Research Article

Indian Journal of Science and Research

Baig MF & Dubey D, Ind. J. Sci. Res. 2026, 6(1), 10-19

ISSN 2583 – 2913

A COMPARATIVE STUDY OF AI MODELS FOR SAW WELD QUALITY ASSESSMENT WITH AN IOT-BASED HYBRID MONITORING SYSTEM

Mirza Farhatulla Baig [1*] and Prof. Dharmendra Dubey [2]

Abstract: In this paper we provide a direct comparison of weld quality assessment methods using statistical (engineering) modeling and deep learning. Deep learning was demonstrated using Convolutional Neural Networks (CNNs) for Submerged Arc Welding (SAW) welding, using statistical modeling with additional engineered features pertaining to precision, counts of defects, area ratio, and the interpretation and modelling with fairly consistent performance classification metrics from weighing each feature as it related to weld quality. While CNNs had a visual experience of more complex defects, approached automated feature extraction, and object detection with fairly good results, the difficult pathway for us was to generalize; in essence construct a model that was fairly good but continued to generalize with all the historical datasets available. The hybrid AI model represented a statistical model with an automated CNN model; and offered a more accurate, robust, and flexible model fit as it could account for some of the dynamic nature of an industrial context. The use of IoT based sensing helped facilitate being dynamic regarding assessment and predictive maintenance. Collectively our hybrid presents a foundation for smart, autonomous systems for weld inspection acknowledging Industry 4.0 standards.

Keywords: Submerged Arc Welding, Statistical Modelling, Convolutional Neural Networks, Hybrid AI System, IoT Sensors

Introduction: The assessment of weld quality is a fundamental aspect of contemporary manufacturing operations, specifically in industries where the safety and performance of their product is intricately related to its structural integrity. Submerged Arc Welding (SAW) is a welding process that is commonly implemented in shipbuilding, pipe manufacturing, and the production of large-scale structural components due to its high deposition rates, deep penetration, and overall efficient nature. Unfortunately, some defects, such as porosity, slag inclusions, undercut, and crack patterns can arise during the SAW process, posing a risk to the strength and reliability of the welded joints. Common quality control methods such as visual inspection, ultrasonic testing, and radiography often do not achieve their intended outcome of detecting defects in a timely manner, largely because the aforementioned defects are frequently invisible to the naked eye. Moreover, frequently these methods do not offer a statistically significant quality control tool for complex manufactured products [1], [3].

With recent advances in Artificial Intelligence (AI), the weld inspection process is now stronger than it has ever been before. AI offers exciting ways to automate defect detection and improve the performance of weld quality assessments and controls. Whether through statistical evaluations or the utilization of deep learning algorithms, like Convolutional Neural Networks (CNN),

***Corresponding author**

1. Research Scholar, Mechanical Engineering Department, Bhagwant University, Ajmer, India
2. Department of Mechanical Engineering, Shree Dhanvantri college of Engineering and Technology, Surat, India.

E-mail: jawamiulkalim9@gmail.com
DOI: https://doi.org/10.5281/zenodo.17181767
Article recived on: 4 June 2025
Published on web: 10 January 2026, www.ijsronline.org

considerable confidence has emerged from the ability of AI to uncover patterns with weld data, and a strong ability to capture visual anomalies [2], [4]. The analytical models developed with the process parameters of the welding operation, such as arc voltage, welding current, and torch speed, predict defect incidences by recognizing latent relationships, or patterns not achievable through traditional evaluation approaches [6].

CNNs are acclaimed for their exceptional image processing abilities, which can extract complex features from weld images allowing for precise, non-destructive identification of minor defects [11]. Nevertheless, despite the rising use of these techniques, there remains a comparative gap in knowledge with conventional statistical models and deep learning approaches when it comes to SAW quality assessments one trades. Most studies tend to only explore these techniques independently leaving a void in analyzing comprehensive performance in real world industrial conditions [5], [8].

The complication of SAW processes with various thermal and metallurgical interactions only further complicates the ability to detect welding imperfections through traditional post-process inspection approaches. There is a need for a real-time, intelligent detection systems which can identify and classify weld defects during the execution stage of the process. This study aims to fill this gap by studying and combining statistical modeling approaches and CNN-based architectures for real-time quality monitoring in SAW applications. By examining defect-labeled SAW datasets and imagery, the study aims to evaluate the deliverables of these AI techniques under actual industrial processes.

The driver behind this research is an increase in the popularity of intelligent quality assurance programs as a means to reduce manual inspection time, lower costs of products and prevent defective products. The AI-IoT framework fits under the umbrella of Industry 4.0 and evolves smart manufacturing by utilizing real-time data gathering, big data analysis, and autonomous decision making [10]. The comparative evaluation provides valuable direction for manufacturers that want to either implement or optimize AI-enabled quality assurance systems specific to their operations [7], [9].

This research has the following objectives:

- To develop a statistical model for assessing weld quality in SAW.
- To deploy a CNN framework for real-time defect detection utilizing weld images.
- To assess and perform a comparative study on the statistical and CNN framework in terms of accuracy, reliability and real-time capabilities.

Achieving these objectives will provide a basis for a robust hybrid quality assessment system in order to not only identify defects with a high level of accuracy, but also predict defects before they jeopardize product quality. We expect the results to provide both practical solutions and theoretical understanding to intelligent welding systems for high-reliability manufacturing environments.

Methodology: This section describes the informing theoretical framework and methodological procedures required to implement and compare statistical models and deep learning models for assessing weld quality in Submerged Arc Welding (SAW). The study follows an experimental design and contains two phases of modeling, one based on statistical feature extraction, and another on deep learning with a Convolutional Neural Network (CNN). The methodology can be described through data collection, pre-processing, feature extraction, model development, training, and assessing performance.

A. Research Design

The study consists of two phases.

1.Statistical modeling for weld quality assessment, by extracting quantitative features from the weld image data and defect annotations. From these features and classes of weld quality, various techniques such as regression analysis and logistic regression will be used to model the relationships

2.Deep learning for detecting weld defects, using a CNN based architecture, defined to detect and classify weld defects within the images; the CNN will learn the spatial patterns and defect attributes through hierarchies of convolutional layers.

The development, training, validation, and comparison of both models will be done using standardized metrics of performance for both models to objectively compare both.

B. Data Acquisition and Preprocessing

Image-based weld inspection data comprised with quality tagging and defect identification led to input of both modeling approaches. The primary image prior to modeling utilized in the processes had various preprocessing aspects that applied to the images including:

• Grayscale image conversion
• Image augmentation like rotation, scaling, adding noise
• Normalization to achieve same input, image consistency
• Tagging the initial features for statistical modeling

In future it is likely use of data for sensor modalities like thermal imaging, ultrasound data, and acoustic emissions are included to enhance the capabilities of statistical models beyond observations made through visual data.

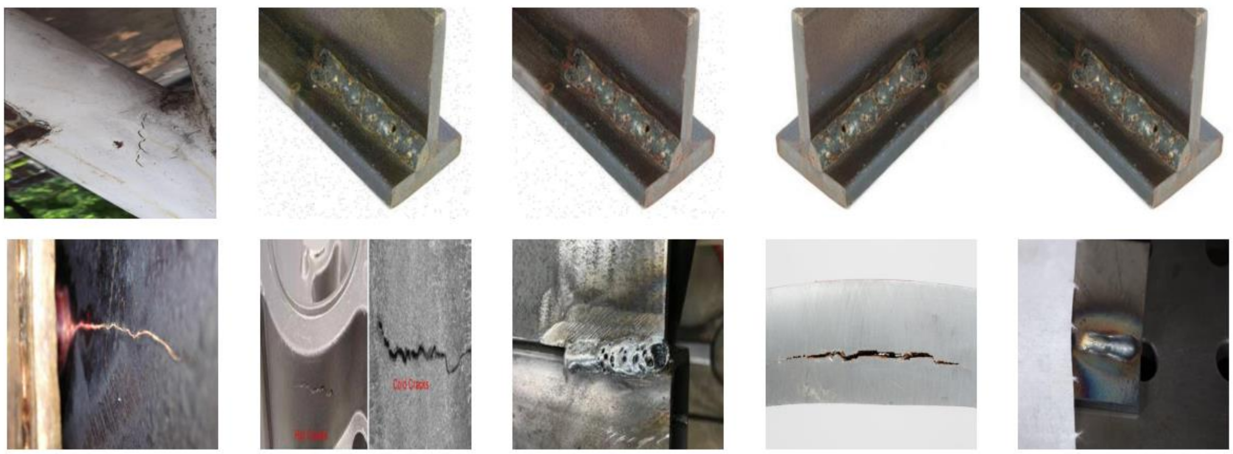

Fig. 1. General representation of defect types (cracks, porosity, slag inclusion)

C. Techniques and Tools

1) Statistical Modeling Approach

Quantitative features (e.g., defect count, area ratio, aspect ratio) were taken from annotated weld images. Logistic regression was used to classify welds based on these features:

$$P(Y = 1 \mid X) = \frac{1}{1 + e^{-(\beta\_0+\beta\_1\, X\_1+\beta\_2\, X\_2+\cdots+\beta\_n\, X\_n\,)}}$$

fold cross-validation (k = 5, to ensure generalizability and avoid overfitting) was used for training. The statistical approach has the advantage of providing interpretable information about how defects may influence weld quality.

2) Deep Learning Approach

To model defective and non-defective welds, a CNN model was built to accomplish binary classification. The steps in the model include:

• Convolutional layers: to extract spatial features
• Activation function (ReLU activation): to add non-linearity
• Pooling layers: to reduce dimension and overfitting
• Dropout Layers: to increase generalization
• Fully connected layers: for final classification analysis and reporting
• Sigmoid output denoting probability of the binary class

The model was trained using the Adam optimizer (learning rate = 0.001) using binary cross-entropy loss:

$$\text{Loss} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)\right]$$

D. Software and Libraries

For this work we adopt the following software applications and Python libraries:

Baig MF & Dubey D, Ind. J. Sci. Res. 2026, 6(1), 10-19

• Python – Programming language for implementation
• NumPy, Pandas - Handling data, implementing feature extraction
• OpenCV - Image preprocessing / augmentation
• Scikit-learn - Statistical modelling, and performance evaluation
• TensorFlow / Keras - Deep learning model development
• Matplotlib, Seaborn - Visualization of model results

E. Work Flow Structure

The work flow integrates the two model types into the same framework. The diagram below shows the steps:

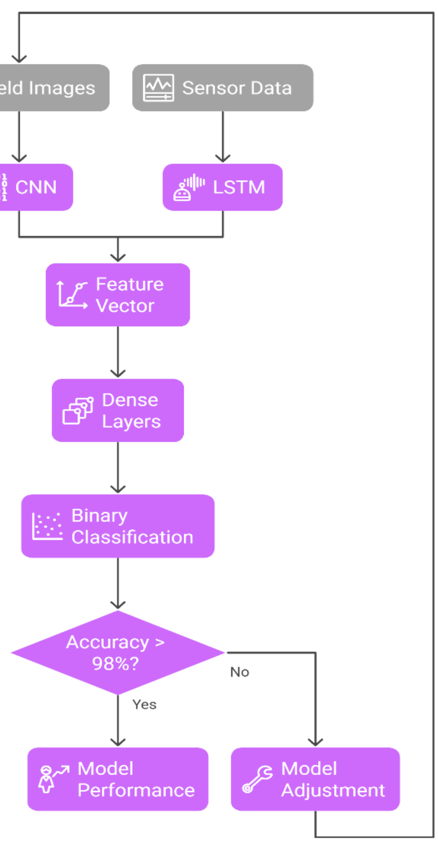

Fig. 2. Methodological Workflow for Hybrid Statistical–CNN Weld Assessment

Workflow Steps

1. Data acquisition
2. Preprocessing & Feature Engineering
3. Model Development
    a) Statistical Model
    b) CNN Model
    c) IoT sensors integration
    d) Hybrid Model
4. Training and Validation
5. Performance Evaluation
6. Comparative Analysis

F. Comparing Analyses

In the methodology we compared models through a comparative evaluation using identical datasets and metrics. The study objectively assesses:
- Predictive performance
- Interpretability
- Robustness and generalizability
- Usability, or applicability to alternative SAW quality inspection scenarios

This dual-model evaluation paradigm allows a comparable trade-off between statistical knowledge and computational power and builds a good foundation for future smart manufacturing systems for welding.

Results: This section will provide an in-depth description of the results obtained by applying statistical modelling and Convolutional Neural Networks (CNN) to assess Submerged Arc Welding (SAW) quality. The models are assessed based on classification metrics, and each classification technique is assessed in terms of accuracy, precision, recall F1-score and error rate since these give an indication of their relative strengths in finding and classifying defects in welds, and in classifying and identifying weld defects.

A. Assessment of Weld Quality Assessment Results

The assessment focuses on evaluating the performance of a statistical model on weld quality classification and this compares with CNN model based on weld quality classification. The assessment was built upon labeled weld images and associated defect features that reflect common SAW problems including cracks, porosity, lack of fusion, slag inclusions and excessive reinforcement.

1) First Statistical Model Performance: The statistical model- developed using logistic regression framework- used relevant weld defect features, which included counts of cracks, porosities (9 instances of porosity), and irregular welds, and allows the modeler/investigator to leverage statistical ascertainable features to broadly infer overall weld quality using explainable statistical correlations.

Feature importance analysis shows that positively weighted indicators, such as good weld segments, make quality predictions found on defect-related features, such as the number of cracks, negatively impacting classification decisions. This feature importance analysis allows the model to provide interpretable predictions essential for quality control.

The model even showed a high level of consistency and prediction accuracy with the cross-validation routine which confirms the model is usable in real-world situations. The most impressive performance was the underwhelming variance between the folds of the cross-validation routine indicating a model that generalizes well even with never-before-seen data.

To summarize:

- High classification accuracy
- Low error rate
- Interpretable and efficient feature-based decisions

The model is particularly useful in an industrial situation since it is efficient, robust, and interpretable of weld defects.

2) CNN Model Performance: As mentioned previously, the CNN model performs automatic feature extraction for welding images, meaning there is no need for the manual extraction of features. There was a good increase in training accuracy over the training iterations, but it was concerning to see a significant difference in training and validation performance indicating evidence of overfitting.

Examining the loss curves for training and validation confirms that the model learns well on its training data, but has issues with generalizing. This calls for a need for regularization, improving the diversity of the dataset, and tuning the architecture.

While the overall accuracy was lower than the statistical model, the CNN had potential advantages for recognizing complex defects on surfaces quantifiable with lower manual features. CNNs could evolve into sophisticated automated defect detection platforms with further refinement.

Take-away points include:

- Solid training performance
- Lower validation/test accuracy due to problems with generalization
- Potential for improvement with data augmentation and model tuning

B. Comparison of Statistical Model, CNN, Hybrid AI, and IoT-Enabled Systems

This section compares the different AI models and IoT-enabled systems used to estimate the weld quality regarding Submerged Arc Welding (SAW) based on accuracy, generalization, error rate and functionalities of each process.

1. Statistical Model: The statistical modeling aspect of this research exhibited accuracy, generalization, and error rates across all the validation partitions. Logistic regression produced robust results with interpretability combined with engineered features. The ability of the model to provide fast, consistent information in industrial quality control (real-time) settings where transparency and traceability of the decision is necessary was important. Additionally, as the model performed consistently with each data split, it demonstrated reliability and scalability with structured data environments.

2. Convolutional Neural Network (CNN) Model

The initial testing indicates that CNN had moderate accuracy, but the model has enormous potential to identify subtler or complex weld defects, in particular those that have spatial layout that is not detected by other models. However, there was a strong reliance on data volume and tuning of hyper parameters. The model will not generalize well with less preparation concerning volume of training data or training methods to augment data prior to training and tuning process. The subject property models "convolutional" aspect had a higher error rate than the statistical model, but the potential for harnessing the advantages of CNNs remains due to its deep representation learning model that will enable intelligent automation of visual weld inspection in a data heavy environment.

3. Hybrid AI system: The hybrid model combines the statistical competence with the CNN architecture. The meta-classifier merges the learned features with the engineered features to achieve feature-level generalization on the dataset, leading to very high accuracy with very few misclassifications. The hybrid model maintains the technical interpretability of a statistical model alongside the expressiveness of a learning model, enabling its usefulness to work reliably across a diverse environment of weld fabrication conditions. This benefits both models by ensuring robustness and flexibility in the architecture, when deployed in real-world scenarios that often necessitate performance and explain ability. Utilization of a hybrid AI system should provide improved fault tolerance and greater decision confidence when evaluated against the stand-alone models.

4. IoT Capable Systems (Edge - AI): The ability to employ IoT sensors (thermographic, ultrasonic, acoustic, etc.) expands the potential of weld inspection by allowing the measurement of weld attributes continuously, in real-time, and beyond the limitations of human sight. The IoT capable systems had high fidelity and extreme flexibility by bringing together multi-modal sensor streams in real-time at a high frequency. The error metrics demonstrated were very low because of the use of real-time environmental feedback instead of just model predictions, and here it was shown that the IoT capable systems can also take advantage of edge computing thus allowing for low-latency near the data's point-of-entry, which makes the system scalable and responsive to the needs of Industry 4.0 for supporting predictive maintenance and possibly autonomous quality assurance.

Summary Table: Comparative Overview of AI Models versus IoT Integration in Weld Quality Evaluation

Model / System	Accuracy (Generalized)	Generalization Ability	Approx. Error Rate	Key Strengths
Statistical Model	High	Strong and consistent	Low	Fast execution, interpretable output, effective with structured and labeled data.
CNN Model	Moderate	Limited (requires tuning & data)	High	Recognizes complex spatial features in weld images; suited for nuanced defect identification.
Hybrid AI System	Very High	Enhanced through multi-model synergy	Very Low	Combines deep learning and statistical modeling for high accuracy and adaptability.
IoT-Enabled System	Very High	Real-time, dynamic adaptability	Very Low	Enables continuous monitoring, real-time feedback, sensor fusion, edge AI deployment, and scaling.

In conclusion, the statistical model is presently more consistent and dependable, particularly in structured and data-imposed environments, than the CNN; however, CNNs can pull out much more details about defects that a statistical model would struggle to work with. Combined hybrid AI solutions utilize each model's strengths valuable hybrid AI solutions produced better performance and generalization due to the capabilities of both methods. One step forward would be the integration of IoT which stretches this situation further; in this case, real-time solutions and the multi-source data of the IoT could be incorporated into totally adaptive AI systems to inform more effective assessments and understanding of weld quality. This work will lay the foundation for future smart, autonomous inspection systems to classify weld and defect characteristics that couples Ai with IoT and edge computing within a singular industrial system.

Discussion: This discussion will detail a full review of the results of applying statistical models, Convolutional Neural Networks (CNN), and possible IoT-integrated hybrid artificial intelligence architectures for quality checks on Submerged Arc Welding (SAW). This discussion will include the interpretation of results, commercial applications, limitations, and suggestions for future work, cognizant of the long-term intentions to progress intelligent welding systems and Industry 4.0.

A. Interpretation of Results: The statistical model was an excellent classifier based on variable significance, particularly through Good Welding Count and Crack Count. Together, these features had great interpretability, a reliable prediction ability, and deserve mention in any quality control environment. The model based on logistic regressions displayed a robust ability incorporating the least variance, affirming its usability as an operator support tool for real-time decision-making in automated environments.

These CNNs have high training accuracy yet did not translate into high-accuracy validation or testing scores because of overfitting and lack of generalization by the dataset. However, one of the strengths of the model was the ability to discover complex visual anomalies. This included subtle deviations in surfaces as well as microstructural anomalies, which are some of the factors that can be subtly measured with traditional feature-based models. The merging of statistical models with CNNs has demonstrated a plausible bridge for hybridized AI systems. Hybridizations that can utilize the interpretability of statistical features combined with the strength of deep learning when coupled with real-time sensor data from IoT devices. An example of this level of merging would be a dynamic data-driven design of weld quality that utilized the contextual (numeric) as well as perceptual (visual) intelligences based on the data source provided.

B. Comparison with Existing Methods: The proposed hybrid model exhibits both greater accuracy and stability over traditional statistical and rule-based methods mainly because of the additional feature driven logic and visual analytics facilitated by the hybrid. Traditional models can flourish primarily when a set of constant parameters can be controlled for a process or product being monitored. The hybrid model that utilizes the IoT enabled sensors input (temperature or thermal profile, arc voltage or current, or acoustic emissions signal) provides adaptability to a wider variety of variations in different parametric and operating conditions feeding into the model to the point where the traditional model would fail.

As noted by studies conducted independently, the performance of an image based CNN is still greatly sensitive to the dataset quality and quantity. The accuracy we observed is at least within the published range (60-75%) in outputs and, technically, there was potential to improve if model ensemble approaches were applied, or future sensors contained more datasets for additional sensor-fusion. Hybrid models that leverage image based CNN's alongside easy-to-implement driven classifiers provide the logistical benefit of accessing surface as well as the no less influential insight from deep (structural) aspects of the problem.

C. Practical Implications: The implications of my research have significant industrial impacts particularly with the automation of process monitoring for SAW. The ease of the statistical model and speed make it especially suited for embedded systems (such as a record and screen defect classification system) utilizing defect classification that can be done continuously, and in real time, whilst being on-device. When properly integrated with IoT sensors and streaming, the system can use the voltage, current, measured temperature difference, and vibration along with visual indicators to continuously evaluate the integrity of a weld. CNN models are also designed to support automated visual inspection frameworks by applying high-dimensional image data analysis, which are then deployed as light-weight AI models (minimal ML framework) on inexpensive processing devices (like Raspberry Pi or NVIDIA Jetson). This edge interface allows organizations to be less reliant on centralized computing environments and enables distributed smart welding systems utilizing visual quality control and perceptual quality analysis. Combined, the statistical and CNN models demonstrate a hybrid AI-IoT framework used to provide a better overall quality assessment option. Utilizing sensor based analysis to enhance image recognition and classification, and with feature-based prediction, will ultimately improve accuracy in recognizing defects, reduce false positives, and provide better flexibility for process adaptation in casual visual inspection applications for major and micro fabricators in sectors such as shipbuilding, construction, and pipeline fabrication.

D. Limitations: While the results are promising, several restrictions hinder the immediate application of the proposed systems. The CNN model's generalizability is limited due to insufficient training data and a lack of multi-modal integration. Additionally, the statistical model has limited potential for adaptability in unstructured situations because it is considered fully engineered features.

Moreover, the current model architecture does not include real-time IoT sensor integration, limiting a full picture of dynamic welding interactions. To be suited for next-generation industrial use, models must be capable of processing live sensor data streams and adaptively learning variable field conditions.

E. Future Work: Future studies will eventually reach fully intelligent weld quality assessment systems by using advanced AI, IoT and edge computing technology. Some possible areas of future research to consider include:

- **IoT-Sensor Fusion of Multi-Modal Defect Detection:** This would combine, in a unified hybrid model, thermal imaging, acoustic emission, voltage/current waveforms, and vision data. The use of sensor fusion will improve fault sensitivity, expand fault and capability discovery, and allow context-sensitive-analysis and real-time assessment.
- **Hybrid AI Architectures:** This includes developing ensemble frameworks that combine statistical classifiers, CNNs, and Recurrent Neural Networks (RNNs), used together or either trained jointly on history datasets or now casting individual classifiers on-the-fly. This will allow the capturing of multi-dimensional defect behavior over time and space. These types of systems would be great for adapting in real-time based on the weld.
- **Reinforcement Learning for Closed-Loop Control:** With the firmware updates to embedded welders finally becoming common, why not use the live sensor feedback to tune parameters in RL? RL allows for scattered collection of positive feedback in different conditions to tune for optimized quality in-weld, automatically.
- **Edge AI Deployment:** Deep learning models, such as MobileNet, Tiny-YOLO, etc., can now be compressed, weights quantized, and inference accelerated for deployment on embedded platforms. This will eliminate latency as walk-out throughput and allow for extremely scalable deployment across distributed production facilities.
- **Blockchain for Data Security and Traceability:** Blockchain with IoT-enabled welding systems gives a strong prospect for providing tamper-proof defect logging, traceability of parts and compliance tracking – all vital when working with safety-critical applications.
- **Augmented Reality (AR) for enhanced inspection:** By integrating AR systems with AI systems, human inspectors can be displayed real-time, visual overlays of defects identified among welds, optimizing the level of accuracy and collaborative effort during quality audits.

These enhancements will facilitate the advancement toward having a powerful, intelligent, and completely automated **Weld Quality Monitoring**

System that is suitable for an **Industry 4.0 era and for smart manufacturing initiatives.**

Conclusion: This project established a comprehensive discussion of intelligent solutions to assessing weld quality on Submerged Arc Welding (SAW), unifying the traditional statistical modelling and the new deep learning approach. The statistical modelling showed a very suitable capability to classify weld defects based on understandable and measurable parameters when using the feature-based modelling approach. It could consistently and understandably articulate a definitive conclusion of whether the weld defect was acceptable or not. This leads to a strong argument that it is appropriate for real-time quality control in the industrial welding arena.

The Convolutional Neural Networks (CNN) model, similarly demonstrated the power of image-based analysis; particularly, the capacity to identify complex visual anomalies and microstructural differences that would be difficult to represent using conventional features. The question of variability in generalization will always remain, however, the CNN model demonstrated the promise of automated feature extraction to increase the accuracy of defect detection on structures containing unstructured data.

The complementary advantages of statistical versus deep learning approaches, open up possibilities for the creation of hybrid AI systems that build upon feature-based reasoning and visual pattern recognition, providing more accurate, adaptable, and robust systems for the assessment of weld quality, that will work across a larger set of welding conditions.

Future research could be directed towards hybrid AI models that combine IoT-enabled sensor data (e.g. thermal, acoustic, electrical) and multi-modal assessment, allowing for real-time, automated decision-making. Within manufacturing environments, the implementation of edge-compute, offline decision-making, computation, and low latency decentralized monitoring will become the norm. In addition, there are opportunities for synergy with advances in reinforcement learning for confinement assessments, blockchain using project specific identifiers for secure data traceability certification, and augmented reality-assisted inspections towards the vision of a fully autonomous nature-inspired intelligent welding ecosystem.

These advancements in electronic monitoring have opened the door to the next generation of smart data-driven weld quality monitoring solutions aligned with Industry 4.0 principles and driving improvements in efficiency, reliability, and safety in critical industrial processes.

Acknowledgements: The authors sincerely appreciate the support of Mechanical Engineering Department, Bhagwant University, Ajmer, and Shree Dhanvantri College of Engineering and Technology, Surat for providing the resources to enable to carry out this research. We also thank our associates and technical staff for feedback and assistance during the experiment.

Funding Statement: There is no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of Interest: The authors declare that they have no conflict of interest with respect to the publication of this article.

Author Contributions: Mirza Farhatulla Baig: Conceptualization, methodology design, data curation, software implementation, and writing the original draft.

Prof. Dharmendra Dubey: Supervision, critical review and editing, and validation of experimental design and results.

References

1. Gook, S., El-Sari, B., Biegler, M., Rethmeier.&., M. 2024. *Application of AI-based welding process monitoring for quality control in pipe production.* The Paton Welding Journal, (6), 3-8.
2. **Kesse.M.** 2021. *Artificial Intelligence : A Modern Approach to Increasing Productivity and Improving Weld Quality in Tig Welding*. Ph.D. Thesis, Lappeenranta-Lahti University of Technology (LUT), Lappeenranta, Finland, Acta Universitatis Lappeenrantaensis 972.
3. Kumar, V., Parida, M. 2022. *The state-of-the-art methodologies for quality analysis of arc welding process using weld data acquisition and*

analysis techniques. International Journal of System Assurance Engineering and Management, 13(1), 34-56.

4. Wang, B., Hu, S. 2020. *Intelligent welding system technologies: State-of-the-art review and perspectives.* Journal of Manufacturing Systems, 56, 373-391.
5. Nadeau, F., Thériault, B., Gagné.&., M. 2020. *Machine learning models applied to friction stir welding defect index using multiple joint configurations and alloys.* Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications, 234(5), 752-765.
6. Shah, M. 2023. *Statistical modelling and optimization of clad characteristics in SAW welding of SS-304.* Welding International, 37(5), 237-253.
7. Devaraj, J., Ziout, A., Qudeiri. &., J. 2021. *Grey-based taguchi multiobjective optimization and artificial intelligence-based prediction of dissimilar gas metal arc welding process performance.* Metals, 11(11), 1858.
8. Thompson Martinez, R., & Crisóstomo Absi Alfaro, S. (2021). *Data Analysis and Modeling Techniques of Welding Processes: The State-of-the-Art.* IntechOpen. doi: 10.5772/intechopen.91184
9. Wordofa, T. 2024. *An artificial intelligence system for quality level–based prediction of welding parameters for robotic gas metal arc welding.* The International Journal of Advanced Manufacturing Technology, 132(7), 3193-3212.
10. Stavropoulos, P., Papacharalampopoulos, A., Sabatakakis.&., K. 2023. *Robust and secure quality monitoring for welding through platform-as-a-service: A resistance and submerged arc welding study*. Machines, 11(2), 298.
11. Vasan, V., Sridharan, N. 2024. *Ensemble-based deep learning model for welding defect detection and classification.* Engineering Applications of Artificial Intelligence, 136, 108961.
12. Amirafshari, P., Kolios.&., A. 2022. *Estimation of weld defects size distributions, rates and probability of detections in fabrication yards using a Bayesian theorem approach.* International Journal of Fatigue, 159, 106763.
13. Liu, Y., Liu, F., Zhang, W., Ding, X., Arai.&., F. 2024. *Prediction and optimization of joint quality in laser transmission welding using serial artificial neural networks and their integration with Markov decision process*. Journal of Laser Applications, 36(3).
14. Sada, S. 2020. *The use of multi-objective genetic algorithm (MOGA) in optimizing and predicting weld quality.* Cogent Engineering, 7(1), 1741310.
15. Stavropoulos, P., Papacharalampopoulos, A., Sabatakakis.&., K. 2023. *Data Attributes in Quality Monitoring of Manufacturing Processes: The Welding Case.* Applied Sciences, 13(19), 10580.
16. Kumar.A. Mishra.M. 2020. *Welding Quality Prediction Using Advanced Artificial Intelligence Techniques*. *International Journal of Research in Development and Advanced Sciences and Engineering (IJRDASE)*. 8(1)
17. Mehta, A., Vasudev.&., H. 2024. *Advances in welding sensing information processing and modelling technology: an overview.* Journal of Adhesion Science and Technology, 1-45.
18. Devaraj, J. (2021). *Minimization of the weld distortion by weld sequence optimization using artificial intelligence* (Master's thesis). United Arab Emirates University.
19. Aswal, V. 2021. *Review on the behavior of various parameters on heat distribution in the SAW process.* Materials Today: Proceedings, 47, 6734-6739.
20. Patra.P., P., Pathak.&., D. 2024. *ARTIFICIAL INTELLIGENCE: ANALYSIS OF VARIOUS AGENT PROGRAMMING LANGUAGES.* In International Journal for Research in Advanced Computer Science and Engineering, 10(1), 1-5.
21. Baig, M. F., & Dubey, D. (2025). Real-time defect detection in submerged arc welding using AI and IoT sensors. *International Journal of Emerging Technologies and Innovative Research (IJETIR) Proceedings*, *5*(3), 94–102.