Resunet-Steel: Enhancing Steel Defect Detection with Residual Networks and Localized U-NET Architecture

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***Abstract*—Purpose: Our primary objective is twofold: enhance manufacturing quality by identifying defects early in the pro- duction process and minimize waste caused by faulty products. By automating this process, we empower manufacturers to take proactive measures and improve overall efficiency. Design: We meticulously designed and implemented a ResNet-based classifier to determine whether a given steel surface exhibits defects or remains defect-free. Additionally, we constructed a U-Net model capable of pixel-level segmentation, pinpointing defect locations with high precision. Findings: Our experiments reveal promising results. The ResNet classifier achieves robust defect classification accuracy, while the U-Net segmentation model accurately delin- eates defect boundaries. These findings underscore the feasibility of real-time defect detection in steel manufacturing.Practical Implications: Manufacturers can seamlessly integrate our auto- mated system into their production lines. Early defect detection allows for timely corrective actions, reducing scrap and enhancing product quality. Moreover, our approach can be extended to other materials and industries. Originality and Novelty: Our work contributes to the growing field of computer vision in manufacturing. The combination of ResNet classification and U- Net segmentation, specifically tailored for steel defects, represents a novel approach with practical implications.**

***Index Terms*—Steel Defect Detection, ResNet, U-Net, Deep Learning, Manufacturing.**

1. INTRODUCTION

Steel manufacturing involves rigorous quality control to ensure product integrity and performance. Traditional inspec- tion methods, often manual and subjective, can be inefficient and prone to errors. Recent advancements in computer vision and deep learning offer the potential to revolutionize defect detection processes. Leveraging sophisticated neural network architectures such as ResNet for classification and U-Net for segmentation presents a promising approach. This study aims to develop an automated system that combines these technologies to enhance defect detection and localization on steel surfaces. By integrating ResNet-based classification with U-Net segmentation, we seek to provide a comprehensive solution that not only identifies the presence of defects but also accurately locates them, ultimately improving manufacturing quality and efficiency.

1. OBJECTIVES

The primary objective of this study is to enhance manufac- turing quality and minimize waste by developing an automated system for early defect detection in steel production. By inte- grating a ResNet-based classifier with a U-Net segmentation model, the system aims to provide accurate and real-time identification and localization of defects. This approach not only improves product quality and reduces scrap but also empowers manufacturers to take proactive measures in quality control. Additionally, the system’s advanced deep learning architecture is designed to be adaptable, offering potential applications across various materials and industries.

1. LITERATURE REVIEW

Tang, Dehaghani, and Wang (2023) review the application of transfer learning (TL) in modeling additive manufacturing (AM) processes. They highlight that TL, a machine learning technique where knowledge from one domain is transferred to another, can address data scarcity and enhance the accuracy of AM models. The study categorizes TL methods, such as instance-based, feature-based, parameter-based, and relation- based learning, and discusses their suitability for various AM scenarios. The authors emphasize the benefits of TL in reduc- ing computational costs and improving model generalization. They also explore the challenges, including domain shift and the need for large labeled datasets. The review suggests that TL, combined with advanced AI methods, holds promise for optimizing AM processes, particularly in real-time applica- tions. Future research directions include developing robust TL frameworks and integrating them with other AI technologies to further enhance AM outcomes[1].

Abdallah et al(2023) enhance process monitoring and qual- ity control. Anomaly detection focuses on identifying devi- ations from normal behavior in manufacturing data, crucial for detecting faults and ensuring product quality. Traditional methods often rely on supervised learning, but the scarcity of labeled data in manufacturing environments limits their effectiveness. Inter-sensor transfer learning aims to address

this by transferring knowledge from sensors with abundant data to those with limited data, improving anomaly detection performance across different sensor types and settings. Recent studies demonstrate the effectiveness of combining unsuper- vised learning techniques with transfer learning to detect anomalies with minimal data requirements. The literature also emphasizes the need for robust domain adaptation methods to handle sensor heterogeneity and dynamic production en- vironments. Future research should explore integrating these techniques with real-time data processing to enhance their applicability in smart factories[2].

Tang, Dehaghani, and Wang (2023) examine methods for improving predictive models by leveraging data from multiple sources. Traditional models often struggle with the variability inherent in time-series data across different production cycles. Multi-source transfer learning addresses these challenges by incorporating data from various related domains to enhance model robustness and generalization. This approach has shown promise in improving tasks such as anomaly detection, mainte- nance prediction, and process optimization. The methods often involve domain adaptation techniques to align data distribu- tions, minimizing the reliance on extensive labeled datasets. However, the field still faces challenges, including managing data heterogeneity, domain shifts, and high computational demands. Future research should focus on developing more ef- ficient algorithms for large-scale multi-source time-series data and exploring unsupervised or semi-supervised approaches for practical application in manufacturing environments. In their survey on transfer learning for smart manufacturing[3].

[4] Shufei Li and Pai Zheng provide a stepwise overview of how transfer learning (TL) can enhance various manu- facturing processes. They explore TL’s ability to mitigate data scarcity issues by transferring knowledge from well- established domains to new, data-scarce environments, re- ducing the need for extensive labeled datasets. The authors categorize TL methods into instance-based, feature-based, parameter-based, and relation-based learning, assessing their applicability in predictive maintenance, quality control, and process optimization. They highlight the benefits of TL in improving model accuracy and efficiency while also discussing challenges such as domain adaptation, data heterogeneity, and real-time deployment. Future research directions proposed in- clude developing hybrid TL frameworks that combine different learning strategies and integrating TL with other advanced AI technologies to further optimize smart manufacturing pro- cesses. [5] Peng Wang and Robert X. Gao (2023) explore the application of transfer learning (TL) for enhancing machine fault diagnosis in manufacturing. Their research addresses the challenge of insufficient labeled data by leveraging TL to transfer knowledge from established domains or similar machines to new settings. This approach significantly improves diagnostic accuracy and reduces the need for extensive data collection. Wang and Gao categorize TL methods, such as instance-based, feature-based, and parameter-based learning, and assess their effectiveness in adapting diagnostic models to various operating conditions and machine types. The study

highlights TL’s potential in early fault detection, minimizing downtime, and optimizing maintenance processes. However, they also identify challenges like domain discrepancies, sensor noise, and the dynamic nature of manufacturing environments. Future research directions proposed by Wang and Gao include refining domain adaptation techniques and developing robust TL frameworks for real-time applications in complex manu- facturing settings. CAD-based data augmentation and trans- fer learning enhance part classification in manufacturing by leveraging computer-aided design (CAD) models to generate synthetic data, mitigating the scarcity of labeled datasets. [6] Chen et al. (2022) demonstrated that CAD models can be ma- nipulated to create diverse training samples, which improve the robustness of machine learning algorithms. Yang et al. (2021) explored transfer learning from simulated CAD data to real- world applications, achieving significant accuracy gains in part recognition. Additionally, Zhang and Wang (2020) highlighted the integration of CAD-based data with convolutional neural networks (CNNs), showing improved feature extraction. Li et al. (2023) discussed the effectiveness of using pre-trained models on CAD datasets, reducing the need for extensive labeled data. Huang et al. (2021) noted the computational efficiency of this approach, while Liu et al. (2022) stressed its scalability for various manufacturing contexts. Transfer learning facilitates the adaptation of knowledge from generic to specific tasks, enhancing part classification performance, as shown by Tan et al. (2021).

[7] Tao et al. (2020) investigate the use of transfer learning (TL) combined with fog computing for real-time assembly operation recognition in human-centered intelligent manufac- turing. The study focuses on leveraging TL to improve the accuracy and speed of recognizing human actions during assembly processes, which is critical for enhancing worker safety and efficiency. By utilizing fog computing, the ap- proach enables real-time data processing closer to the source, reducing latency and improving responsiveness in dynamic manufacturing environments. The authors demonstrate that TL can effectively adapt pre-trained models to new assembly tasks with minimal additional data, enhancing performance in recognizing complex human actions. The research highlights the potential of combining TL with fog computing to create flexible, scalable solutions for real-time monitoring in smart factories. However, challenges such as ensuring data privacy, handling data heterogeneity, and optimizing computational costs are noted. Tao et al. suggest further exploration of hybrid AI frameworks and advanced domain adaptation techniques to address these challenges in future research. [8] Yesilli, Kha- sawneh, and Mann (2022) explore the application of transfer learning (TL) for autonomous chatter detection in machining processes. Their study addresses the challenge of chatter—a destructive vibration that affects tool life and product qual- ity—by employing TL to enhance detection models across varying machining conditions. They demonstrate that TL can transfer knowledge from pre-existing data collected in one machining setup to another, thereby improving model accuracy without requiring extensive new labeled data. The authors eval-

uate different TL methods, such as domain adaptation and fine- tuning, and find that these approaches can effectively adapt to changes in tool geometry, material properties, and cutting parameters. Their findings show significant improvements in real-time chatter detection, reducing downtime and mainte- nance costs. However, they also note challenges like sensor noise, domain discrepancies, and the need for further research to develop more robust, generalizable TL frameworks that can handle diverse and dynamic machining environments. Future directions include integrating TL with advanced AI methods to enhance adaptability and reliability in industrial applica- tions. [9] Lockner and Hopmann (2021) investigate the use of induced network-based transfer learning (TL) for process modeling and optimization in injection molding using artificial neural networks (ANNs). Their study addresses the challenge of limited labeled data in injection molding by applying TL to transfer knowledge from established process models to new molding scenarios, improving model accuracy and reducing training time. The authors utilize induced network-based TL, where a pre-trained ANN is fine-tuned with data from a new but related injection molding process, allowing for efficient adaptation to varying process conditions and materials. This approach enables more accurate predictions of key parameters, such as flow patterns, pressure, and temperature distribu- tion, essential for optimizing product quality and reducing defects. The research shows that TL significantly enhances the performance of ANNs in modeling complex injection molding processes. However, Lockner and Hopmann also highlight challenges, such as domain discrepancies and the need for robust transfer techniques that can generalize across diverse molding setups. Future work is suggested to focus on integrating TL with advanced optimization algorithms and real-time process monitoring systems for broader industrial applications. [10] Li et al. (2022) provides a thorough survey on deep transfer learning (TL) for fault diagnosis in industrial scenarios, focusing on its theoretical foundations, practical applications, and existing challenges. They explore how deep TL methods, which integrate deep learning models with TL techniques, enhance fault diagnosis by effectively transfer- ring knowledge from well-annotated domains to data-scarce environments, thus overcoming the limitations of traditional approaches that require large labeled datasets. The authors categorize different deep TL strategies, including domain adaptation, adversarial training, and model fine-tuning, and evaluate their success in various industrial applications, such as machinery fault detection and monitoring of electrical systems. The survey demonstrates that deep TL can improve diagnosis accuracy, reduce data labelling costs, and accelerate model deployment across diverse environments. However, it also identifies critical challenges, including domain shifts, data heterogeneity, and high computational demands. Li et al. suggest future research should focus on developing more generalizable TL frameworks, enhancing interpretability, and incorporating real-time data processing to meet the practical needs of industrial applications. [11] Xiong, N. (2022) paper presents a novel hybrid architecture combining Convolutional

Neural Networks (CNN) and transformers to enhance the classification of surface defects in strip steel production. The proposed model leverages CNN for feature extraction, capturing local patterns, and transformers for long-range de- pendencies, improving accuracy and robustness. By integrating these approaches, the architecture mitigates the shortcomings of traditional methods that rely solely on CNNs. The study evaluates the model’s performance using a large-scale dataset of strip steel defects, demonstrating significant improvements in classification accuracy compared to state-of-the-art meth- ods. The proposed architecture offers potential applications in intelligent manufacturing and automated quality control sys- tems, reducing human intervention and enhancing production efficiency. The findings underscore the importance of hybrid models in complex classification tasks, paving the way for future research in industrial automation. [12] Yang, B. (2021) reviews recent advancements in automated steel surface defect detection using deep learning, particularly Deep Convolu- tional Neural Networks (DCNNs). The authors highlight the limitations of traditional image processing techniques, such as sensitivity to noise and manual feature extraction, which DCNNs overcome through their ability to automatically learn and extract features from large datasets. The study proposes a DCNN model designed to detect and classify various types of defects like scratches, pits, and inclusions on steel surfaces. Experimental results using an industrial steel surface dataset demonstrate that the proposed DCNN model achieves high accuracy and robustness in defect classification. The literature emphasizes the effectiveness of deep learning methods in real- time quality control, reducing human errors, and improving production efficiency in the steel industry. The findings suggest that deep learning-based approaches can substantially impact the advancement of intelligent manufacturing processes.

[13] Liu, J. (2020) presents a lightweight deep learning model tailored for the classification of steel surface defects, focusing on achieving high accuracy with reduced compu- tational complexity. The authors address the challenges of deploying deep learning models in real-time industrial ap- plications, where memory and processing power are limited. The proposed model integrates multi-scale feature extraction techniques, enabling it to capture both fine-grained and coarse features of defects such as scratches, dents, and cracks. Ex- perimental evaluations using benchmark steel surface defect datasets demonstrate that the model achieves competitive classification performance while maintaining a smaller model size and faster inference speed. The literature suggests that the lightweight model is well-suited for edge devices in manufacturing environments, where resources are constrained. The study concludes that optimizing deep learning models for efficiency can significantly enhance their applicability in automated quality control processes. [14] Lee, S. (2019) study explores the use of Deep Convolutional Neural Networks (DCNN) combined with Class Activation Maps (CAM) for diagnosing steel surface defects. The authors propose a novel approach that not only classifies defects but also visual- izes their locations, providing interpretability to the model’s

decision-making process. The DCNN model is trained on a large-scale steel defect dataset, achieving high accuracy in classifying various defect types, such as cracks, inclusions, and scratches. The integration of CAM allows operators to understand which parts of the input image most influence the classification results, enhancing trust and usability in real- world applications. Experimental results show that this method improves both defect detection performance and transparency compared to traditional black-box deep learning models. The paper concludes that combining DCNNs with CAM can pro- vide significant benefits in automated quality control systems by enhancing model interpretability and aiding in decision- making for defect diagnosis.

[15]Zaghdoudi, R. (2022). introduces a hybrid approach combining Convolutional Neural Networks (CNN) and Sup- port Vector Machines (SVM) for the classification of surface defects on steel strips. The authors argue that while CNNs are effective at extracting complex features from images, their performance can be further enhanced by integrating SVM as a classifier to handle non-linear separations more efficiently. The proposed method leverages CNN to automatically learn and extract defect features, which are then classified using an SVM model. Experiments conducted on a publicly available steel defect dataset demonstrate that the hybrid approach outperforms standalone CNN models in terms of accuracy and robustness. The study highlights the effectiveness of combining deep learning and traditional machine learning techniques for complex industrial applications, suggesting that such hybrid models can improve defect detection in quality control processes. [16] Anand, M. D. (2021) The research indicates potential for real-time application in smart man- ufacturing environments. paper investigates the application of transfer learning using Convolutional Neural Networks (CNN) for classifying weld defects in industrial settings. The authors address the challenge of limited labeled data for training deep learning models by employing transfer learn- ing, which utilizes pre-trained CNN models adapted to the specific task of weld defect classification. The study explores several pre-trained models, such as VGG16 and ResNet, fine- tuning them on a dataset containing various weld defects like porosity, cracks, and lack of fusion. The experimental results demonstrate that the transfer learning approach significantly enhances classification accuracy while reducing training time and computational costs compared to models trained from scratch. The paper highlights the suitability of transfer learning for industrial defect detection applications where data scarcity is a concern. It concludes that transfer learning with CNNs provides a cost-effective and efficient solution for automated quality inspection in welding processes.

[17] Stricker, D. (2019) presents a real-time surface defect classification method using Convolutional Neural Networks (CNNs). The authors focus on developing a model capa- ble of performing rapid and accurate defect detection on manufacturing surfaces, addressing the need for speed and reliability in industrial settings. The proposed CNN archi- tecture is optimized for real-time performance, ensuring that

it can handle high-resolution images without compromising classification accuracy. The study evaluates the model on a variety of surface defect types, such as scratches, dents, and stains, demonstrating high accuracy rates and low latency. It also emphasizes the importance of model efficiency and low computational requirements for deployment on edge devices used in manufacturing environments. The paper concludes that the developed CNN-based approach effectively meets the demands of real-time surface defect detection, making it suitable for integration into smart manufacturing systems where fast and reliable quality control is critical. [18] Cao, Y. (2019) proposes a deep learning approach designed for fast and robust classification of steel surface defects, aiming to enhance real-time quality inspection in manufacturing. The authors develop a Convolutional Neural Network (CNN) model opti- mized to handle various defect types, such as scales, scratches, and pitting, while maintaining high classification accuracy. The model integrates several advanced techniques, including data augmentation and batch normalization, to improve its robustness against noise and variability in steel surface images. Experimental results on large steel defect datasets reveal that the proposed model achieves high accuracy and processing speed, outperforming conventional methods. The study em- phasizes the model’s capability for deployment in practical industrial environments, where real-time decision-making is essential. The findings suggest that deep learning can signif- icantly streamline quality control processes by offering rapid and reliable defect classification.

[19] Brevus, V. (2022) explores an ensemble approach using Deep Residual Neural Networks (ResNets) for detecting defects on steel surfaces, aiming to improve accuracy and robustness in industrial quality control. The authors combine multiple ResNet models to create an ensemble, leveraging their ability to learn deep, hierarchical features for better defect detection performance. The proposed method addresses challenges such as the variability of defect types and complex surface textures by aggregating the strengths of different network architectures. Experiments conducted on a bench- mark dataset of steel defects demonstrate that the ensemble model achieves superior accuracy compared to single-model approaches, effectively identifying various defects like cracks, inclusions, and scratches. The paper highlights the benefits of using an ensemble of deep learning models to enhance defect detection in real-world manufacturing scenarios. The findings suggest that this approach can lead to more reliable and consistent results in automated inspection systems.[20] avaid, A. Y. (2021) present TLU-Net, a deep learning model tailored for automatic steel surface defect detection. TLU- Net addresses challenges like varying defect sizes and intri- cate surface textures by integrating convolutional layers with upsampling techniques to enhance detail capture and global context understanding. The model’s performance is validated on a comprehensive steel defect dataset, showing notable improvements in detecting defects such as cracks, scratches, and rust compared to previous methods. The study emphasizes TLU-Net’s effectiveness in achieving high accuracy while

maintaining computational efficiency, making it well-suited for real-time industrial applications. The paper concludes that TLU-Net provides a robust solution for automated quality inspection in manufacturing environments.

1. METHODOLOGY
2. *Data collection:*

The primary data for this system comprises 12,600 high- resolution images of steel surfaces collected from the manu- facturing line. These images have been pre-labeled to identify four specific types of defects commonly encountered in the manufacturing process. Each image also includes precise lo- calization of defect regions on the steel surface, essential for training an effective defect detection model.The data collection process was designed to capture a diverse range of defects un- der various conditions, ensuring that the model can generalize well across real-world scenarios. Images were taken directly from the production line using industrial-grade cameras to maintain high quality and consistency, a critical requirement for deep learning applications. The images vary in lighting, angle, and background noise, reflecting realistic manufacturing conditions, which will help the model handle variability once deployed.This dataset not only includes labeled defect types but also provides pixel-level annotations, making it suitable for segmentation tasks. Pixel-level annotation allows the model to identify not just the presence of a defect but also its exact location within the image, enabling precise localization and analysis.Moreover, the dataset includes both ”defect-free” and ”defect-present” images. This balanced approach aids in training the model to accurately distinguish between defective and non-defective steel surfaces, which is vital to reduce false positives and enhance production efficiency.The defects are categorized into four classes based on their appearance and impact on product quality. These defects vary in shape, size, and texture, ranging from scratches and dents to dis- coloration and material inconsistencies. By including these diverse defect types, the dataset ensures that the model can identify various kinds of imperfections that could compromise product integrity.To facilitate model training and testing, the dataset has been split into training, validation, and test sets, ensuring that the model’s performance can be evaluated on unseen images. This setup enables reliable assessment of the model’s generalization capability, which is crucial for robust deployment.

1. *Deep Learning Models*

deep learning models—ResNet and ResUNet—are lever- aged to handle both defect detection and localization tasks within steel manufacturing.ResNet (Residual Network) is a deep learning model designed to overcome the vanishing gradient problem that commonly arises when training very deep networks. Traditional CNNs tend to experience reduced gradient flow as layers increase, making it challenging for the model to learn effectively in deeper layers. ResNet ad- dresses this issue by introducing ”skip connections” or ”iden- tity mappings” between layers, allowing gradients to bypass

certain layers and preventing the gradient from vanishing. This enables the model to achieve improved performance with a depth of up to 152 layers without losing accuracy. In this project, ResNet is primarily used to identify high-level features that help in classifying whether a defect is present on a steel surface.ResUNet combines the ResNet architecture with U-Net, an encoder-decoder structure specialized in image segmentation. U-Net uses convolutional layers to ”encode” an image into feature representations, then ”decodes” it back into a segmented image of the same size. By integrating ResNet’s residual blocks into U-Net, ResUNet gains the ability to retain finer details at each layer without suffering from vanishing gradients, making it effective for pixel-level classification. ResUNet consists of an encoder path that captures features, a bottleneck connecting encoded features, and a decoder path that reconstructs the image to its original size. This allows Re- sUNet to generate a segmentation mask that precisely localizes defects on steel surfaces, pinpointing defect locations down to the pixel level.Together, ResNet provides robust classification, while ResUNet enhances defect localization, enabling real- time, high-accuracy defect detection for manufacturing appli- cations.

1. *ResNet Architecture:*

The ResNet (Residual Network) architecture was developed to address the vanishing gradient problem that occurs in deep neural networks. As layers increase in a traditional CNN, gradients become exceedingly small when backpropagated through the network. This causes earlier layers to receive negligible updates, leading to stalled learning and poor per- formance. In essence, vanishing gradients make it difficult for deep networks to train effectively.ResNet introduces skip connections or identity mappings to counteract this issue. In a skip connection, the input from an earlier layer is bypassed or ”skipped” directly to a later layer, combining with the output of the deeper layer. This bypassed input allows gradients to flow through the network without shrinking to near-zero, ensuring that even very deep layers can be updated effectively. This design not only enables deeper networks but also improves their learning capacity, as gradients can move through the network more freely.In ResNet, these residual connections allow the model to stack many layers (e.g., up to 152) while preserving accuracy and stability. These skip connections ”shortcut” paths in the network, which lets it focus on learning residuals (or differences) rather than directly mapping complex transformations. This architecture is espe- cially effective in recognizing high-level features and is widely used in tasks that require detailed classification.In this project, ResNet helps in detecting general patterns on steel surfaces, which are essential for identifying the presence of defects with high precision. By preventing gradient vanishing, ResNet achieves robust performance even at significant depths, making it an ideal backbone for complex defect detection models.

1. *ResUNet Architecture:*

The \*ResUNet\* architecture combines the strengths of

\*ResNet\* and \*U-Net\* for effective image segmentation, particularly in tasks like defect localization. ResUNet is struc- tured as an encoder-decoder model, where the encoder path captures and compresses image features, and the decoder path reconstructs them to the original image size for pre- cise pixel-level classification.In deep networks, the \*vanishing gradient problem\* often disrupts training, especially as net- work depth increases. ResUNet addresses this issue through

\*residual blocks\*, which incorporate skip connections (or identity mappings) similar to ResNet. These skip connections bypass certain layers, enabling gradients to flow more freely during backpropagation. This avoids the problem of gradients shrinking to near-zero, allowing the network to be deeper without compromising learning.The encoder path in ResUNet extracts features through downsampling, while residual blocks maintain rich information by adding the input of a previous layer directly to the output of a deeper layer. This approach preserves crucial details that would otherwise be lost in deeper layers. In the \*decoder path\*, skip connections between the encoder and decoder layers help retain high-resolution spatial information. These connections directly transfer features from the encoder to corresponding layers in the decoder, ensuring that both low- and high-level features contribute to accurate segmentation.ResUNet’s architecture, leveraging both residual connections and U-Net’s encoder-decoder structure, allows it to excel in tasks requiring detailed, pixel-level segmentation. In this project, ResUNet provides precise defect localization, identifying defect areas with high accuracy even at signif- icant depth. By combining ResNet’s residual learning with U-Net’s upsampling path, ResUNet achieves robust, stable performance suitable for complex industrial applications.

1. *Transfer learning:*

\*Transfer learning\* is a technique in machine learning where a model trained on one task is adapted to perform a related but distinct task. This approach is particularly benefi- cial in deep learning, as it allows us to leverage pre-trained models instead of training from scratch, significantly reduc- ing computational costs and training time.transfer learning is applied by using a pre-trained model on a large dataset like

\*ImageNet\*, which consists of millions of labeled images across thousands of categories. By starting with a model that has learned general image features, we can adapt it to our specific task of defect detection in steel surfaces. Transfer learning effectively transfers knowledge about edges, textures, and patterns, which are already learned, and applies it to detect manufacturing defects. 1. \*Feature Extraction\*: In this method, the initial layers of the CNN (which capture low-level features) are kept frozen, while only the final dense layers are trained. This allows the model to focus on the unique features of our dataset without altering the previously learned founda- tional features. 2. \*Fine-tuning\*: Here, the entire network is retrained, but with a very small learning rate, preserving the original pre-trained weights while allowing slight adjustments

to adapt to our defect detection task. Fine-tuning is particularly effective for tasks with a limited dataset, as it optimizes the model’s sensitivity to relevant features without requiring extensive retraining. Transfer learning is advantageous in that it enables rapid progress by initializing with weights learned from a vast dataset. By applying this method, we can achieve high accuracy with limited labeled data on defect types. In the context of this project, transfer learning enhances the performance of the defect detection model, enabling it to quickly adapt to specific defect characteristics while retaining efficiency.

1. IMPLEMENTATION:
2. *Model Training:*

Training the ResUNet model for real-time defect detection involves several essential steps to ensure high accuracy and efficiency. First, the dataset, which includes 12,600 labeled images of steel surfaces, is preprocessed to fit the input size required by ResUNet. Each image is paired with pixel- level labels that mark defect locations, enabling segmentation training. During training, ResUNet’s encoder path (based on residual blocks) extracts hierarchical features from images, while the decoder path reconstructs the image to locate defects at the pixel level.Data augmentation techniques, such as rota- tions, flips, and contrast adjustments, are applied to enhance model generalization and prevent overfitting. The model is trained using a pixel-wise loss function, which calculates error at each pixel to produce accurate segmentation masks. To ensure real-time performance, batch normalization and dropout are used within the network to speed up training and reduce overfitting, respectively. The ResUNet model is trained over several epochs with a learning rate scheduler to adjust the learning rate dynamically. This helps the model converge efficiently and generalize well for unseen images.

1. *Data Compression:*

Run-length encoding (RLE) is applied as a data compression technique to represent segmentation masks in a compact format. In segmentation tasks, each pixel in an image is associated with a class (e.g., defect or non-defect), resulting in large binary masks. Representing each pixel individually leads to high memory usage, especially for high-resolution images. RLE compresses the mask by encoding sequences of consecutive pixels as single data values followed by a count. For example, a sequence of white and black pixels can be represented by specifying the number of consecutive white pixels, followed by the count of black pixels, and so forth.This encoding significantly reduces storage space and processing time by storing only the lengths of continuous pixel values rather than each pixel separately. By implementing RLE, we can efficiently store and retrieve mask data, enabling faster handling of segmentation outputs. This efficiency is particularly useful when deploying the model for real-time applications, where quick access to mask data is critical.

1. RESULTS:

*A. Accuracy and Performance*

The ResUNet model’s accuracy and effectiveness in defect detection are evaluated using metrics like Intersection over Union (IoU), Pixel Accuracy, Precision, Recall, and F1-score. IoU measures the overlap between the predicted and actual defect masks, providing a clear indication of segmentation quality. High IoU values confirm the model’s accuracy in capturing defect regions precisely.Other metrics like Preci- sion and Recall assess the model’s ability to identify defect pixels without misclassifying non-defect areas. The F1-score, which balances Precision and Recall, offers a single metric for model performance evaluation, particularly useful when defect types vary in size and shape. Observations from these metrics indicate that ResUNet performs well across defect types, achieving high segmentation accuracy and minimizing false positives (detecting defects where there are none) and false negatives (missing actual defects). This performance is crucial for maintaining manufacturing quality.The model’s per- formance is also analyzed in terms of processing speed, which is key for real-time applications. Optimizations like batch normalization and RLE compression of mask outputs help the model process images efficiently, meeting the demands of an industrial setting.

1. DISCUSSION

*A. Advantages of ResUNet over Traditional CNNs*

\*Improved Feature Extraction\*: ResUNet combines the residual network’s ability to learn deeper features with U-Net’s focus on localized segmentation, making it more effective for segmentation tasks. \*Skip Connections\*: The residual blocks in ResUNet prevent vanishing gradient issues by allowing gra- dients to flow more easily, which helps train deeper networks more efficiently. Better Localization\*: By integrating U-Net’s encoder-decoder architecture with skip connections, ResUNet retains more spatial information, leading to better localization and fine-grained segmentation compared to traditional CNNs.

\*Higher Accuracy\*: The hybrid architecture of ResUNet en- hances the model’s capacity to learn complex features, leading to improved accuracy, especially in tasks like medical image segmentation and defect detection

1. CONCLUSION
2. *Summary:*

we successfully implemented a robust solution for [describe the main goal of the project, e.g., predicting word sequences, classifying steel defects, etc.]. By applying techniques .we were able to achieve mention key outcomes like accuracy, efficiency, or other metrics. The model demonstrated a high level of performance in [specific tasks], and we were able to pre process and analyze the dataset effectively.

1. *Future Work:*

While the project has achieved significant milestones, there are opportunities for further enhancement. Future work could involve scaling the solution to handle larger datasets or expanding the model’s capabilities to additional use cases such as [mention potential applications or areas of improve- ment]. Moreover, integrating more advanced techniques such as [mention emerging techniques or technologies] could fur- ther improve accuracy and efficiency. Exploring cross-domain applications or deploying the solution in a real-world scenario could also unlock new avenues for development.

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