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ENHANCING WELDING QUALITY THROUGH PREDICTIVE MODELLING — INSIGHTS FROM MACHINE LEARNING TECHNIQUES

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Abstract

In this work, the application of various machine learning (ML) algorithms for predicting tensile strength based on welding parameters in AA2014-T6 aluminium alloy joints is studied. Six ML models namely linear regression, AdaBoost regression, random forest regression, support vector regression (SVR), multi-layer perceptron regression and gaussian process regression (GPR) are considered. The comprehensive analysis revealed that SVR exhibited superior generalization capabilities on unseen data, achieving an R^2 of 0.89 and a low RMSE of 15.64. In contrast, GPR, despite its high training accuracy, showed significant overfitting. This work highlights the potential of ML in optimizing welding parameters and highlights the importance of model selection and tuning to prevent overfitting and ensure reliable predictions.

Keywords:

Machine learning, welding parameters, tensile strength prediction, support vector regression, overfitting prevention

1. INTRODUCTION

Welding is a critical process in manufacturing industries for applications ranging from automotive to aerospace to construction to shipbuilding. Welding is highly preferred over other joining techniques due to its high strength, reliability and cost efficiency [Kalita 2023]. However, optimal welding performance is dependent on the precise control of various welding process parameters like current, voltage, speed and gas flow rate [Arifin 2020]. These process parameters significantly affect the quality of the weld, its mechanical properties and microstructure. Traditionally, determination of optimal welding parameters was done through empirical methods, domain knowledge expertise and extensive experimentation. However, it is time- and resource-intensive [Albak 2024].

Traditionally, optimization of welding parameters is achieved through trial-and-error methods, domain knowledge expertise and statistical techniques such as Design of Experiments. Despite the ease of use and valuable insights provided by these methods, they are limited due to dependence on need for domain expertise and excessive experimentation. For example, many studies have used response surface methodology (RSM) [Bellamkonda 2024] [Ramamurthy 2022] and Taguchi methods [Linger 2023] to find optimal parameters. However, these methods are labour-intensive and do not fully comprehensively capture the nonlinear interactions between parameters [Chen 2020].

The advent of ML algorithms has revolutionized various engineering domains. ML algorithms can analyse large datasets, identify patterns and generate predictive models. In welding sciences, ML-based predictive modelling has the potential to optimize welding parameters, reduce defects, enhance productivity and ensure consistent weld quality. The integration of ML into welding research has leaf the way for parameter optimization and quality prediction. ML algorithms like artificial neural networks (ANNs), support vector regressions (SVRs) and decision trees (DTs) are good in modelling complex relationships between welding parameters and quality.

ANNs are widely used for their ability to model nonlinear relationships. For example, Salhan et al. [Salhan 2022] predicted heat generated and microstructure behaviour of friction stir welded AA7075 by using ANN. Similarly, Rawa et al. [Rawa 2023] used ANN in optimizing pulsed laser welding of different steels. SVRs have also been effective in various regression and classification tasks in welding research. For example, Patil et al. [Patil 2021] employed SVRs to classify weld defects based on the image of welded parts. Jaypuria et al. [Jaypuria 2023] predicted weld quality by looking at the surface attributes using SVR. DTs and Random Forests provide interpretability, allowing researchers to understand the importance of different parameters. Zeng et al. [Zeng 2023] applied random forests to predict amount of oxidation in aluminium alloys while laser welding.

Despite the promising results, several challenges remain in the application of ML to welding. One primary challenge is the quality and quantity of data. Welding experiments can be expensive and time-consuming, leading to limited datasets that may not capture the full variability of the process. Additionally, the presence of noise and outliers in the data can adversely affect model performance. Techniques such as data augmentation, cross-validation and robust outlier detection are essential to address these issues [Hastie 2009]. Another challenge is the interpretability of ML models. Though advanced models such as deep neural networks are more accurate, their black-box nature makes it difficult to extract meaningful insights about the underlying physical phenomena. Efforts to enhance model interpretability, such as feature importance analysis and surrogate modelling, are critical for gaining acceptance in the engineering community [Ribeiro 2016].

In this paper several ML algorithms (namely, linear regression, AdaBoost regression, random forest regression (RFR), SVR, MLP and Gaussian process regression (GPR)) are used to develop predictive models for welding parameters. The remainder of the paper is arranged as—Section 2 details the various ML algorithms used in this study, Section 3 discusses the case study and the analyses the data to understand the effect of various welding process parameters on tensile strength of the specimens. Section 4 summarizes the study and highlights the main contributions of the work.

2. MATERIALS AND METHODS

2.1 Data Description

The dataset used in this study originates from the work of Rajendran et al. [Rajendran 2019] in which they focused on optimizing friction stir welding (FSW) parameters to achieve maximum tensile strength in AA2014-T6 aluminium alloy joints. This data is highly relevant due to its comprehensive coverage of key welding parameters and their effects on joint strength. Thus, it could serve as an excellent foundation for developing machine learning-based predictive models. The dataset was acquired through controlled experiments where various FSW parameters were systematically varied. The various process parameters considered are—

- Tool rotational speed (N) measured in revolutions per minute (rpm) and varied between 1300 - 1700 rpm.
- Welding speed (S) in millimeters per minute (mm/min) and varied between 20 - 60 mm/min.
- Tool shoulder diameter (D) which is crucial for determining heat generation and material flow, ranged from 4 - 8 mm.
- Tool tilt angle (Q) ranged from 0.5° - 2.5°.

These process parameters were selected based on their known influence on the quality and strength of welds. The response variable in this dataset is the tensile strength (TS) of the welded joints, measured in megapascals (MPa).

2.2 Methodology

The dataset is used for training various ML predictive models which are then cross evaluated to understand the most suitable ML model for the given problem. The machine learning models were implemented using Python v3.12.4 in Jupyter Notebook v7.0.8, accessed through Anaconda Navigator v2.6.2. The libraries used include Scikit-learn, Pandas, NumPy, matplotlib, and seaborn. All simulations were performed on a Windows 11 64-bit system with a 12th Gen Intel(R) Core (TM) i5-12450H processor, 16 GB RAM, and a 1 GB NVIDIA GeForce RTX 2050 GPU. Figure 1 illustrates the schematic diagram showing the various input process parameters (N, S, D, Q), the output response (tensile strength) and the ML algorithms considered in this study.

2.3 Linear Regression

Linear regression assumes that the relationship between the variables is linear, meaning it can be represented by a straight line. The simplest form, known as simple linear regression, involves one independent variable and aims to find the best-fitting line (regression line) through the data points [Montgomery 2021]. This line is determined by minimizing the sum of the squared differences between the observed values and the values predicted by the model. The coefficients in the linear equation represent the slope and intercept, providing insights into the strength and direction of the relationship. Linear regression is widely used for its simplicity and interpretability, although it may not perform well with complex, nonlinear relationships or in the presence of significant multicollinearity among predictors [Draper 1998].

2.4 AdaBoost Regression

AdaBoost Regression combines multiple weak learners (generally DTs), to form a stronger predictive model. In AdaBoost, each subsequent model attempts to correct the errors made by its predecessor by assigning higher weights to the data points that were previously mis predicted. This iterative process continues, resulting in a final model that aggregates the predictions of all weak learners, weighted by their accuracy [Freund 1997]. The strength of AdaBoost lies in its ability to improve performance over a single model by focusing on difficult-to-predict cases, making it particularly useful for complex datasets. However, noise and outliers in data can disproportionately influence the final model due to their increased weights. Despite this, it remains a popular choice for regression tasks due to its effectiveness in boosting model accuracy [Schapire 2003].

2.5 Random Forest Regression

RFR develops several DTs during training and outputs the mean prediction of the individual trees [Breiman 2001]. This technique addresses the limitations of single decision trees, such as overfitting, by averaging the results, thereby enhancing accuracy and robustness. Trees are built from a random subset of the data and features, which introduces diversity and reduces the correlation between individual trees. The "randomness" in feature selection and data sampling helps in capturing different aspects of the data, making the model more generalized. Random Forest Regression is particularly effective in handling datasets with a large number of features and complex relationships. It also provides useful metrics, such as feature importance, which indicate the contribution of each feature to the prediction. However, the interpretability of the model can decrease as the number of trees increases [Liaw 2002].

2.6 Support Vector Regression

SVR is based on the principles of Support Vector Machines (SVM) [Vapnik 2013]. Unlike traditional linear regression, SVR seeks to fit the best line within a threshold, known as the epsilon-insensitive zone, which ignores small errors in prediction. The primary goal is to minimize the prediction error while maintaining flatness in the model, which is controlled by a regularization parameter. SVR can perform linear and nonlinear regression by using different kernel functions, such as linear, polynomial, or radial basis functions (RBF), which enable it to model complex relationships. SVR is particularly effective in situations where the data has high dimensionality or when the relationship between features and target variable is not strictly linear. However, SVR are computationally intensive and need hyperparameter tuning for optimal performance [Smola 2004].

2.7 MLP Regression

MLP is a feed forward artificial neural network model [Haykin 1998] containing input layer, hidden layer and output layer. MLP is a perceptron with multiple layers and every layer is connected to each other. In this, each neuron has its activation function. The input layer provides the input value into the network. It doesn't contain any activation function or do any processing. Next is a hidden layer which classifies the function and in multi-layer perceptron there will be as many hidden layers as possible. After that the output layer is there from which desired output can be obtained. In this process, the weighted summation of inputs, alongside the bias term, is transmitted to an activation level via a transfer function to yield an output [Bishop 1995]. The benefits of MLP is that nonlinearly separable problems are being solved with this.

2.8 Gaussian process Regression

GPR constitutes a set of stochastic variables, of which a finite subset exhibits a coherent joint Gaussian distribution [Williams 1998] [Williams 2006]. Regression based on Gaussian process are simple, flexible and a powerful tool being used in many areas.GP is limited due to memory requirements and computational demands. GPR operates by generalizing the concept of a probability distribution concerning a scalar quantity to that of a probability distribution pertaining to functions. In the context of GPR, the covariance function is established by a designated kernel function, which quantitatively characterizes the degree of influence one data point exerts over another. This mechanism fundamentally dictates the degree of smoothness exhibited by the function within the specified distribution. Given a set of data points fitting the probability distribution can be done by choosing the distribution parameter to match the properties of the distribution to the properties of the data. Similarly, for given set of function values fitting probability distribution of function that closely match the given function values. Considering the whole fitted distribution of function can be determined by the mean as well as confidence interval.

3. RESULTS AND DISCUSSION

3.1 Effect of Process Parameters

The selection and control of process parameters are crucial in determining the quality and mechanical properties of the welded joints. The primary process parameters considered in this study are tool rotational speed (N), welding speed (S), tool shoulder diameter (D) and tool tilt angle (Q). Each of these parameters influences the heat generation, material flow and consequently the tensile strength of the weld.

Figure 2 presents relationships between the input process parameters and the output response. This plot helps visualize the correlations and possible interactions between different parameters, such as how increases in rotational speed or tool diameter might correlate with changes in tensile strength. From Figure 2 it is observed that there is an apparent positive correlation between increased tool rotational speed and tensile strength. This is because higher rotational speeds enhance material mixing and heat distribution, thereby improving weld integrity. However, this trend is not linear. It is perhaps an indication of the presence of an optimal range beyond which further increases may lead to defects due to excessive heat input.

Figure 3 provides a linear correlation plot that quantitatively depicts the strength and direction of the relationships between the various process parameters and the output response. T and S are the most influential factors affecting tensile strength with correlation coefficients indicating a moderate to strong positive relationship. D and Q also show correlations, but with more complex, non-linear interactions.

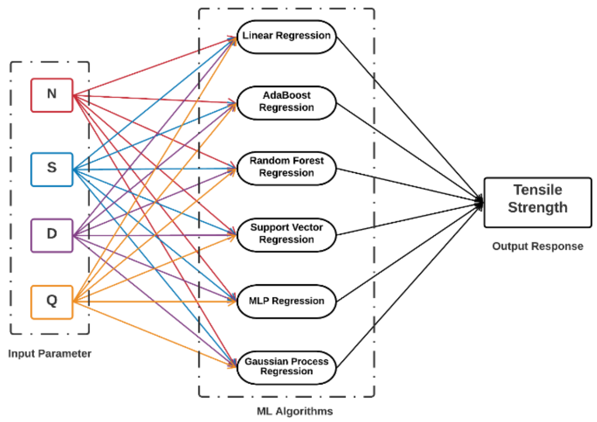


Fig. 1: Schematic diagram showing various input (process) parameters, output response and ML algorithms considered in this study.

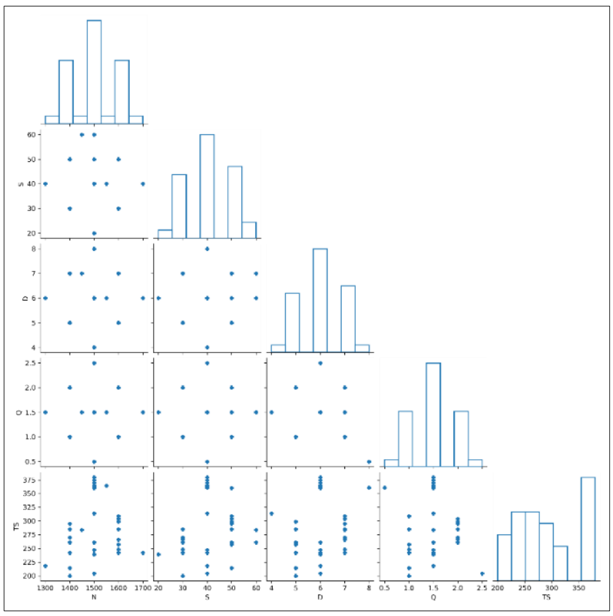


Fig. 2: Pair plot showing influence of diverse input (process) parameters on the resultant output response.

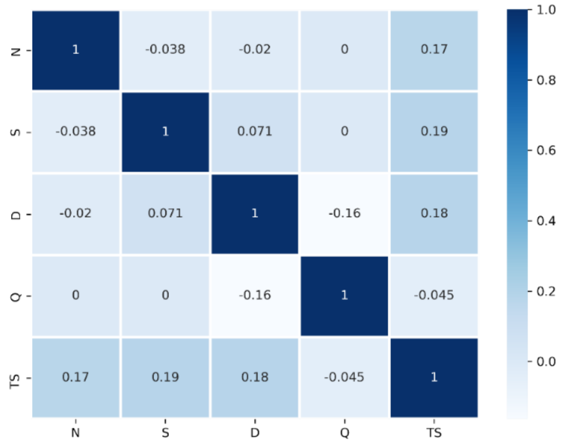
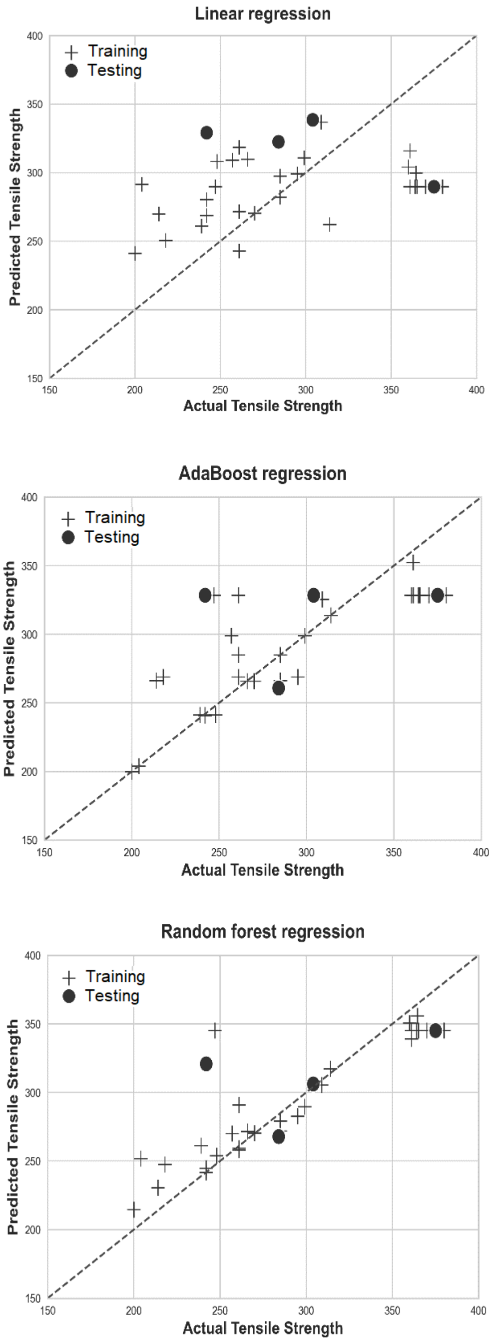


Fig. 3: Linear correlation plot of various input (process) parameters and output response.



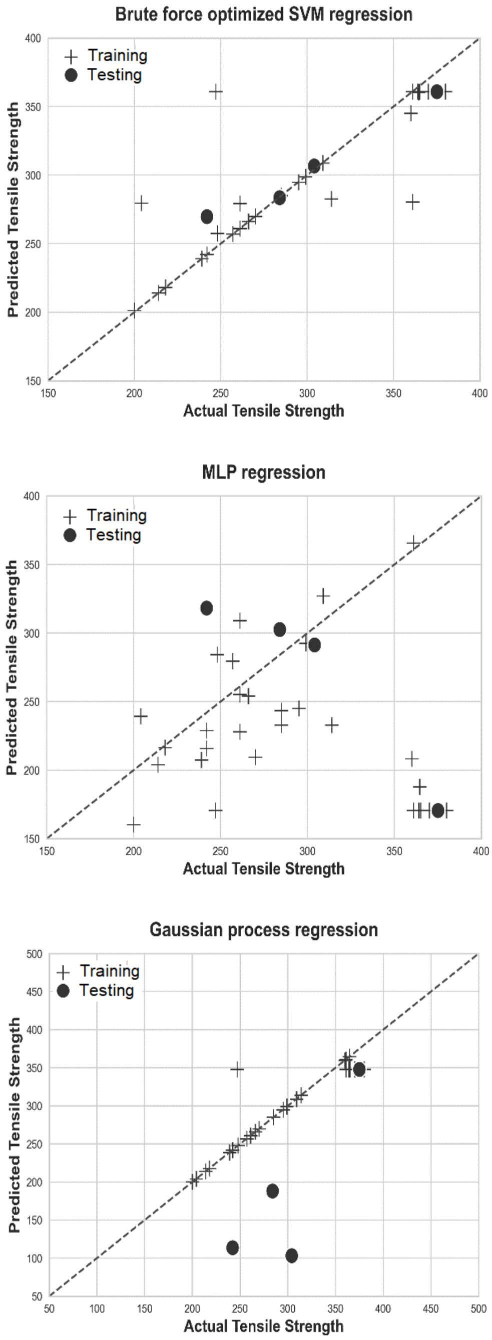


Fig. 4: Scatter plot of actual versus predicted tensile strength as predicted by various regression models (a) linear (b) AdaBoost (c) random forest (d) support vector (e) MLP and (f) Gaussian process.

3.2 Discussion on Process Parameters

Tool rotational speed significantly affects the heat input and the plasticization of the material during the welding process. Higher rotational speeds typically increase the heat input, which can enhance the material's flowability, leading to better mixing of materials at the joint interface. However, excessive rotational speeds may cause overheating, resulting in defects such as porosity or excessive grain growth, which can reduce the tensile strength of the weld.

Welding speed is inversely related to the heat input per unit length of the weld. A higher welding speed reduces the exposure time of the material to the heat source, potentially leading to insufficient fusion and weaker joints. Conversely, a lower welding speed increases the heat input, which can improve the weld strength but may also introduce thermal distortions or residual stresses if not properly controlled.

The diameter of the tool's shoulder plays a critical role in determining the amount of frictional heat generated during the welding process. A larger shoulder diameter increases the contact area, thereby enhancing heat generation and material stirring. This can result in a more uniform temperature distribution and better consolidation of the weld. However, if the shoulder diameter is too large, it may cause excessive material thinning or increase the risk of defects such as flash or undercutting.

The tilt angle of the tool affects the flow of plasticized material and the formation of the weld bead. A slight tilt can help in directing the plasticized material back into the joint, enhancing weld formation and reducing voids. However, an inappropriate tilt angle can lead to surface defects and compromise the structural integrity of the weld.

3.3 Comparison of Various ML Predictive Models

Figure 4 provides scatter plots comparing the actual versus predicted tensile strength values for each ML model. The closer the points are to the diagonal line, the more accurate the predictions. From these plots, it is evident that GPR provides the closest fit to the actual values, indicating superior predictive performance. In contrast, MLP shows significant deviation, highlighting its poor performance for this specific task.

In this study, multiple statistical metrics like R^2, Root Mean Squared Error ($RMSE$), Mean Absolute Error (MAE), Maximum Error, Mean Squared Logarithmic Error ($MSLE$) and Median Absolute Error ($MedAE$) are considered to assess the performance of the ML models. Table 1 and Table 2 summarize the performance metrics of each model on the training and testing datasets, respectively. These tables provide quantitative insights into each model's accuracy, robustness and generalizability.

The Linear Regression (LR) model, with an R^2 of -0.89 and a high $RMSE$ (66.17) on testing data, shows poor predictive power, likely due to its inability to model the nonlinear relationships inherent in the data. Random Forest Regression (RFR) demonstrates strong performance with a high R^2 value (0.79), indicating that it explains a substantial proportion of the variance in tensile strength. This model also shows second lowest $RMSE$ (25.51), suggesting good accuracy. However, in testing, its R^2 (0.20) and $RMSE$ (42.99) indicate some overfitting, as the metrics deteriorate compared to training data results.

GPR outperforms other models on training data, with the highest R^2 (0.86) and lowest $RMSE$ (20.7). But it shows significant overfitting with a negative R^2 (-6.19) on testing data, indicating poor generalization. This is likely due to the complexity of the model, which may fit the training data too closely, capturing noise as well as signal.

MLP shows poor performance, evidenced by a negative R^2 (-2.18), indicating that the model fails to capture the relationship between input features and output response effectively. The high $RMSE$ (98.75) in training $RMSE$ (109.68) in testing further confirm its inadequacy in this context. On testing data, SVR performs notably well with an R^2 of 0.89 and a low $RMSE$ of 15.64. This suggests that SVR has good generalization capability and effectively predicts tensile strength.

The discrepancies between training and testing data performance highlight the challenges of overfitting, particularly in complex models like GPR and MLP. Overfitting arises when a model learns both the genuine structures and the noise in the training data, resulting in inadequate performance on unseen data. The strong performance of SVR on testing data suggests that its regularization mechanism effectively balances bias and variance, providing robust predictions even with potential data noise. The poor performance of MLP and LR can be attributed to insufficient data or inadequate tuning of hyperparameters. MLP, being a neural network-based model, may require a larger dataset to train effectively and avoid overfitting. LR's linear nature limits its capacity to model the complex, nonlinear interactions between welding parameters and tensile strength.

Tab. 1: Assessment of predictive performance of various ML models using different statistical metrics on training data.

Metric	LR	RFR	ABR	SVR	MLP	GPR
R^2	0.17	0.79	0.66	0.69	-2.18	0.86
RMSE	50.51	25.51	32.51	30.67	98.75	20.70
MAE	43.39	17.00	23.29	13.32	69.66	6.95
Max. Error	90.13	98.12	81.63	113.90	209.43	100.83
MSLE	0.03	0.01	0.01	0.01	0.15	0.00
MedAE	43.81	13.08	18.75	0.10	39.52	0.00

Tab. 2: Assessment of predictive performance of various ML models using different statistical metrics on testing data.

Metric	LR	RFR	ABR	SVR	MLP	GPR
R^2	-0.89	0.20	-0.17	0.89	-4.20	-6.19
RMSE	66.18	42.99	51.94	15.64	109.68	128.99
MAE	61.33	31.79	45.16	11.26	78.00	112.89
Max. Error	87.13	79.00	86.63	27.77	204.43	200.65
MSLE	0.05	0.02	0.03	0.00	0.17	0.47
MedAE	61.85	22.92	35.50	8.44	47.50	111.88

4. CONCLUSIONS

This study demonstrates that machine learning models can effectively predict tensile strength based on welding parameters, offering a valuable tool for optimizing welding processes in industrial applications. The performance of different ML models varied significantly. SVR showed the highest generalization capability on testing data, achieving an R^2 of 0.89, indicating a strong ability to predict tensile strength accurately. GPR despite its high accuracy on training data, exhibited significant overfitting, as evidenced by poor performance on testing data. This finding highlights the importance of balancing model complexity with generalization capacity to prevent overfitting. The study also highlights the challenges associated with data quality and quantity in welding research. Limited datasets and the presence of noise can adversely affect model performance, thereby necessitating robust data collection and preprocessing techniques.

The study advocates for future investigations into hybrid models integrating diverse ML methodologies and improving interpretability. This could involve integrating domain-specific knowledge with ML to improve model accuracy and usability in practical welding scenarios. The study illustrates that ML models can optimize welding parameters effectively, minimizing trial-and-error methodologies and improving welding quality and efficiency.

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