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Development of an Anomaly Detection System using Neural Network for the Improvement and Quality of TIG Weld Inspection in the Metallurgical and Fabrication Industry

***Abstract*—In the field of metallurgy and manufacturing, TIG weld inspection represents a vital component in ensuring the integrity and safety of structures and products. Accurate identification of weld defects is crucial, as even the smallest imperfections can trigger catastrophic events. Historically, this process has relied on manual techniques, which, although effective, are subject to limitations in speed and susceptibility to human error. In response to these challenges, this study embarked on an investigation to explore innovative solutions using artificial intelligence and neural networks. Employing an incremental methodology, three specialized neural networks were developed. One focused on detecting pores, another on identifying burns, and the third was a combination of both, enabling comprehensive detection of potential defects in TIG welding. The resulting system achieved a remarkable 91.8% accuracy, according to the Mean Average Precision (mAP) obtained. This proposed approach represented a break with the traditional methodology, prioritizing automation and reliability in defect detection. The implementation was based on deep learning technologies, with the collaboration of Roboflow for the training and validation of the neural networks. This effort not only seeks to improve the efficiency and accuracy of weld inspection, but also to promote a safer and more reliable approach. This breakthrough represents a significant milestone in the application of artificial intelligence in industry, with important implications for quality and safety assurance in products and structures crucial for various industrial applications.**

***Index Terms*—Convolutional neural network, defects, Roboflow, TIG welding**

I. Introduction

In recent years, TIG welding, renowned for its precision and cleanliness in metal joining, has seen significant advancements, solidifying its crucial role across sectors like aerospace and shipbuilding; notably, the Twin Tungsten Inert Gas (T-TIG) welding technique, utilizing dual tungsten electrodes and pulsed hot wire power, has emerged to enhance metal deposition rates, proving effective across diverse material welding applications[12]. There are several approaches in optimizing process parameters to achieve dissimilar joints, such as those between stainless steel and mild steel, with the objective of achieving high tensile strength and a finely characterized microstructure [13]. A range of issues can arise in TIG welding, including insufficient gas shielding, improper electrode positioning, and excessive welding current [5]. Problems associated with TIG welding, such as cracking, porosity, burn-through, slag inclusion and root fusion failure, can cause defects, especially noticeable in aluminum alloys, highlighting the importance of carefully addressing these challenges to ensure the integrity and quality of welded joints in various industrial processes [10]. Advances in TIG welding have strengthened its importance in sectors such as aerospace and shipbuilding, but it faces challenges such as gas shielding issues and defects such as cracking and porosity, underscoring the need to carefully address these issues to ensure the integrity and quality of welded joints in various industrial processes.

II. Theoretical Framework

Recent research has demonstrated the potential of neural networks in TIG welding.The examination encompassed a thorough review of 18 scholarly works focusing on the utilization of CNN models within the welding domain, these studies shed light on the CNN models' efficacy in undertaking both classification and regression tasks pertinent to welding processes [6].There was a development an AI-powered TIG welding algorithm using a fuzzy deep neural network, achieving a high predictive accuracy for weld bead width [1]. An optimization has been made to the TIG welding process through the utilization of a backpropagation neural network, resulting in efficient modeling and optimization [8]. A proposition was made of a system for defect classification in TIG welding using a high dynamic range camera and artificial neural networks, achieving significant progress in accuracy [7]. These studies collectively demonstrate the vast potential of neural networks in significantly enhancing various aspects of TIG welding, ranging from improving weld quality and productivity to optimizing parameters and predicting welding outcomes with greater accuracy and reliability.

A. Argon and amperage in TIG welds

Research on TIG welding has shown that the flow rate of argon gas can significantly impact the weld bead characteristics, with lower flow rates leading to increased porosity and weld contamination [2].The use of argon as a shielding gas in TIG welding has been found to enhance weld characteristics, with a study on alloy steels showing that a mixture of argon and carbon dioxide can improve weld penetration and the number of root passes [9]. Furthermore, the use of jet flow argon gas

31 backing has been found to stabilize the weld pool in TIG welding, allowing for a stable keyhole welding process and fully penetrated welds [4]. The collective findings underscore
33 the critical role of argon gas flow rates, the effectiveness of argon as a shielding gas, and the benefits of jet flow argon gas backing in TIG welding processes, showcasing the nuanced impacts and potential enhancements achievable through careful gas selection and control strategies.

15 Research on TIG welding has shown that the arc voltage and welding current significantly influence the arc length [3]. The cathode fall voltage of TIG arcs in pure argon is found to be about 7V, independent of the current [14]. The use of activated TIG welding, with optimized process parameters,
1 has been found to improve the quality and accuracy of the welding process [11]. The research highlights the profound
15 influence of arc voltage and welding current on arc length in TIG welding, with additional insights into the cathode fall voltage of TIG arcs in pure argon, underscoring the importance of optimized process parameters in activated TIG welding for enhanced welding quality and precision.

III. Methodology

For the study, an incremental methodology was used, which consisted of performing gradual increments of images for each trained neural network. This approach allowed us to evaluate the performance and generalization capability of the networks at different stages of the training process, as well as to identify possible improvements as more data and complexity were added to the model. The use of this methodology provided a deeper understanding of the behavior of the neural networks in response to different data sets and complexity levels, thus facilitating the continuous optimization of the training process and the improvement of model performance on specific tasks.

A. Approach

The approach to be used in this research is a mixed one, where the objective is not only to develop a technical system based on sound quantitative principles but also to ensure that this system is practical and useful in the real context of the welding industry. This approach allows both technical and applicative dimensions of the research problem to be addressed. In the following, the approaches that make this research mixed will be detailed:

Quantitative experimental design: the quantitative aspect focuses on the collection and analysis of numerical data, such
29 as the results of the accuracy and mAP of the neural network model in the detection of defects in TIG welds.

Qualitative analysis: the qualitative component is present in the design and training phase, where it is required to interpret and select the relevant features of the welding images for model training.

B. Variables

In this study the main dependent variable is the effectiveness of anomaly detection in TIG welds, which can be measured through model accuracy, mAP, sensitivity and processing time.

The independent variables are as follows:

- Type of weld anomaly: specifically defect categories such as TIG weld pores and burn-through.
- Welding process parameters: this includes welding current and argon level.
- Material preparation: this includes the process of forming gas (purging) the stainless steel using argon to prevent internal burnthrough.

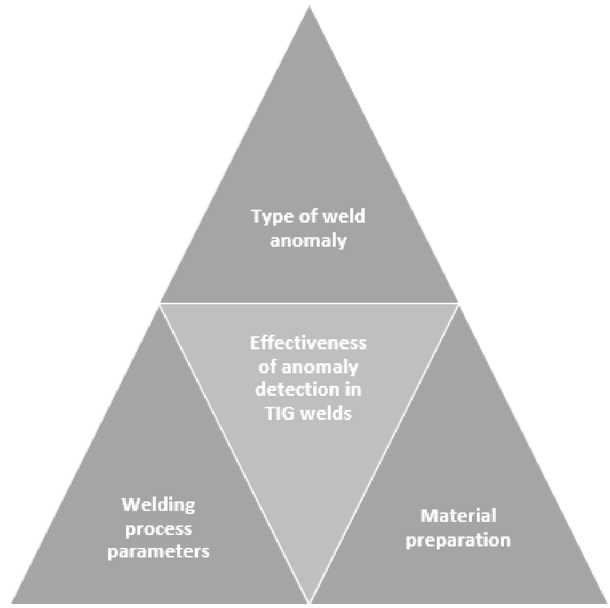

Fig. 1. Relationship between dependent and independent variables

C. Multiple neural network augmentations

The incremental methodology is fundamental in the creation of neural networks due to its ability to manage and adapt to constantly evolving data sets. By incorporating data incrementally, this methodology allows a better understanding of the complexity of the problem and a progressive optimization of the network. Furthermore, by training the network in successive stages, errors can be identified and corrected as they arise, thus improving the robustness and overall performance of the model. This incremental approach also facilitates network scalability by allowing new layers to be added or the architecture to be modified as needed to address emerging challenges or improve prediction accuracy. In summary, the incremental methodology offers a systematic and effective way to build neural networks that can dynamically adapt to changing data and continue to improve their performance over time. The increments applied to each of the neural networks are detailed below: the first designed for pore recognition, the second for burn detection, and the third, a mixed network combining features from both areas.

1) Pores: The pore recognition network started its training with 501 images and then six additional increments were performed as more images were collected, in order to reach the desired mAP value. At each increment, the corresponding images were labeled to perform the appropriate training.

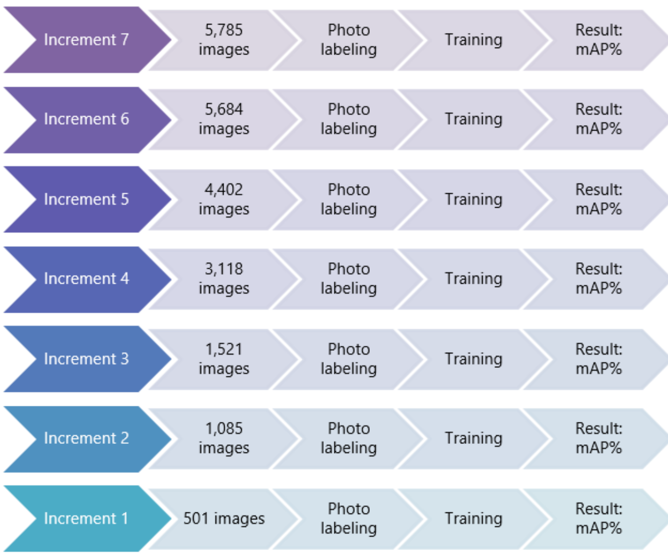

Fig. 2. Process for the elaboration of the pore CNN

2) Burns: For the neural network dedicated to burn detection, training commenced with an initial set of 100 images. Subsequently, two additional increments were made, resulting in a total of 310 images. It's worth noting that the burn samples were obtained internally, from inside the welded tube, presenting imaging challenges and prompting the collection of a smaller dataset compared to the pore network.

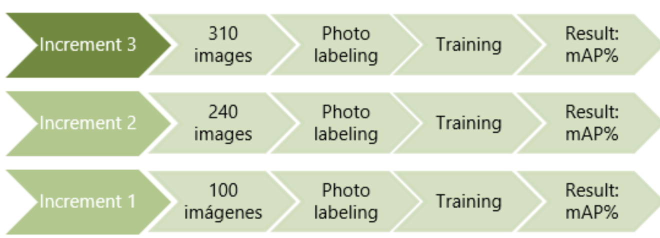

Fig. 3. Process for the elaboration of the burns CNN

3) Mixed defects: For the creation of the mixed network, a combination of data from the two previously developed neural networks was used. The process began with the training of the version of the pore network that had reached the highest mAP. Then, in a second increment, the burn detection network was integrated. Crucially, a thorough review of the images was carried out again before proceeding with the training of this combined network, thus ensuring the quality and accuracy of the data used in the process.

IV. Results

A. Convolutional neural network for pore detection

The neural network designed for pore identification initially showed mAP performance ranging from 84% to 89%. As more images were added to the data set, it was observed that this performance stabilized in a constant range between 88% and 89%. However, after multiple training and increments, it was necessary to reach a total of 5,785 images to achieve a significant increase in mAP, finally reaching a value of 90.7%.

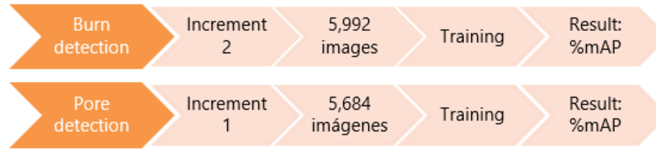

Fig. 4. Process for the elaboration of the final CNN

Images	mAP	Precision	Recall
501	89.60%	86.50%	88.80%
1,085	84.70%	85.80%	79%
1,521	88.80%	85.90%	85.80%
3,118	89%	86.30%	84.20%
4,402	88.60%	84.80%	86.10%
5,684	89.80%	87.60%	87.30%
5,785	90.70%	87.30%	86%

B. Convolutional neural network for burn detection

The development of a neural network specialized in burn detection represented a significant challenge, mainly due to the difficulty in acquiring an adequate data set in the form of images. Initially, the process started with a modest set of 100 images available for training. However, to improve the network's capacity and generalizability, the data set was expanded to a total of 310 images. Importantly, the turning point in performance was observed when a data set of 240 images was reached, at which point the maximum mAP of 77% was achieved. This milestone highlights the critical importance of dataset size and quality in the effective development of artificial intelligence models, especially in medical applications such as burn detection.

Images	mAP	Precision	Recall
100	74.30%	81.20%	68.60%
240	77.00%	91.70%	69.90%
310	73.30%	84.40%	68.30%

C. Mixed defect convolutional neural network

For the construction of the final convolutional neural network, the training sets with the highest mAP values for pore and burn detection were selected. It is essential to note that, prior to training this network, a thorough review of each image in the dataset was carried out to ensure that they were correctly labeled. This meticulous verification process was crucial to ensure the quality and accuracy of the dataset, leading to an impressive mAP of 91.8%. This achievement underscores the importance of data quality and meticulous attention during the dataset preparation phase in the development of high-performance artificial intelligence systems.

Images	mAP	Precision	Recall
5684	89.80%	87.70%	85.10%
5993	91.80%	91.50%	89.9%

D. mAP comparison

During the training processes for the dedicated pore and burn detection networks, notable disparities in mAP results were observed. The pore-focused network exhibited markedly superior performance, achieving a mAP of 90.7%, compared to the burn network, which achieved 77%. However, by merging both networks into one, a highly satisfactory result was obtained, with a combined mAP of 91.8%, underscoring the effectiveness of integrating multiple approaches to improve the accuracy and performance of the detection system.

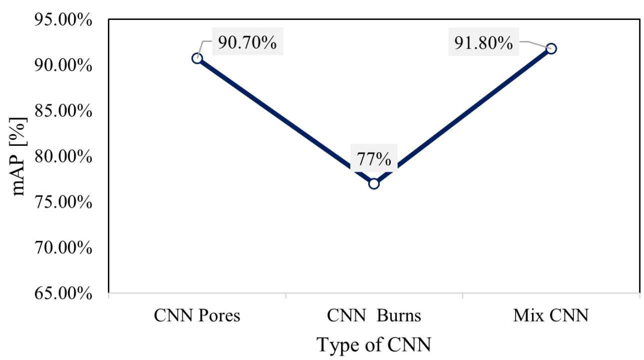

Fig. 5. Comparison between the different CNNs and their mAP

E. Argon level, electric current and pore count

A comparative study was carried out that analyzed the argon level, current and number of pores in the process. In relation to the argon level, increments of 10 units were performed, starting from 30 and culminating at 70. As for the current, four different studies were carried out, starting with 50 amperes, followed by 60, 70 and ending with 80 amperes. For each of these scenarios, pore number counts were recorded, allowing a comprehensive comparative view of how these parameters varied in relation to pore formation in the process.

1) 50 Ampere Current: During the study, it was identified that the highest number of pores is generated when the electric current reaches 50 amps and the argon level is maintained at 50 psig. However, as the argon level increases, a noticeable decrease in the number of pores present in the TIG welding process is observed. This finding reveals an inverse correlation between argon level and pore formation, highlighting the critical importance of controlling both parameters precisely to optimize the quality of the final result and ensure the structural integrity of the weld.

2) 60 Ampere Current: When the electric current exceeds the argon level, the number of pores produced tends to increase. On the other hand, as the argon level increases, a decrease in the number of pores generated is observed.

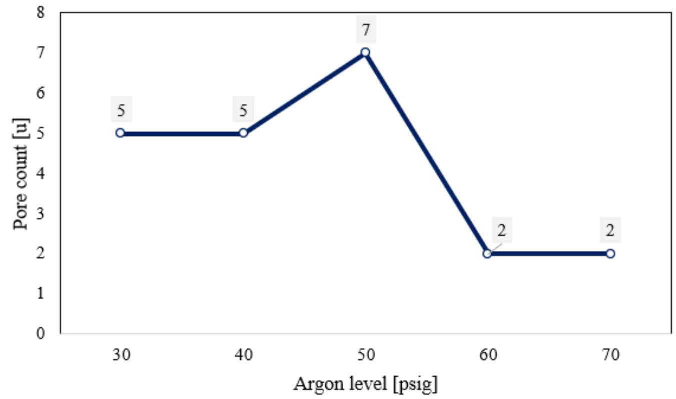

Fig. 6. Comparison of argon level with 50 amp current

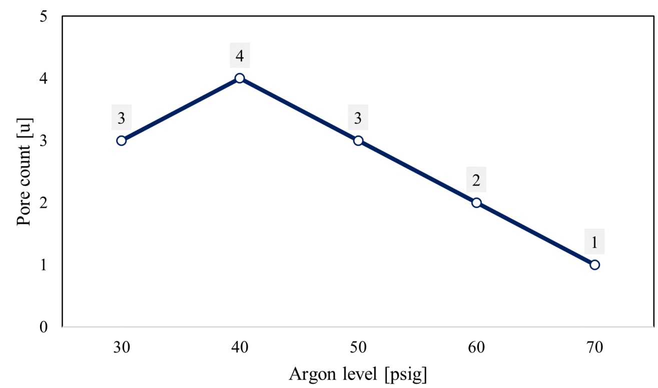

Fig. 7. Comparison of argon level with 60 amp current

3) 70 Ampere Current: As the current increases, a decrease in pore number is observed. In addition, a similar trend of decreasing pore number is noted as the argon level increases.

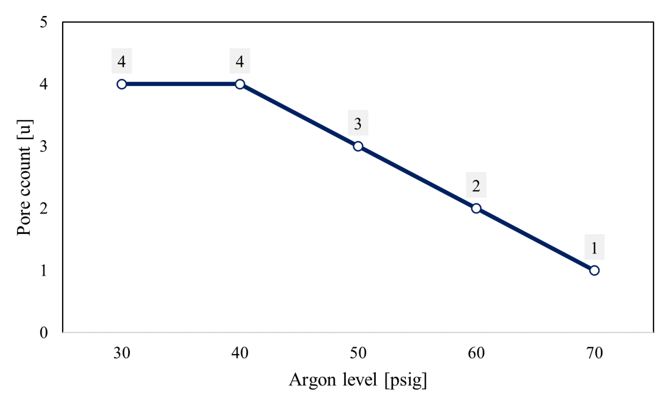

Fig. 8. Comparison of argon level with 70 amp current

4) 80 Ampere Current: A remarkable behavior has been noted when the current reaches 80 amperes: a significant decrease in pore formation is observed as the argon level increases. This phenomenon clearly illustrates how, as the argon level increases, the weld quality improves significantly, reflected in a cleaner weld with fewer defects.

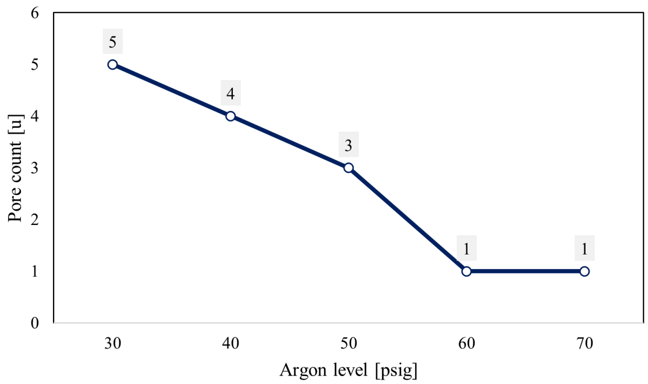

Fig. 9. Comparison of argon level with 80 amp current

5) Overall Comparison : When analyzing all the scenarios together, a clear trend is evident: the lower the current, the more defects the weld tends to have, while higher argon levels are associated with a cleaner and better quality weld. Therefore, it is crucial to maintain a proper relationship between current and argon level to ensure optimal results in the welding process. This balance between both parameters is fundamental to minimize defects and obtain high quality welds.

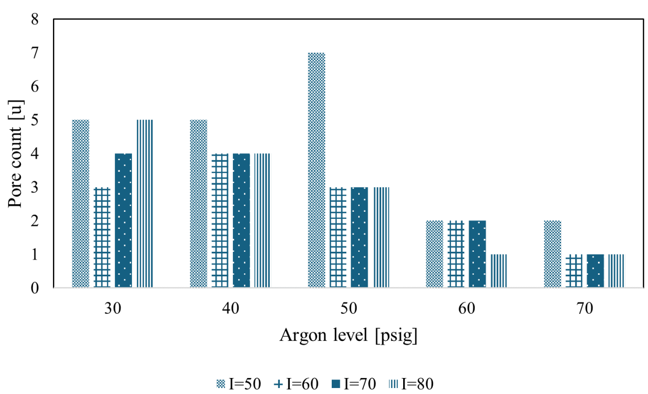

Fig. 10. Relationship between argon level, current and pore number

V. Discussion

Based on the research findings, a state-of-the-art convolutional neural network specifically designed for accurate defect detection in TIG welds has been conceived and developed. What significantly distinguishes this study from others in the field is the inclusion of a comprehensive comparative analysis of the argon level and current applied during the welding process. This unique methodology not only allows for accurate and reliable defect identification, but also provides an in-depth understanding of how subtle variations in welding parameters can influence the quality and integrity of the final welded joint. The extensive research conducted provides a solid foundation for the development of a highly effective and adaptive neural network capable of detecting and classifying defects with unprecedented accuracy. The integration of detailed comparative analysis of welding process parameters, such as argon level and applied current, adds an additional level of depth and robustness to the methodology, allowing not only to identify defects, but also to understand the underlying causes and relationships between process parameters and weld quality. Ultimately, this combination of innovative and rigorous approaches opens up new possibilities for improving the quality and efficiency of TIG welding processes in a wide range of industrial applications, from aerospace component manufacturing to shipbuilding and industrial equipment fabrication.

VI. Conclusions

This study demonstrated that the amount of the training dataset has a significant impact on the accuracy of the Convolutional Neural Network (CNN) for defect detection in TIG welds. As the size of the dataset is increased, a noticeable improvement in model accuracy is observed. This highlights the importance of collecting and using data sets as complete and varied as possible to train artificial intelligence models for defect detection in TIG welds, which can lead to a significant improvement in the quality and reliability of the results obtained.

The training of the Convolutional Neural Network (CNN) using the Roboflow platform has resulted in exceptional performance, achieving a Mean Average Precision (mAP) of 91.8%, an accuracy of 91.5% and an F1 value of 89.9%. These results highlight the ability of the CNN to accurately identify burns and pores, underscoring the effectiveness of the training process and the importance of Roboflow in preparing highly accurate and reliable artificial intelligence models.

The results of the individual trainings for pore and burn detection revealed disparities in terms of their Mean Average Precision(mAP), with notably superior performance in the network dedicated to pore detection, reaching a mAP of 90.7%, compared to the 77% obtained in the burn detection network. However, the combination of both networks resulted in a satisfactory overall result that met the established objective, highlighting the importance of integrating multiple approaches to obtain optimal performance in the detection of different types of anomalies in medical images.

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