CNN-Vit: A Hybrid CNN–Vision Transformer Framework for Accurate and Real-Time Welding Defect Classification With GAN-Based Data Augmentation

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Abstract

Deep learning–based welding defect classification often faces challenges such as limited training data, class imbalance, and high model complexity, which restrict real-time industrial applications. To address these issues, this paper proposes a hybrid CNN–Vision Transformer framework with GAN-based data augmentation for welding defect classification. First, welding images acquired using a wide dynamic range visual sensor are pre-processed through binarization, median filtering, morphological dilation, and cropping to enhance defect features. A Generative Adversarial Network (GAN) is then employed to generate synthetic samples and alleviate dataset imbalance. A lightweight CNN extracts local spatial features and reduces feature dimensionality, after which the resulting feature maps are converted into tokens and processed by a Vision Transformer encoder to capture global contextual relationships via self-attention. The proposed model classifies welding images into four categories: normal, burn-through, undercut, and welding collapse. Experimental results demonstrate that the hybrid architecture achieves improved classification accuracy and computational efficiency compared with conventional lightweight CNN models. In addition, the model attains 98.25% accuracy on the MNIST dataset, validating the effectiveness of the proposed framework.

Keywords: Welding defect; defect classification, deep learning, lightweight CNN; Vision Transformer

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1. Introduction

Ensuring the structural integrity and long-term reliability of welded joints is essential in safety-critical industries such as aerospace, energy, transportation, and civil infrastructure [1]. Welding forms permanent metallurgical bonds through localized melting and solidification, producing joints with high load-bearing capacity and structural continuity. Its cost effectiveness, design flexibility, and ability to join complex geometries make welding a dominant fabrication technique in modern manufacturing [2]. However, the intense thermal cycles associated with welding introduce residual stresses, microstructural heterogeneity, and process-induced imperfections, making weld zones particularly vulnerable to defects. Common flaws—including cracks, porosity, slag inclusions, lack of fusion, and incomplete penetration—can significantly reduce mechanical strength, fatigue life, and fracture resistance [3]. If undetected, these defects may propagate during service and lead to catastrophic failures, economic losses, and safety risks. Therefore, reliable detection and classification of welding defects are critical for quality assurance and predictive maintenance [4].

Traditional non-destructive evaluation (NDE) techniques, such as visual inspection, ultrasonic testing, and radiographic analysis, are widely used for weld assessment [5]. While effective in many cases, these methods often rely on skilled operators and subjective interpretation, which can introduce variability and reduce inspection consistency [6]. Complex weld geometries, heterogeneous materials, and subtle defect characteristics further complicate accurate detection. Manual inspection is also time-consuming and difficult to scale for high-volume manufacturing, increasing the likelihood of missed defects and delayed decision making. Conventional image-processing approaches based on handcrafted features frequently lack robustness to variations in lighting, noise, and defect morphology [7]. These limitations highlight the need for automated inspection systems capable of delivering reliable, fast, and objective evaluation.

Recent advances in artificial intelligence, particularly deep learning, have enabled significant progress in automated visual inspection. Convolutional Neural Networks (CNNs) have demonstrated strong capability in learning hierarchical feature representations directly from raw images, eliminating the need for manual feature engineering and improving classification accuracy across diverse conditions. In welding defect inspection, many studies have improved CNN performance by increasing network depth and expanding feature representations [5]. Although deeper architectures enhance representation capability, they also significantly increase computational complexity, parameter count, and memory requirements, which may limit their suitability for real-time industrial applications.

In intelligent welding inspection systems, defect classification models are expected to operate in real time during the welding process, which requires efficient and lightweight architectures. Consequently, research on lightweight CNN models has attracted considerable attention in recent years. Existing architectures such as SqueezeNet, MobileNet, and ShuffleNet aim to reduce model parameters and computational cost while maintaining competitive classification performance [7]. In addition to model compression techniques, some studies have focused on manually designing compact CNN architectures that balance feature representation capability and computational efficiency [2], [7].

Despite the advantages of CNN-based approaches, convolution operations mainly focus on local receptive fields, which limits their ability to capture global contextual relationships and long-range dependencies within images. In welding defect classification, such global contextual information may play an important role in identifying complex defect patterns that extend across larger regions of the weld seam [8].

Recently, Vision Transformers (ViTs) [9], have emerged as a powerful deep learning architecture capable of modeling global dependencies between image regions through self-attention mechanisms. Transformer-based models have demonstrated strong performance in many computer vision tasks by capturing long-range feature relationships and improving contextual understanding [10]. However, pure transformer architectures generally require large-scale datasets and high computational resources, which can limit their deployment in industrial inspection environments.

To overcome the limitations of both architectures, recent studies have explored hybrid CNN–Transformer models that combine convolution-based local feature extraction with transformer-based global attention mechanisms. Such hybrid architectures have shown promising performance in various computer vision tasks, including defect detection, medical imaging, and industrial inspection [11], [6]

Another challenge in welding defect classification is the limited availability and imbalance of defect datasets, since certain defect types occur less frequently in real manufacturing environments. Insufficient and imbalanced datasets may degrade model generalization ability and introduce bias in classification results. To address this problem, Generative Adversarial Networks (GANs) have been widely used for data augmentation, enabling the generation of realistic synthetic samples that enhance dataset diversity and improve model robustness [12].

Motivated by these challenges, this study proposes a hybrid CNN–Vision Transformer framework for welding defect classification with GAN-based data augmentation. In the proposed approach, a lightweight CNN module first extracts discriminative local features from welding images while reducing spatial dimensionality. The extracted feature maps are then transformed into feature tokens and processed by a Vision Transformer encoder to capture global contextual relationships through self-attention mechanisms. Additionally, GAN-based data augmentation is employed to generate synthetic welding defect samples, addressing dataset imbalance and improving training robustness. By integrating CNN feature extraction, transformer-based global modeling, and GAN-driven data augmentation, the proposed framework aims to achieve accurate, efficient, and robust welding defect classification suitable for real-time industrial inspection applications.

1.1. Research Contributions

The main contributions of this study are summarized as follows:

1. Hybrid CNN–Vision Transformer Architecture

A novel hybrid deep learning framework is proposed that integrates a lightweight CNN feature extractor with a Vision Transformer encoder to simultaneously capture local spatial features and global contextual relationships for welding defect classification.

2. GAN-Based Data Augmentation Strategy

A Generative Adversarial Network is employed to generate synthetic welding defect images, addressing data scarcity and class imbalance while improving the robustness and generalization capability of the classification model.

3. Lightweight and Efficient Model Design

The proposed framework adopts a compact CNN architecture combined with transformer-based attention, enabling reduced computational complexity and efficient inference suitable for real-time industrial inspection systems.

4. Enhanced Feature Representation

By combining convolutional feature learning with transformer-based global attention mechanisms, the proposed model improves the ability to distinguish between different welding defect categories.

5. Improved Classification Performance for Welding Inspection

Experimental results demonstrate that the proposed hybrid model achieves high classification accuracy and reliable defect identification, highlighting its potential for intelligent weld quality assessment in modern manufacturing environments.

The remainder of this paper is organized as follows. Section 2 presents the proposed hybrid CNN–Vision Transformer methodology. Section 3 discusses the experimental setup and results. Finally, Section 4 concludes the paper and outlines future research directions.

2- The Proposed Method

This section describes the proposed model for welding defect classification based on a hybrid Convolutional Neural Network [13]–Vision Transformer (CNN–ViT) architecture with GAN-based data augmentation [14]. The main objective of the proposed method is to achieve high classification accuracy while maintaining computational efficiency suitable for real-time welding inspection systems.

Conventional CNN-based methods can effectively capture local spatial features, but they are limited in modeling global contextual relationships within images. On the other hand, Vision Transformers can model long-range dependencies using attention mechanisms but require large datasets and high computational resources. To overcome these limitations, the proposed model combines lightweight CNN feature extraction with transformer-based global attention.

In addition, welding defect datasets often suffer from insufficient samples and class imbalance, which may degrade model generalization. Therefore, a Generative Adversarial Network (GAN) is incorporated to generate synthetic defect images and increase training data diversity. The overall workflow of the proposed method consists of four main stages (See Figure 1):

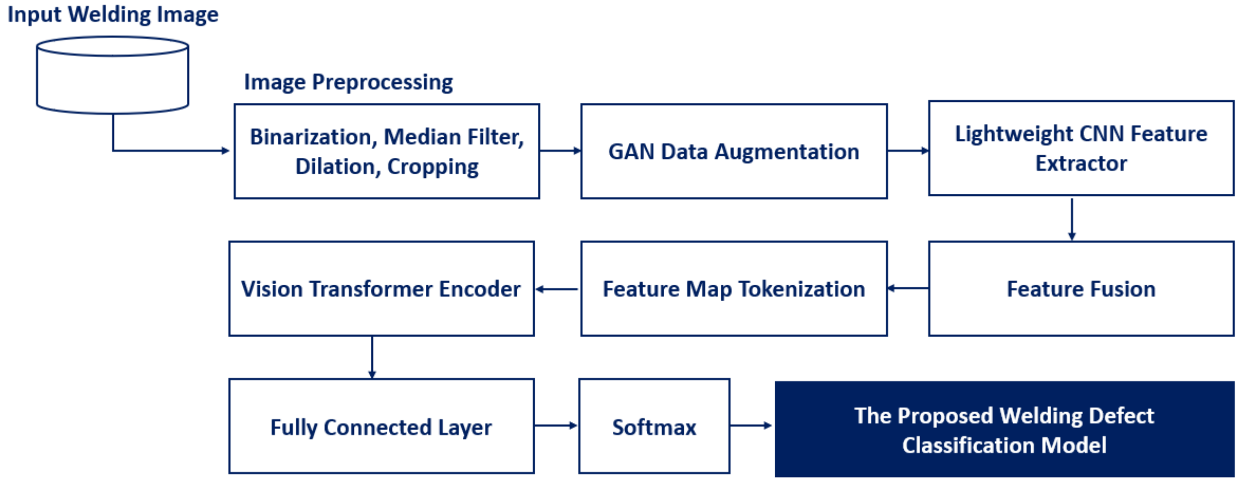


Figure 1. The proposed CNN–ViT model for welding defect classification

2.1. Image Preprocessing

The welding images are acquired using a wide dynamic range visual sensor during the welding process. Due to environmental factors such as lighting variation, sensor noise, and background interference, the captured images may contain irrelevant information that negatively affects model performance (See Figure 2). Therefore, an image preprocessing stage is applied to enhance the quality of the input data.

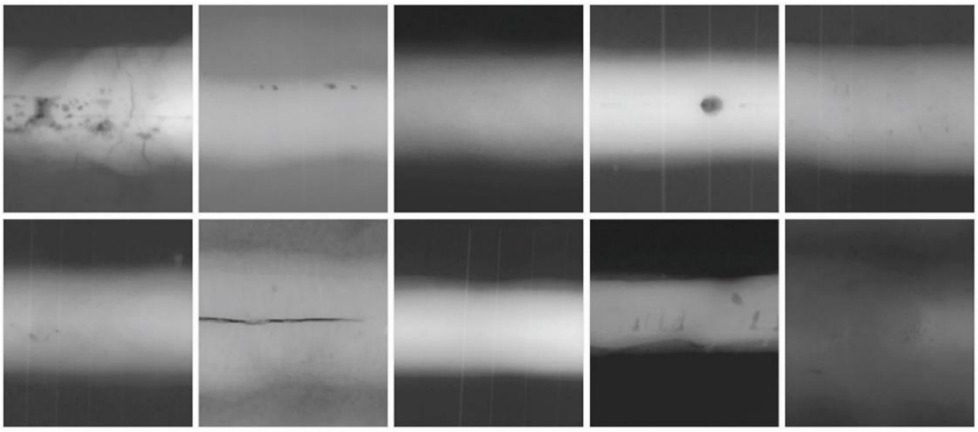


Figure 2. Welding images of defect types using a wide dynamic range visual sensor

The preprocessing procedure includes the following steps:

1. Image binarization [15], which enhances the contrast between the weld seam and background regions.
2. Median filtering [16], which suppresses impulsive noise while preserving edge structures.
3. Morphological dilation [17], which strengthens the defect regions and fills small discontinuities.
4. Image cropping [18], which extracts the weld seam region and removes irrelevant background areas.

Among these operations, median filtering is used to remove noise while preserving defect boundaries. The filtering operation can be expressed as

$$I'(x,y) = median\{I(i,j) \mid (i,j) \in \Omega(x,y)\} \tag{1}$$

where $I(x, y)$represents the original image, $\Omega(x, y)$denotes the neighborhood window centered at pixel (x, y), and $I'(x, y)$is the filtered image.

After preprocessing, the resulting images contain clearer defect structures and are used as input for the data augmentation and classification stages.

2.2. GAN-Based Data Augmentation

One of the main challenges in welding defect classification is the limited number of labeled defect samples. In many industrial datasets, some defect categories occur less frequently than others, resulting in class imbalance. This imbalance may cause deep learning models to favor majority classes and reduce classification accuracy for rare defects.

To address this issue, the proposed method employs a Generative Adversarial Network (GAN) to generate synthetic welding defect images. A GAN consists of two competing neural networks:

- Generator G, which generates synthetic images from random noise
- Discriminator D, which distinguishes real images from generated images

The generator aims to produce realistic defect images, while the discriminator attempts to correctly classify images as real or generated. The adversarial training objective is defined as

$$\min_G \max_D V(D, G) = E_{x \sim p_{data}(x)}[\log D(x)] + E_{z \sim p_z(z)}[\log(1 - D(G(z)))] \quad (2)$$

where $x$represents real welding, images sampled from the dataset distribution and $z$denotes random noise input to the generator.

Through this adversarial training process, the generator learns to produce synthetic images that resemble real defect samples. The generated images are then combined with the original dataset, thereby improving dataset diversity and class balance.

2.3. Hybrid CNN–Vision Transformer Feature Learning

To effectively capture both local spatial features and global contextual relationships, the proposed framework integrates CNN and Vision Transformer architectures.

The CNN component extracts low-level and mid-level spatial features, such as edges, textures, and defect shapes. These features are then converted into token representations and processed by the Vision Transformer, which models global dependencies across the image.

This hybrid architecture allows the model to simultaneously learn fine defect details and global structural information, improving classification performance.

2.3.1. CNN Feature Extraction

The CNN module serves as the initial feature extractor. It captures local spatial patterns and performs spatial downsampling to reduce the dimensionality of the feature maps.

The convolution operation is defined as

$$F_{i,j}^{(k)} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} W_{m,n}^{(k)} X_{i+m,j+n} + b^{(k)} \quad (3)$$

where Xrepresents the input feature map, $W^{(k)}$denotes the convolution kernel of the k^{th}filter, and $F^{(k)}$represents the output feature map.

A nonlinear activation function such as ReLU is then applied

$$f(x) = \max(0, x) \quad (4)$$

which improves the ability of the network to learn nonlinear feature representations.

The CNN layers also reduce the spatial size of the feature maps, which decreases the computational burden of the subsequent transformer module.

2.3.2 Token Embedding

The output feature maps produced by the CNN are converted into tokens before being processed by the Vision Transformer.

Assume that the CNN outputs a feature map

$$F \in \mathbb{R}^{H \times W \times C} \quad (5)$$

The feature map is divided into smaller patches and flattened into token vectors. Positional embeddings are added to maintain spatial information

$$z_0 = [x_1, x_2, \dots, x_N] + E_{pos} \quad (6)$$

where $x_i$represents the embedding of the i^{th}patch and E_{pos}denotes the positional encoding.

2.3.3 Vision Transformer Encoder

The token sequence is then processed by the Vision Transformer encoder, which captures global relationships using the self-attention mechanism.

The scaled dot-product attention is defined as

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (7)$$

where Q, K, and Vdenote the query, key, and value matrices respectively.

To enhance representation capability, the transformer employs multi-head self-attention, defined as

$$MultiHead(Q, K, V) = Concat(head_1, \dots, head_h)W^O \quad (8)$$

Each transformer block also includes residual connections and feed-forward layers

$$z_l = MSA(LN(z_{l-1})) + z_{l-1} \quad (9)$$
$$z_{l+1} = MLP(LN(z_l)) + z_l \quad (10)$$

which help stabilize training and improve feature learning.

2.4 Feature Fusion and Classification

To improve representation capability without increasing network depth, feature fusion is applied to integrate complementary features extracted from the CNN module.

The fusion process is expressed as

$$F_{fusion} = \alpha F_{pos} + (1 - \alpha) F_{neg} \quad (11)$$

where $F_{pos}$and F_{neg}represent complementary feature representations.

The fused feature vector is finally passed to a fully connected classification layer, and the probability distribution of the defect classes is obtained using the Softmax function

$$P(y = i \mid x) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}} \quad (12)$$

where $C$is the number of welding defect classes?

The model classifies welding images into four categories:

i. Normal
ii. Burn-through
iii. Undercut
iv. Welding collapse

The proposed model integrates image preprocessing, GAN-based data augmentation, lightweight CNN feature extraction, and transformer-based global attention within a unified architecture. By combining local feature learning and global contextual modeling, the hybrid CNN–ViT model improves welding defect classification performance while maintaining computational efficiency suitable for real-time industrial inspection systems.

3- Experimental Results and Analysis

3.1. Experimental Environment

All experiments were implemented using the Python programming language with common deep learning libraries including TensorFlow, Keras, NumPy, Pandas, and OpenCV for data preprocessing, model development, and performance evaluation. All tests were performed on a laptop with an Intel(R) Core (TM) i9-9900K CPU @ 3.60 GHz, 32 GB RAM, and an NVIDIA GeForce RTX 3080 Ti GPU. The GPU significantly accelerated the training of the proposed hybrid CNN–ViT model and the GAN-based data augmentation, enabling efficient model training and near real-time inference.

3.2. Research Evaluation Metrics

In testing process, many metrics where be used to assess the proposed model's performance including recall, accuracy, f1-score, and precision [15], [16], [17]. All these metrics rely on True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Equations 13,14,15, and 16 illustrate the utilized performance metrics.

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \quad (13)$$

$$Precision = \frac{TP}{TP + FP} \quad (14)$$

$$Recall = \frac{TP}{TP + FN} \quad (15)$$

$$F - Measure = 2\,Precision \cdot Recall\,Precision + Recall \quad (16)$$

3.3. Results and Discussion

This section presents and analyzes the experimental results obtained using the proposed hybrid CNN–Vision Transformer (CNN–ViT) framework with GAN-based data augmentation for welding defect classification. The analysis focuses on evaluating the impact of data augmentation, the effectiveness of the hybrid architecture in feature extraction, and the comparative performance of the proposed model against several existing deep learning models. The evaluation is conducted using key performance metrics including classification accuracy, Recall, and average processing time per frame, which are essential indicators for both classification reliability and real-time industrial applicability.

3.3.1. Comparative Performance Analysis

To further evaluate the effectiveness of the proposed CNN-ViT model, comparative experiments were conducted using several widely used deep learning models, including MobileNetV3, ShuffleNet, DenseNet, VGG16, and AlexNet. Due to the different probabilities of defect occurrence in welding processes, the dataset exhibits a certain degree of class imbalance. Therefore, 60% of the dataset was used for training, while the remaining 40% was equally divided into validation and test sets.

The comparative results are presented in Figure 3. The proposed CNN–ViT model with GAN-based augmentation achieves a classification accuracy of 99.69%, outperforming both lightweight and traditional convolutional neural network models. In addition to its high accuracy, the proposed model demonstrates efficient computational performance. The average processing time per frame is 95.37 ms, which is lower than that of several lightweight architectures such as MobileNetV3, ShuffleNet, and DenseNet.

The welding defect classification accuracy of the proposed model is also higher than that of the traditional VGG16 and AlexNet models. At the same time, the average prediction time per frame is shorter, demonstrating that the proposed model achieves a favorable balance between classification accuracy and real-time performance.

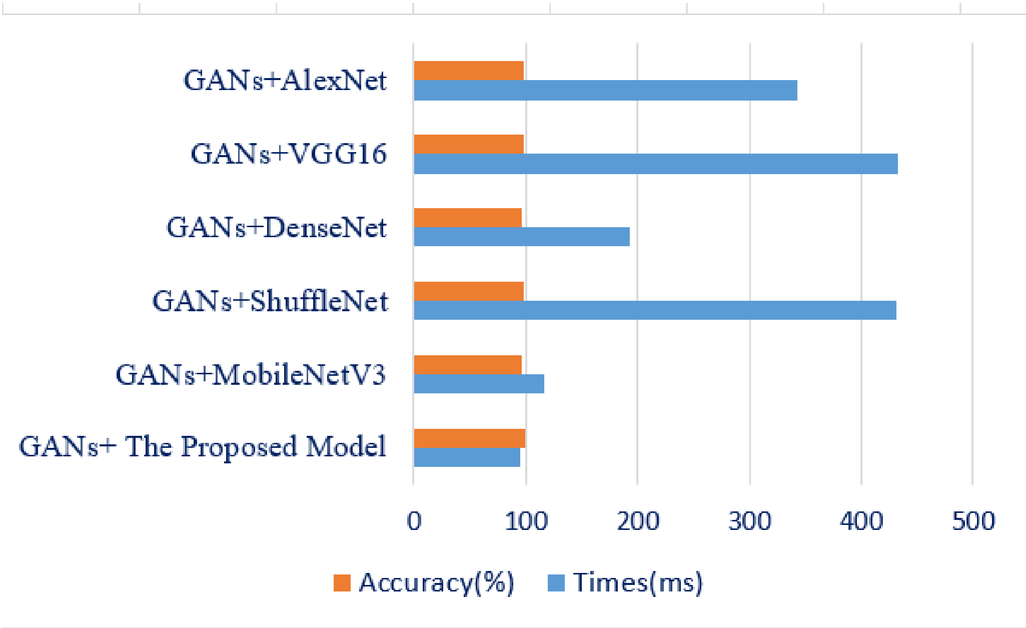


Figure 3. Comparison of classification accuracy and real time of welding defects in each model.

3.3.2 Recall Performance Evaluation

To further assess the detection capability of the proposed model, the Recall values for different welding defect categories were compared with those of the other five models, as shown in Figure 4. For normal welding images, all models achieved very high recognition performance. However, the proposed model achieved the highest overall Recall among the compared approaches.

Even for visually ambiguous defects such as welding collapse, the proposed model achieved a Recall value of 0.97, which is significantly higher than that of the comparative models. This indicates that the hybrid CNN–ViT architecture is capable of effectively distinguishing subtle defect patterns that are difficult to identify using conventional CNN models. Figure 4 illustrates Comparison the recall of welding images.

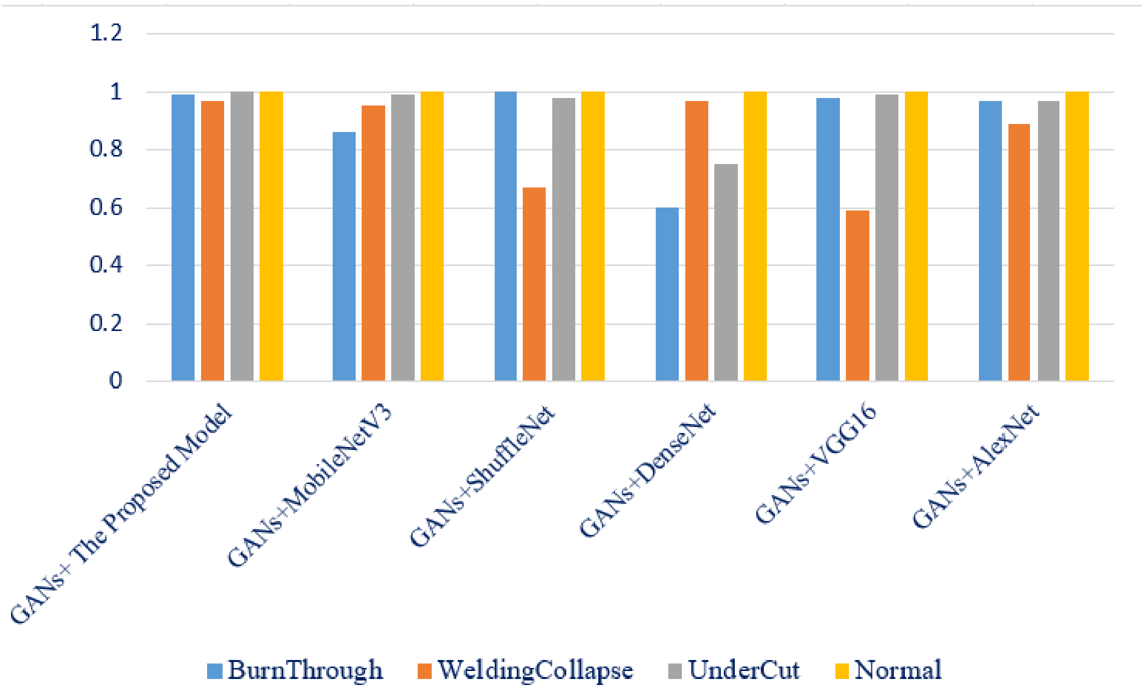
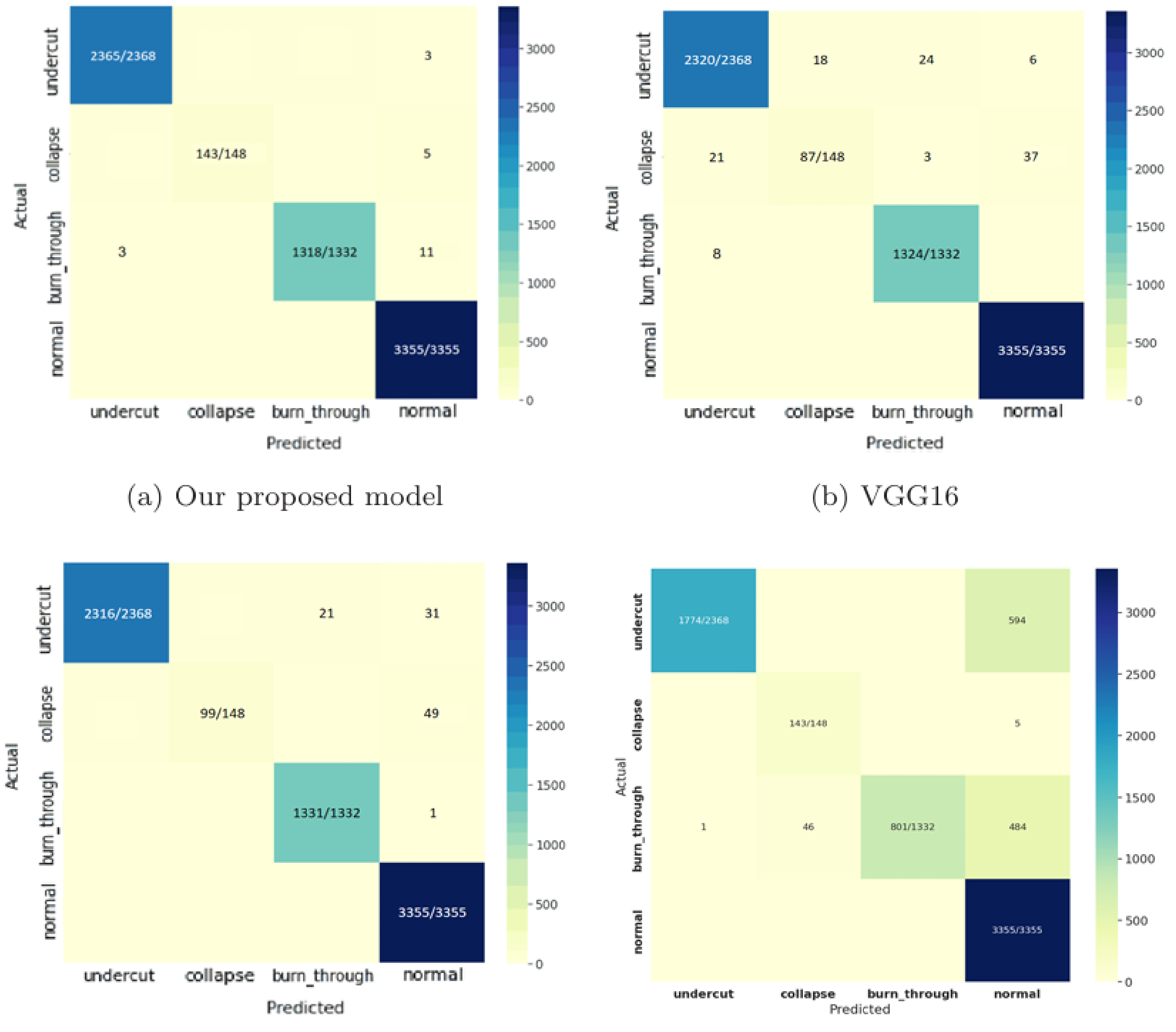


Figure 4. Comparison the recall of welding images.

3.3.3. Confusion Matrix Evaluation Matrix

The confusion matrix results of the proposed model, which integrates MobileNetV3, ShuffleNet, and DenseNet, on the test dataset are illustrated in Figure 11. The results clearly indicate that the number of misclassified defect samples produced by the proposed model is significantly lower than those generated by VGG16, ShuffleNet, and DenseNet individually. As shown in Figure 5, both VGG16 and ShuffleNet exhibit relatively higher false positive rates when detecting welding collapse defects. Although DenseNet achieves higher detection accuracy for welding collapse defects, its performance in recognizing the other two defect categories remains relatively limited. In contrast, the proposed model demonstrates a very low probability of incorrectly classifying welding defects as normal welding images during the detection process. Consequently, the proposed approach achieves superior overall detection accuracy compared with the other evaluated models.



(a) Our proposed model (b) VGG16

(c) ShuffleNet (d) DenseNet

Figure 5. Comparison of Confusion matrices with various model.

4- Conclusion and Future Directions

4.1. Conclusion

This study proposed a hybrid CNN–Vision Transformer framework with GAN-based data augmentation for welding defect classification, aiming to address common challenges in automated welding inspection, including limited training data, dataset imbalance, and high computational complexity. In the proposed framework, welding images are first preprocessed through binarization, median filtering, morphological dilation, and image cropping to enhance defect visibility and reduce noise. To overcome the problem of insufficient and imbalanced datasets, a Generative Adversarial Network (GAN) is used to generate synthetic welding defect images and increase training data diversity.

A lightweight CNN module is employed to extract local spatial features from the welding images while reducing feature dimensionality. The extracted feature maps are then transformed into feature tokens and passed to a Vision Transformer encoder, which captures global contextual relationships through a self-attention mechanism. By combining convolution-based local feature extraction with transformer-based global representation learning, the proposed hybrid architecture effectively improves defect classification performance while maintaining computational efficiency suitable for real-time industrial applications.

Experimental results demonstrate that the proposed method achieves reliable classification of welding defects and outperforms conventional lightweight CNN models. Furthermore, the model achieves 98.25% accuracy on the MNIST dataset, confirming the robustness and effectiveness of the proposed framework. The proposed hybrid approach therefore provides a promising solution for automated weld quality inspection and intelligent manufacturing systems

4.2. Future Work

Although the proposed framework demonstrates promising results, several directions can be explored in future research to further enhance the system performance and practical applicability.

First, the proposed model can be deployed on edge computing platforms or embedded industrial devices to evaluate its real-time performance in actual welding environments. Second, more advanced transformer architectures, such as hierarchical vision transformers or Swin Transformers, could be investigated to improve feature representation and classification capability.

Third, future work may explore multimodal welding inspection systems by integrating visual images with other sensing data, such as thermal imaging or ultrasonic signals, to improve detection reliability. Fourth, advanced generative models, including conditional GANs or diffusion-based models, could be applied to generate higher-quality synthetic defect images for improved training datasets.

Finally, extending the proposed framework from defect classification to defect localization and segmentation would enable more detailed weld quality analysis, which is important for intelligent welding monitoring and automated manufacturing systems.

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