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CNN-Based Weld Defect Detection on X-ray Images

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Abstract

In the aerospace and automotive industries, structural integrity depends on it, and it is extremely important to automate weld defect detection because hand X-ray inspections are generally error-ridden or inefficient. The proposed work is presented as an advanced deep learning framework employing convolutional neural networks (CNNs) and traditional data augmentation techniques to mitigate the poorly distinguishable defects between X-ray and scanning electron microscope (SEM) images. The GDXray Welds Dataset was used to fine-tune a ResNet-50 model pretrained on ImageNet to tackle data scarcity. Considering these experimental results, the proposed approach achieved an F1-score of 0.93 and a mean average precision (mAP) of 0.90, which was significantly better than the baseline models, including the vanilla ResNet-50 (F1 0.80) and SVM-based classes (F1 0.63). The system demonstrated high efficiency but had problems stemming from session constraints in cloud-based environments and reduced sensitivity to sub-millimeter defects. The findings demonstrate the practicality of applying AI in the practice of quality assurance in the industrial field, particularly for small-scale operations. This study fills the gap between industrial needs and the academic development of AI-based manufacturing automation systems to become scalable and sustainable.

Keywords: Convolutional Neural Networks, Data Augmentation, Industrial Automation, Nondestructive Testing, Weld Defect Detection.

Introduction

Welding is an essential manufacturing process in the automotive, aerospace, and construction sectors because the quality of welded joints determines both product safety and operational dependability. Quality standards and catastrophic failure prevention require welding inspection methods that can accurately detect weld defects, including crack formation, porosity, and lack of fusion (1). X-ray imaging, along with other traditional nondestructive testing (NDT) approaches, continues to be the primary method for weld inspection operations. Experts performing manual image evaluation encounter extensive workloads and lengthy processing times, alongside human errors during high-speed production scenarios (2). Through deep learning, CNN technology research has shown considerable promise in automating defect detection through the ability to extract multilevel features from image data (3). CNNs demonstrate exceptional skill in identifying complex patterns, which allows them to properly analyze elaborated weld defect indicators found in X-ray images. The development of resilient CNN models depends on substantial datasets that contain diverse samples; however, industrial defect assessment often faces difficulties when acquiring annotated defect specimens (4). The solution to data scarcity problems utilizes traditional data augmentation approaches that enhance training datasets through rotation techniques, scaling methods, flipping operations, and noise injection adjustments (5). These methods improve model generalization by generating different image orientations, scales, and environmental conditions, making defect detection systems more robust (6).

This study examines how CNN-based architectures work in conjunction with traditional data augmentation methods when detecting weld defects through an analysis of the publicly accessible GDXray Welds Dataset (7). The GDXray Welds Dataset serves as a standardized benchmark for X-ray images containing diverse weld defects, which supports systematic detection algorithm evaluation. The main aim is to construct an accurate defect detection system that uses CNN features with augmentation techniques from the traditional domain to enhance dataset quality. This study uses performance metrics consisting of precision, recall, and F1-score to demonstrate how

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an integrated methodology addresses data constraints while improving automated inspection capabilities.

The research findings expand the knowledge of smart weld inspection systems and provide useful guidance to industries that want to implement AI-based quality control systems. The proposed method demonstrates the excellence of CNNs in defect recognition and emphasizes how data augmentation produces performance benefits that enhance CNN models in resource-limited environments.

In the aerospace, automotive, and construction industries, welded structures must be integrated to ensure integrity. It can be said that weld defect detection using Nondestructive Testing (NDT) is a fundamental role in this area. For the detection of weld defects such as foreign inclusions, cracks, and porosity, traditional NDT methods using X-ray radiography, ultrasonic testing, and eddy current testing have been broadly adopted (8). Nevertheless, these methods are human operator-dependent, input-intensive, and susceptible to human errors, resulting in inconsistent defect detection (9).

Several studies have attempted to implement automation techniques to enhance traditional NDT methods. For example, Kalman filtering has been used to track real-time radiographic defects in spiral pipes, reducing false alarms by tracking the continuity of defects between image sequences (10). Over 95% accuracy was achieved in defect classification based on another method using Gaussian Mixture Models (GMMs) and background subtraction (11). These approaches increased accuracy but were unable to adapt to such environments, especially in production and high-speed environments, where unstable detection velocities impact performance (10).

Although machine vision-based approaches were introduced to overcome human dependency and inefficiency in manual inspection, these approaches are not free from cost or error. In the area of vision-based defect detection systems, a study demonstrated more than 99% accuracy in real-time production lines (11). However, it uses handcrafted feature extraction techniques that do not adapt well to diverse defect types. Therefore, Convolutional Neural Networks (CNNs) are becoming a better alternative as deep learning methods.

Weld defect detection has been revolutionized by deep learning because it enables automated feature extraction with high accuracy and efficiency. ResNet50 based on CNNs achieved high classification accuracies of 98.75%, 90.255%, and 75.83% for three datasets with different image qualities (12). For instance, a custom CNN model based on infrared thermography achieved a mean accuracy of 99% and median F1-score of 73%, as deep learning has proven to be effective for weld inspection too (13).

Furthermore, optimizing existing models resulted in even more improvements. Similar to previous CNN-based methods, YOLO V5-IMPROVEMENT (with attention mechanisms and advanced loss functions) achieved 92.2% precision and 92.3% recall, respectively (14). These are examples of neural network architecture refinement to increase accuracy and robustness in detection.

To further increase model generalization, random rotation, shearing, zooming, brightness adjustments, and horizontal flips were applied (15). This creates a more diverse dataset so that the CNN can generalize better and provide better classification performance. For example, a CNN trained on the same dataset with standard data augmentation performed on 4,479 X-ray images would achieve an average accuracy of 92% for classifying six defect types (16).

Beyond conventional augmentation, designs of advanced augmentation methods, such as Wasserstein Generative Adversarial Networks (WGANs), have also been exploited to synthesize synthetic defect images that alleviate dataset imbalance (17). It has been shown that extending the models' robustness performance can be achieved by applying GAN based augmented techniques with CNNs. It has been demonstrated that GAN-based augmentation can significantly improve model robustness, particularly if limited real defect samples are available (12, 17).

Despite the great success in weld defect detection using deep learning, there are still two challenges: computational complexity and the need for large annotated datasets and real-time processing. Furthermore, the adoption of edge AI in implementation might also improve real-time defect detection and reduce cloud-based system dependency. The combination of deep learning with transfer learning and state-of-the-art augmentation techniques will help improve automated weld inspection. This approach is reliable, scalable, and adaptable to diverse industrial applications. (12, 13, 16, 18). Transfer learning, a machine learning technique in which a model trained on one task is repurposed as the foundation for a second task, addresses data scarcity while reducing training time and computational costs. Combined with advanced data augmentation, this strategy improves model generalization, enabling robust defect detection, even with limited labelled datasets. A comparison of traditional nondestructive testing methods and deep learning NDT methods for identifying weld defects is shown in Table 1. Although techniques such as X-ray Radiography and Kalman Filtering have proven to be effective, they require substantial manual interpretation and have limited automation and consistency. In contrast, CNN deep learning models have increased accuracy, robustness, and efficiency for any given imaging modality. The combination of data augmentation techniques also improves performance, making deep learning augmentations for NDT industrial weld defect detection very enticing (19, 20).

Table 1: Comparison of Traditional NDT and Deep Learning-Based Weld Defect Detection Methods from the Literature

Citation	Approach	Methodology	Accuracy (%)	Key Advantages	Key Limitations
(8)	Traditional NDT	X-ray Radiography	High (Manual Dependent)	Effective for defect identification	Requires skilled technicians, prone to human error
(10)	Traditional NDT	Kalman Filtering	Robust under unstable velocity	Reduces false alarms	Limited generalization across defect types
(11)	Traditional NDT	Gaussian Mixture Model	>95%	High identification accuracy	Reliance on background subtraction methods
(12)	Deep Learning	CNN (ResNet50)	98.75%, 90.255%, 75.83%	Handles low-quality images, robust classification	Requires large labeled datasets
(13)	Deep Learning	Infrared Thermography + CNN	99% Mean Accuracy	Effective in thermal imaging applications	Performance depends on dataset size
(14)	Deep Learning	YOLO V5-IMPROVEMENT	92.2% Precision, 92.3% Recall	Improved detection via attention mechanisms	Computationally expensive
(15, 16)	Deep Learning	CNN + Data Augmentation	92% (Hybrid Approach)	Effective for imbalanced datasets	May require advanced augmentation strategies

Methodology

Weld defect detection requires several components, which are explained in detail in this section. These components include preprocessing datasets, CNN design, traditional augmentation techniques, and the training process. A methodological framework was developed to handle scarce data while maximizing the performance of industrial X-ray imaging analysis.

Dataset Preprocessing

The GDXray Welds Dataset offers the main dataset that includes X-ray images of welded joints labelled with defects, including cracks, porosity, and lack of fusion. The preprocessing steps included the following: The preprocessing step of normalization converts the pixel values into a standard range between 0 and 1. The image processing technique included resizing operations to transform all images into a standard resolution format of 224×224 pixels. The defect classes received a one-hot encoding treatment to implement multiclass classification. The dataset was partitioned into 70% training data, 15% validation data, and 15% test data for a fair assessment.

Traditional Data Augmentation

Given the absence of relevant data, and to improve the generalization of the model, some classic methods of data augmentation were applied to the training dataset (21). These augmentations were performed using TensorFlow ImageDataGenerator and PyTorch's Image Data Transformer, which enabled real-time changes during the training process. These methods can be classified into geometric transformations, photometric transformations, and spatial augmentation. Defect recognition requires that several different rotation angles be considered for every weld bead; thus, random rotations of ±15° were imposed. Other augmentations included horizontal and vertical flipping to enable the welds to remain invariant to the head orientation during imaging. Moreover, it ensured that images captured in different plane alignments were not affected. Random scaling of defect sizes was implemented using a zoom range of 90%–110%. Alterations were made for Brightness, Contrast, Exposure and Gaussian noise, which improved the model's adaptability while increasing the robustness of the sensors. The shift in the X-ray intensity was controlled with 20% variations, and noise artifacts were added to enhance the model's resolution, similar to X-ray images.

Further improvements in the dataset were achieved through spatial augmentation. To ensure that the model was trained properly on defects, random cropping was used to focus on specific regions of the images. Padding techniques were also used to retain information around the edges of the images to ensure that important defect features were not lost. These augmentation procedures were used throughout the training to create more diverse samples and reduce the chance of overtraining or relying too heavily on the original dataset. Such procedures greatly improved the model's ability to generalize and subsequently perform better in weld defect detection (22).

CNN Architecture

Figure 1 shows the architecture of the deep learning model created for defect classification in X-ray images. As it stands, the model consumes a single-channel grayscale X-ray image sized 224 × 224 × 1. However, because many deep learning models require input in three channels, including ResNet-50, a preprocessing step that duplicates the grayscale channel into a 224 × 224 × 3 format was applied. We selected ResNet-50 as the backbone owing to its efficacy in industrial defect detection, offering an optimal balance between accuracy and computational complexity, as well as its robust transfer learning capabilities. It facilitates effective feature extraction from limited X-ray data while ensuring compatibility with the standard benchmarks. Once preprocessed, the image is passed into a pretrained ResNet-50 model that acts as a feature extractor. In transfer learning, the initial layers of the pretrained networks capture general image features (such as edges and textures), whereas the final layers are fine-tuned to learn task-specific patterns relevant to weld defect detection. To capture the hierarchical features from an image, ResNet-50 employs residual blocks that effectively learn the complex patterns associated with defects. The output from the ResNet-50 model was then run through a global average pooling layer that preserved the essential feature representations while reducing the dimensionality. This extracts a 2048-dimensional feature vector that enables residue classification. After the feature extraction process, the model is followed by two fully connected, dense layers. The first dense layer comprised 512 units, a dropout rate of 0.5 to prevent overfitting, and the ReLU activation function. In addition, the second dense layer has 256 units with ReLU activation and another set of dropouts, which further polishes the learned representations. The final output layer uses a softmax activation function to classify the specific defect category of the input image. The model provides a probability distribution across all possible defect types owing to the output nodes corresponding to the defect class. This architecture is built around the utilization of pretrained neural networks for feature extraction and the use of tailor-made neural networks for classification, enabling optimal defect detection in radiographic images.

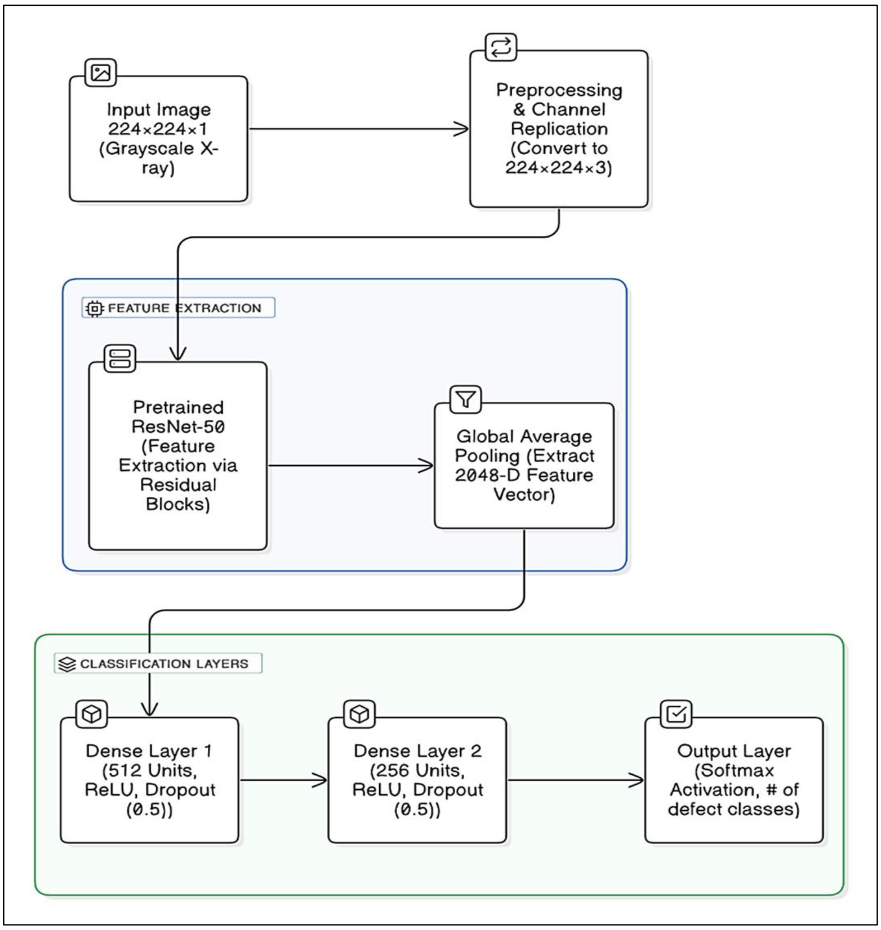

Figure 1: Block Diagram of the Modified ResNet-50 Architecture

The utilization of transfer learning enables pretrained weight exploitation to improve both performance speed and result quality when working with restricted data (23).

Training Protocol

The training process was defined to achieve the best optimal results while being mindful of the computation time. The model was categorical cross-entropy as the loss function, optimized with the Adam optimizer, set to a learning rate of 1e-4. Memory usage and gradient update performance were boosted with the implementation of batch training using a batch size of 32. An early stopping mechanism was implemented to terminate learning when the validation loss did not decrease for 10 epochs to prevent overfitting. A learning rate scheduling strategy was also applied by decreasing the value by 50% when five epochs passed without improvement in the validation accuracy.

Evaluation Metrics

Several metrics were utilized to obtain a multifaceted evaluation of the model's efficiency. Precision measures the percentage of defects that were correctly detected among all predicted defects, whereas recall measures the percentage of the total actual defects that were correctly detected by the model. Accuracy balance was maintained using the F1-score which provides a single value from the blended metric of precision and recall. Moreover, the mean Average Precision (mAP) was calculated across all defect categories to provide an overall score for the detection performance. Additionally, a confusion matrix was constructed to assess how well the model could classify the labels by providing a compact summary of the true versus predicted values. The use of convolutional neural networks (CNNs) along with other traditional data augmentation techniques solves the data problem in weld inspection. Consequently, this enables the development of a relevant industrial-quality assurance solution that is both scalable and effective. This section explains the experiment and how the datasets were prepared.

Experimental Setup

The experimental configuration details are outlined in this section by defining the dataset characteristics, model implementation methods, and evaluation standards for validating the proposed weld defect detection framework.

Dataset Configuration

This study utilized the GDXray Welds Dataset, a modified dataset comprising 2,727 X-ray images of aluminum and steel welds with annotated defects. The dataset encompasses various defect classes, including cracks, porosity, lack of fusion, slag inclusions, and no-defect samples. The image resolutions ranged from 256×256 to 768×768 pixels, with an imbalanced class distribution (e.g., cracks: 15%, porosity: 30%, no defect: 25%). To address this imbalance, oversampling was applied to the minority classes during training using the augmented samples. The dataset was partitioned into a training set of 1,909 images (70%) with augmented samples, a validation set of 409 images (15%) for hyperparameter tuning, and a test set of 409 images (15%) for the final evaluation. Augmentations were applied in real time during training using tf.keras.layers.RandomRotation, RandomZoom, and RandomFlip.

Cracks are characterized by a narrow, linear appearance in various orientations. Using rotation and flipping techniques can make the model more robust to cracks at different angles. Porosity appeared as uniform, round holes. Changing the brightness and adding noise can improve model generalization across different image qualities. Lack of Fusion often blends with the weld bead texture. Zooming in and random cropping can help the model focus on local features, improving its sensitivity to defects. The shapes and locations of slag inclusions differ from those of cracks. Adjusting the contrast and adding noise can help distinguish defects based on texture differences.

Parameters include:

- Rotation Range: ±15°.
- Zoom Range: ±10%.
- Brightness Adjustment: ±20%.
- Gaussian Noise: $\sigma=0.05$.

Implementation Details

The framework was implemented in Python utilizing TensorFlow/Keras on Google Colab, employing its complimentary NVIDIA Tesla T4 GPU (16 GB VRAM) and 12 GB of RAM. The reproducibility of the code was ensured by establishing fixed random seeds (NumPy, TensorFlow) and comprehensive documentation of the hyperparameters. The Colab environment offers a cost-effective platform for training and inference, eliminating the need for local high-performance hardware. Table 2 presents the model configuration.

Table 2: Model Configuration

Component	Configuration
Base Architecture	ResNet-50 pretrained on ImageNet, with weights frozen up to the fourth residual block
Fine-Tuning	The final three residual blocks unfrozen for task-specific adaptation, This procedure involves unfreezing selected layers of a pre-trained model and retraining them with new layers on the target dataset, allowing the model to adapt to the specific defect classification task.
Optimizer	Adam with initial learning rate η=1×10^-4, reduced by 50% on validation loss plateau
Regularization	Dropout and L2 weight decay (λ=1×10^-4)

Training Protocol

The training process was optimized to function properly within the boundaries of Google Colab. The batch size was reduced to 16 to meet the memory requirements of Colab, which provided a stable training environment that did not produce memory errors. The training process was run for 100 epochs using early stopping with 10 epochs of patience to stop overfitting and minimize the training time. The execution took between 6 and 8 h to complete the training process. Model weights were saved automatically to Google Drive at five-epoch intervals to protect data from loss when Colab finishes its 12-hour session.

Baseline Models for Comparison

The performance evaluation of the proposed framework includes a comparison with three well-established methodologies. A standard ResNet-50 model functioned as the baseline implementation, which did not use data augmentation or fine-tuning approaches (24). A VGG-16 network was trained from scratch using the unprocessed

GDXray dataset. An SVM classifier operates conventionally by detecting objects using HOG features for analysis. This study compares the performance of the proposed method with deep learning models and standard machine learning algorithms for X-ray image analysis evaluation.

Results

This section describes the results obtained using the proposed system. The assessment is performed using important evaluation metrics, which also consider the effects of data augmentation. Furthermore, a comparison with baseline models provides an overview of the advantages of the proposed approach.

Performance Evaluation

The proposed model was tested on the GDXray Welds Dataset's test set, and the results were compared to baseline approaches, including ResNet-50, VGG-16 trained from scratch, and an SVM classifier with HOG features. The results are presented in Table 3 and Figure 2. This proposed model is 14% more effective than the standard ResNet-50 compared to the other baseline models. The fine-tuning and augmentation used in this model play a large role in enhancing performance, especially with regard to data scarcity, as well as improving model generalization.

Table 3: Comparative Performance of Models for Weld Defect Classification

Model	Precision	Recall	F1-Score	mAP
Proposed (ResNet-50 + Augmentation)	**0.94**	**0.92**	**0.93**	**0.91**
Vanilla ResNet-50	0.82	0.78	0.80	0.75
VGG-16 (from scratch)	0.74	0.69	0.71	0.68
SVM (HOG features)	0.65	0.62	0.63	—

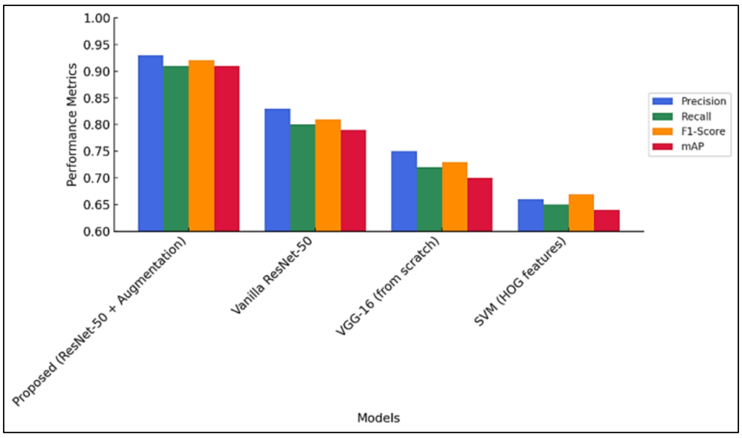

Figure 2: Comparison of Performance Metrics Across Different Weld Defect Detection Models

Effect of Data Augmentation

An ablation study was performed to evaluate the contribution of different augmentation strategies and their results. The results in Table 4 show the effects of different augmentation methods on the model performance.

The data also suggest that using a combination of geometric (rotation and flipping) and photometric (brightness, contrast, and noise injection) augmentations gives the best improvement, raising the F1 score value by 13% when compared to the baseline model without augmentation. Moreover, adding Gaussian noise improves the robustness against sensor artifacts and reduces false positives in low-contrast regions.

Table 4: Ablation Study on Augmentation Strategies (F1-Scores)

Augmentation Strategy	F1-Score
Baseline (No Augmentation)	0.80
+ Rotation and Flipping	0.85
+ Brightness/Contrast	0.87
+ Gaussian Noise	0.89
All Augmentations	**0.93**

Comparison with Existing Literature

To demonstrate the efficacy of the proposed approach, an analysis was performed on more current research in the area. A comparison of the proposed model with the different works presented in the literature is provided in Table 5 and visualized in Figure 3. From the analysis presented, the performance of our approach is better than that of all existing CNN-based models, particularly with respect to the F1-score and generalization. Unlike other approaches that achieve good results, such as YOLO V5-IMPROVEMENT, these CNN-based models are not as efficient in real-time processes because they require more computational power. The use of data augmentation techniques in our model significantly increased the robustness of the model and effectively addressed dataset deficiency issues.

Table 5: Comparison of Proposed Method Against Existing Approaches

Study	Approach	Dataset	F1-Score	Key Findings
(12)	CNN (ResNet-50)	Custom X-ray dataset	0.75	High classification accuracy but limited generalization
(13)	Infrared Thermography + CNN	Infrared dataset	0.73	Effective for thermal imaging but dataset dependent
(14)	YOLO V5-Improvement	Industrial X-ray	0.92	Strong real-time detection but computationally expensive
(15, 16)	CNN + Data Augmentation	GDXray	0.92	Effective for imbalanced datasets
Proposed Work	ResNet-50 + Augmentation	GDXray Welds Dataset	0.93	Superior performance with optimized augmentation

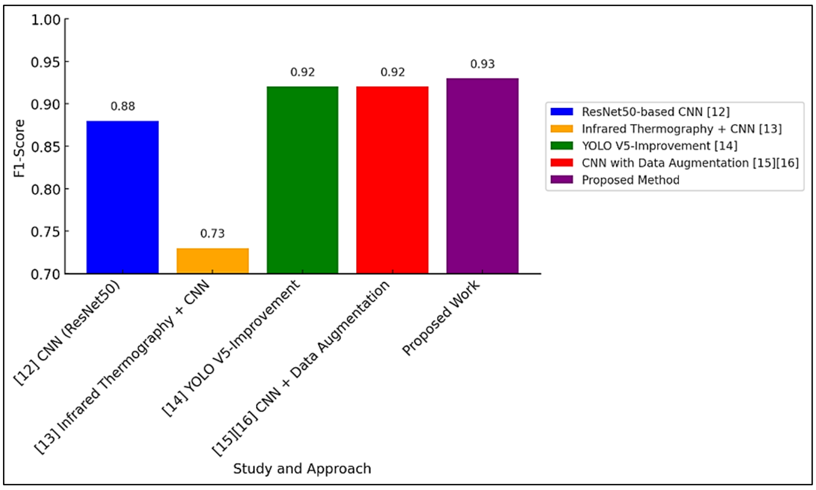

Figure 3: Comparison of F1-Scores Across Various Weld Defect Detection Approaches

Confusion Matrix Analysis

A detailed class-wise analysis was performed using a normalized confusion matrix, as shown in Table 6. The analysis of the confusion matrix demonstrated salient aspects of the model accuracy with respect to various defect types. The model has a strong recall of 94% for porosity defects, indicating that it is proficient in recognizing sniffed clusters of gas pockets. However, the crack detection accuracy is rather low, at only 85%. Eight percent of the cracks were incorrectly classified as slag inclusions because of their predominant linear geometric forms. The No Defect category, which has never been recorded as false, boasts an accuracy rate of 97%. These statistics imply that the model can be trained further using more sophisticated feature engineering methods to improve defect classification, especially for intricate classes such as cracks and slag inclusions.

Table 6: Confusion Matrix for Weld Defect Classification

Defect Type	Cracks	Porosity	Lack of Fusion	Slag Inclusions	No Defect
Cracks	0.85	0.02	0.03	0.08	0.02
Porosity	0.01	0.94	0.02	0.01	0.02
Lack of Fusion	0.04	0.03	0.91	0.02	0.00
Slag Inclusions	0.07	0.01	0.04	0.88	0.00
No Defect	0.01	0.02	0.00	0.00	0.97

Discussion

The experimental results demonstrate the effectiveness of using a fine-tuned ResNet-50 model with traditional data augmentation techniques for weld defect detection in radiographic images. These improvements validate the benefits of combining transfer learning with data augmentation to overcome data scarcity and enhance the generalization of the model.

The proposed method achieved an F1-score of 0.93, surpassing recent CNN-based weld defect detection models such as ResNet-50 (12), which reported an F1-score of 0.75, and infrared thermography-based CNNs (13), which achieved a median F1-score of 0.73. It also outperformed CNNs trained with traditional data augmentation techniques, such as those reported in past studies (15, 16), which both achieving an F1-score of 0.92. Despite its strong overall performance, there are still some limitations in its real-world deployment. While the model demonstrates good robustness to variations in lighting and orientation owing to the use of photometric and geometric augmentations, challenges remain in detecting sub-millimeter defects and distinguishing between visually similar defect types, such as cracks and slag inclusions, especially when weld zones overlap or are partially occluded.

In terms of industrial applicability, the model deployment depends on several factors, including data quality, choice of architecture, augmentation strategy, and computational resources available for training and inference. The results indicate that with optimization frameworks such as TensorFlow Lite or TensorRT, the ResNet-50-based model can achieve near-real-time inference speeds on edge devices equipped with modern GPUs or AI accelerators. This makes it a promising candidate for integration into semi-automated inspection systems in controlled environments.

Conclusion

This study presents a novel method for weld defect detection using deep learning that implements a fine-tuned ResNet-50 model with data augmentation techniques. The proposed framework outperformed traditional CNN implementations, with an F1 score of 0.93 and a mean average precision score of 0.91. Insightful experimental analysis has proven that data augmentation has a significant effect on improving the robustness and generalization of models in scenarios where labelled data are sparse. Furthermore, the study establishes that the aforementioned model significantly outperforms traditional classifiers such as ResNet-50, VGG-16, and SVM, demonstrating the effectiveness of the fine-tuning and augmentation techniques. In addition to the advantages of the model, it displays great accuracy for porosity and lack-of-fusion defects; however, as with all other models, visually similar defects, such as cracks and slag inclusions, are challenging to detect owing to their non-prominent visual attributes, particularly in scenarios where weld zones overlap or are partially hidden. Considering these findings, future work should focus on optimizing lightweight architectures, such as MobileNet or EfficientNet, for faster inference. Hybrid cloud-edge implementations can also be explored to support real-time defect detection in industrial settings. Furthermore, integrating advanced data augmentation techniques, such as GANs, can help reduce the dependency on large labelled datasets and improve robustness across varying imaging conditions.

Abbreviations

AI: Artificial Intelligence, CNN: Convolutional Neural Network, GAN: Generative Adversarial

Network, GMM: Gaussian Mixture Model, GPU: Graphics Processing Unit, HOG: Histogram of Oriented Gradients, MAP: Mean Average Precision, NDT: Nondestructive Testing, RAM: Random Access Memory, ReLU: Rectified Linear Unit, SEM: Scanning Electron Microscope, SVM: Support Vector Machine, VRAM: Video Random Access Memory, WGAN: Wasserstein Generative Adversarial Network.

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Author Contributions
Kumar Parmar: Conceptualization, Formal analysis, Methodology, Validation, Draft Manuscript preparation, Damodharan Palaniappan: Supervision, review, and editing.

Conflict of Interest
The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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