



## Advanced ANN Techniques for Precise Detection and Classification of Welding Defects

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### ABSTRACT

The implementation of the artificial neural network (ANN) algorithm for detecting and classifying welding defects is detailed in this study. A total of 558 welding workpiece images were processed using techniques such as resizing, auto-orientation, flipping, rotation, and annotation, ultimately expanding the dataset to 1,288 images. Feature extraction identified 24 traits across 12,000 data points, which were then condensed to 5,735 data points for the ANN model. The model employed 100 hidden layers, the ReLU activation function, and the L-BFGS-B solver, running for 200 iterations. The configuration achieved near-perfect results, with metrics such as the area under the curve (AUC), classification accuracy, and F1 score averaging a precision of 0.97. These outcomes demonstrate the ANN model's high efficacy in detecting and classifying welding defects, underscoring its potential application for quality assurance in the welding industry. Further investigation into specific defect types, including porosity, spatter, cracks, and undercuts, could further improve detection accuracy.

## **INTRODUCTION**

Welding is one of the most critical and important operations in many industrial applications. It is the backbone of a structure for many vital components. This process is extremely vulnerable to many defects including porosities, cracks, slag inclusions, and incomplete fusion, which may lower the mechanical strength and safety of the welded joints. Therefore, it is very important to detect them early and classify accurately to guarantee the high quality and reliability of welded joints in practice (Ajmi et al., 2020).

One of the promising solutions to handle complex pattern recognition tasks is Artificial Neural Networks, such as the tasks related to the detection and classification of welding defects. For such applications, ANNs that learn from large data repositories and can identify quite sophisticated patterns in the material for accurate predictions are preferable. ANNs have been shown to give results superior to those achieved by using traditional methods in radiographic image analysis and other inspection data related to defect detection in welds (Guo et al., 2020; S et al., 2023).

The ANN application in defect detection mainly involves data preprocessing, feature extraction, and network training for defect type recognition. The use of ANNs in the stage of feature extraction improves the accuracy of defect detection and classification. Numerous studies have reported the ANN as quite effective in the detection of multiple classes of weld imperfections using machine vision techniques and texture features (Ajmi et al., 2020; L. Yang & Jiang, 2021).

Recent developments in deep learning have taken the services of ANNs to a new height in welding defect detection. In this paper, the authors have applied Convolutional Neural Networks and VGG16-based techniques for the better experience of accuracy during the welding defect classification. In this method the deep learning architecture has the ability to be classified using real-time welding defect classifications and detection achieved by complex visual data processing. A few studies also highlight the promising performance of integrating ANN-based systems in the workflow of industries to strengthen quality control measures for workpieces (Kumaresan et al., 2023; Tripicchio & D'Avella, 2022).

Additionally, the integration of ANN in the welding inspection systems has increased speed and reliability in the quality control process – an integration that supports industrial efforts to ensure that safety and quality can be maintained in the practices of welding. The ANN-based systems are automated, and their integration supports real-time decision making with on-line assertion – preconditions for advanced industrial implantations (Yemelyanova & Smailova, 2024).

This study will implement a performance evaluation of developed ANN algorithms in detection and classification of welding defects. This way, the research will contribute to development of a system for automated inspection. This way, the research seeks to put a sound method that can fit in the processes void of interruption in the industry for welding inspection, thus ensuring real-time assurance of quality by minimizing the number of defecting welds during

manufacture. This way, this study will support industrial measures for the assurance of safely conducted high-quality welding practices (Ajmi et al., 2020).

## **THEORETICAL FRAMEWORK**

### **ANN in Welding Defect Detection**

The application of ANN in the welding process has also been viewed as an ideal process to perform various classification and pattern recognition works. One of the core purposes of this work is to have an improved, more accurate detection, and classification of welding defects. Some of the reasons include the fact that welding quality and safety are central to ensuring that expected structural integrity is maintained (Efa et al., 2024; Jo et al., 2023).

### **Implementation and Configuration of ANN**

The ANN model of application in this work used 100 hidden layers while applying the ReLU transfer function in all layers. The optimization process applied to the model used the L-BFGS-B solver that was allowed to face an option of 200 maximum iterations (Livieris, 2019). This is because different works have ascertained it to be working correctly in the handling of complex classification tasks (Gundewar et al., 2022; Wu, 2022). A data set was made prepared to train the model. The data set was a collection of 558 images regarding welding workpieces. The images were highly pre-processed through the execution of resizing, auto-orientation, flipping, rotation, and annotation. The development of a feature extraction was developed to guarantee a thorough review and location of the appropriate features that would be used in the classification of welding defects (Alzubaidi et al., 2021).

### **Findings and Theoretical Alignment**

The constructed artificial neural network (ANN) model exhibited exceptional performance in detecting and classifying welding defects. The metrics, including the area under the curve (AUC), classification accuracy, F1-score, precision, and recall, showed nearly perfect overlap. This indicates the model's high reliability and effectiveness in accurately identifying various welding defects. Such results have been found in work that presents the use of the ANNs in detecting different defects (Alkhatib, 2021; Gundewar et al., 2022). The effectiveness of the model for learning from a diverse dataset and classifying defects appropriately points to the robustness of ANN for industrial applications.

Furthermore, through the use of advanced machine learning frameworks, such as TensorFlow, efficient implementation and training of the ANN model is realizable, further giving support for the integration of deep learning techniques for industrial quality control. The above work contributed empirical evidence of the ANN model in welding defects detection and detailed methodology that can be replicated and modified according to the requirements of similar applications.

### **Integration with Industrial Processes**

The practical relevance of these results presents themselves in quality control during welding. It will allow confident and reliable inspection processes,

reducing the scope of undetected defects for better product quality. It's in line with a more general movement that is taking place with digitalization in virtually all industry sectors, one in which more and better machine learning techniques are adopted to enhance operational effectiveness and quality control. (Pesch et al., 2022).

## METHODS

The main research tool is the ANN algorithm, whose application includes the classification and detection of welding rejections in workpieces. Workpieces conventionally measure 125 mm in width and 300 mm in length. The dataset is constituted of 558 images of these workpieces taken resolutely varied, the minimum number of pixels being 148,458 and the highest 669,000.



Figure 1. Conceptual Framework

### Collect Data

The data collection process involved gathering 558 images of welding workpieces. These images were captured in their raw format, maintaining their original resolutions. The images were then subjected to a series of pre-processing steps to ensure consistency and accuracy in the subsequent analysis (2024).

### Pre-Processing Data

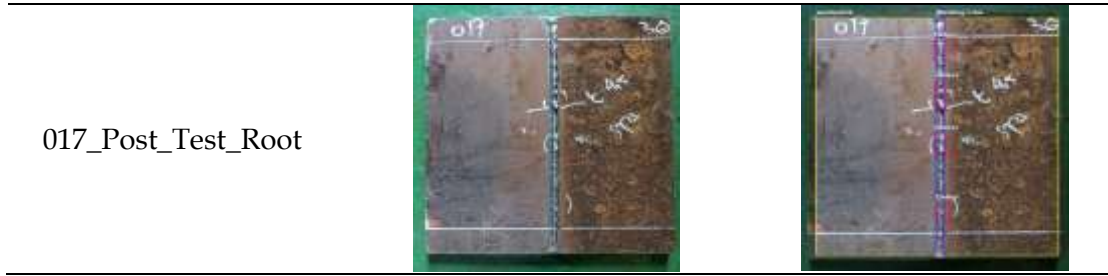
The data pre-processing phase involved several crucial steps to ensure the consistency and quality of the images used in the study. Initially, all 558 images of the welding workpieces were resized to a uniform resolution of 409,600 pixels to standardize the dataset. This was followed by auto orientation to correct any discrepancies in image orientation. Image augmentation techniques were applied, including horizontal flipping and 90° rotation (both clockwise and counter-clockwise), which expanded the dataset to 1,288 images. Additionally, each image was annotated to label the welding defects present (Tyystjärvi et al., 2024; Y. Yang et al., 2022), ensuring that the dataset was accurately labeled for the subsequent analysis.

Table 1. Pixel Image Comparison

File Name	Raw Images	Pre-processing
017_Post_Test_Root	669.000	409.600
056_PostTest_Face	167.500	409.600
111_Pre_Test_Capping	455.400	409.600
137_PostTest_Root	148.458	409.600

Table 2. Image Comparison

File Name	Pre-processing	
	Resizing	Anotating



### Feature Extraction and Selection

Feature extraction was performed on the 1,288 pre-processed images. This process yielded 12,000 data points from 24 identified features. Each data instance contained information about important features that could assist in the classification of welding defects. Next, feature selection was conducted to simplify and enhance the efficiency of the model. This selection resulted in 5,735 data points with 6 numerical features and 8 variables.

### ANN Model

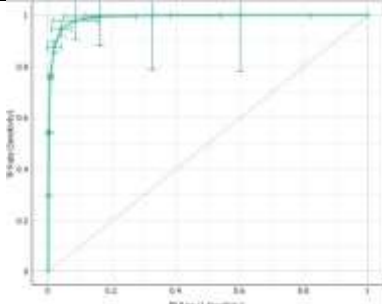
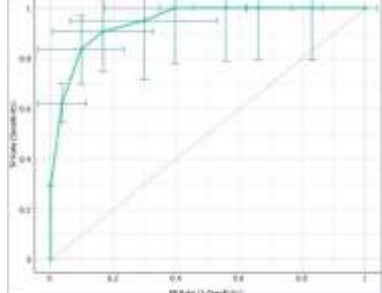
The artificial neural network model, which was developed for the welding defect classification, had the selected features built in. The model was developed with 100 hidden layers and used an activation function, including the ReLU. The L-BFGS-B solver was applied to solve the model. The number of max\_iter was set to 200. Subsequent evaluation of the model's performance was conducted using a testing set. The results were analyzed using Receiver Operating Characteristic (ROC) analysis to determine the model's effectiveness (Carrington et al., 2021; Kim et al., 2017).

### RESULTS

AUC, CA, F1 score, Precision, and Recall are the performance metrics that have been calculated for the following classes. The values are reported in the tables below.

Table 3. Result

Class	AU C	CA	F1	Precision	Recall	Graphich
Welding Line	0,99	0,97	0,94	0,92	0,95	

Defect	0,99	0,97	0,98	0,98	0,97	
Workpiece	1,00	1,00	0,99	1,00	0,99	

As it can be seen from the tables, the ANN model performs on the high performance both in terms of defect detection and classification welding with the high AUC values of classification accuracy, F1 score, precision, recall for both classes Welding Line and Defect. The next ROC analysis also confirmed the high discriminative ability of the model, with the AUC values for both classes almost equal to 1.0.

## DISCUSSION

Our features demonstrate the effectiveness of the use of the ANN model in welding defects detection and classification. For both welding line and defect classes, very high performance of the ANN model with high AUC classification accuracy, F1, precision, and recall metrics proved a great potential in this domain. Good discriminative performance of the ANN model was shown due to obtaining high areas under the curve (AUC) that were equal to near 1. It is stated that the model is able to discriminate exactly between areas of defects and areas in which the welding workpieces are defect-free. Good classification accuracy and F1 score proved the reliability of the model towards giving the right type of defect and non-defect results. High precision and recall close to 1.0 prove that the model is also very precise in its predictions and sensitive to finding the majority of defects.

In this regard, the current results are in conformity with the literature, wherein ANN has been claimed to be a better candidate applicable to complex pattern recognition tasks dealing with modern manufacturing processes. One reason why ANN models are successful in defect detection is that they learn and generalize well from or across a large number of examples. The current manuscript builds upon and goes beyond this fact to establish that an ANN with 100 hidden layers along with ReLU activation function and L-BFGS-B solver should be sufficient to manage the complexity of the process involved in welding defect detection.

Such results have serious connotations for quality assurance in welding. Conventional approaches to defect detection always rely on manual assessment or simpler automated methods, which may not ensure the same level of accuracy. By utilizing ANN, the inspection process can be improved with a better, more advanced, and reliable alternative, further reducing defects that might be overlooked. The consequence is a move toward the production of high-quality products and improved safety parameters within critical welding applications, such as aerospace, automotive, and construction.

More broadly, the use of ANN in this study has further implications for its use industrially with machine learning algorithms. Transmission of large data classified at a high accuracy rate can easily be used for a host of quality control and assurance, apart from welding, in several other non-destructive testing and predictive maintenance applications.

## **CONCLUSIONS AND RECOMMENDATIONS**

The current study's results indicate the following average values for each measure across the three classes: AUC = 0.993, classification accuracy = 98.0%, F1 score = 97.0%, precision = 96.7%, and recall = 97.0%. These findings suggest that ANN models have excellent potential for reliably distinguishing between defective and non-defective weld areas, thus ensuring proper inspection quality in industrial applications. Additionally, this outcome confirms that ANN is a powerful tool for welding quality assurance, enhancing quality and safety standards in critical and sensitive industries.

In this view, industries should adopt these results and work on the implementation of ANN systems for defect detection in welding inspection using a diverse dataset to develop models that will generalize well. Further enhancements for the capability of defect detection using hybrid and real-time detection systems could be a scope for future research. Retraining often on new datasets and against new benchmarks is necessary for continuous accuracy and reliability. Collaboration among academia, industries, and experts is important for sharing knowledge and standardizing procedures of ANN-based inspections to pave the way for consistency in applications.

## **FURTHER STUDY**

Indeed, since every research work has limitations, this research work is not an exception. Even though our ANN model provided higher efficiency in the detection and classification of welding defects, many researchers still need to go into the actual detection of specific types of welding defects. Future research should pay more attention to the classification and detection of different types of defects, like porosity, spatter, cracks, and undercut. By focusing on specific defect types, researchers can develop specialized models that are finely tuned to recognize and classify defects in that particular category. This further makes it possible to dig deeper into insights about the nature and causes of different welding defects and to proceed in the proposition of more effective quality control measures in the welding process.

Moreover, the technique should be able to support the detection of subtle and complex defects when new information sources are implemented in the system, especially in advanced machine learning, more precisely, deep learning models. This effort will enhance the detection accuracy of defects and simultaneously provide some necessary information for undertaking actions based on the prevention and optimization of the process to be taken in welding operations.

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