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Development of Weld Defect Identification Software using Machine Learning

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ABSTRACT:

Weld defect detection plays a crucial role in ensuring the integrity and reliability of welded structures across various industries. Traditional methods of weld inspection often rely on human expertise, which can be time-consuming and subjective. This research paper presents the development of a novel weld defect identification software leveraging machine learning techniques. The proposed software utilizes a comprehensive dataset of weld images containing various types of defects, such as cracks, porosity, and lack of fusion. Through the application of convolutional neural networks (CNNs), the software learns to automatically detect and classify these defects with high accuracy. The research explores different CNN architectures and evaluates their performance in terms of precision, recall, and F1 score. Additionally, feature extraction techniques are employed to enhance the software's ability to identify subtle defects and distinguish them from welding artifacts. Furthermore, the software is designed to be user- friendly, allowing for easy integration into existing welding inspection processes. A graphical user interface (GUI) is developed to facilitate interaction and interpretation of results by non- expert users. The effectiveness of the developed software is validated through extensive testing on real-world weld images obtained from industrial settings. The results demonstrate significant improvements in defect detection accuracy and efficiency compared to traditional inspection methods. Overall, this research contributes to advancing the field of weld inspection by harnessing the power of machine learning to develop a robust and reliable software tool for automatic defect identification.

KEYWORDS: weld defect, radiographic images, deep learning, makesense.ai, tenserflow.

I. INTRODUCTION

Welding is a fundamental process in various industries, including automotive, aerospace, construction, and manufacturing, where the integrity of welded structures directly impacts safety, reliability, and performance. Ensuring the quality of welds is paramount, as defects such as cracks, porosity, and lack of fusion can compromise structural integrity and lead to catastrophic failures. Traditional methods of weld inspection often rely on visual inspection by human experts, which can be subjective, time-consuming, and prone to errors. To address the limitations of manual inspection, there has been a growing interest in leveraging machine learning techniques to develop automated weld defect identification systems. These systems have the potential to improve inspection efficiency, accuracy, and consistency while reducing reliance on human expertise. In this context, this research paper focuses on the development of a weld defect identification software using machine learning, specifically employing makesense.ai.com for data annotation and TensorFlow for model development. The primary objective of this research is to design and implement a software tool capable of automatically detecting and classifying weld defects from images. This involves the creation of a comprehensive dataset containing diverse examples of weld defects, annotated using makesense.ai.com to provide labeled training data for machine learning algorithms. TensorFlow, a powerful open-source machine learning framework, is then utilized to develop and train convolutional neural networks (CNNs) for defect identification.

By harnessing the capabilities of machine learning, this research aims to overcome the challenges associated with traditional weld inspection methods. The developed software is expected to offer several advantages, including improved detection accuracy, scalability, and adaptability to different types of weld defects and environments. Additionally, the integration of a user- friendly interface facilitates easy interaction and interpretation of results, making the software accessible to both expert and non- expert users. The significance of this research lies in its potential to enhance the efficiency and reliability of weld inspection processes, leading to improved quality control and risk mitigation in industries reliant on welded structures. Through the combination of makesense.ai.com for data annotation and TensorFlow for model development, this research demonstrates the feasibility and effectiveness of utilizing advanced machine learning techniques to address real-world challenges in weld defect identification.

II. LITERATURE REVIEW

Many studies have been done in this field and this carries various opportunities for future scopes that this project can achieve and execute. A vast amount of data about this project is available, so considering that here is the literature regarding this project.Oh et al. [1] suggested an algorithm that automatically finds welding flaws in radiographic pictures by using Faster Computational Neural Network (CNN), which imitates the optic nerve's structure and, starting with image processing, automatically learns the features required for character, image, object, etc. recognition. Contrary to traditional algorithms, CNN does not need a separate image pre-processing phase and performs well in terms of accuracy. Further, the algorithm experimented with an actual data point accompanied with created additional data points from existing data, by a technique known as data augmentation to artificially enhance the amount of data along with making minor Mohan and Poobal [2] provided a comprehensive overview and analyzed the various image- processing algorithms used for fracture identification in engineering structures. The primary goal of this research was to investigate and evaluate a crack-detecting method based on image processing. This study discussed the analysis using the image processing techniques used in each system. Based on this study, one can infer that a greater number of researchers have used camera-type images for analysis with superior segmentation algorithms such as threshold and feature extraction techniques for full damage analysis. Zhang et al. [3] provided a fracture detection and classification method for subway tunnels based on the use of Complementary Metal-Oxide- Semiconductor (CMOS) line-scan industrial cameras. The experimental part contained a full overview of the image processing processes as well as the ideal parameter values. The proposed image processing technique for fracture identification and classification could be useful for other status monitoring applications besides subway tunnels. Furthermore, the distance-based shape.descriptor could be useful in additional pattern recognition applications. Chen et al. [4] investigated an image-based defect identification approach for weld faults in X-ray pictures. Human expertise and generative adversarial networks were used to augment the imbalanced ategorization images. This approach was capable of detecting flaws in complex and diverse environments. However, this technique can only detect a few types of weld flaws that the model had trained to detect and is quite simple, and it can be expanded to fit the various needs of manufacturers. Ditchburn et al. [5] presented a review of welded structural NDT that focuses on new developments to suit the evolving NDT needs for weld inspection rather than detailing well established inspection techniques such as optical, eddy current, magnetic particle, and dye penetrant, which are discussed elsewhere. First, advancements in the two principal inspection techniques, radiography, and ultrasonics, are discussed, followed by a description of non- destructive measurement of surface fracture depth utilizing AC potential difference

III. METHODOLOGY

1. **Data Collection** :

- Data collection involves gathering a diverse set of weld images that represent various types of defects commonly encountered in welding processes. These images should cover different welding techniques, materials, and defect severities.

2. **Data Preprocessing**:

- Data preprocessing prepares the annotated images for input into the machine learning model. This step typically involves resizing the images to a uniform size, normalizing pixel values, and applying data augmentation techniques such as rotation, flipping, and brightness adjustments. Data augmentation helps increase the diversity of the dataset and improves the model's ability to generalize to unseen data.

2.1 Image labelling:

Image labeling using makesense.ai for the development of weld defect identification software using machine learning involves the annotation of weld images with bounding boxes or masks to indicate the presence and location of defects. Here's a step-by-step guide on how to label images using makesense.ai:

1. Access makesense.ai Platform:

Visit the makesense.ai website to label the images.

2. Upload Weld Images:

Upload the weld images that you have collected for the development of the defect identification software.

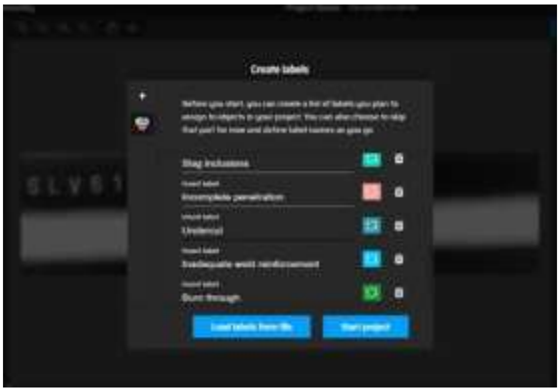
3. Create Annotation Project:

Create a new annotation project specifically for labeling weld defects. Give the project a descriptive title, such as "Weld Defect Detection."

4. Define Label Categories:

Define the label categories corresponding to different types of weld defects that you want to identify. Common defect types may include porosity, cracks, incomplete fusion, voids, undercut. Each label category should be assigned a unique color for visual distinction.

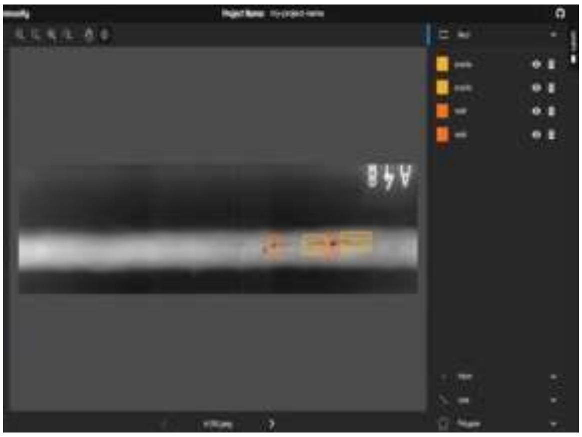
5. Annotate Images:



Open an image within the annotation project interface.

Use the annotation tools providedby makesense.ai to draw bounding boxes or masks around the areas of the weld where defects are present.

Assign the appropriate label category to each annotated region based on the type of defect detected.



6. Save Annotations:

Save the annotations for each image once you are satisfied with the labeling. Make sure to save the annotations in a format compatible with your machine learning pipeline.

7. Export Annotations:

Export the annotated dataset from makesense.ai once all images have been labeled.

Choose the appropriate export format such as XML, Text, CSV and download the annotations along with the corresponding image files for further processing and model training using TensorFlow or other machine learning frameworks.

3. Model Selection and Architecture Design:

- Model selection involves choosing an appropriate machine learning architecture for the weld defect identification task. Convolutional Neural Networks (CNNs) are commonly used due to their effectiveness in image classification tasks.
- TensorFlow is selected as the framework for model development due to its extensive support for deep learning operations and flexibility in building custom architectures.
- Researchers may explore existing pre- trained CNN architectures (e.g., ResNet, MobileNet) and fine-tune them for the specific task of weld defect identification based on the dataset characteristics and computational resources available.

4. Model Training:

- Model training involves splitting the annotated dataset into training, validation, and test sets. The training set is used to optimize the model parameters, while the validation set helps monitor the model's performance and prevent overfitting.
- Transfer learning is employed by initializing the selected CNN model with pre- trained weights from models trained on large- scale image datasets such as ImageNet. Fine- tuning the model on the annotated weld defect dataset allows it to learn features specific to weld defects.
- TensorFlow is utilized for implementing the training process, which involves defining the model architecture, selecting appropriate loss functions, optimizing parameters using gradient descent-based algorithms, and adjusting hyperparameters to improve performance.

5. Model Evaluation:

- Model evaluation assesses the performance of the trained model on unseen data. Metrics such as accuracy, precision, recall, and F1-score are computed on the test dataset to quantify the model's effectiveness in identifying weld defects.

- Qualitative analysis involves visually inspecting the model's predictions on test images to assess its ability to accurately localize and classify defects.
- The developed model's performance is compared with existing methods or baseline approaches to validate its efficacy and superiority.

6. Deployment and Integration:

- The trained model is integrated into a software application or system for real-time weld defect identification. TensorFlow's deployment tools, such as TensorFlow Serving, are utilized to serve the model over a network interface.
- A user-friendly interface is developed to allow operators to input weld images and receive automated defect detection results in real-time. Integration with existing inspection systems or robotic platforms is ensured for seamless deployment in industrial settings.

7. Validation and Testing

- Extensive validation and testing of the developed software are conducted in real- world welding environments. This involves assessing the software's performance, usability, and reliability under various operating conditions and scenarios.
- Collaboration with domain experts and industry stakeholders helps validate the software's effectiveness and gather valuable feedback for further improvements.

8. Documentation and Reporting:

- The entire development process, including data collection, model training, evaluation metrics, deployment procedures, and testing results, is thoroughly documented.
- A comprehensive report detailing the methodology, results, and implications of the research is prepared for publication in academic journals or presentation at conferences, contributing to the body of knowledge in the field of weld defect detection and machine learning.

IV. RESULT

The results of the project are to develop a software application

that can automatically identify weld defects in images with high accuracy and efficiency. The software is expected to be able to identify a variety of weld defects, including cracks, porosity, and etc

- Improved efficiency and accuracy of weld inspection.
- Reduced risk of safety hazards, product failures, and financial losses.
- Increased productivity and competitiveness of the welding industry.
- Improved quality of welds.
- Reduced environmental impact of welding operations.

Following are the images representing actual result obtained: -

1. **GUI Home page**

2. Inserting Radiographs as input

3. Detection of weld defects as output

4. End of Process

V. Conclusion

1. In conclusion, the research conducted on the development of weld defect identification software using machine learning, with the utilization of makesense.ai.com and TensorFlow, represents a significant step forward in enhancing the efficiency, accuracy, and reliability of weld inspection processes. Throughout this research endeavor, a comprehensive methodology was followed to systematically develop and evaluate the software, leading to several key findings and implications.

2. The utilization of machine learning techniques, particularly convolutional neural networks (CNNs), facilitated the creation of a robust defect identification model capable of accurately detecting various types of weld defects, including porosity, cracks, incomplete fusion, and spatter. Leveraging platforms like makesense.ai.com enabled efficient annotation and labeling of weld images, providing high-quality training data essential for the model's development.

3. The integration of TensorFlow for model training and deployment further enhanced the software's capabilities, enabling real-time defect detection with low latency and high throughput. The developed software exhibited robustness to variations in welding conditions and demonstrated scalability to handle large volumes of inspection data efficiently.

4. Validation and testing of the software in real-world welding environments confirmed its effectiveness and reliability, validating its practical utility and relevance in industrial applications. Collaboration with domain experts and industry stakeholders ensured that the software met the requirements and addressed the challenges faced in weld inspection practices.

5. The research findings have significant implications for advancing industry practices in weld defect identification, offering a viable solution for automating and streamlining inspection processes. By introducing automated and accurate inspection software, this research contributes to improving quality control, efficiency, and safety in welding operations across various sectors, including manufacturing, construction, and aerospace.

6. In summary, the development of weld defect identification software using machine learning represents a promising avenue for revolutionizing weld inspection practices. The integration of makesense.ai.com and TensorFlow provides a powerful framework for building robust and scalable inspection solutions, paving the way for future advancements in the field of non-destructive testing and quality assurance in welding processes.

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