

Thermal Data-Driven Quality Prediction in Wire Arc Additive Manufacturing via Machine Learning and Anomaly Detection

Muhammad Zaiyad Muda^{1*}, Muhammad Azri Bidin¹,
Mohammed Abdullah Ali Baharoon¹, Muhd Faiz Mat^{1,2}

¹Faculty of Mechanical Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor

²Smart Manufacturing Research Institute (SMRI), Universiti Teknologi MARA, 40450 Shah Alam, Selangor

ARTICLE INFO

Article history:

Received 6 January 2026

Revised 11 July 2026

Accepted 13 July 2026

Published 15 September 2026

Keywords:

Wire arc additive manufacturing

Machine learning

Anomaly detection

Quality prediction

DOI:

10.24191/jmeche.v23i3.9993

ABSTRACT

Maintaining consistent quality control is a significant challenge in Wire Arc Additive Manufacturing (WAAM). However, real-time monitoring remains difficult due to the impracticality of manual labelling of complex, continuous thermal data during production. This paper proposes a framework utilizing temperature data and the combination of machine learning and anomaly detection algorithms. The temperature data was collected during the fabrication process of a five-layer wall using six thermocouple sensors attached to the baseplate. DBSCAN clustering algorithm was employed to identify the anomalies in the temperature data to classify them into 'normal' and 'anomaly' categories. In this study, six supervised machine learning algorithms were applied to predict the weld quality. Across the ten experimental trials, it was demonstrated that Random Forest scored the highest accuracy of 98.62% and AUC of 99.45%. Results proved that the combination of anomaly detection and machine learning algorithms with the thermal data is highly effective in predicting the quality in the WAAM process.

Introduction

Additive manufacturing (AM) provides a high degree of flexibility and speed for producing parts. Unlike subtractive manufacturing, which involves removing material from a workpiece, AM creates parts layer by layer (Dhanola & Prasad, 2024). Wire Arc Additive Manufacturing (WAAM) is a process where an electric arc is combined with a wire as deposition material (Treutler & Wesling, 2021; Musa et al., 2025). Among the applications of WAAM are load-bearing components in the construction and aviation sector (Baier et al., 2022), and components in automotive, marine and energy sectors (Hussein et al., 2023; Sarıkaya et al., 2024).

^{1*} Corresponding author. E-mail address: zaiyad@uitm.edu.my
<https://doi.org/10.24191/jmeche.v23i3.9993>

In the WAAM process, metal components are made using 3D CAD models, layer by layer. Among the benefits of WAAM are its ability to manufacture complex shapes, as well as reducing the material waste (Hamrani et al., 2024). Even though it is known for its high speed, it still suffers from the huge amount of heat input (Zeng et al., 2021). The heat produced during WAAM process may cause residual stress and thermal distortion, which have an effect on the quality of final products (Siddiqui et al., 2025). Fig. 1 shows a sample of WAAM product.



Fig. 1. Sample of WAAM product.

Ensuring consistent part quality remains an intricate issue in the WAAM processes. Specifically, it is difficult to foresee defects during the parts production. Significant temperature gradients may cause material stress, leading to cracking or deformation in thin-walled structures (Boopathy et al., 2025). Furthermore, conventional post-process inspections lack the speed required for real-time monitoring, making it impossible to intervene during production (Inayathullah & Buddala, 2025).

Recent machine learning studies in WAAM have focused heavily on modeling the relationships between static process parameters, such as current, voltage, and the resulting track or bead geometry (Xiao et al., 2022; Mamedipaka et al., 2024). Concurrently, in-situ temperature and interlayer thermal monitoring have emerged as critical determinants of heat input and final surface quality, making them essential for achieving consistent wall geometry during the layer-by-layer deposition process (Kumar & Mandal, 2023; Baier et al., 2022, 2023).

The definition of quality in this framework is structural integrity against thermal-stress-induced defects, particularly solidification cracking. The target variable is binary: Anomaly (1) indicates irregular temperature profiles and Normal (0) indicates steady thermal gradients. According to Nie et al. (2022), one of the main causes of solidification cracking is the inability of molten metal to adequately feed gaps between emerging dendrites due to uneven temperature profiles. Unlike previous studies that rely on manual defect labelling and static input parameters, the novelty of this work lies in using an unsupervised DBSCAN algorithm to automatically generate quality pseudo-labels directly from raw, in-situ thermal profiles to enable fully autonomous real-time monitoring.

This study proposes a machine learning-based framework for quality prediction in WAAM using thermal data. DBSCAN clustering is employed on the unlabeled data to identify the anomalies, where the data points are automatically labelled as normal or anomaly. Using this fully labelled data, six supervised machine learning algorithms - AdaBoost, Decision Tree (DT), K-Nearest Neighbors (KNN), Support

Vector Machine (SVM), Random Forest (RF), and Gradient Boosting Machine (GBM), are applied to predict the quality of WAAM product.

This paper presents a preliminary hybrid framework that integrates unsupervised anomaly detection with supervised classification. This study departs from conventional parametric evaluations of WAAM inputs by examining the capability of predictive models trained using DBSCAN-generated pseudo-labels, with the aim of enabling automated quality monitoring in manufacturing environments where label data are unavailable.

Methodology

This research combines unsupervised anomaly detection with multiple machine learning techniques to overcome the difficulties of real-time quality monitoring in WAAM. This section outlines the WAAM process, data collection and labeling, and the development of machine learning models capable of predicting the quality of WAAM products.

WAAM process and data collection

The Metal Inert Gas (MIG) method was used to produce a five-layer wall. Six thermocouples were installed on the baseplate to collect the temperature data at six different locations. As a result, a dataset consisting of 6,382 temperature samples from six different sensors was formed, as well as the recorded time. The completed dataset did not have any label at this stage, making it possible to perform an unsupervised learning process. Fig. 2 is a diagram showing the WAAM wall and the position of the thermocouple sensors.

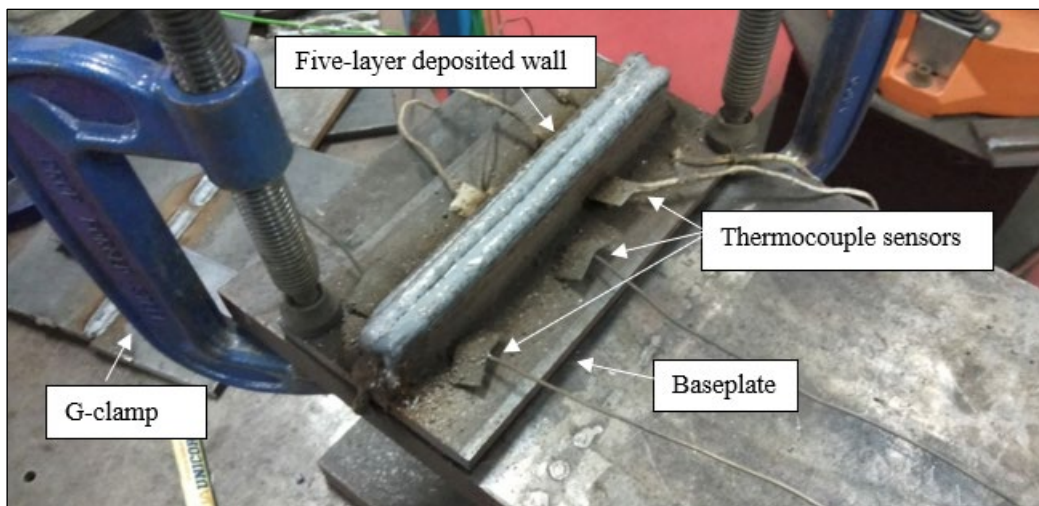


Fig. 2. WAAM wall and thermocouples position.

Fig. 3 shows the time-series thermal profiles during the WAAM process. The cyclical temperature peaks (440-550 °C) correspond to the successive torch passes during the deposition of the five layers. Rapid temperature increases indicate localized heat input from the electric arc, while the subsequent declines represent substrate cooling between deposition passes.

The experimental setup in the laboratory, as shown in Fig. 4, comprises a Metal Inert Gas (MIG) torch integrated with a multi-axis robotic arm. The wire electrode melting process is done by the torch, which is controlled by the multi-axis robotic arm (top panel). The bottom panel of Fig. 4 indicates the layered metal substrate, which is the final component produced in the WAAM process.

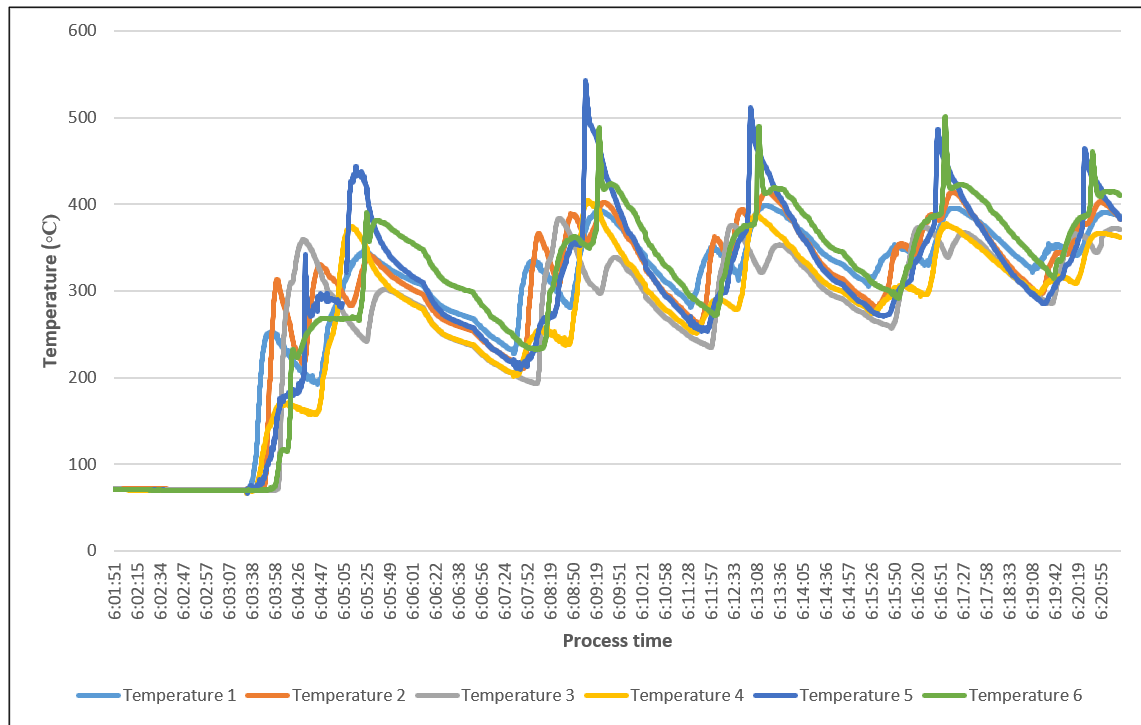


Fig. 3. Time-series temperature profiles for 6 thermocouples.

Unsupervised anomaly labelling using DBSCAN

The data collected in the previous section was then transferred to MATLAB for training and analysis. In this semi-supervised setting, pseudo labelling was needed so that the clusters of data could be assigned with meaningful labels through anomaly detection. In the anomaly detection stage, DBSCAN clustering technique (Widyawati & Fauzan, 2025) was applied to generate pseudo-labels for initially unlabeled thermal data. This involved computation of statistical features of the temperature dataset. Data points that were identified as outliers were labelled as anomaly whereas all other data points were classed as normal (Khan et al., 2024). Since we are distinguishing between ‘anomaly’ and ‘normal’ states, we treated this as a binary classification problem.

Step 1: Multi-dimensional feature extraction

The continuous raw temperature profiles from the six thermocouples were segmented into welding cycles, from which statistical features were extracted. In this study, statistical features from each thermal sequence T_i were extracted to form the input for DBSCAN:

$$x_i = [\mu_i, \sigma_i, \max(T_i), \min(T_i)] \quad (1)$$

where x_i is the feature vector for instance i , μ_i is the average of the temperature signal T_i , σ_i is the standard deviation of the temperature signal T_i , $\max(T_i)$ and $\min(T_i)$ are the highest and lowest points reached during that welding cycle, respectively.



Fig. 4. Experimental setup for wire arc additive manufacturing.

Step 2: Spatial distance computation

DBSCAN has two key parameters: epsilon, ε which specifies the neighborhood's radius around a point x , and minimum points (*MinPts*), representing the minimum number of neighboring points required within the ε radius (Ramadan et al., 2022). The DBSCAN algorithm operates by computing the Euclidean distance between any two vectors, p and q , in the transformed 4D feature vector x_i (as shown in Equation 1), which is defined as:

$$d(p, q) = \sqrt{\sum_{i=1}^n (p_i - q_i)^2} \quad (2)$$

where n is the number of dimensions, which is four (mean, standard deviation, max, min). For a specific point p , DBSCAN identifies the ε - Neighborhood $N_\varepsilon(p)$ (set of all points q within distance ε) (Jain et al., 2022).

Step 3: Neighborhood density evaluation

The algorithm scans the feature space to map the density surrounding every point p . It determines the ε - Neighborhood denoted as $N_\varepsilon(p)$, which is defined as the set of all data points q whose spatial distance from p lies within a specified radius ε :

$$N_\varepsilon(p) = \{q \in D \mid d(p, q) \leq \varepsilon\} \quad (3)$$

Step 4: Core, border, and anomaly classification

- (i) Core Point: A point p is classified as a core point if its neighborhood contains at least the minimum number of points ($|N_\varepsilon(p)| > MinPts$). These points represent areas of stable and repeatable thermal behavior.
- (ii) Border Point: A point that contains fewer neighbors than $MinPts$ but is within the ε -radius of an established core point.
- (iii) Anomaly (Noise) Point - Any points that fail to satisfy the density criteria and do not belong to any cluster are classified as anomaly (Groll et al., 2024).

$$|N_\varepsilon(p)| < MinPts \quad (4)$$

Step 5: Pseudo-label generation

Hence, the Classification Rule Used in this study (Emane et al., 2024) is as follows:

$$Classification = \begin{cases} \text{Anomaly if DBSCAN cluster} = 1 \\ \text{Normal if DBSCAN cluster} = 0 \end{cases} \quad (5)$$

The values of ε and $MinPts$ were set to be 4 and 8, respectively. The selection of $MinPts = 8$ was based on the heuristic approach $MinPts = 2n$ (Schubert et al., 2017) and the epsilon ε was chosen to maintain a maximum anomaly ratio of 10% (Sencan et al., 2025).

It is important to note that the generated pseudo-labels act as a proxy for process instability rather than a post-process material defect. Obtaining physical ground-truth labels through manual inspection is impractical for large-scale time-series manufacturing data. Instead, statistical features capturing sudden temperature fluctuations were used as mathematical indicators of localized thermal gradients and potential process anomalies.

Machine learning algorithms classification and evaluation

Once the anomaly labels were generated, the original six thermocouple readings were used as input features for classification. The fully labelled dataset was split into training and testing data, with a ratio of 70:30. To identify the most suitable model for predicting WAAM quality, an analysis was conducted using six supervised algorithms. To assess stability and robust performance, each algorithm was trained and evaluated for ten trials, and the average results were recorded. Table 1 shows the machine learning model configurations and their hyperparameter settings.

Table 1. Model configurations and hyperparameter settings

Algorithm	Hyperparameter Settings
AdaBoost	- Ensemble Method: AdaBoostM1 - Number of Learners: 100
Decision Tree	Split Criterion: Gini's diversity index
K-Nearest Neighbors (KNN)	- Number of Neighbors (k): 5 - Distance Metric: Euclidean
Gradient Boosting Machine (GBM)	- Ensemble Method: LogitBoost - Number of Trees: 200 - Learning Rate (η): 0.1
Random Forest	Number of Trees: 100
Support Vector Machine (SVM)	- Kernel Function: RBF / Gaussian - Kernel Scale: Auto - Box Constraint (C): 1

Fig. 5 shows the flowchart illustrating the methodology for WAAM quality prediction. The first step involved the acquisition of real-time temperature data from six thermocouples during the WAAM process, followed by feature engineering to extract statistical characteristics for anomaly detection using DBSCAN. The identified anomalies were then used to label the dataset. Six machine learning algorithms were deployed to perform binary classification of the WAAM deposition quality based on the temperature data.

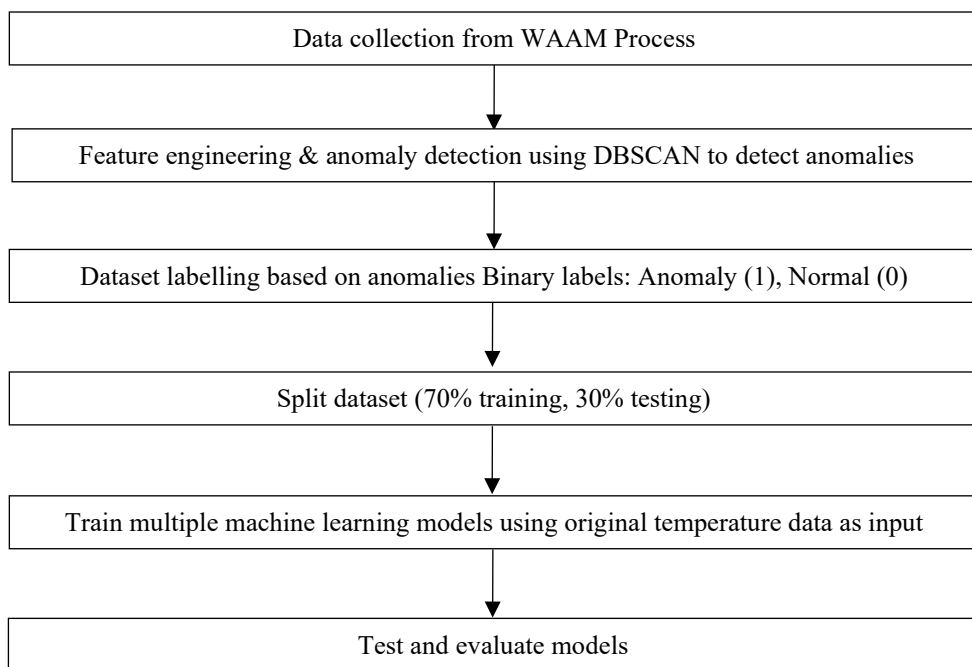


Fig. 5. Flowchart for thermal data-driven quality prediction in WAAM.

The machine learning models were evaluated using metrics shown in Equation 6 to 9. Each predicted binary label has four options: True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The formulas (Rainio et al., 2024) are given by:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (6)$$

$$Precision = \frac{TP}{TP + FP} \quad (7)$$

$$Recall = \frac{TP}{TP + FN} \quad (8)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (9)$$

Results and Discussion

A dataset was created consisting of 6,382 temperature samples collected from six thermocouple sensors, along with their corresponding timestamps. From the DBSCAN technique, the labels were assigned for each instance, where 610 out of 6,382 instances were labelled as anomaly. Fig. 6 shows the temperature signals from six thermocouple sensors with marked anomalous rows. Significant number of anomalies can be observed during the start of WAAM process due to the irregular temperature spikes and drops before the thermal conditions stabilize.

The performance of six machine learning methods was assessed in the experiment. The results were averaged over 10 independent random trials and are displayed in Table 2. This repeated random partitioning ensures that the high predictive performance is robust and not biased by a single data split. Overall, every model demonstrated outstanding classification accuracy, with each exceeding 97%. All other metrics also showed performance of above 80%, except some models in Recall. Fig. 7 shows the ROC curves and AUC performance across six machine learning models.

Among them, Random Forest recorded the highest performance for all metrics, including Accuracy (98.62%), Recall (90.84%), F1 Score (92.71%) and AUC (99.45%). These results indicate that Random Forest efficiently distinguishes between normal and anomalous states while maintaining high sensitivity to true anomalies.

GBM achieved the second highest AUC (99.12%); however, its Recall was substantially lower at 76.96%. AdaBoost and KNN also demonstrated competitive performance, with AUC of 97.51% and 97.3%, respectively. A good balance of Precision and Recall was attained by AdaBoost, whereas KNN showed a lower Recall of 85.01%. AdaBoost also recorded lowest standard deviation across most metrics, demonstrating its robustness.

It was also observed that Decision Tree performed well with 97.42% accuracy and stable performance throughout all metrics. It showed its capability in detecting the anomalies (Recall = 84.43%) which was better than complex models like SVM and GBM (76.88% and 76.96%, respectively).

Overall, comparative evaluation suggested selection of machine learning models that not only achieved excellent predictive accuracy but also were sensitive to anomalies. Although SVM and GBM achieved high accuracy, their lower Recall highlights a limited capacity for anomaly identification. These findings demonstrate that integrating unsupervised anomaly detection with supervised machine learning algorithms, particularly Random Forest, effectively forecasts WAAM products quality.

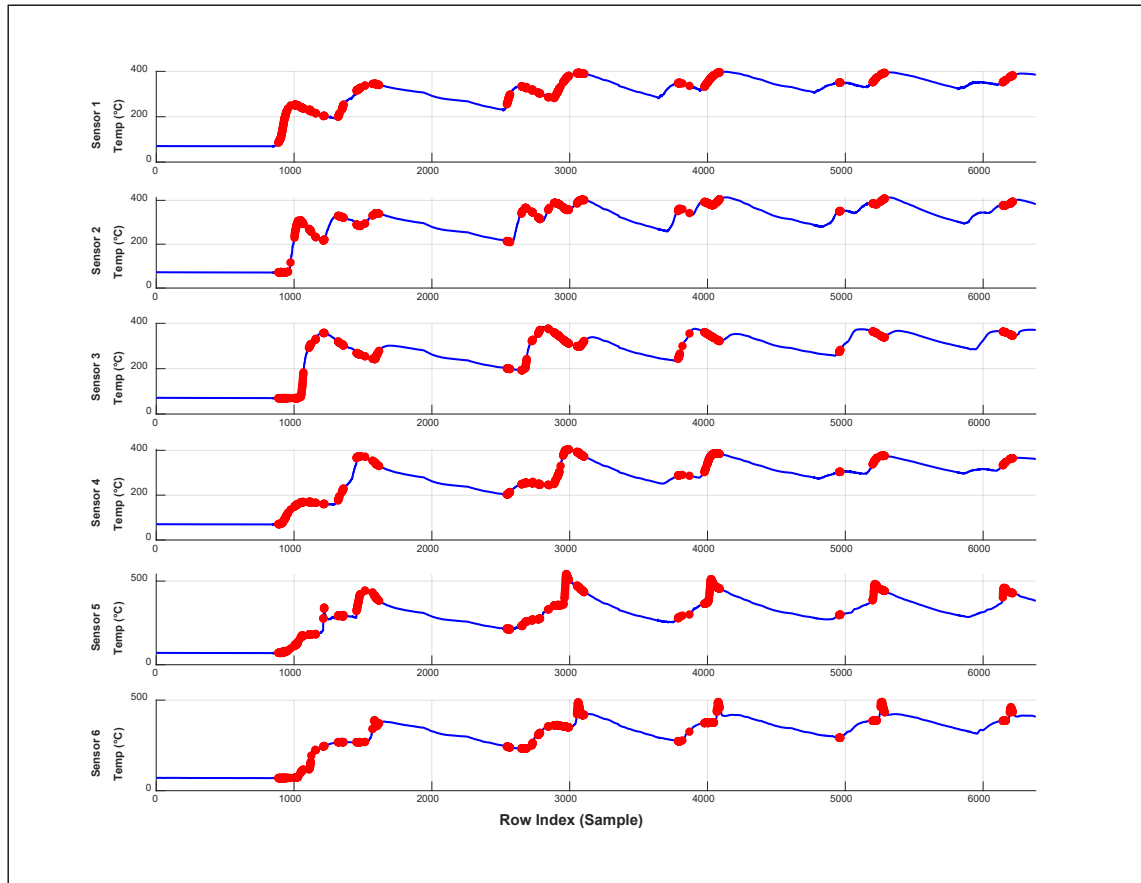


Fig. 6. Temperature signals from 6 thermocouple sensors with marked anomalous rows.

Table 2. Performance of machine learning models for WAAM quality prediction averaged over 10 independent trials

Model	Accuracy $\pm$ SD	Precision $\pm$ SD	Recall $\pm$ SD	F1 Score $\pm$ SD	AUC $\pm$ SD
AdaBoost	0.986 $\pm$ 0.0029	0.9486 $\pm$ 0.0192	0.8985 $\pm$ 0.0292	0.9226 $\pm$ 0.0171	0.9938 $\pm$ 0.0028
Decision Tree (DT)	0.9742 $\pm$ 0.0037	0.876 $\pm$ 0.033	0.8443 $\pm$ 0.0253	0.8595 $\pm$ 0.0212	0.9488 $\pm$ 0.0105
KNN	0.9792 $\pm$ 0.0036	0.9288 $\pm$ 0.0218	0.8501 $\pm$ 0.0287	0.8875 $\pm$ 0.0207	0.9872 $\pm$ 0.0057
Support Vector Machine (SVM)	0.9703 $\pm$ 0.0031	0.914 $\pm$ 0.0205	0.7688 $\pm$ 0.0357	0.8341 $\pm$ 0.0175	0.9746 $\pm$ 0.0147
Random Forest (RF)	0.9862 $\pm$ 0.0037	0.947 $\pm$ 0.023	0.9084 $\pm$ 0.03	0.9271 $\pm$ 0.0221	0.9945 $\pm$ 0.0034
Gradient Boosting Machine (GBM)	0.9728 $\pm$ 0.0054	0.937 $\pm$ 0.0307	0.7696 $\pm$ 0.0404	0.8444 $\pm$ 0.0292	0.9912 $\pm$ 0.0019

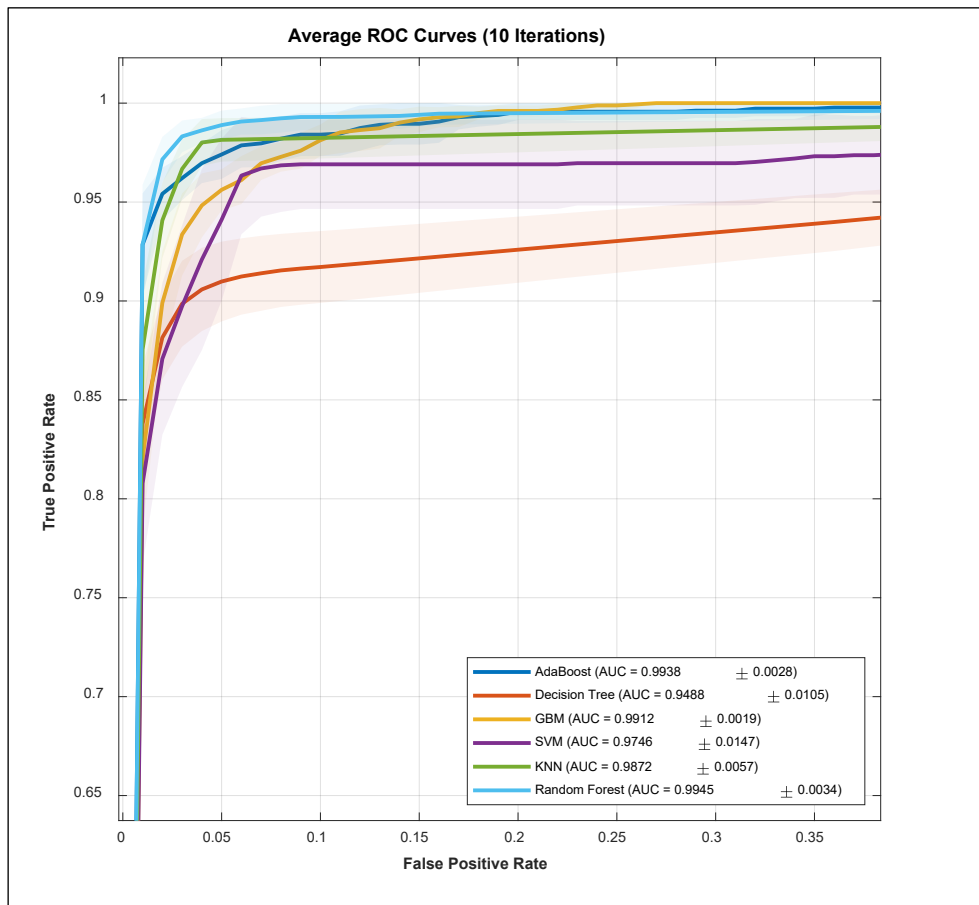


Fig. 7. ROC curves and AUC performance across six machine learning models.

The results of this study were benchmarked against related research in literature. For example, Li et al. (2022) reported a high accuracy of 98%, 97.67% Recall, 98.44% Precision and F1-score of 98.05% for the defect detection system using incremental learning. They used a Support Vector Machine within an incremental learning framework to detect potential defects by tracking welding signal disturbance. In another research, Westphal and Seitz (2021) utilized Convolutional Neural Network for defect detection and attained accuracy of 97.1%, Precision of 96.3%, Recall of 98%, F1-score of 97.2% and AUC of 99.3%. Their study addressed the additive manufacturing process by employing transfer learning to classify powder bed defects. This comparison suggests that the integrated approach of using DBSCAN and supervised machine learning algorithms is highly effective for real-time quality prediction in the WAAM process.

A temporal density analysis of the anomaly occurrence was performed to assess process stability throughout the fabrication. The first 20% of the process produced a higher anomaly ratio of 11.05% compared to 9.18% in the remaining steady state phase. This can be observed in Fig. 8, where a substantial number of anomalies is recorded near the 1000-row index due to the initial thermal shock that occurred as the welding arc hits the cold baseplate (Su et al., 2025). Subsequent clusters, for example at the 3000 and 4000 indices, corresponded to interlayer transitions and arc re-strikes for new layers. It was also observed that there were some gaps around the 2000-row index, which corresponded to period of steady-state deposition. Overall, this pattern accurately reflected the physical stages of the WAAM deposition process.

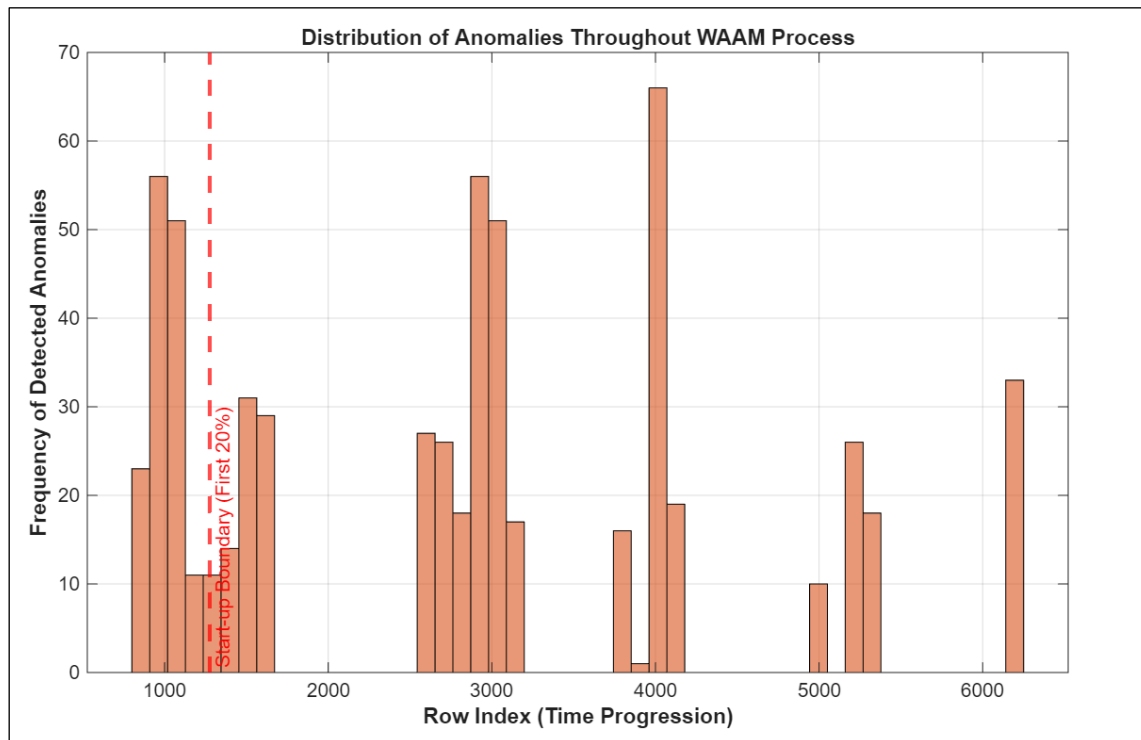


Fig. 8. Temporal distribution of detected anomalies across the WAAM deposition sequence.

For future research, the unsupervised learning framework used in this research (particularly in the anomaly detection phase) can be modified to a semi-supervised setting. Currently, the developed models learn the profile of non-anomalous thermal data points to identify any deviating instances. In a semi-supervised setting, small percentage of the WAAM products need to be tested and labelled to serve as the ground truth data, while the remaining unlabeled products are labelled through techniques like pseudo-labelling or consistency regularization.

Conclusion

This study proposed a framework that evaluated six machine learning techniques for quality prediction in WAAM. An unlabeled thermal dataset consisting of six thermocouples data was produced from manufacturing process of a five-layer wall. Anomaly detection based on DBSCAN algorithm was applied to detect unusual patterns in the thermal profile, leading to labelling the sensors data as either ‘normal’ or ‘anomaly’.

From the experiments, it was demonstrated that Random Forest consistently surpassed all other machine learning models in predicting the weld quality in WAAM with accuracy of 98.62% and AUC of 99.45%. KNN, Decision Tree and AdaBoost also showed good performance, while SVM and GBM recorded slightly lower Recall compared to others.

As a preliminary study, this research focused on the feasibility of an automated framework that eliminated the need for manual, time-consuming data labelling. Since compiling ground-truth labels for large-scale production is often impractical in WAAM environments, an unsupervised DBSCAN clustering was used to automatically identify thermal and process instabilities and generate labels for subsequent supervised classification. The results demonstrated the technical viability of this approach, providing a highly autonomous mechanism for instability detection while reducing reliance on post-process human inspection.

Acknowledgements/ Funding

The authors would like to acknowledge Faculty of Mechanical Engineering, UiTM for the financial support, facilities, and guidance that were provided throughout the duration of this project.

Conflict of Interest Statement

One of the authors, Muhd Faiz Mat is an editorial member of the Journal of Mechanical Engineering. The authors declare no other conflict of interest.

Authors' Contributions

The authors confirm their contribution to the paper as follows: study conception and design: M. Z. Muda; data collection: M. F. Mat; analysis and interpretation of results: M. Z. Muda; draft manuscript preparation: M. Z. Muda, M. A. Bidin, M. A. A. Baharoon. All authors consented to the submission of this manuscript.

Declaration of Generative AI in the Writing Process

During the preparation of this work, the authors used Gemini to assist with drafting, structuring, and editing the text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication

Data Availability/ Supplementary Materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics Statement

The authors declare that this research did not involve human or animal subjects. All experimental procedures were performed following the institutional Safety, Health, and Environmental (HSE) protocols of Universiti Teknologi MARA.

References

- Baier, D., Wolf, F., Weckenmann, T., Lehmann, M., & Zaeh, M. F. (2022). Thermal process monitoring and control for a near-net-shape wire and arc additive manufacturing. *Production Engineering Research and Development*, 16(6), 811–822. <https://doi.org/10.1007/s11740-022-01138-7>
- Baier, D., Weckenmann, T., Wolf, F., Wimmer, A., & Zaeh, M. F. (2023). Underlying methodology for a thermal process monitoring system for wire and arc additive manufacturing. *Journal of Manufacturing and Materials Processing*, 7(1), 10. <https://doi.org/10.3390/jmmp7010010>
- Boopathy, G., Srinivasan, V., Krasnikovs, A., & Ganesan, B. (2025). Thermal and mechanical analysis of materials in additive manufacturing. *Modeling, Analysis, and Control of 3D Printing Processes* (pp. 193-236). IGI Global Scientific Publishing. <https://doi.org/10.4018/979-8-3373-0533-2.ch008>
- Dhanola, A., & Prasad, D. S. (2024). A comprehensive review of wire arc additive manufacturing for metallic functionally graded materials. *Engineering Research Express*, 6(4), 042501. <https://doi.org/10.1088/2631-8695/ad82a4>
- Emane, R. D., Song, S., Lee, H., Choi, D., Lim, J., Bok, K., & Yoo, J. (2024). Anomaly detection based on GCNs and DBSCAN in a large-scale graph. *Electronics*, 13(13), 2625. <https://doi.org/10.3390/electronics13132625>
- Groll, A., Khanna, A., & Zeldin, L. (2025). A machine learning-based anomaly detection framework in life insurance contracts. *Journal of Insurance Issues*, 48(1), 84-114. <https://doi.org/10.48550/arXiv.2411.17495>
- Hamrani, A., Agarwal, A., Allouhi, A., & McDaniel, D. (2024). Applying machine learning to wire arc additive manufacturing: a systematic data-driven literature review. *Journal of Intelligent Manufacturing*, 35(6), 2407–2439. <https://doi.org/10.1007/s10845-023-02171-8>
- Hussein, N. I. S., Ket, G. C., Abd Rahim, T., Ayof, M. N., Zainal Abidin, M. Z., & Srithorn, J. (2023). Process and heat resources for wire arc additive manufacturing of aluminium alloy ER4043: a review. *Journal of Mechanical Engineering*, 20(1), 21-41. <https://doi.org/10.24191/jmeche.v20i1.21077>
- Inayathullah, S., & Buddala, R. (2025). Review of machine learning applications in additive manufacturing. *Results in Engineering*, 25, 103676. <https://doi.org/10.1016/j.rineng.2024.103676>
- Jain, P., Bajpai, M. S., & Pamula, R. (2022). A modified DBSCAN algorithm for anomaly detection in time-series data with seasonality. *The International Arab Journal of Information Technology*, 19(1), 23-28. <https://doi.org/10.34028/iajit/19/1/3>
- Khan, I. U., Jeong, S., & Sim, S. H. (2024). Investigation of issues in data anomaly detection using deep-learning- and rule-based classifications for long-term vibration measurements. *Applied Sciences*, 14(13), 5476. <https://doi.org/10.3390/app14135476>
- Kumar, V., & Mandal, A. (2023). Effect of heat input on the wire-arc additive manufactured steel structures. *MIST International Journal of Science and Technology*, 11(1), 11–20. [https://doi.org/10.47981/j.mijst.11\(01\)2023.419](https://doi.org/10.47981/j.mijst.11(01)2023.419)
- Li, Y., Polden, J., Pan, Z., Cui, J., Xia, C., He, F., Mu, H., Li, H., & Wang, L. (2022). A defect detection system for wire arc additive manufacturing using incremental learning. *Journal of Industrial Information Integration*, 27, 100291. <https://doi.org/10.1016/j.jii.2021.100291>
- Mamedipaka, R., Hemachandra, M., Mishra, A., Sinhar, S., & Thapliyal, S. (2024). Machine learning-assisted wire arc additive manufacturing and heat input effect on mechanical and corrosion behaviour <https://doi.org/10.24191/jmeche.v23i3.9993>

- of 316L stainless steels. *Structures*, 68, 107126. <https://doi.org/10.1016/j.istruc.2024.107126>
- Musa, N., Adenan, M. S., Saedon, J., Manurung, Y. H. P., & Mat, M. F. (2025). Wire-arc additive manufacturing – forging process chain simulation analysis of aluminium alloy. *Nigerian Journal of Technological Development*, 22(1), 148–158. <http://dx.doi.org/10.4314/njtd.v22i1.3035>
- Nie, S., Li, L., Wang, Q., Zhao, R., Lin, X., & Liu, F. (2022). Effects of thermal stress on the formation and cracking behavior of nickel-based superalloys by selective laser melting based on a coupled thermo-mechanical model. *Materials*, 15(24), 8968. <https://doi.org/10.3390/ma15248968>
- Rainio, O., Teuho, J., & Klén, R. (2024). Evaluation metrics and statistical tests for machine learning. *Scientific Reports*, 14, 6086. <https://doi.org/10.1038/s41598-024-56706-x>
- Ramadan, H. S., Maghawry, H. A., El-Eleamy, M., & El-Bahnasy, K. (2022). A heuristic novel approach for determination of optimal epsilon for DBSCAN clustering algorithm. *Journal of Theoretical and Applied Information Technology*, 100(7), 2243–2253.
- Sarıkaya, M., Önlér, D. B., Dağlı, S., Hartomacıoğlu, S., Günay, M., & Królczyk, G. M. (2024). A review on aluminum alloys produced by wire arc additive manufacturing (WAAM): applications, benefits, challenges and future trends. *Journal of Materials Research and Technology*, 33, 5643–5670. <https://doi.org/10.1016/j.jmrt.2024.10.212>
- Schubert, E., Sander, J., Ester, M., Kriegel, H. P., & Xu, X. (2017). DBSCAN revisited, revisited: why and how you should (still) use DBSCAN. *ACM Transactions on Database Systems*, 42(3), 1-21. <https://doi.org/10.1145/3068335>
- Sencan, E., Lee, Y. C., Casey, C., Schwaller, B., Leung, V. J., Brandt, J., Kulis, B., Egele, M., & Coskun, A. K. (2025). Refine: A robust approach to unsupervised anomaly detection for production HPC systems. *Proceedings of the 40th International Conference on High Performance Computing* (pp. 1–12). IEEE Publisher. <https://doi.org/10.23919/ISC.2025.11018307>
- Siddiqui, N. A., Muzamil, M., Jamil, T., & Hussain, G. (2025). Heat sources in wire arc additive manufacturing and their impact on macro-microstructural characteristics and mechanical properties – an overview. *Smart Materials in Manufacturing*, 3, 100059. <https://doi.org/10.1016/j.smmf.2024.100059>
- Su, J., Xiao, G., Zhao, L., Abbas, Z., Li, J., Li, L., Li, M., & Kao-Walter, S. (2025). Thermal shock effect on microstructure, electrical properties and corrosion performance of ultrasonically welded wire harness-terminal joints. *Materials & Design*, 260, 114949. <https://doi.org/10.1016/j.matdes.2025.114949>
- Treutler, K., & Wesling, V. (2021). The current state of research of wire arc additive manufacturing (WAAM): a review. *Applied Sciences*, 11(18), 8619. <https://doi.org/10.3390/app11188619>
- Westphal, E., & Seitz, H. (2021). A machine learning method for defect detection and visualization in selective laser sintering based on convolutional neural networks. *Additive Manufacturing*, 41, 101965. <https://doi.org/10.1016/j.addma.2021.101965>
- Widyawati, D. K., & Fauzan, A. (2025). An ST-DBSCAN approach to spatio-temporal clustering of earthquake events in West Java, Indonesia. *Jurnal Teori dan Aplikasi Matematika*, 9(4), 1292–1308. <https://doi.org/10.31764/jtam.v9i4.33079>
- Xiao, X., Waddell, C., Hamilton, C., & Xiao, H. (2022). Quality prediction and control in wire arc additive manufacturing via novel machine learning framework. *Micromachines*, 13(1), 137. <https://doi.org/10.3390/mi13010137>

Zeng, J., Nie, W., & Li, X. (2021). The influence of heat input on the surface quality of wire and arc additive manufacturing. *Applied Sciences*, 11(21), 10201. <https://doi.org/10.3390/app112110201>



© 2026 by the authors. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY-NC-SA) license (<https://creativecommons.org/licenses/by-nc-sa/4.0/>)