework that combines region proposal networks (RPN) with CNN-based classification. It improves upon earlier R-CNN models by integrating the proposal generation process with the detection network, allowing for faster computation while maintaining high detection accuracy. Wang et al. (2019) applied Faster R-CNN to detect surface defects in hot-rolled steel strips. They demonstrated that the model could accurately detect defects such as scratches, holes, and scale, even under challenging conditions like noise and varying lighting. The researchers compared Faster R-CNN with traditional machine vision methods and showed a significant improvement in detection accuracy and processing speed. Huang et al. (2020) focused on improving the Faster R-CNN model for defect detection in cold-rolled steel sheets. They modified the backbone network by incorporating ResNet architecture to enhance feature extraction, which led to better performance in detecting subtle defects like minor cracks and scratches. Sun et al. (2021) employed Faster R-CNN in combination with a data augmentation strategy to increase the robustness of defect detection under different conditions. They applied this model to a steel defect dataset and reported improvements in defect classification, especially for smaller or less visible defects. Liu et al. (2022) used Faster R-CNN for automated visual inspection in a steel mill. They proposed a multi-scale detection method by incorporating feature pyramids to better handle defects of varying sizes. This method was effective in detecting defects such as pitting and edge cracks, which often vary in scale. Detecting surface defects on industrial plates is critical for maintaining product quality. Faster R-CNN, with its robust two-stage architecture, is widely used in defect detection. However, challenges such as multi-scale defects, intricate textures, and varying lighting conditions necessitate modifications for enhanced performance. Modifications to Faster R-CNN often incorporate feature pyramid networks (FPN) or enhanced feature extraction to improve detection of small and large defects. Improved anchor box generation techniques tailored to defect size ranges, combined with attention mechanisms, effectively address small defect detection issues. Enhanced pre-processing methods and custom loss functions (e.g., focal loss) improve model robustness against textured surfaces. Using deeper backbones, such as ResNet-50 or ResNet-101, enhances feature extraction capabilities, crucial for complex surfaces. Adjusting the Region Proposal Network (RPN) with optimized proposals enhances localization accuracy for defects of varied scales. Rapid R-CNN includes four sections. The planned enhanced rapid R-CNN module integrates an adjustable convolution remaining network, ResNet 50 with an enhanced trail combination feature pyramid network and fodder plots into focus area proposed system with a fused convolutional focus model.Mia et. al proposes the paper proposes a novel Deformable Attention Network (DANet) that integrates several state-of-the-art techniques to enhance the detection of small objects, such as defects and cracks, in manufacturing environments. The authors proposed a novel model called DANet that integrates Faster R-CNN with cutting-edge methods to enhance small object detection in manufacturing environments. - The proposed DANet model outperformed other state-of-the-art object detection models on the NEU-DET dataset, achieving the highest mean Average Precision (mAP) of 78.27%. Taewook Wi et. al proposed that proposed an efficient framework that combines deep learning-based defect detection and segmentation to accurately identify and analyse surface defects in the steel manufacturing process, using only bounding box annotations to generate detailed segmentation labels and reduce the high cost of manual annotation. The study proposes an efficient framework to detect and segment steel surface defects using only bounding box annotations, reducing the cost and time required for detailed pixel-level annotations. The framework uses recursive learning with bounding box annotations and the GrabCut algorithm to train a segmentation model, which progressively improves the segmentation predictions. - The proposed framework can effectively detect and accurately define steel surface defects in randomly collected images, contributing to improved quality control and cost reduction in the steel manufacturing industry. Researchers have incorporated FPNs into Faster R-CNN to enhance multi-scale feature extraction. This approach improves the model's ability to identify small defects while maintaining robustness against background noise. Attention-based modules such as Convolutional Block Attention Module (CBAM) have been added to focus on defect-prone areas, improving the detection accuracy of subtle anomalies. Baizhan Xia et. al proposes an improved Faster R-CNN algorithm for detecting surface defects on plates, with key improvements including texture background smoothing, multiscale feature extraction, attention-based region proposal, and deformable convolution. An enhanced dual riddling step to swift the picture surface backup that is feature layers network with shape diversified form convolution of Resnet to determine the faults which is aligned for precise fault finding. The focus on defects and suppress complex background - K-means clustering to derive better anchor frames for the region proposal network. An improved Faster R-CNN algorithm for multi-scale defect detection in steel surfaces, utilizing a path aggregation network and an enhanced ResNet50 backbone, achieving a mean average precision of 80.2% and addressing challenges of complex surface characteristics. Xang et. al the paper does not provide a literature review on "Multi-Scale Defect Detection Using Modified Faster R-CNN for Plates with Complex Surfaces." It focuses on an AINDANE-Faster R-CNN method for metal plate defect detection under complex. Chen et. al focuses on a novel multi-scale defect detection model for bottled products using variable receptive fields and feature fusion. Baizhanzia et. al proposes an improved Faster R-CNN model incorporating a feature pyramid network, attention mechanisms, and deformable convolutions to enhance multi-scale defect detection on plates with complex surfaces, achieving high accuracy and real-time performance compared to existing methods. Faiyang et. al. It does not provide a literature review on "Multi-Scale Defect Detection Using Modified Faster R-CNN for Plates with Complex Surfaces." It focuses on a multisite plate detection algorithm using an improved Mask RCNN for plate processing.It focuses on a deep learning model that incorporates multiscale features and parameter compression for surface defect inspection in complex. Image Pre-filtering computation includes the two sections: Consistency backup levelling and dataset improvement. consistency backup swiftness algorithm that distortions the feel backup to a certain level while managing constructional corner elaboration to decrease the influence of complicated and adjustable feel backup on raw fault detection. The wooden panel superficial has a complicated and adjustable texture backup, and the panel faults for a tiny ratio of the entire imagery depends on dual which can impact the fault recognition impact. Thus, an efficient feel swiftly procedure is needed at the time of image precomputation to haze the texture backup to some amount while upholding the particulars of the construction corners. It will enhance the precision and sturdiness for recognition faults includes the distinct consistent backups. Recently, consistency swiftly is basically performed by utilizing riddling approaches, that is chiefly categorized as Gaussian filtering, bilateral riddling and international optimizing riddling algorithms. Gaussian riddling is an improved for consistency backup swiftly but that gives some distant view of construction corner detailing that is not better for fault feature holding. International optimization riddling is needed in the procedure of consistency swiftly to assure that the distinction among the imageries after consistency swiftly and the initial image is decreased. The worldwide optimization riddling can attain very robust incline consistency swiftly with the shortcoming that it could not be swift scale changing surfaces. Dual riddling algorithm enhances the area of surface swiftly. It is basis on the gaussian riddling assuming both the gray parameter surrounding the pixel indications and the location relation among the resolution indications estimating that can be elaborated as:

$$m = exp\left[\frac{(x-z)^2+(y-l)^2}{2\sigma_d^2} - \frac{\|X(x,y)-X(z,l)\|^2}{2\sigma_r^2}\right]$$

$$X_D(x,y) = \frac{\sum_{z.l} X(z.l)m}{\sum_{z,} l^m}$$

Where x,y, and z are the resolution locating attainment. X (x,y) is the grayscale value of the (x,y) resolution points. σd is the smoothed weight value associated with the spatial location. σr is the smoothed weight value associated with the pixel. XD(x,y) is the grayscale value of the pixel point after smoothing. After testing, it was found that the defect also become blurred after the bilateral filtering algorithm for the wood panel images.

$$L(z,l) = \{max(L(w,t)+1)\}$$

$$L(z,l) = \begin{cases} \max(L(w,t)+1), & \text{if} |(w-z)(t-l)| < \ = 1 \text{ and } X(w,t) = X(z,l), \\ 0, & \text{for else.} \end{cases}$$

Where σl is the value of the smoothing weight associated with the pixel edge length. The improved bilateral filtering algorithm smooth the texture background, while the thin scratches on the wood panel surface are better maintained, as shown in Figure 2. To quantitatively evaluate the effect of texture smoothing of the improved bilateral filtering algorithm, the higher the similarity of the two images. As can be seen from Table 1, the improved bilateral filtering algorithm can maintain the defect characteristics better while smoothing the texture background.

III. METHODOLOGY

Rapid R-CNN includes of four stages. The planned enhanced faster R-CNN model associates a variable CNN residual channel, ResNet50 with an enhanced path aggregation features layers network (PA-FPN) and feeds the extracted multiple feature maps into attention area proposed network with a fused CNN focus module. The module construction is illustrated below: Faster R-CNN (Region-based Convolutional Neural Network) is a powerful deep learning framework widely used for object detection, including the identification of steel defects. It integrates feature extraction, region proposal, and classification into a unified network, making it efficient and accurate for defect detection tasks. In this approach, a pre-trained CNN backbone (e.g., ResNet or VGG) extracts features from steel surface images, which are then analyzed by a Region Proposal Network (RPN) to generate candidate bounding boxes for potential defects. These regions are refined through Region of Interest (RoI) pooling, ensuring compatibility with subsequent classification and bounding box regression layers. Faster R-CNN can identify different types of defects, such as cracks, dents, scratches, and corrosion, while accurately localizing them within the image. To enhance performance, the model benefits from data augmentation, fine-tuning on defect-specific datasets, and optimization techniques such as smooth L1 loss for regression and cross-entropy loss for classification. Its robustness and precision make it a valuable tool for automated quality inspection in steel manufacturing, enabling efficient, real-time defect detection and reducing reliance on manual inspection.

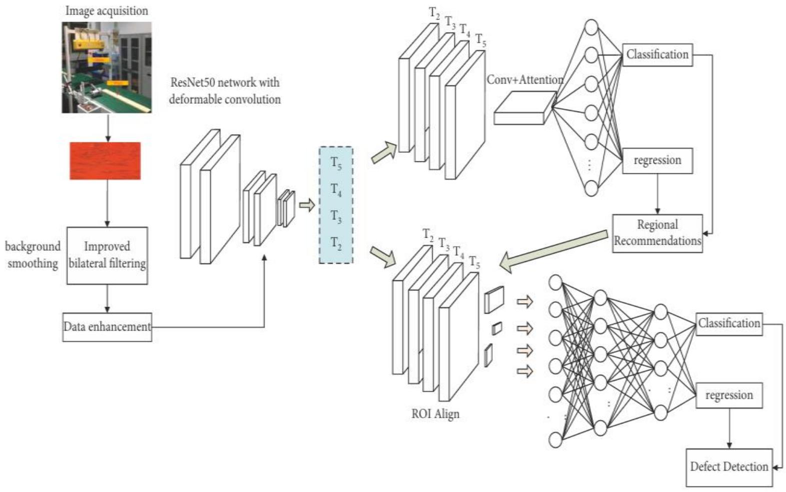

Fig.2. Modified Architecture of R-CNN

Multiscale Feature Extraction Network. the work in this paper detects defects in plate images. However, cut plate defects are characterized by large scale variations and different shapes. e existing Faster R-CNN directly utilizes the features output as the subsequent classification regression. As the feature information contained in the shallow layer network is easily lost, there will be small defects appearing as missed detections.

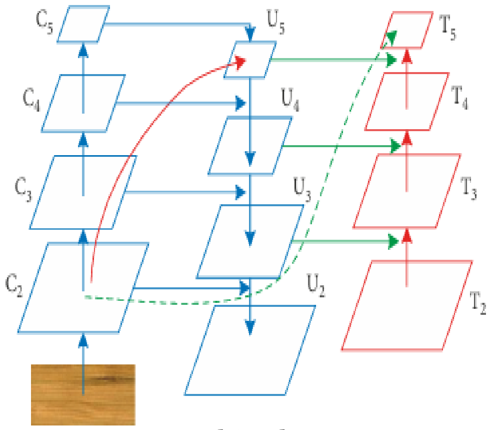

Fig.3. Multiscale RCNN

{C2, C3, C4, C5}. The compact indications give the reverse processing of the fast forward network to produce the features. It sums up the reverse processing to construct a feature addition to attain the feature with efficacy of the material {U2, U3, U4, U5}. Fast providing network restricts the processing and side connection to form the feature layers to attain the multiple feature maps with the efficient material. To reserve the low feature of the image, a reverse path additional model that sums up as illustrated by the virtual arrows in the figure 4, to better improve the reserve the shallow feature extraction info that has decreased number of stages of network constructions involves VGG-16, ResNet50, and ResNet101. Res Net system gives the less interactions to address the tests of slope disappearing and slope explosive while going down the network to assure the enhancement of the entire network pursuance. Thus, ResNet50 is applied to use as a feature extraction stage in this manuscript. To enhance the efficiency of recognition of distinct T2 shapes of the wooden panels, deformity of the CNN that are making them familiar in the work. RCNN (Region-based Convolutional Neural Network) is a pioneering object detection framework that effectively combines region proposals with deep learning techniques. The process begins with an input image, which undergoes selective search to generate potential bounding boxes that may contain objects. Each proposed region is then fed into a Convolutional Neural Network (CNN) for feature extraction, resulting in fixed-length feature vectors. These vectors are classified using a Support Vector Machine (SVM) to identify the object class within each region. To enhance localization, a bounding box regression model is applied to refine the coordinates of the proposed boxes. Finally, non-maximum suppression is employed to eliminate overlapping detections, yielding a final output that includes the detected objects along with their corresponding classes and refined bounding boxes. This innovative approach laid the groundwork for subsequent advancements in object detection, influencing models like Fast RCNN and Faster RCNN. The structure of an RCNN (Region-based Convolutional Neural Network) comprises several essential components designed for effective object detection. It begins with an input image, which is processed using a selective search algorithm to generate a set of region proposals bounding boxes that potentially contain objects. Each of these proposed regions is then passed through a Convolutional Neural Network (CNN) for feature extraction, producing a fixed-length feature vector that captures important visual information. These feature vectors are subsequently classified using Support Vector Machines (SVMs) to determine the presence and class of objects within the regions. To improve the accuracy of the bounding boxes, a bounding box regression model refines the initial coordinates. Finally, non-maximum suppression is applied to filter out redundant overlapping detections, resulting in a final output that includes the detected objects along with their class labels and refined bounding box coordinates. This structured approach enables RCNN to effectively identify and localize objects within images, setting the stage for further advancements in the field of object detection.

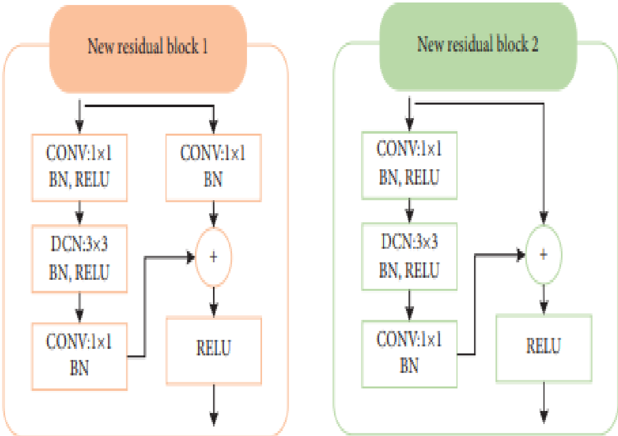

Fig.4. Residual block after introducing deformable convolution

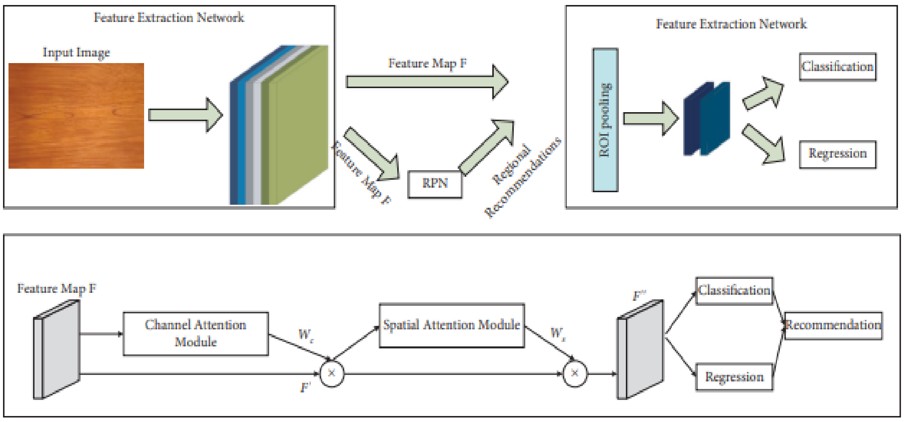

Fig.5. Regional recommendation network detection model with fused attention CBAM

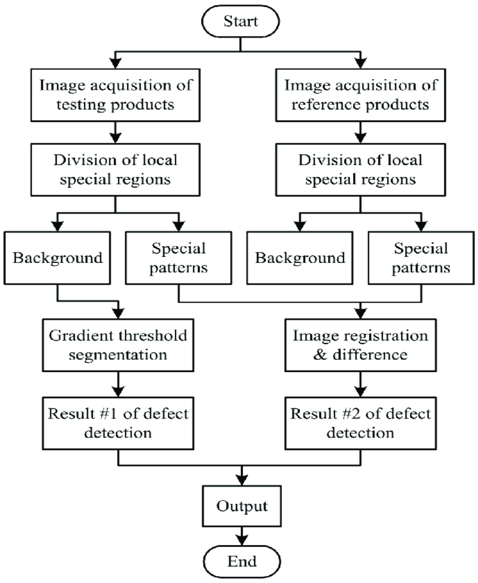

Fig.6. Flowchart of the Proposed System

Region based CNN algorithm for defect detection in steel plate manufacturing plant.

Work Flow

1. Data base creation using plant and online steel plate data.
2. Feature extraction
3. Training of proposed algorithm
4. Testing of proposed algorithm with different numbers of images
5. Performance calculations

Accuracy: Accuracy measures how often the model correctly classifies both positives and negatives out of all predictions. It is calculated as:

$$\text{Accuracy} = \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{Total Predictions (TP + TN + FP + FN)}}$$

Precision

Precision focuses on the correctness of positive predictions. It is defined as:

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

Recall (Sensitivity or True Positive Rate)

Recall measures the ability of a model to identify all relevant instances. It is expressed as:

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

Confusion Matrix

A confusion matrix is a tabular representation of a model's predictions, helping evaluate its performance. It has four components:

- **True Positives (TP)**: Correctly predicted positive cases.
- **True Negatives (TN)**: Correctly predicted negative cases.
- **False Positives (FP)**: Negative cases wrongly predicted as positive.
- **False Negatives (FN)**: Positive cases wrongly predicted as negative.

	Predicted Posotve	Predicted Negative
Actual positive	True positive	False Negative (FN)

Actual negative	False positive	True Negative (TN)

The confusion matrix enables detailed performance analysis, helping compute metrics like precision, recall, F1-score, and accuracy.

IV. PROPOSED WORK

Step- 1 Create data set using plant images and online images data set.

Step-2 Creation of feature matrix using dataset.

Step-3 Training of Proposed Algorithm using 70 percent of data.

Step 4 Classification of defects using data test.

Step 5 Performance calculation

V. RESULTS & DISCUSSION

Material & Methods

The database is a collection of the five most common types of errors encountered during the steel mill manufacturing process. These flaws have been mentioned before in this publication. A total of 3000 photos are considered for database preparation. Consider 3500 faulty photos and 1000 non-defected images while validating proposed methods. For training the suggested system, 1500 images are considered, with 1000 images representing a combination of the key five faults. 200 photographs are captured for each fault, while the remaining 500 images are non-defective. Feature matrix is created by determining the features of each image.

RESULTS

This section provides a detailed analysis of the validation results obtained from the proposed system. To evaluate the system's effectiveness, the training dataset is first fed into the proposed network to initiate the training process. During this phase, the system's accuracy is continually monitored to assess its learning capabilities. To further establish the reliability of the proposed framework, the accuracy of detecting each defect type is calculated independently. This ensures that the system performs consistently across various defect categories, highlighting its robustness and precision in identifying diverse steel surface anomalies.

After the completion of the training phase, the system undergoes rigorous testing to validate its performance. Multiple performance metrics, including accuracy, precision, recall, and F1-score, are computed to comprehensively evaluate the system's efficiency and reliability. The suggested framework is implemented, trained, and validated using MatlabR2023 software, which provides a versatile platform for system design and experimentation. This software environment facilitates seamless execution of the training and testing procedures while offering robust tools for performance analysis. The findings from these validation experiments demonstrate the proposed system's capability to deliver accurate and reliable defect detection, making it a promising solution for industrial applications.

Table 1.1 Training Accuracy of proposed system with Considering All Defects

Number of Images	Defected Images	Non-Defected Images	Accuracy
500	350	150	90.52
800	600	200	92.65
1000	750	250	93.58
1200	900	300	94.09
1500	1150	350	96.13

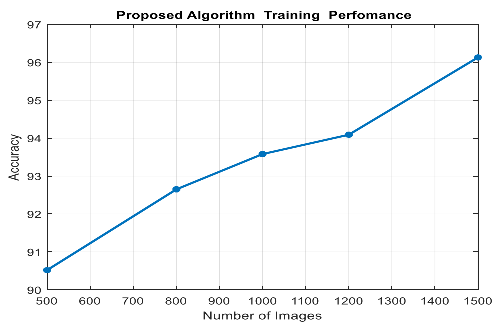

Fig.7. Training Accuracy of proposed algorithm with all Defects

The results presented in the above table highlight the performance of the proposed system following the completion of the training process. To thoroughly evaluate the system's effectiveness, a dataset comprising a mixture of defective and non-defective images was input into the model. This approach ensures a comprehensive assessment of the system's ability to accurately distinguish between defect-free and defective steel surfaces, thereby allowing for a more reliable evaluation of its robustness and durability.The analysis revealed that the proposed system achieved an impressive accuracy of 96.13% when tested on a dataset of 1,500 images. This high level of accuracy underscores the system's capability to perform reliably across a diverse range of input conditions, reflecting its suitability for practical industrial applications. To provide further insights, a graphical representation of the performance data from Table 1.1 was generated using MATLAB software. The resulting curve offers a clear visual depiction of the system's accuracy trends and reinforces the numerical findings. This graphical analysis, combined with the statistical results, serves to validate the efficiency and reliability of the proposed framework in accurately identifying steel defects while maintaining a high level of performance.

Table 1.2 Testing Accuracy of Proposed System

No of Images	Type of Defect	Overall Accuracy
500	Crazing & Inclusion	90.35
800	Folding & Scratch	91.74
1000	Pitted & Rolled Surface	92.98
1500	All Type	94.61
2000	All Type	96.52

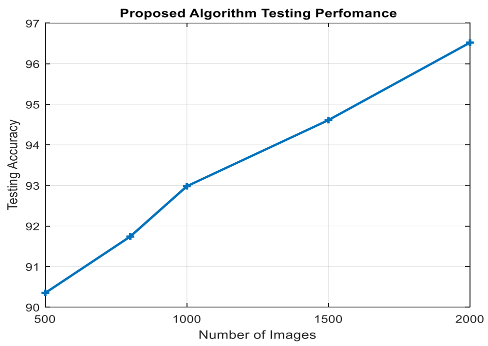

Figure8. Testing accuracy with Different types

Above table 1.2 and figure is showing testing accuracy of proposed system with considering dual defect and with all types of defects. Overall accuracy is 96.52%. In testing, two type similar defect is taking in account for validating proposed system performance, when different combination of defect images is considered.Proposed algorithm is capable for detection and classification of defect in steel plant manufacturing. Accuracy of both training and testing is very high and performance of detection is more accurate.

Table 1.3 Different performance of proposed system

No. of Images	Accuracy	Precision	Recall	F-Measure
500	90.31	91.03	84.93	87.25
800	91.05	92.85	86.63	88.14
1000	93.02	93.57	88.06	89.02
1500	94.98	94.00	89.01	91.23
2000	96.56	95.69	91.35	93.45

The suggested algorithm has a higher F-measure, indicating that it is more accurate at differentiating between faulty and non-defective images. Figures 9 and 10 show the performance of the suggested method, which uses thirteen features and industrial data. The feature matrix consists of features matrix, which are then fed into the classification network.

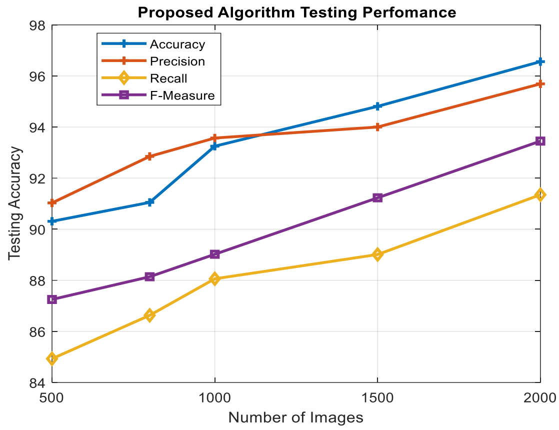

Fig.9. Curve of different Performance index

VI. CONCLUSION & FUTURE SCOPE

An enhanced rapid R-CNN basis on fault recognition steps is planned for detecting and placement surface faults for the plates with complicated consistent. To improve the prototype capability to recognize the faults in distinct texture experiences the manuscript planned four kinds of enhancements: (i) An enhanced dual riddling procedure is planned to swift the image surface backup. (ii) A rapid prototype network that has the capabilityto recognize the faults in distinctive manner to amalgamate the features to attain a multitype feature that maps to tends an additional multitype feature that is improved for multiple faults recognition specifically for small scale faults. (iii) RPN includes the focus model of CBAM to enhance the weight of the channel for crack faults and unidentified examples that enhances the model's capability to detect the faults from the backup and enhances the recognition precision also. The outline of the deformity in the system that is to be enhanced by the feature extraction capability of the model for distinct scratch figures. The model planned in this manuscript was verified on an actual panel surface fault data, and the regular recognition rate of the model has gone up to 95.71% and the optimistic recognition ratio was 90% when verified applying a novel surface backup wooden backup illustrating the model that consists of versatile common ability. The comparative analysis showed that the enhanced model which has a big enhancement in the recognition capability of the board faults. Validating the model with the existing procedures with efficient pursuance confirms the precision of the planned model for the recognition of faults. The very following stage will be to proceed the illustration of the high precision of the mark recognition procedures and in future discovers how to improve the fault features to overpower the intrusion of the environment.

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