



Article

Predictive Modelling of Weld Bead Geometry in Wire Arc Additive Manufacturing

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Abstract: This study investigates the predictive modelling of weld bead geometry in wire arc additive manufacturing (WAAM) through advanced machine learning methods. While WAAM is valued for its ability to produce large, complex metal parts with high deposition rates, precise control of the weld bead remains a critical challenge due to its influence on mechanical properties and dimensional accuracy. To address this problem, this study utilized machine learning approaches—Ridge regression, Lasso regression and Bayesian ridge regression, Random Forest and XGBoost—to predict the key weld bead characteristics, namely height, width and cross-sectional area. A Design of experiments (DOE) was used to systematically vary the welding current and travelling speed, with 3D weld bead geometries captured by laser scanning. Robust data pre-processing, including outlier detection and feature engineering, improved modelling accuracy. Among the models tested, XGBoost provided the highest prediction accuracy, emphasizing its potential for real-time control of WAAM processes. Overall, this study presents a comprehensive framework for predictive modelling and provides valuable insights for process optimization and the further development of intelligent manufacturing systems.



Academic Editor: Mohamed Elbestawi

Keywords: wire arc additive manufacturing (WAAM); predictive modelling; machine learning; weld bead geometry; XGBoost

Received: 1 February 2025

Revised: 13 February 2025

Accepted: 17 February 2025

Published: 19 February 2025

Citation: Šket, K.; Brezočnik, M.; Karner, T.; Belšak, R.; Ficko, M.; Vuherer, T.; Gotlih, J. Predictive Modelling of Weld Bead Geometry in Wire Arc Additive Manufacturing. *J. Manuf. Mater. Process.* **2025**, *9*, 67. <https://doi.org/10.3390/jmmp9020067>

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1. Introduction

Wire Arc Additive Manufacturing (WAAM) has emerged as a transformative approach within the broader spectrum of Additive Manufacturing (AM) technologies. By utilizing arc welding as the heat source and wire as the material input, WAAM enables the production of large, complex metal components with high deposition rates at low costs [1,2]. This unique approach differs from other AM processes such as Powder Bed Fusion (PBF) and Directed Energy Deposition (DED) as it enables the production of large-sized metal components, making it particularly relevant for industries such as aerospace, automotive, shipbuilding and heavy machinery production [3,4].

However, despite these promising advantages, WAAM has several process-related challenges that must be addressed to improve its industrial applicability. One of the most critical issues with this technology is the high heat input, which contributes to uneven thermal cycles and microstructural inconsistencies during layer-by-layer deposition [5]. This results in coarse and anisotropic grain structures, increasing residual stresses and reducing mechanical performance compared to other AM methods [6]. Additionally, rapid heating and cooling cycles can lead to porosity, cracking, and poor interlayer bonding,

which further degrades component quality [7]. These defects are particularly pronounced in aluminum and titanium alloys, where oxidation and gas entrapment exacerbate microstructural weaknesses [5].

Beyond material-specific concerns, thermal distortions due to excessive heat input result in unwanted geometrical deviations, internal stresses, and part warping, which compromise dimensional accuracy [6]. The control of bead geometry, surface roughness, and defect formation also remains a major challenge [7,8], as these parameters significantly influence the mechanical properties, surface finish, and post-processing requirements.

Accordingly, considerable efforts have focused on data-driven methods by integrating machine learning (ML) techniques [3,6,9]. Other areas include precise trajectory planning [10], integrating cooling conditions and material properties into trajectory design [11], employing thermal management to produce geometrically correct parts while reducing residual stresses [12–14] and, more recently, using artificial intelligence-based real-time multi-parameter control has demonstrated significant potential for error-free manufacturing [15].

In addition to the areas mentioned, effective process monitoring underpins the production of high-quality WAAM components. Closed loop and real-time monitoring enable parameter adjustment that affect weld pool temperature and surface properties without compromising mechanical performance [16,17]. Thermal imaging cameras track temperature distribution, while laser scanners measure layer geometry and surface quality in real time [18]. Non-destructive evaluation methods—such as x-ray computed tomography (CT) and ultrasonic testing—help detect internal porosity and defects, ensuring part integrity [19,20]. High-speed cameras capture the dynamic behavior of the weld pool and metal transfer, offering insights into process stability [21,22]. Spectrometers, meanwhile, monitor the composition of deposited material, identifying any impurities or deviations from the target alloy [23].

Despite these advances, the control of weld bead geometry remains critically dependent on the fundamental process parameters of travel speed and current. In this study, the influence of variations in these parameters on bead geometry is therefore examined, with the aim of refining WAAM process models and ultimately improving final part quality.

Related Work

Machine learning for WAAM

ML has proven invaluable for process optimization, quality control, and predictive modelling in WAAM. By predicting and controlling parameters such as electric current and travel speed, ML-based methods reduce trial-and-error iterations, enhance bead geometry, and minimize material waste [2,9]. Decision Trees, Random Forest, Support Vector Regression, Back Propagation Neural Networks, and XGBoost have all been employed to predict variables like surface roughness and defect formation [9,24]. Notably, XGBoost and artificial neural networks often deliver higher accuracy, especially with nonlinear input–output relationships [3,4]. In addition, advanced outlier detection techniques (e.g., local outlier factor) can help detect anomalies in welding data [25] while nested K-fold cross-validation reduces overfitting and yields robust performance estimates [26].

Parametric studies in WAAM

Parametric studies frequently focus on the influence of wire feed rate, travel speed, voltage, and interpass temperature across diverse welding materials and modelling methods. For instance, the authors of [27] employed a Taguchi test plan to optimize parameters affecting weld bead geometry and spatter, while in [28], wire feed rate and interpass temperature were investigated using an SVM-based weld bead modelling system. More complex parts were manufactured in [29] by systematically varying energy input, travel speed, and wire feed rate; however, further optimization and mechanical testing were deferred.

Study justification

Despite these advances, prior studies often address isolated aspects of WAAM modelling. This research provides a more comprehensive framework. The main aspects are presented in Table 1.

Table 1. Main aspects of study justification.

Aspect	Previous Studies	This Study
Data acquisition and cleaning	Focused on individual aspects of data collection and process modelling, often lacking systematic experimental design and advanced outlier detection [5,10,11,20]. Real-time monitoring limitations were highlighted [17]	Implements systematic Design of Experiments (DOE) and LOF-based outlier detection ([30]) for improved data robustness. Enhances real-time data acquisition for WAAM process monitoring
Feature extraction and dimensionality reduction	Relied on manual or basic feature extraction for bead geometry prediction with limited refinement [1,9,15,23]. AI-based process monitoring is emerging [18]	Automates 3D point cloud feature extraction and refines data for better interpretability and model performance. Incorporates advanced feature engineering for defect prediction
Model validation	Conventional k-fold cross-validation used, but concerns remain regarding bias mitigation and generalization [3,9,12,24]	Employs nested k-fold cross-validation ([31]) to improve model generalization and selection robustness
Polynomial feature transformation	Nonlinear relationships in WAAM were noted but lacked systematic polynomial feature transformation [7,8,16,22]	Systematically explores polynomial transformations to capture nonlinear bead geometry variations
Model explainability	ML models were treated as “black boxes” with limited feature importance analysis [6,9,10,14,25]	Integrates SHAP analysis for feature contribution transparency, improving model interpretability
Model comparison	Previous studies compared ML models for WAAM outcomes but lacked a unified framework and ensemble methods [3,6,9,19,26,27]	Conducts a comprehensive ML model comparison, integrating ensemble and hybrid approaches for WAAM predictions

By uniting these methods, particularly FE, PF, rigorous validation, and model explainability, this study aims to establish a more holistic and reliable approach to ML-driven process modelling in WAAM.

2. Materials and Methods

A three-stage process was employed to investigate the influence of welding parameters on the geometry of the resulting weld bead. This process included welding tests, measure-

ment of weld seams, and computational analysis for extracting geometric properties. A summary of the process is presented in Figure 1.

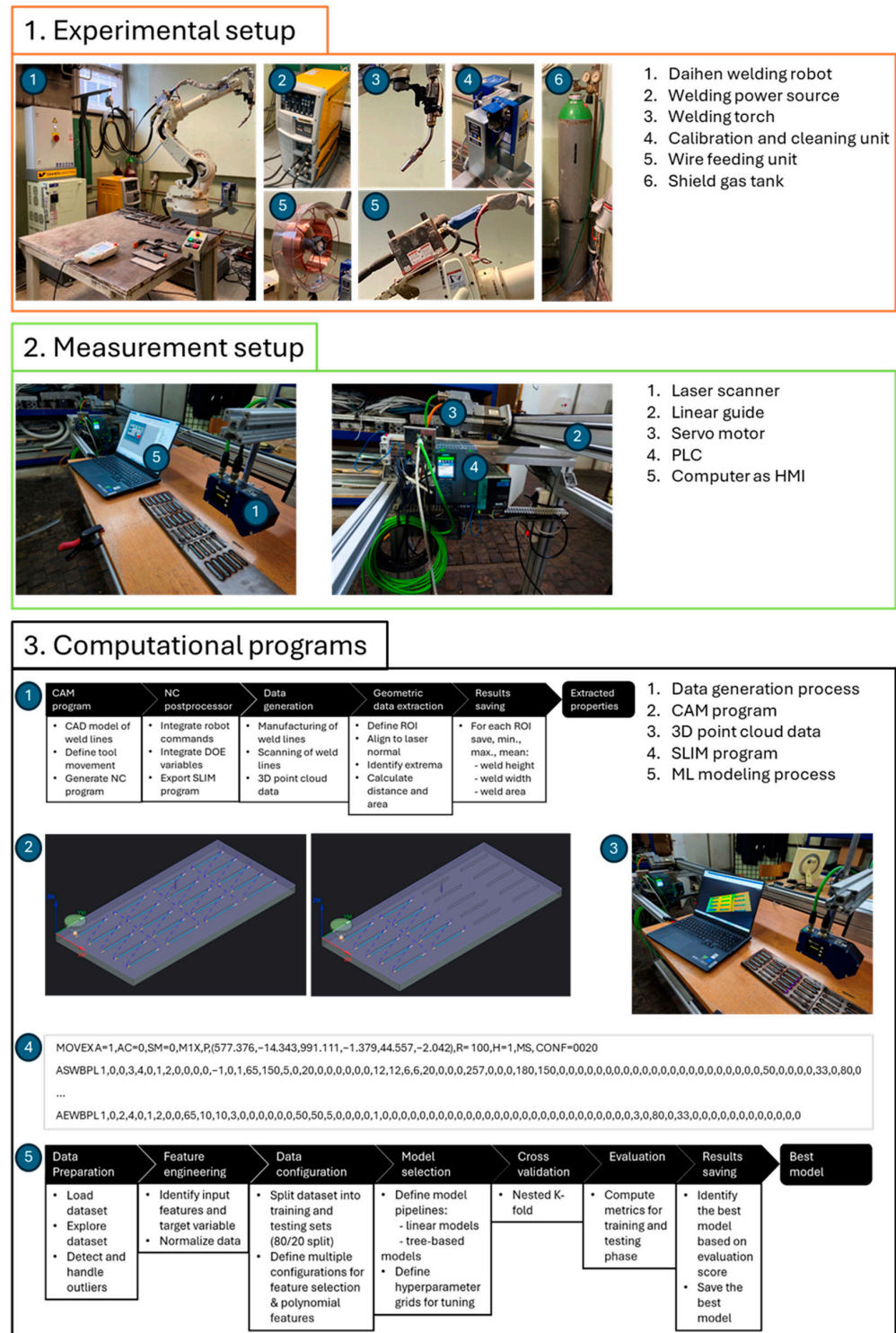


Figure 1. Materials and methods for modelling of weld bead geometry in wire arc additive manufacturing.

2.1. Experimental Setup

An experiment was conducted to examine how welding parameters influence the geometry of the resulting weld bead. The test utilized an S355 steel plate measuring 250 mm by 120 mm, along with a solid copper-coated welding wire (VAC 60) with a 1.2 mm diameter. The wire's chemical composition is presented in Table 2.

Table 2. Chemical composition of VAC 60 welding wire.

Element	Weight Fraction [wt%]
C	0.08
Si	0.90
Mn	1.50
P	<0.025
S	<0.025

2.1.1. Robotic Cell

In the robotic cell, a Daihen NV8L-NEFC welding robot was paired with an FD1 controller. A WB-P500L DC welding power source was employed, and the robot was outfitted with an MTX group welding torch (featuring an integrated shock sensor), and a Daihen AF-4012 wire feeder. A mixture of argon and carbon dioxide was used as shielding gas. A J. Thielmann BRG-2000 DE served for calibration and cleaning. The robotic cell with all components was provided by Daihen Varstroj Slovenia.

Offline programming in SLIM (Standard Language for Industrial Manipulator) language which complies with the JIS B8439 standard was performed, requiring only three commands: MOVEX for motion and ASWBPL/AEWBPL for arc start/end. Robot motion control was restricted to movement type (linear or point-to-point), coordinates, speed, and configuration; welding current and travel speed were the adjustable parameters for the process.

2.1.2. Experimental Matrix

A full factorial design was applied with two independent variables (welding current and travel speed) and three dependent variables (bead height, width, and cross-section area). Welding current ranged from 65–155 A (in 10 A increments) and travel speed ranged from 20–40 cm/min (in 5 cm/min increments), resulting in 50 welded lines (testing samples). Arc start/end parameters remained constant and “Synergic Mode” automatically adjusted voltage based on welding current. Table A1 presents experimental data together with the extracted features.

2.2. Measurement Setup

A Wenglor MLWL 132 laser scanner (Tettnang, Germany) was used to measure the weld bead surface. The sensor was mounted on a servo-driven linear guide for three-dimensional scanning. A Siemens PLC S7-1500 (Munich, Germany) with an S120 CU310 controller (Munich, Germany) controlled the linear unit, and the scanning was initiated at 0.5 mm intervals. The measurement data was transmitted via TCP/IP to a computer running MATLAB R2023b, where it was stored in PLY format. The computer also served as a virtual human–machine interface (HMI).

2.3. Computational Programs

Several computer programs were developed to support the WAAM process and analyze the results. A CAM setup was modelled in Siemens NX, generating toolpaths and G-code for post-processing. A custom post-processor handled welding activation and welding and non-welding movements. Robot-specific commands were added, including work frame setup and tool cleaning. A custom algorithm extracted geometric properties from 3D scan data. Since the definition of the regions of interest for the extraction of the geometric features was done manually and based on the visual identification of the start and end zones of the weld bead arc, an outlier detection algorithm was integrated to

identify possible poorly defined regions of interest. Different ML algorithms were trained on the prepared data to model geometric properties, and the best was chosen based on performance metrics.

2.3.1. CAM Programming

In Siemens NX, a base plate and 50 welding lines of 40 mm each were modelled to prepare the CAM setup for the welding process. The manufacturing coordinate system was defined in the plate's corner. The `freeform_additive_fixed_axis_thinwall` operation from the NX Additive Manufacturing add-on was used to generate the tool paths. Linear movements were specified for engagement, retraction, and transfer, with a 10 mm safety distance above the plate for transfers.

2.3.2. Postprocessor

NC code exported from Siemens NX was automated through the postprocessor, which converted motion commands into the required SLIM format and integrated DOE variables for welding. The NC code text file was loaded and analyzed, and the robot frame was aligned with the manufacturing coordinate system. Robot configuration and linear/point-to-point commands were adjusted to ensure desired speeds, and position/orientation coordinates were extracted with process-specific transformations applied. The DOE welding process was integrated by replacing deposition-activation commands with arc-start commands and adding experimental variables for robot travel speed and welding current. Safety and cleaning routines were added at the start of the program. Finally, a modified SLIM-format program was generated, ensuring the required structure and robot compatibility.

2.3.3. Algorithm for Extraction of Geometric Properties

An algorithm was developed to extract geometric properties from the line laser scanner data by processing 3D point clouds and isolating regions of interest (ROIs). ROIs were individually and manually defined for each weld bead by filtering data points on spatial coordinates. Because the plate and laser scanner were not aligned and the base plate was curved due to thermal stress, point cloud data had to be realigned with the sensor's XY plane. First, welded bead points were separated from base plate points. Next, a plane was fitted to the base plate, rotated to align with the XY sensor plane, and translated to the $Z = 0$ plane. A transformation matrix was created from these steps and applied to each point in the constrained ROI. After the transformation, geometric features (height, width and area) were extracted. For each scan line in the Y direction, height, width, and area were calculated using maximum/minimum X and Z values, and a polygon-based area calculation. Finally, minimum, average, and maximum values for each feature were calculated across the Y direction.

2.3.4. Data Analysis and Modelling Techniques

Once the geometric properties were extracted, data analysis and modelling techniques were used to transform the raw data into actionable insights. In the first phase, outliers were detected so that anomalies could be identified and corrected to ensure cleaner and more reliable datasets. The data were then standardized to ensure that feature scales were aligned for improved model stability and performance. As the framework progressed, ML modelling techniques were implemented to create predictive models that capture relationships within the data. Regression metrics were used to evaluate the performance of the models created. This structured approach enabled comprehensive data analysis and predictive modelling. The employed ML modeling process is schematically shown in Figure 1.

2.3.5. Modelling Methods Overview

To predict the target variable, both regularized linear models and tree-based methods were evaluated, with hyperparameters tuned to optimize performance. Table 3 presents an overview of the methods considered, including their descriptions, hyperparameter search spaces, and references. The models were selected to ensure a balance between interpretability, regularization, and predictive power.

Table 3. Overview of the methods used.

Method	Description	Parameters Tuned	Method Reference
RR	Introduces an L2 penalty on model coefficients to mitigate overfitting.	Alpha: {0.1, 1.0, 10.0}	[32]
LR	Applies an L1 penalty, shrinking some coefficients to zero and effectively performing feature selection.	Alpha: {0.001, 0.01, 0.1}	[33]
BR	Extends Ridge by assigning a Gaussian prior to coefficients and inferring hyperparameters from the data. This typically removes the need for extensive manual tuning of alpha.	None tuned	[34]
RF	Trains an ensemble of decision trees on bootstrap samples of the data.	Number of estimators: {50, 100, 200}, max depth: {none, 5, 10}, max features: {none, "sqrt", "log2"}, min samples split: {2, 5, 10}	[35]
XGBoost	Uses gradient-boosted trees with advanced regularization and efficient computations.	Number of estimators: {100, 200, 500}, max depth: {3, 5, 7}, learning rate: {0.01, 0.05, 0.1}, subsample: {0.6, 0.8, 1.0}, alpha: {0, 0.1, 0.5}, lambda: {1, 1.5, 2}	[36]

2.3.6. Discovering Outliers

Outlier detection was performed to ensure the robustness and reliability of the model by identifying and addressing extreme values that could have a negative impact on the model's performance [37]. Outliers were detected using the local outlier factor (LOF) method proposed by Breunig et al. [30]. LOF is a density-based anomaly detection algorithm that identifies outliers by comparing the local density of a data point with the local densities of its neighbors. Settings used for LOF are presented in Table 4.

Table 4. Settings used for LOF.

Parameter	Value
<i>n</i> -neighbors	20
contamination	0.05 (5%)
metric	Euclidean

Explanation:

- *n*-neighbors is the number of neighbors considered in the calculation of local densities to ensure a balance between sensitivity to local and global outliers.
- Contamination is the proportion of data expected to be outliers. A value of 5% is a common assumption for the detection of rare anomalies.
- Metric is the standard distance metric for numeric and scaled data.

2.3.7. Data Standardization

To eliminate possible discrepancies in the size and units of the entered features, a normalization of the features was applied to the numerical data using z-score normalization. This technique transforms the data so that each feature has a mean of zero and a standard deviation of one [38]. This step prevents certain features from disproportionately influencing the model due to their larger size.

2.3.8. Nested K-Fold Cross-Validation for Model Improvement

The models were evaluated and the hyperparameters were tuned using nested k-fold cross-validation to obtain an unbiased estimate of the model's generalization performance [31]. The nested cross-validation approach comprises two loops: an inner loop for optimizing the hyperparameters and an outer loop for evaluating the predictive ability of the model on unseen data. This prevents overfitting and allows for a more reliable evaluation of the model's performance on new data. Grid search cross validation was used to fine-tune the hyperparameters of the created models.

2.3.9. Regression Metrics for the Model Evaluation

The metrics used to evaluate the regression models created were R^2 , mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE). Metric R^2 provides a general indication of the predictive power, MAE reflects the closeness of the predictions to the actual values, RMSE is used to highlight larger errors, MAPE is used to assess the percentage error to provide a relative measure of accuracy. The variability of the prediction errors is indicated by the standard deviation of the residuals. These metrics were used to provide a comprehensive assessment of the accuracy, consistency and reliability of the model.

2.3.10. Addressing Potential Model Overfitting

Overfitting was mitigated through a comprehensive strategy that combined model regularization, hyperparameter tuning, and data preprocessing. Regularized linear models such as RR (using an L2 penalty) and LR (using an L1 penalty) inherently reduce model complexity by shrinking coefficients and eliminating irrelevant features, while BR leverages a Gaussian prior to naturally control coefficient sizes. In parallel, tree-based methods like RF and XGBoost were fine-tuned with constraints on parameters such as tree depth, the number of estimators, and regularization terms, further curbing the risk of overfitting. This approach was bolstered by a nested k-fold cross-validation framework that isolates hyperparameter optimization from model evaluation, ensuring unbiased estimates of predictive performance. Additionally, data standardization and outlier detection using the LOF contributed to a cleaner, more consistent dataset, preventing skewed model behavior due to noise or extreme values. These measures were undertaken not only to address potential pitfalls of overfitting but also to fully leverage the relatively small dataset, ensuring that its inherent quality and subtle patterns were effectively captured without succumbing to noise.

3. Results and Discussion

3.1. Manufacturing and Geometric Properties Extraction

The weld beads produced are displayed in Figure 2, featuring three base plates, each divided into two scan areas. The welding sequence, determined experimentally, is indicated by numbers 1–50 and arrows.

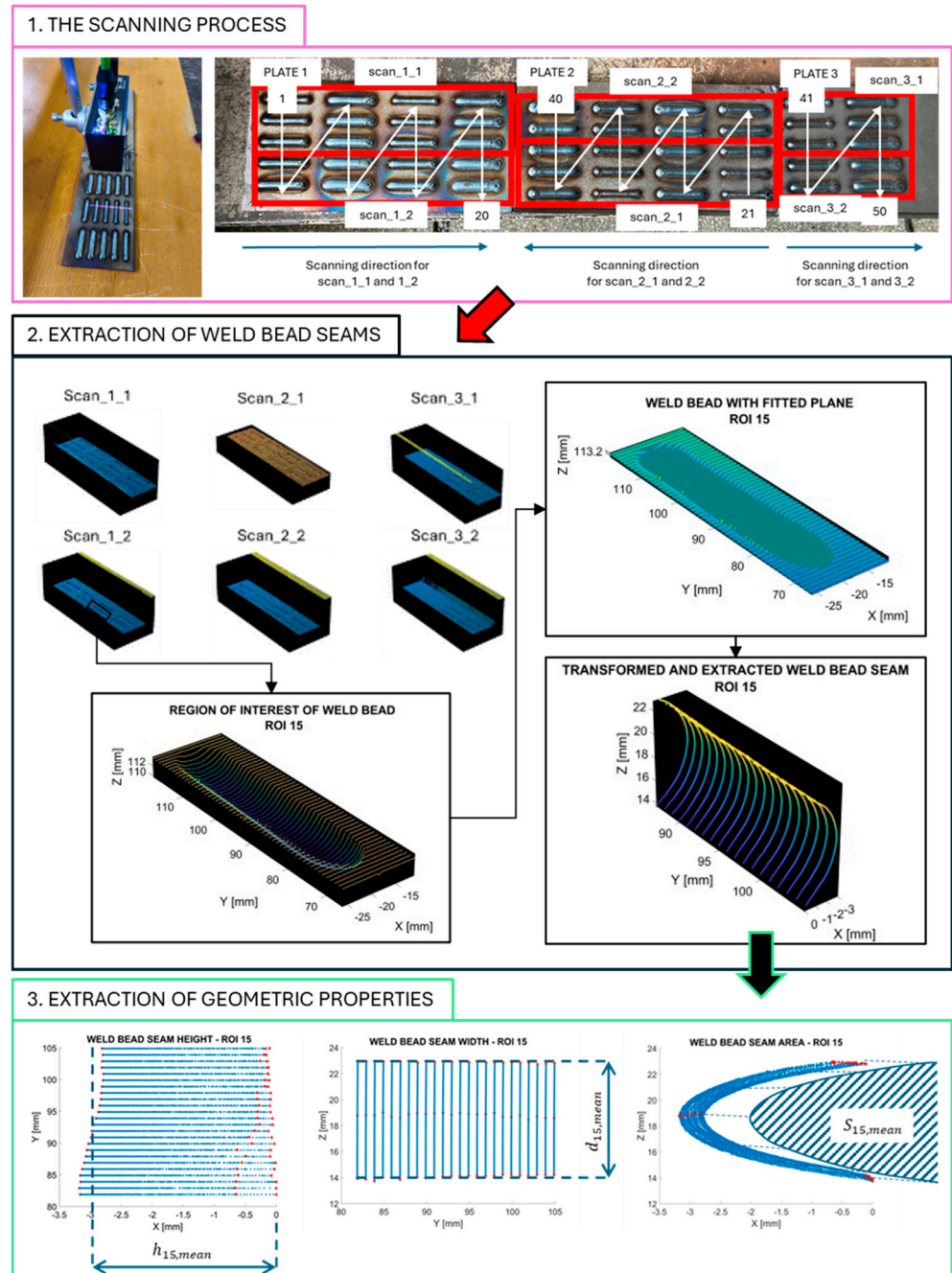


Figure 2. The process of extracting weld bead seams from scanned point clouds.

Each base plate is represented by two point clouds. Scan_1_1 and scan_1_2 represent the first base plate. When evaluating the geometric properties of the weld beads, each weld bead was extracted separately from the point cloud of the corresponding base plate by defining regions of interest (ROI). The extracted point clouds were then split into the points that represent the base plate and were used to align the scanned data to the scanner normal plane, and the points that represent the weld beads. The weld bead seams were determined by a narrower ROI that also excludes the arc start and end areas, which were not considered in this study, from the overall geometry of the weld bead.

For each of the extracted weld bead seams nine features were computationally extracted: minimum, average and maximum weld height, width and area. For each scan line, the maximum point in the Z direction (red points in Figure 2) was used to determine the weld bead height. The maximum and minimum points in the X direction (also marked as

red points in Figure 2) were used to calculate the weld bead width. The weld bead area was obtained by polygonizing all scan line points with respect to the Z axis. From these data, the minimum, average, and maximum weld height, width, and area of the entire weld bead seam were determined. The processed results are shown in Table A1, where the first column is the experiment number and the second and third columns are the independent parameters current and travel speed. The remaining columns are the minimum, average and maximum weld height, width and area.

3.2. Outlier Detection

The LOF settings used in the study—a configuration with 20 neighbors, a 5% contamination rate, and the Euclidean metric—represent a balanced approach to anomaly detection. However, since no outliers were detected, there are two possible interpretations: the dataset itself might be inherently robust, or the chosen settings may not be stringent enough to capture subtler anomalies. It is also important to consider that overly rigorous detection can be counterproductive; if the criteria are too strict, legitimate data points might be erroneously classified as outliers and removed, leading to a loss of valuable information and potentially harming the model's generalizability. Thus, while the current parameter settings may be adequate for certain anomalies, they might overlook less obvious ones, and overly strict detection could compromise model performance. Future work might benefit from further parameter tuning or incorporating complementary methods to ensure a more comprehensive detection of all anomalies.

3.3. Methods Comparison

Table 5 presents the best metrics achieved with the chosen modelling methods for the designated outputs.

Table 5. Best metrics achieved for outputs with different methods.

Model	Metric	Output					
		Mean Weld Bead Height Train Dataset	Mean Weld Bead Height Test Dataset	Mean Weld Bead Width Train Dataset	Mean Weld Bead Width Test Dataset	Mean Weld Cross-Section Area Train Dataset	Mean Weld Cross-Section Area Test Dataset
		(R ² , MAE, RMSE, MAPE,	(R ² , MAE, RMSE, MAPE,	(R ² , MAE, RMSE, MAPE,	(R ² , MAE, RMSE, MAPE,	(R ² , MAE, RMSE, MAPE, r)	(R ² , MAE, RMSE, MAPE, r)
RR		0.834, 0.195, 0.237, 11.61%, 0.913	0.258, 0.180, 0.223, 12.04%, 0.689	0.819, 0.430, 0.637, 7.70%, 0.905	0.923, 0.364, 0.444, 6.62%, 0.964	0.799, 1.673, 2.150, 21.46%, 0.894	0.656, 1.593, 2.107, 24.75%, 0.930
LR		0.834, 0.194, 0.237, 11.52%, 0.913	0.237, 0.183, 0.226, 12.23%, 0.689	0.828, 0.428, 0.621, 7.79%, 0.910	0.944, 0.310, 0.379, 5.99%, 0.973	0.772, 1.669, 2.287, 22.81%, 0.879	0.657, 1.570, 2.104, 24.84%, 0.932
BR		0.834, 0.195, 0.237, 11.55%, 0.913	0.246, 0.182, 0.225, 12.15%, 0.689	0.828, 0.432, 0.621, 7.87%, 0.910	0.941, 0.323, 0.389, 6.26%, 0.972	0.799, 1.673, 2.149, 21.44%, 0.894	0.654, 1.599, 2.113, 24.71%, 0.930
RF		0.958, 0.101, 0.120, 6.34%, 0.984	0.863, 0.075, 0.096, 5.35%, 0.940	0.961, 0.227, 0.297, 4.71%, 0.986	0.957, 0.248, 0.333, 4.69%, 0.979	0.940, 0.806, 1.176, 12.81%, 0.986	0.845, 1.272, 1.414, 29.39%, 0.978
XGBoost		0.980, 0.065, 0.083, 3.91%, 0.990	0.868, 0.068, 0.094, 4.65%, 0.933	0.993, 0.092, 0.128, 1.79%, 0.997	0.992, 0.105, 0.146, 1.96%, 0.996	1.000, 0.064, 0.101, 0.92%, 1.000	0.931, 0.703, 0.945, 12.14%, 0.988

The performance of each model was assessed using the scoring Equation (1).

$$S = R^2 - MAE - RMSE - MAPE + r \quad (1)$$

Here:

- R^2 : measures how well the model explains the variability of the target variable (higher is better).

- MAE: represents the average error in predictions (lower is better).
- RMSE: quantifies the spread of prediction errors (lower is better).
- MAPE: evaluates the percentage error in predictions (lower is better).
- r: reflects the strength of the correlation between predicted and actual values (higher is better).

The equation assigns equal weights ($w = 1$) to all metrics, treating them with equal importance. Scores were calculated separately for the training and testing datasets, with the combined score computed as presented in Equation (2).

$$S_{\text{combined}} = \frac{S_{\text{train}} + S_{\text{test}}}{2} \quad (2)$$

This approach ensures a balanced evaluation of model performance across both datasets.

Results and scores for the model evaluation are presented in Table 6.

Table 6. Evaluation scores for each method and output.

Output	Model	Train Score	Test Score	Combined Score
Mean weld bead height	RR	−10.295	−11.496	−10.896
	LR	−10.204	−11.713	−10.959
	BR	−10.235	−11.622	−10.929
	RF	−4.619	−3.718	−4.169
	XGBoost	−2.088	−3.011	−2.550
Mean weld bead width	RR	−7.721	−6.449	−7.085
	LR	−7.719	−6.252	−6.986
	BR	−7.741	−6.331	−7.036
	RF	−4.597	−3.491	−4.044
	XGBoost	−1.020	−0.855	−0.937
Mean weld cross-section area	RR	−23.026	−27.106	−25.066
	LR	−23.067	−27.129	−25.098
	BR	−23.028	−27.035	−25.032
	RF	−12.032	−17.018	−14.525
	XGBoost	−0.087	−9.869	−4.978

Observations:

- Mean weld bead height: XGBoost achieved the highest combined score of −2.5495, making it the best-performing model for this output.
- Mean weld bead width: for the width output, XGBoost again emerged as the best model. Its ability to maintain high accuracy while minimizing errors such as MAE, RMSE, and MAPE led to the highest combined score.
- Mean weld cross-section area: in predicting cross-section area, XGBoost continued its dominance. It delivered the highest scores across key metrics, including the lowest error percentages and the strongest correlation.

XGBoost consistently outperformed all other models across the three outputs—height, width, and cross-section area which correlates to findings in [3]. The performance of the prediction models created with XGBoost is explained in more detail in Section 3.4 (Model Analysis).

3.4. Model Analysis

3.4.1. Model: Mean Weld Bead Height

The XGBoost model shows strong performance in predicting the mean weld height. The inclusion of FE and PF improved the predictive ability of the model.

Feature Importance Analysis

The values for the significance of the characteristics are summarized in Table 7. Travel speed proves to be the most influential predictor, contributing 59.2% to the overall significance of the model. This result emphasizes its role in determining weld height. Current follows with a considerable influence of 29.7%, confirming its importance. Finally, the interaction term current $\times$ travel speed has a contribution of 11.1%, indicating that the combined effect of these features is significant but less dominant compared to their individual contributions.

Table 7. Features importance score for model: mean weld bead height.

Feature	Importance Score
travel speed	0.592
current	0.297
current $\times$ travel speed	0.111

SHAP value analysis

The summarized SHAP plot (Figure 3a) reveals an interesting discrepancy when compared to the feature importance scores. While the feature importance analysis identifies travel speed as the dominant predictor with the highest contribution to the model, the SHAP plot shows that current has a broader range of SHAP values. This suggests that current exhibits greater variability in its influence on individual predictions, even though its average contribution to the model is lower than that of travel speed. Travel speed, on the other hand, maintains a consistently high impact across predictions, aligning with its dominance in the feature importance analysis. The current $\times$ travel speed interaction term has both the smallest SHAP value range and the lowest importance score, confirming its minor role. This comparison highlights how SHAP values provide a localized, instance-specific perspective, while feature importance scores reflect the global, aggregate contributions of features, offering complementary insights into the model's behavior.

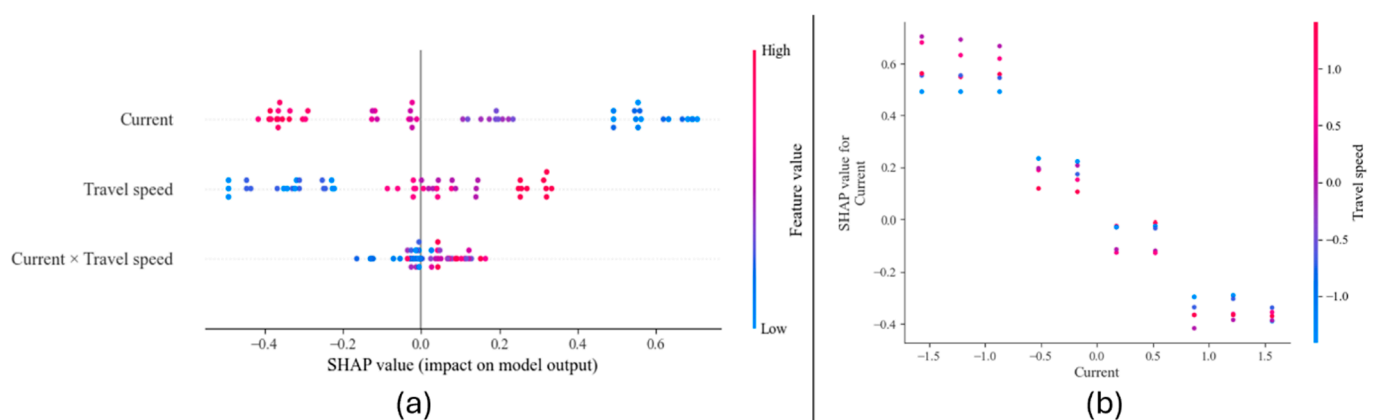


Figure 3. Summarized SHAP plot (a) and SHAP dependence plot for current (b) for mean weld bead height.

The SHAP dependence plot for current (Figure 3b) provides insights into its influence on model predictions. There is a clear negative relationship between current and its

SHAP values, highlighting that higher current values contribute to lower predicted weld height. The wide range of SHAP values for current underscores its impact across different predictions, indicating that current is a key driver of variability in the model output. The color gradient, representing the interaction with travel speed, shows that this effect is further influenced by the interplay between the two features, with the interaction becoming particularly pronounced at lower current levels. These results affirm that current is a pivotal factor influencing mean weld bead height.

Model Performance

The model's performance metrics are summarized below (Table 8).

Table 8. Evaluation metrics for model: mean weld bead height.

Metric	Training	Testing
R ² Score	0.980	0.868
MAE	0.065	0.068
RMSE	0.083	0.094
MAPE	3.91%	4.65%
Pearson's correlation coefficient	0.990	0.933

The training R² of 0.980 and the test R² of 0.868 reflect model fit and generalization. Low error metrics such as MAE (0.068) and MAPE (4.65%) emphasize the accuracy of the predictions, and the high Pearson correlation (0.933) indicates a reliable relationship between predictions and actual values.

The predicted vs. actual values for both the training and test sets are visualized in Figure 4. Both scatter plots align closely with the diagonal line (indicating a perfect prediction), though the training set predictions were more tightly clustered around the line, reflecting the slightly better fit noted in the R² values. The test set predictions, while slightly more dispersed, still follow the line closely, underscoring strong external validity of the model.

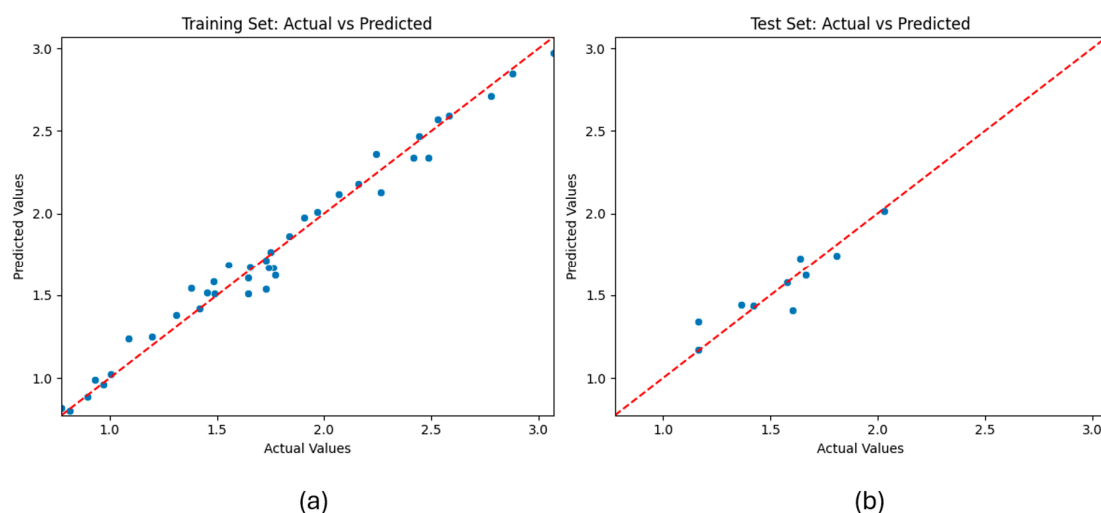


Figure 4. Predicted vs. actual weld bead height, scatter plots for (a) the training set and (b) the predictions of the test set.

The XGBoost model with polynomial features achieves high accuracy and generalization in predicting the mean weld height. Minimal errors confirm the reliability of the model for practical use.

3.4.2. Model: Mean Weld Bead Width

The XGBoost model shows high accuracy in predicting weld width, with FE and PF improving the model's performance.

Feature Importance Analysis

Feature importance scores (Table 9) show that current is the most important predictor, contributing 64.30% to the overall model result, followed by travel speed at 25.9%. The interaction term current $\times$ travel speed contributes a smaller but notable share of 9.80%, which emphasizes its subordinate role.

Table 9. Features importance score for model: mean weld bead width.

Feature	Importance Score
current	0.643
travel speed	0.259
current $\times$ travel speed	0.098

SHAP value analysis

The analysis of the SHAP values confirms these results. The SHAP summary (Figure 5a) shows that current has the widest range of SHAP values, emphasizing its primary influence on predictions. Conversely, travel speed shows a smaller but consistent impact, while the interaction term has nuanced, albeit less significant, effects on the behavior of the model.

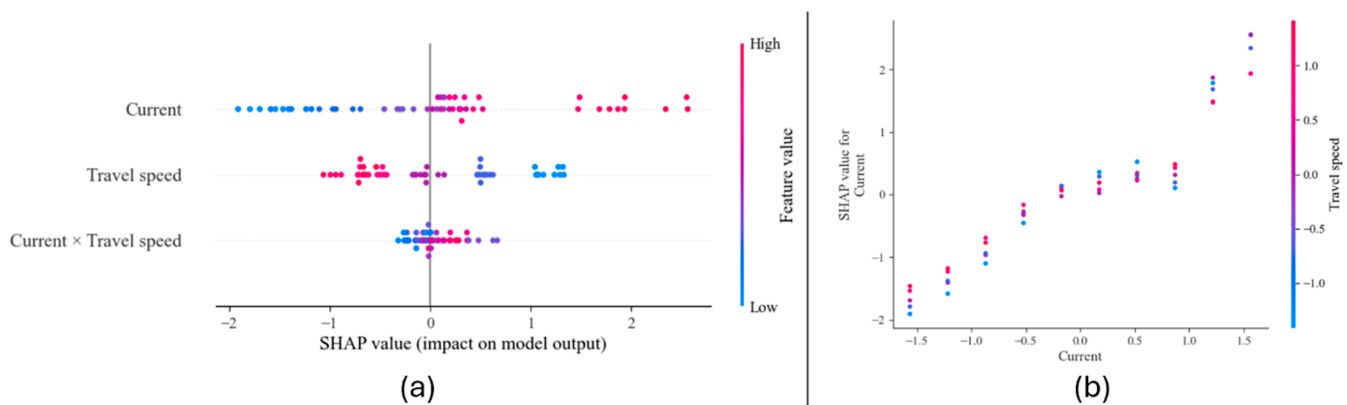


Figure 5. Summarized SHAP plot (a) and SHAP dependence plot for current (b) for mean weld bead width.

The plot of the SHAP dependence for the current (Figure 5b) shows a positive linear relationship with the SHAP values, with higher current values consistently leading to higher predictions for the weld width. The color gradient in the graph highlights the subtle influence of travel speed, especially at extreme current values, and emphasizes the combined effect of these variables. Current is the most important determinant of weld width, while travel speed plays a supporting role. The interaction between these variables is of lesser importance but increases the complexity which increases the prediction accuracy of the model.

Model Performance

The detailed metrics for model performance are summarized in the following Table 10.

Table 10. Evaluation metrics for model: mean weld bead width.

Metric	Training	Testing
R ² Score	0.993	0.992
MAE	0.092	0.105
RMSE	0.128	0.146
MAPE	1.78%	1.96%
Pearson's correlation coefficient	0.997	0.996

The training R² value of 0.993 indicates that the model captures over 99% of the variance in the training dataset. Similarly, the test R² value of 0.992 confirms the model's ability to generalize well to unseen data. Error metrics such as MAE (0.105) and MAPE (1.96%) in the test phase remain low, emphasizing the predictions' accuracy. Additionally, the Pearson's correlation coefficient of 0.997 for training and 0.996 for testing signifies a near-perfect linear relationship between the predicted and actual values.

Figure 6 illustrates the close agreement between predicted and actual weld width for both the training and test sets. The scatter plots show that the data points cluster around the best fit line, indicating a strong agreement between the predictions and the actual values.

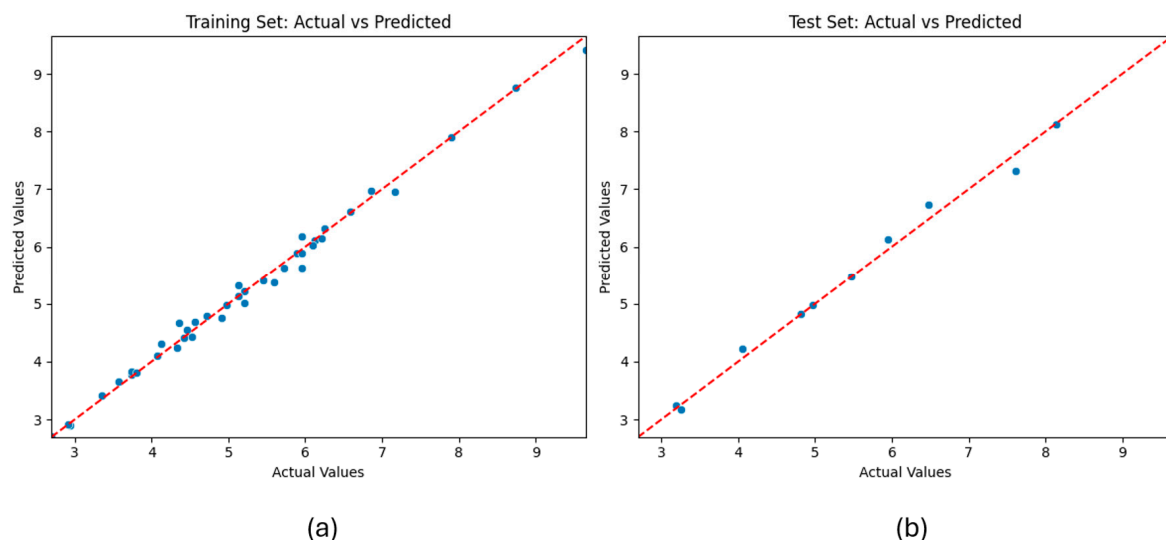


Figure 6. Predicted vs. actual weld bead width, scatter plots for (a) the training set and (b) the predictions of the test set.

The created model performs exceptionally well in predicting the mean weld width, achieving high prediction accuracy and low error rates. The dominance of current indicates that it is a crucial factor in modelling the target variable.

3.4.3. Model: Mean Weld Cross-Section Area

The analysis of the results of the generated model shows a strong predictive performance in the estimation of the mean weld cross-section area, thereby improving the understanding of the welding process.

Feature Importance Analysis

The feature importance scores derived from the model are presented in Table 11.

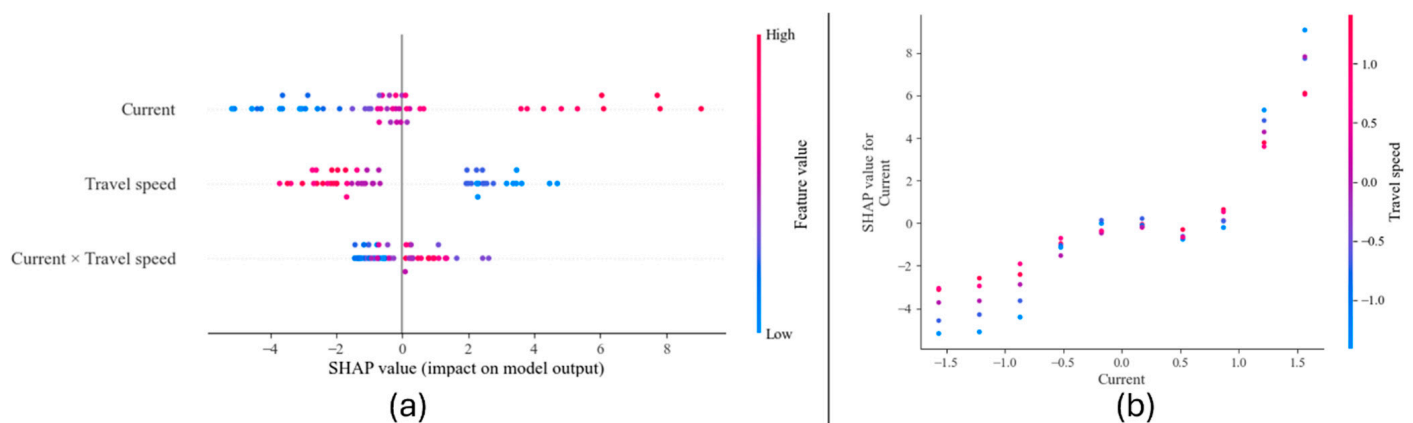
Table 11. Features importance scores for model: mean weld cross-section area.

Feature	Importance Score
current	0.554
travel speed	0.394
current $\times$ travel speed	0.052

The current dominates the predictions with a share of 55.40% of the total meaning. This shows its influence on the determination of the weld cross-section area. The travel speed follows with a significant contribution of 39.4%, which illustrates its complementary role. The current $\times$ travel speed interaction term is smaller at 5.20%, but still plays a role as it captures the non-linear relationships between these key variables.

SHAP Value Analysis

The summarized SHAP representation (Figure 7a) confirms the results of the feature importance. The current has the widest range of SHAP values, which emphasizes its primary role in the predictions. While travel speed is secondary, it consistently influences the model outcome, and the interaction term contributes to localized effects that refine the overall prediction accuracy.

**Figure 7.** Summarized SHAP plot (a) and SHAP dependence plot for current (b) for mean weld cross-section area.

The SHAP dependence diagram for the current (Figure 7b) shows a clear positive relationship between the current and its SHAP values. As the current increases, the predicted weld cross-section area also increases. The color gradient in the dependency plot shows that the travel speed changes the strength of this relationship, especially at higher current values, which is a subtle interaction effect. The analysis shows that current is the most important predictor of weld cross-section area, while travel speed plays an important but minor role. The interaction term, current $\times$ travel speed, adds depth by capturing synergistic effects between the individual features.

Model Performance

The performance metrics for the best created model are summarized in Table 12.

The R^2 value for training of 0.999 indicates that the model can explain virtually all the variance in the training dataset, while the R^2 value for testing of 0.931 still shows robust predictive power for unseen data. Although MAE and RMSE were minimal during training, indicating a good fit, these values increase to MAE = 0.703 and RMSE = 0.945 in the test set, suggesting that the model generalizes well. In addition, the MAPE of approximately 12.14% could indicate the presence of certain difficult instances or data ranges where the

predictions were less accurate. Nonetheless, the Pearson correlation coefficient of 0.988 on the test data confirms a strong linear relationship between the predicted and actual values, providing confidence in the overall reliability of the model.

Table 12. Evaluation metrics for model: mean weld cross-section area.

Metric	Training	Testing
R ² Score	0.999	0.931
MAE	0.064	0.703
RMSE	0.101	0.945
MAPE	0.919%	12.136%
Pearson's correlation coefficient	0.999	0.988

Figure 8 shows a comparison between the predicted and actual values of the weld cross-section area for both the training set and the test set. In the training set plot, the data points lie close to the diagonal, reflecting near perfect prediction accuracy. Although the predictions for the test set were more scattered, most points were still close to the ideal line, visually confirming a strong agreement between predictions and actual reality.

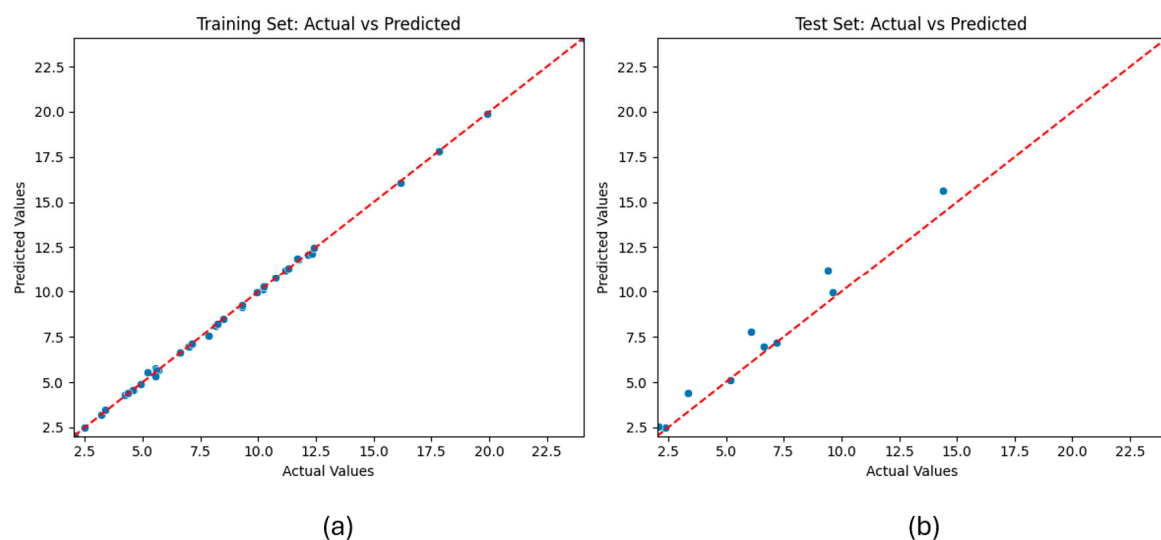


Figure 8. Predicted vs. actual weld bead cross-section area, scatter plots for (a) the training set and (b) the predictions for the test set.

The XGBoost regressor model, improved by FE and PF, shows a strong ability to predict the mean weld cross-section area. The dominance of current, along with the significant influence of travel speed and their interaction, highlights the complexity of the welding process. While the test errors and MAPE indicate room for improvement—perhaps through further feature refinement, hyperparameter tuning or data enrichment—the overall high R² and strong correlation metrics reflect a reliable predictive model.

4. Conclusions

The XGBoost regression models augmented with feature engineering and polynomial transformations showed the strongest predictive performance for all three target variables—mean weld height, mean weld width and mean weld cross-section area.

Mean weld height

The model achieved a training R² of 0.980 and a test R² of 0.868, indicating that it captured most of the variance and generalized well to unseen data. Contrary to feature

importance analysis, the SHAP analysis revealed that current was the most influential parameter, exhibiting the broadest range of SHAP values, indicating its impact on the model's predictions. The SHAP dependence plot further illustrated a generally positive correlation between current and its impact on predictions, with variations in travel speed influencing this relationship. Additionally, the interaction term (current $\times$ travel speed) showed increased significance at higher travel speeds, suggesting a complex interplay between these factors in determining the output.

Mean weld width

With a training R^2 of 0.993 and a test R^2 of 0.992, the model exhibited both exceptional fit and robust generalization. Current was the most important predictor, exhibiting the largest range of SHAP values and influencing weld width largely linearly.

Mean weld cross-section area

The model achieved a training R^2 of 0.999 and a test R^2 of 0.931, demonstrating both remarkable precision and stability. Current was again the most important factor, accounting for 55.40% of the feature's importance, closely followed by travel speed at 39.41%. The SHAP analysis confirmed the dominant influence of current as it had the widest range of SHAP values.

These results emphasize the importance of current in predicting mean weld height, mean weld width and cross-section area. Although the interaction term between current and travel speed was less influential, it provided important insights into nonlinear and synergistic relationships. The low error metrics of the models (MAE, RMSE, MAPE) and the high Pearson correlation coefficients confirm their reliability. Supported by feature importance analyses and SHAP analyses, these results provide practical guidance for the optimization of welding parameters to achieve precise control of welding results.

Future work

It is planned that the study be expanded in future work by incorporating additional independent variables—namely, voltage, wire feed speed, shielding gas flow rate and composition, electrode/nozzle size, and arc length—and by evaluating key material properties such as tensile strength, toughness, fracture mechanics, microstructure, cracks, and porosity. Moreover, the modelling procedure is to be extended to multi-layer builds, with layer count introduced as a new variable, and investigations on stainless steel as well as combinations of plain and stainless steel to be conducted.

Author Contributions: Conceptualization, K.Š. and J.G.; methodology, K.Š. and J.G.; software, K.Š. and M.B.; validation, K.Š. and M.B.; formal analysis, K.Š., T.K. and R.B.; investigation, J.G., T.K. and K.Š.; resources, T.V., J.G. and K.Š.; data curation, T.K. and R.B.; writing—original draft preparation, K.Š. and J.G.; writing—review and editing, K.Š., J.G., M.B., M.F. and T.K.; visualization, K.Š., J.G. and M.B.; supervision T.K., M.F. and T.V.; project administration, T.K., M.F. and T.V.; funding acquisition, M.F. and T.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was financially supported by the Slovenian Research and Innovation Agency by research core funding No. P2-0157 and from the applied project Self-Learning Collaborative Welding Application (No. L2-60138).

Data Availability Statement: Data will be made available upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Appendix A.1

Table A1 presents experimental data and the extracted features.

Table A1. Experimental data and the extracted features.

DOE	Current [A]	Travel Speed [cm/min]	Mean Weld Bead Height [mm]	Mean Weld Bead Width [mm]	Mean Weld Bead Area [mm ²]	Max. Weld Bead Height [mm]	Max. Weld Bead Width [mm]	Max. Weld Bead Area [mm ²]	Min. Weld Bead Height [mm]	Min. Weld Bead Width [mm]	Min. Weld Bead Area [mm ²]
1	65	20	1.741	4.059	5.204	1.798	4.183	5.204	1.702	3.863	5.204
2	75	20	1.653	4.424	5.688	1.732	4.624	5.688	1.555	4.132	5.688
3	85	20	1.553	4.715	5.615	1.602	5.099	5.615	1.513	4.422	5.615
4	95	20	2.487	5.725	12.153	2.797	6.280	12.153	2.309	5.441	12.153
5	105	20	2.531	6.250	12.434	2.795	6.733	12.434	2.387	5.947	12.434
6	115	20	2.583	6.582	11.177	2.835	7.079	11.177	2.288	6.182	11.177
7	125	20	2.243	7.170	9.963	2.490	7.736	9.963	1.994	6.786	9.963
8	135	20	2.779	5.955	10.773	3.013	5.982	10.773	2.332	5.811	10.773
9	145	20	2.879	8.734	19.924	3.079	9.082	19.924	2.768	8.494	19.924
10	155	20	3.067	9.649	24.063	3.327	10.208	24.063	2.652	9.185	24.063
11	65	25	1.487	3.734	4.895	1.669	3.891	4.895	1.430	3.611	4.895
12	75	25	1.763	4.524	6.951	1.987	4.770	6.951	1.668	4.359	6.951
13	85	25	1.666	4.809	7.126	1.900	5.048	7.126	1.561	4.226	7.126
14	95	25	1.838	5.471	8.509	2.055	5.794	8.509	1.738	5.221	8.509
15	105	25	1.968	6.094	10.249	2.219	6.355	10.249	1.854	5.958	10.249
16	115	25	2.263	6.214	12.321	2.537	6.523	12.321	2.130	5.996	12.321
17	125	25	2.030	6.477	11.752	2.306	7.001	11.752	1.883	6.169	11.752
18	135	25	1.906	5.124	9.613	2.198	5.465	9.613	1.751	4.964	9.613
19	145	25	2.159	7.607	14.407	2.451	8.091	14.407	1.942	7.379	14.407
20	155	25	2.440	8.135	17.807	2.800	8.554	17.807	2.081	8.006	17.807
21	65	30	1.366	3.355	3.359	1.410	3.471	3.359	1.307	3.133	3.359
22	75	30	1.418	3.804	4.240	1.527	3.951	4.240	1.359	3.686	4.240
23	85	30	1.606	4.331	5.537	1.763	4.631	5.537	1.504	4.141	5.537
24	95	30	1.380	4.358	5.210	1.559	4.597	5.210	1.308	4.123	5.210
25	105	30	1.770	5.208	7.851	2.020	5.483	7.851	1.678	5.055	7.851
26	115	30	1.483	4.976	6.103	1.643	5.111	6.103	1.403	4.878	6.103
27	125	30	1.454	5.214	6.618	1.679	5.365	6.618	1.363	5.168	6.618
28	135	30	1.641	5.600	8.167	1.907	5.776	8.167	1.555	5.481	8.167
29	145	30	2.070	6.861	11.676	2.332	7.309	11.676	1.945	6.691	11.676
30	155	30	2.415	7.902	16.176	2.817	8.367	16.176	2.223	7.608	16.176
31	65	35	1.004	2.941	2.097	1.042	3.069	2.097	0.959	2.773	2.097
32	75	35	0.969	3.258	2.361	1.023	3.543	2.361	0.922	3.050	2.361
33	85	35	1.162	3.744	3.380	1.239	3.997	3.380	1.087	3.604	3.380
34	95	35	1.728	5.955	9.285	2.039	6.344	9.285	1.566	5.757	9.285
35	105	35	1.421	4.558	5.573	1.638	4.809	5.573	1.356	4.352	5.573
36	115	35	1.198	4.125	4.380	1.366	4.590	4.380	1.124	3.745	4.380
37	125	35	1.166	4.455	4.586	1.426	5.001	4.586	1.043	4.024	4.586
38	135	35	1.312	4.965	6.608	1.613	5.593	6.608	1.171	4.433	6.608
39	145	35	1.728	5.955	9.285	2.039	6.344	9.285	1.566	5.757	9.285
40	155	35	1.655	5.947	9.405	1.926	6.377	9.405	1.532	5.727	9.405
41	65	40	0.898	2.696	2.041	1.129	2.795	2.041	0.821	2.411	2.041
42	75	40	0.776	2.915	2.017	0.934	2.991	2.017	0.727	2.854	2.017
43	85	40	0.812	3.189	2.493	1.037	3.474	2.493	0.718	3.048	2.493
44	95	40	0.932	3.568	3.193	1.189	3.853	3.193	0.819	3.425	3.193
45	105	40	1.086	4.080	4.594	1.442	4.514	4.594	0.926	3.920	4.594
46	115	40	1.645	4.910	7.005	1.927	5.190	7.005	1.562	4.763	7.005
47	125	40	1.578	5.131	7.195	1.839	5.360	7.195	1.473	4.865	7.195
48	135	40	1.644	5.447	8.216	1.952	5.715	8.216	1.453	5.256	8.216
49	145	40	1.807	5.889	10.182	2.199	6.460	10.182	1.669	5.520	10.182
50	155	40	1.752	6.118	11.308	2.276	6.678	11.308	1.604	5.855	11.308

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