Automated Metallic Weld Defect Detection

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Abstract: In several industries, such as manufacturing, construction, and the automotive sector, welding is an essential procedure. Safety and structural integrity are directly impacted by weld quality. Conventional welding inspection techniques result in inconsistencies and inefficiencies because they are labor-intensive, manual, and prone to human error. This study uses convolutional neural networks (CNN) and machine learning (ML) to offer an automated welding fault diagnosis method. Before assigning the weld to one of six categories—Good Weld, Burn Through, Contamination, Misalignment, Lack of Penetration, and Lack of Fusion—the system first confirms whether welding has been done. The model achieves great accuracy in defect identification after being trained on a variety of datasets. This method is appropriate for industrial applications since it increases efficiency, decreases reliance on humans, and improves the accuracy of defect identification by utilizing deep learning techniques.

Keywords: *Machine Learning, CNN, Welding Fault Detection, Image Processing, Automated Inspection.*

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I. INTRODUCTION

In industrial applications, detecting welding faults is crucial to preserving quality and safety. The subjective, unpredictable, and time-consuming nature of manual inspection might result in possible flaws in welded structures. Deep learning-based automated inspection systems present a viable remedy by increasing precision and effectiveness. This study introduces a CNN-based model that detects the presence of a weld and divides it into six groups.

➢ *Centralized Welding Inspection Systems*

- Conventional inspection techniques are subject to discrepancies since they depend on human knowledge. These systems are: Labor-intensive and slow: manual evaluation raises operating costs and calls for skilled personnel.
- Lack of consistency: Reliability may be diminished by inspectors' differing assessments of flaws.
- Scalability issue: Manual approaches are unable to deliver the quick and precise flaw detection needed for large-scale manufacturing.

➢ *Decentralized Automated Inspection Systems*

- Automated weld inspection with CNNs overcomes these limitations by: Enabling real-time defect detection: Deep learning models classify weld quality in real time, enabling quicker quality control.
- Removing human bias: Machine learning offers consistent, unbiased defect detection.

II. LITERATURE SURVEY

Deep learning application for Metallic weld defect detection through automation has been the focus of great interest in the past few years owing to the necessity of reliable and efficient non-destructive testing (NDT) techniques. The literature review given below summarizes available research based on welding operations, methods for defect detection, and deep learning methodologies like Convolutional Neural Networks (CNNs) used for this purpose.

The American Welding Society (AWS) provides a comprehensive overview of welding techniques, welding metallurgy, and common defects encountered in welded joints. It serves as a fundamental reference for understanding the

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welding process and the types of discontinuities that can occur in metal welds. [1]

Davis discusses various non-destructive testing (NDT) methods for weld inspection, such as radiographic testing (RT), ultrasonic testing (UT), and eddy current testing (ECT). The study highlights the strengths and limitations of each method, emphasizing the importance of accurate defect detection techniques in industrial applications. [2]

Smith and Johnson examine the causes and prevention of welding defects, identifying common issues such as porosity, cracks, and incomplete fusion. Their work provides insights into defect formation mechanisms and suggests methods to minimize welding anomalies through process control and quality assurance.[3]

Rao explores the application of machine learning techniques in welding, discussing various predictive models and classification algorithms used to detect welding defects. The study highlights the potential of artificial intelligence (AI) in enhancing the accuracy and efficiency of defect identification processes. [4]

Brown focuses on advancements in ultrasonic testing (UT) for weld inspection. The study introduces novel techniques that leverage signal processing and AI algorithms to improve defect characterization and localization. [5]

Lee provides a more focused investigation into deep learning applications for weld defect detection. The study explores the use of CNNs to analyze weld images and detect anomalies with high accuracy. The results demonstrate the effectiveness of deep learning models in automating the defect detection process and reducing reliance on manual inspection. [6]

III. PROBLEM STATEMENT

Welding is an elementary process across different industries wherein faults can reduce structural integrity as well as compromise safety. Handheld inspection is a time-consuming process with an element of randomness and hence lacks consistency in controlling quality. This research aims at the creation of an automatic weld fault detection system employing Machine Learning (ML) and Convolutional Neural Networks (CNNs) to deal with the issue.

The system will initially detect welding presence in an image such that only the samples of interest are analyzed. It will then categorize weld quality into any one of six classes: Good Weld, Burn Through, Contamination, Misalignment, Lack of Penetration, and Lack of Fusion. Process automation will improve industrial quality control by minimizing inspection time and maximizing accuracy of defect detection.

IV. METHODOLOGY

A. Dataset Collection

The dataset is comprised of labeled weld images gathered from industry sources and public databases. It contains six classes: Good Weld, Burn Through, Contamination, Misalignment, Lack of Penetration, and Lack of Fusion. Rotation, flip, brightness adjustment, and noise addition data augmentation techniques are used to enhance model generalization.

B. Data Preprocessing

- High to prepare images for training:
- Image normalization: Normalizes pixel values to the same range.
- Grayscale conversion: Minimizes computation complexity while maintaining the most significant features.
- Data augmentation: Enhances dataset diversity, which enhances model robustness.

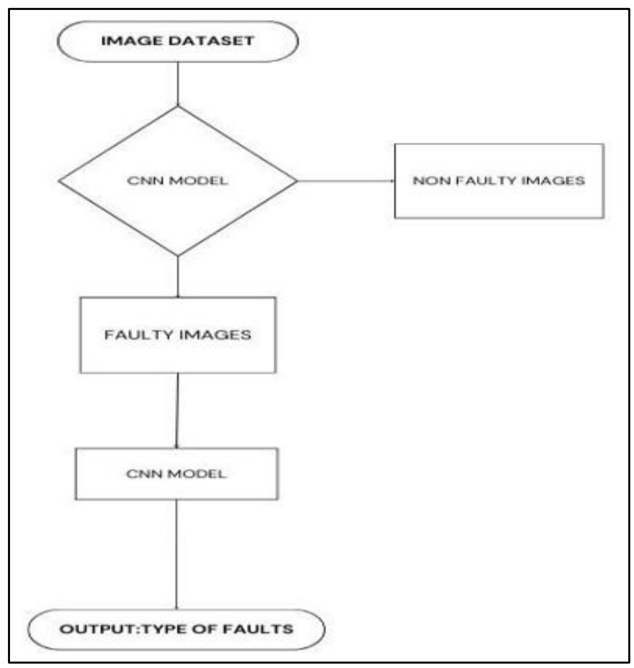

Fig 1: Workflow Diagram

C. CNN Model Structure

➢ *The CNN Model Structure Consists of:*

- Convolutional layers: Detect spatial patterns and features.
- Pooling layers: Down-sample with minimal loss of important information.
- Fully connected layers: Map features to classification output.
- SoftMax activation function: Maps probabilities to classify weld defects.

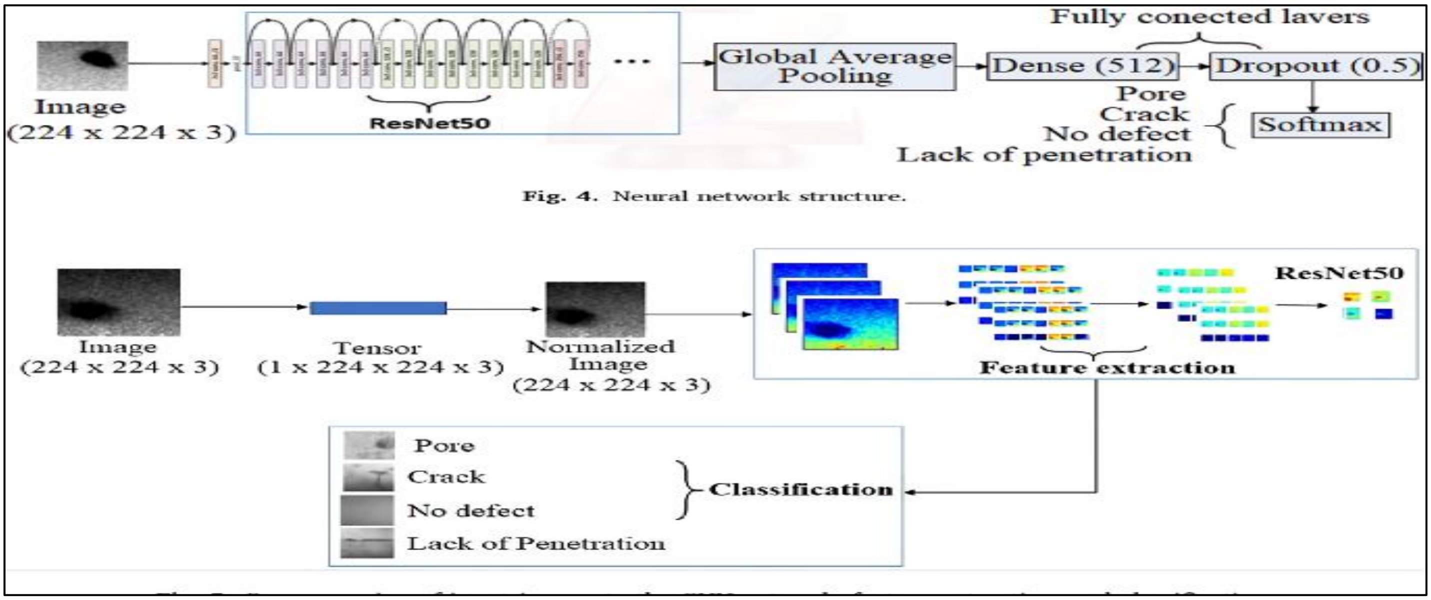

Fig 2: Deep Convolutional Neural Network for Weld Defect Classification based on ResNet50[7]

D. Model Training and Evaluation

- The model is trained on the categorical cross- entropy loss function and optimized with Adam optimizer.
- 50 epochs with a batch size of 32 are performed to learn efficiently.
- Performance is examined in the form of accuracy, precision, recall, F1-score, and a confusion matrix to look for misclassifications.

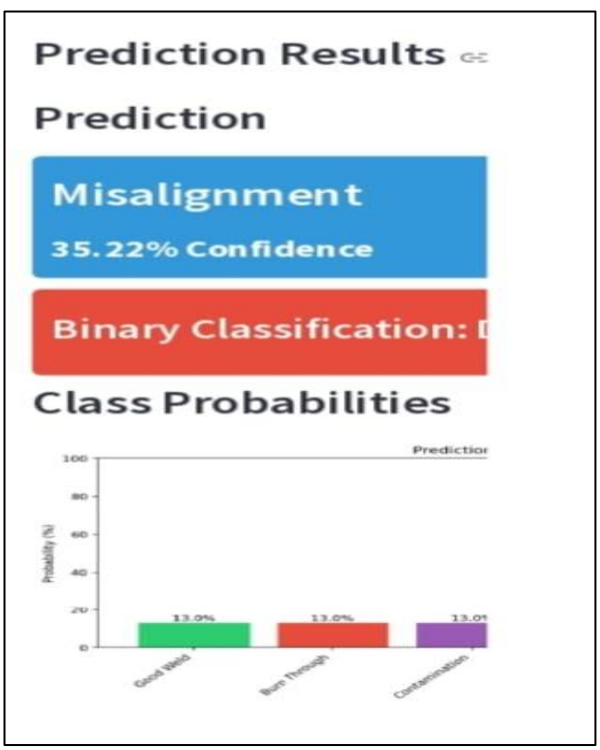

Fig 3: Sample Output

V. CONCLUSION AND FUTURE WORK

Enhancing dataset diversity: Collecting more diversified images to enhance generalization capability.

Real-time deployment: Utilizing the model in factory settings for immediate fault detection This research suggests a welding fault detection system based on CNN that can accurately detect six types of defects. The developed model enhances factory efficiency, reduces human error, and allows enhanced quality control in industrial operations. The future directions are:

Hybrid deep learning techniques: Combining CNNs and transformers to obtain improved defect classification.

Deep learning-based automatic welding inspection greatly enhances quality control, lowers operating expenses, and raises the reliability of welded structures in most industries.

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