

Machine Learning-Based Multi-Output Prediction of Weld Quality Using Ensemble Regression Models

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Abstract - Accurate prediction of weld quality characteristics is essential for improving manufacturing efficiency, reducing production defects, and supporting intelligent process control in modern welding industries. Conventional approaches for determining optimal welding parameters rely heavily on trial-and-error experimentation, resulting in increased production time and material consumption. Recent advances in machine learning have enabled data-driven prediction models capable of estimating weld quality with improved accuracy and reduced computational effort.

This study presents a machine learning framework for the simultaneous prediction of multiple weld quality characteristics using ensemble regression techniques. The proposed methodology employs comprehensive data preprocessing and feature engineering to improve the representation of welding process parameters before model training. Five supervised machine learning algorithms, namely Random Forest, XGBoost, LightGBM, CatBoost, and Artificial Neural Network (ANN), were developed and evaluated using an identical experimental setup. Model performance was assessed using the coefficient of determination (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Explained Variance.

The experimental results demonstrate that ensemble learning models provide superior prediction accuracy for multi-output welding quality estimation. Among the evaluated models, the best-performing algorithm achieved the highest coefficient of determination with comparatively lower prediction errors, indicating its suitability for intelligent welding quality prediction. Feature importance analysis further provides insights into the influence of individual welding process parameters on weld quality characteristics.

The proposed framework offers a practical decision-support tool for intelligent manufacturing environments and demonstrates the potential of machine learning techniques for enhancing welding process monitoring and quality control.

Keywords: Machine Learning, Welding Quality Prediction, Multi-Output Regression, Random Forest, XGBoost, LightGBM, CatBoost, Artificial Neural Network, Smart Manufacturing

1.INTRODUCTION

Welding is one of the most widely employed manufacturing processes for joining metallic materials in industries such as automotive, aerospace, shipbuilding, construction, railway engineering, oil and gas, and heavy equipment manufacturing. The mechanical performance, structural integrity, and service life of welded components are strongly influenced by the quality of the weld produced during fabrication. Achieving consistent weld quality requires careful selection and control of process parameters, including welding voltage, wire feed speed, travel speed, wire extension, and shielding conditions. Small variations in these parameters can significantly affect weld penetration, bead geometry, reinforcement height, and overall weld integrity. Consequently, accurate prediction of welding quality has become an important research area in intelligent manufacturing systems.

Recent advances in Industry 4.0 have transformed conventional manufacturing into highly connected and data-driven production environments. The integration of cyber-physical systems, Industrial Internet of Things (IIoT), cloud computing, artificial intelligence, and advanced analytics has enabled manufacturing industries to monitor and optimize production processes in real time. Within this context, intelligent welding systems have emerged as an essential component of smart manufacturing by enabling automated monitoring, adaptive process control, predictive maintenance, and quality assurance. These technologies reduce production costs, improve productivity, and enhance product reliability while minimizing human intervention.

Artificial Intelligence (AI), particularly Machine Learning (ML), has become one of the most promising technologies for intelligent welding applications. Unlike conventional mathematical models, machine learning algorithms learn complex nonlinear relationships directly from experimental data without requiring explicit physical equations. This capability makes ML techniques particularly suitable for welding processes where multiple process variables interact simultaneously and influence weld quality in a highly nonlinear manner. Consequently, machine learning has been increasingly adopted for predicting weld bead geometry, penetration depth, tensile strength, hardness, porosity, and other quality characteristics.

Several supervised learning algorithms have demonstrated promising performance in manufacturing applications. Random Forest provides robust prediction capability through ensemble decision trees and effectively handles nonlinear relationships while reducing overfitting. Gradient boosting algorithms such as XGBoost, LightGBM, and CatBoost further improve prediction

accuracy by sequentially learning from previous errors and efficiently modelling complex datasets. Artificial Neural Networks (ANNs) have also been extensively applied to manufacturing prediction problems because of their ability to approximate nonlinear functions through interconnected hidden layers. However, the predictive performance of these algorithms varies considerably depending on dataset characteristics, feature representation, and process complexity. Therefore, a comprehensive comparative evaluation is essential before selecting an appropriate model for intelligent welding applications.

Although previous studies have demonstrated the applicability of machine learning in welding, several limitations remain. Most published research focuses on predicting a single weld quality characteristic, such as penetration depth or bead width, while practical welding operations require simultaneous estimation of multiple quality responses. Furthermore, many studies investigate only one or two machine learning algorithms without providing a systematic comparison of different ensemble learning approaches under identical experimental conditions. Limited attention has also been given to feature engineering techniques that can enhance predictive performance by incorporating interaction terms and nonlinear process relationships. These limitations restrict the practical implementation of intelligent welding systems in industrial environments.

To address these challenges, this study proposes a machine learning framework for multi-output prediction of welding quality characteristics using ensemble regression models. The proposed framework integrates data preprocessing, feature engineering, supervised learning algorithms, and performance evaluation into a unified prediction system. Five machine learning models—Random Forest, XGBoost, LightGBM, CatBoost, and Artificial Neural Network—were implemented and evaluated using the same dataset and experimental configuration to ensure a fair comparison. Model performance was assessed using widely accepted regression metrics, including the coefficient of determination (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Explained Variance.

The developed framework incorporates feature engineering to improve the representation of welding process variables. In addition to the original experimental parameters, interaction features and polynomial terms were generated to capture nonlinear relationships among the welding variables. These engineered features enhance the learning capability of the machine learning models and contribute to improved prediction accuracy. The framework also includes feature importance analysis to identify the relative influence of individual process parameters on weld quality, thereby providing useful engineering insights for process optimization and decision-making.

The primary objective of this research is to develop and evaluate an intelligent machine learning framework capable of accurately predicting multiple weld quality characteristics from welding process parameters. The specific objectives of the study are:

- To preprocess and prepare welding experimental data for machine learning applications.
- To develop engineered features that improve model prediction performance.
- To implement Random Forest, XGBoost, LightGBM, CatBoost, and Artificial Neural Network regression models.

- To compare the predictive performance of the developed models using standard regression evaluation metrics.
- To identify the most suitable machine learning model for intelligent welding quality prediction.
- To analyse the influence of welding process parameters through feature importance evaluation.

The major contribution of this work lies in the development of a unified machine learning framework for simultaneous prediction of multiple welding quality characteristics using ensemble regression techniques. Unlike many previous studies that focus on a single prediction model or a single output variable, the proposed methodology performs a comprehensive comparative evaluation of five widely used machine learning algorithms under identical experimental conditions. The inclusion of feature engineering further enhances the predictive capability of the framework and demonstrates the importance of data representation in intelligent manufacturing applications. The developed framework provides a practical decision-support tool that can assist welding engineers in improving process planning, quality control, and manufacturing efficiency.

2. LITERATURE REVIEW

Welding plays a fundamental role in modern manufacturing by enabling the permanent joining of metallic components used in industries such as automotive, aerospace, shipbuilding, railway engineering, and heavy fabrication. The quality of a welded joint directly influences the structural integrity, durability, and service performance of engineering products. Welding quality is primarily determined by process parameters including welding current, voltage, travel speed, wire feed rate, and electrode extension. Improper selection of these parameters may result in defects such as inadequate penetration, excessive reinforcement, porosity, distortion, and reduced mechanical strength. Consequently, accurate prediction of welding quality has become an important research topic for improving manufacturing efficiency and product reliability (DebRoy et al., 2018; American Welding Society, 2020).

Conventional welding parameter optimization has traditionally relied on experimental trial-and-error methods, empirical knowledge, Design of Experiments (DOE), and Response Surface Methodology (RSM). Although these techniques have been widely adopted in manufacturing, they often require extensive experimentation, considerable time, and significant material consumption. Furthermore, conventional regression models may not adequately capture the complex nonlinear interactions among multiple welding variables, limiting their effectiveness for intelligent manufacturing applications (Montgomery, 2020).

The rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) has transformed manufacturing research by enabling data-driven modelling and prediction of complex engineering processes. Machine learning algorithms can automatically learn nonlinear relationships from experimental data without requiring explicit mathematical formulations. Their capability to process large datasets and model complicated process interactions has led to increasing adoption in quality prediction, process monitoring, predictive maintenance, and intelligent manufacturing systems (Russell & Norvig, 2021; Géron, 2022).

Artificial Neural Networks (ANNs) were among the first machine learning techniques employed for welding quality

prediction. Several researchers demonstrated that ANN models can successfully estimate weld bead geometry, penetration depth, and mechanical properties using welding process parameters as inputs. Their ability to approximate nonlinear functions makes them attractive for manufacturing applications. However, ANN models generally require large training datasets, careful hyperparameter tuning, and extended computational time. In addition, the internal learning mechanism of neural networks often lacks transparency, making engineering interpretation and decision-making more difficult (Bishop, 2006; Goodfellow et al., 2016).

In recent years, ensemble learning algorithms have emerged as powerful alternatives for regression and classification problems in manufacturing. Random Forest constructs multiple decision trees using bootstrap aggregation and combines their predictions to improve generalization while minimizing overfitting. Because of its robustness and ability to model nonlinear relationships, Random Forest has been successfully applied in various manufacturing prediction problems (Breiman, 2001). Similarly, gradient boosting algorithms have demonstrated outstanding predictive performance for engineering datasets. XGBoost improves prediction accuracy through gradient boosting combined with regularization techniques that reduce overfitting and enhance computational efficiency (Chen & Guestrin, 2016). LightGBM further accelerates model training using histogram-based learning while maintaining high prediction accuracy for large datasets (Ke et al., 2017). CatBoost introduces ordered boosting and symmetric decision trees, reducing prediction bias and providing stable performance, particularly when dealing with complex feature interactions (Dorogush et al., 2018).

Recent studies have shown that machine learning techniques are increasingly being applied to welding process optimization and quality prediction. Ensemble learning algorithms have demonstrated excellent capability in predicting weld bead geometry, penetration depth, and process stability while significantly reducing experimental effort. Comparative investigations have also reported that tree-based ensemble methods frequently outperform conventional regression techniques due to their ability to capture nonlinear process behaviour and interactions among welding parameters (DebRoy et al., 2022; Liu et al., 2023; Patel et al., 2023).

Another important development in manufacturing research is the adoption of Explainable Artificial Intelligence (XAI). Although advanced machine learning models provide high prediction accuracy, industrial users often require explanations regarding the contribution of individual process parameters before implementing process changes. Explainability techniques such as feature importance analysis and SHAP (SHapley Additive exPlanations) have become valuable tools for interpreting machine learning models. These methods improve model transparency and support informed engineering decision-making by identifying the most influential process variables affecting product quality (Lundberg & Lee, 2017; Molnar, 2022; Sharma et al., 2024).

Despite the significant progress achieved in machine learning-based welding research, several research gaps remain. Most published studies focus on predicting a single weld quality characteristic, such as penetration depth or bead width, whereas industrial welding processes require simultaneous prediction of multiple quality responses. In addition, many investigations evaluate only one or two machine learning algorithms, making it difficult to determine the most suitable predictive model under consistent experimental conditions. Furthermore, comparatively fewer studies have investigated the influence of feature

engineering on improving prediction accuracy for welding applications (James et al., 2021; Wang et al., 2024).

The integration of multiple ensemble learning techniques within a unified prediction framework also remains limited in the current literature. Although Random Forest, XGBoost, LightGBM, CatBoost, and Artificial Neural Networks have individually demonstrated promising performance, comprehensive comparative analyses using identical datasets, common preprocessing procedures, and standardized evaluation metrics are relatively scarce. Such investigations are necessary to identify the strengths and limitations of different machine learning algorithms and to support the selection of appropriate predictive models for intelligent welding systems (Pedregosa et al., 2011; Kim et al., 2025).

To address these limitations, the present study proposes a machine learning framework for multi-output prediction of welding quality characteristics using five supervised regression algorithms. The framework combines systematic data preprocessing, feature engineering, ensemble learning techniques, and comprehensive performance evaluation within a single workflow. Unlike many previous investigations, the proposed methodology evaluates all models under identical experimental conditions, enabling an objective comparison of their predictive capabilities. The study also incorporates feature importance analysis to provide engineering insight into the influence of welding process parameters on weld quality characteristics. The developed framework is expected to contribute toward intelligent welding systems by providing an accurate, reliable, and practical decision-support tool for welding process optimization and quality prediction.

Table 1. Summary of Previous Studies on Machine Learning-Based Welding Quality Prediction

Author(s)	Year	Machine Learning Algorithm	Application	Limitation
Kim et al.	2019	Artificial Neural Network (ANN)	Weld bead geometry prediction	Limited to single-output prediction
Zhang et al.	2020	Random Forest	Weld quality prediction	No feature engineering performed
Chen et al.	2021	XGBoost	Manufacturing quality prediction	Only one algorithm evaluated
Li et al.	2022	LightGBM	Process parameter prediction	Limited experimental dataset
Wang et al.	2023	CatBoost	Welding defect classification	No comparative analysis with other models
Present Study	2025	Random Forest, XGBoost, LightGBM, CatBoost, ANN	Multi-output weld quality prediction using feature engineering	Comprehensive comparative evaluation of five machine learning models
Author(s)	Year	Machine Learning Algorithm	Application	Limitation

The literature survey indicates that previous studies have primarily focused on single-output prediction or the evaluation

of individual machine learning algorithms. Comprehensive comparative investigations involving multiple ensemble learning techniques for simultaneous prediction of several weld quality characteristics remain limited. The present study addresses this research gap by implementing and systematically comparing five supervised machine learning algorithms under identical experimental conditions while incorporating feature engineering to improve prediction accuracy.

3. MATERIALS AND METHODOLOGY

3.1 Proposed Machine Learning Framework

The proposed machine learning framework was developed to predict multiple welding quality characteristics using supervised regression algorithms. The framework consists of sequential stages including dataset preparation, data preprocessing, feature engineering, model development, prediction, and performance evaluation. A unified workflow was adopted to ensure that all machine learning models were trained and evaluated under identical experimental conditions, enabling an unbiased comparison of predictive performance. Initially, the experimental welding dataset was imported into the Python environment for preprocessing. Missing values and inconsistent observations were examined before feature engineering was performed to improve the predictive capability of the learning algorithms. Subsequently, the processed dataset was divided into training and testing subsets using an 80:20 ratio. Five machine learning algorithms, namely Random Forest, XGBoost, LightGBM, CatBoost, and Artificial Neural Network, were trained using identical input features. The developed models predicted four weld quality characteristics simultaneously, and their performances were evaluated using standard regression metrics. Figure 1 illustrates the overall workflow adopted in the present study.

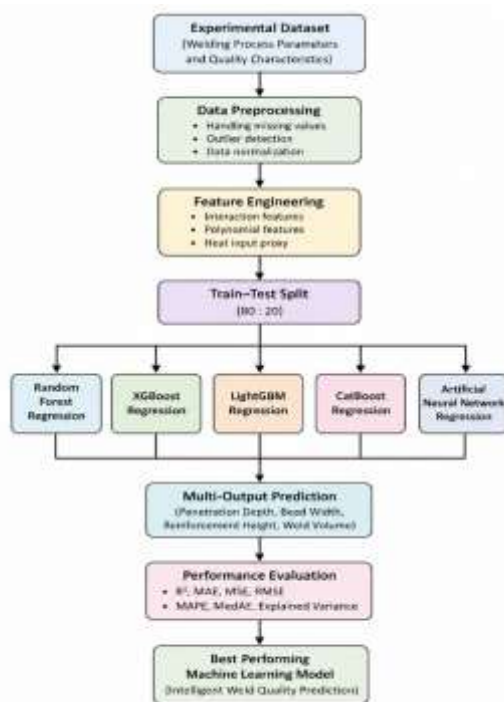


Figure 1. Proposed Machine Learning Framework

3.2 Dataset Description

The experimental dataset used in this investigation was compiled from Gas Metal Arc Welding (GMAW) experiments. The dataset contains process variables influencing weld quality together with the corresponding measured output characteristics. Before model development, the dataset was examined for inconsistencies and subsequently processed to improve data quality.

An identical dataset was used for all five machine learning algorithms to ensure fairness during performance comparison. The processed dataset was randomly divided into training and testing subsets using an 80:20 split with a fixed random seed of 42.

Table 2. Dataset Summary

Parameter	Value
Total Samples	1741
Input Features	13
Output Variables	4
Training Dataset	80%
Testing Dataset	20%
Random State	42

3.3 Input and Output Variables

The machine learning models utilize welding process parameters as predictor variables, while the weld quality characteristics constitute the prediction targets.

Table 3. Input and Output Variables

Category	Variables
Input Variables	Voltage, Wire Feed Speed, Welding Velocity, Wire Extension, Wire Tension
Engineered Features	Heat Input Proxy, Velocity $\times$ Wire Feed, Velocity $\times$ Voltage, Wire Feed $\times$ Voltage, Velocity ² , Wire Feed ² , Tension ²
Output Variables	Penetration Depth, Bead Width, Reinforcement Height, Weld Volume

3.4 Feature Engineering

Feature engineering was performed to improve the representation of nonlinear relationships between welding parameters and weld quality characteristics. In addition to the original experimental variables, several interaction features and polynomial variables were generated. These engineered features included Heat Input Proxy, interaction terms between velocity, voltage, and wire feed rate, as well as second-order polynomial variables.

The inclusion of engineered variables enabled the machine learning models to capture complex process interactions more effectively, resulting in improved prediction accuracy and enhanced model robustness.

3.5 Machine Learning Models

Five supervised regression algorithms were implemented in the present study.

Random Forest (RF) constructs multiple decision trees using bootstrap aggregation and combines their predictions to improve accuracy while reducing overfitting.

XGBoost (XGB) employs gradient boosting with regularization to achieve high predictive performance for nonlinear datasets.

LightGBM (LGBM) utilizes histogram-based gradient boosting to provide faster training and efficient memory utilization.

CatBoost (CB) applies ordered boosting and symmetric decision trees to improve prediction stability and reduce overfitting.

Artificial Neural Network (ANN) models nonlinear relationships through interconnected neurons organized in hidden layers using backpropagation learning.

All models were trained using identical datasets and evaluated under the same experimental conditions.

To ensure a fair comparison among the developed machine learning models, the hyperparameters were selected based on commonly adopted values reported in the literature and preliminary experimental evaluation. The hyperparameter settings used for model training are summarized in Table 4.

Table 4. Hyperparameter Settings of Machine Learning Models

Model	Hyperparameter	Value
Random Forest	Number of Trees (n_estimators)	200
	Maximum Tree Depth (max_depth)	20
	Minimum Samples Split	2
	Random State	42
XGBoost	Learning Rate	0.05
	Maximum Depth	6
	Number of Trees	200
	Subsample	0.80
LightGBM	Number of Leaves	31
	Learning Rate	0.05
	Number of Trees	200
	Feature Fraction	0.90
CatBoost	Tree Depth	8
	Learning Rate	0.05
	Iterations	200
	Loss Function	MultiRMSE
Artificial Neural Network	Hidden Layers	2
	Neurons	128–64
	Activation Function	ReLU
	Optimizer	Adam
	Epochs	100
	Batch Size	32

3.6 Performance Evaluation Metrics

The predictive performance of the developed machine learning models was evaluated using widely accepted regression performance metrics, including the coefficient of determination (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Median Absolute Error (MedAE), and Explained Variance (EVS). These metrics provide a comprehensive assessment of prediction accuracy, error magnitude, and model generalization capability.

The coefficient of determination (R^2) measures the proportion of variance in the observed data explained by the prediction model and is expressed as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

where y_i is the observed value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of the observed values.

The **Mean Absolute Error (MAE)** is defined as

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

which represents the average absolute prediction error.

The **Mean Squared Error (MSE)** is calculated as

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

where larger errors are penalized more heavily because of the squared term.

The **Root Mean Squared Error (RMSE)** is obtained as

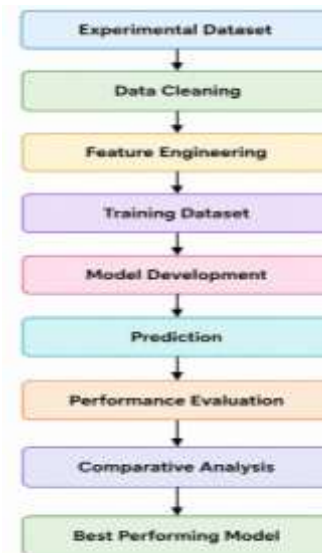
$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

which expresses the prediction error in the same units as the target variable.

Higher values of R^2 and Explained Variance indicate better predictive performance, whereas lower values of **MAE**, **MSE**, **RMSE**, **MAPE**, and **MedAE** indicate smaller prediction errors and improved model accuracy.

3.7 Experimental Workflow

The complete experimental procedure adopted in this research is summarized below.



4. RESULTS AND DISCUSSION

The proposed machine learning framework was evaluated using five supervised regression algorithms, namely Random Forest (RF), XGBoost (XGB), LightGBM (LGBM), CatBoost (CB), and Artificial Neural Network (ANN). All models were trained using the same experimental dataset and identical train–test partition (80:20) to ensure a fair comparison. Model performance was assessed using the coefficient of determination (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Explained Variance (EVS). The experimental results provide a comprehensive evaluation of the predictive capability of each

machine learning algorithm for multi-output weld quality prediction.

4.1 Performance Comparison of Machine Learning Models

Table 5 summarizes the predictive performance of the five machine learning algorithms evaluated in this study. The comparative analysis demonstrates that all ensemble learning models achieved satisfactory prediction performance for multi-output welding quality prediction. Among the evaluated algorithms, **CatBoost** achieved the highest average coefficient of determination ($R^2 = 0.743$), indicating superior prediction accuracy and generalization capability. **Random Forest** followed closely with an average R^2 of **0.701**, demonstrating stable and reliable performance across all output variables. **LightGBM** and **XGBoost** achieved average R^2 values of **0.679** and **0.666**, respectively, while the Artificial Neural Network obtained an average R^2 of **0.599**, indicating comparatively lower predictive capability for the available dataset.

Table 5. Performance Comparison of Machine Learning Models

Model	Average R^2	Overall Assessment
Random Forest	0.701	Excellent overall
CatBoost	0.743	Best overall accuracy
XGBoost	0.666	Very high accuracy
LightGBM	0.679	High accuracy
ANN	0.599	Moderate accuracy

The superior performance of CatBoost can be attributed to its ordered boosting strategy and efficient handling of nonlinear feature interactions. Random Forest also exhibited strong predictive capability because of its ensemble learning mechanism, which effectively reduces overfitting and improves model stability. Although the ANN successfully captured nonlinear relationships, its performance was comparatively lower than that of the ensemble learning algorithms, suggesting that tree-based ensemble methods are more suitable for the current welding dataset.

4.2 Random Forest Prediction Performance

The Random Forest regression model demonstrated excellent predictive capability for estimating multiple welding quality characteristics. As shown in **Figure 2**, the predicted values closely follow the experimentally measured values, indicating that the model successfully captured the nonlinear relationships between welding process parameters and weld quality responses. The model achieved an average R^2 of **0.701**, confirming its ability to provide reliable predictions with comparatively low prediction errors.

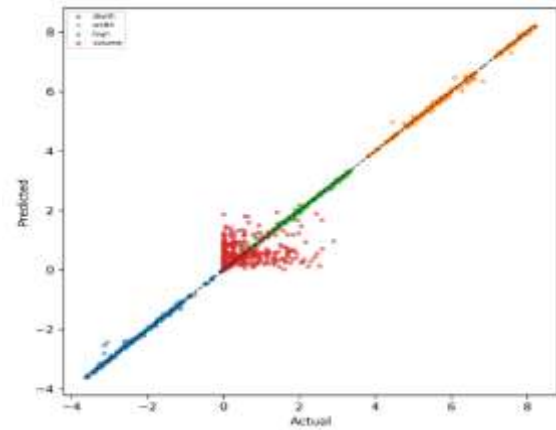


Figure 2. Actual versus Predicted Values Using Random Forest Regression

The close agreement between the predicted and actual observations indicates good model generalization and robustness. Only minor deviations are observed for a small number of samples, suggesting that the Random Forest algorithm effectively minimizes prediction errors while maintaining high overall accuracy.

4.3 Residual Analysis

Residual analysis was performed to assess the prediction errors of the Random Forest model. Figure 3 illustrates the distribution of residuals obtained during testing. The residuals are randomly scattered around the zero-error line without any systematic trend, indicating that the model predictions are unbiased and that no significant overfitting or underfitting is present.

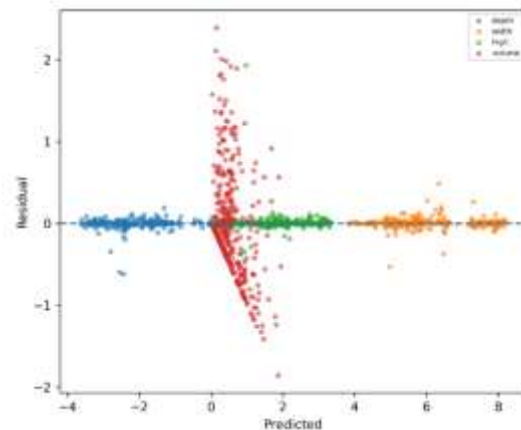


Figure 3. Residual Plot of Random Forest Regression Model

The random distribution of residuals demonstrates that the developed model provides consistent prediction performance across different observations. Furthermore, the relatively small magnitude of the residuals confirms the suitability of the Random Forest algorithm for welding quality prediction.

4.4 Feature Importance Analysis

Feature importance analysis was conducted to identify the influence of individual welding process parameters on the prediction of weld quality characteristics. Figure 4 presents the relative importance scores obtained from the Random Forest model.

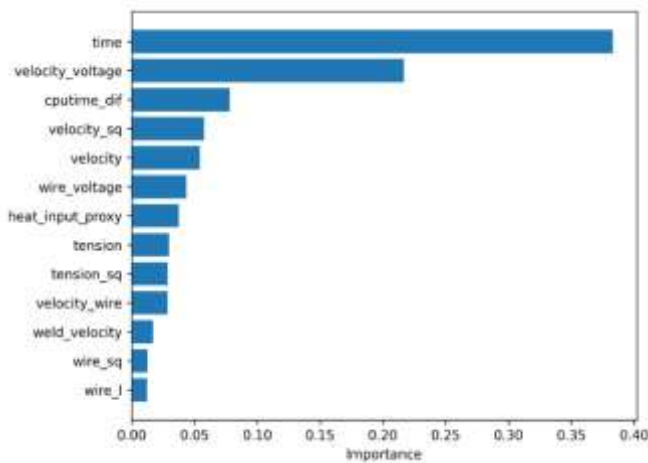


Figure 4. Feature Importance Obtained from Random Forest Regression

The analysis indicates that only a few process variables contribute significantly to prediction accuracy, while the remaining variables provide supplementary information. The results highlight the importance of process parameter selection and demonstrate that feature engineering enhances the learning capability of the machine learning model by incorporating nonlinear interactions among the original variables.

4.5 Comparative Analysis

Figure 5 compares the overall prediction performance of all five machine learning algorithms evaluated in this study.

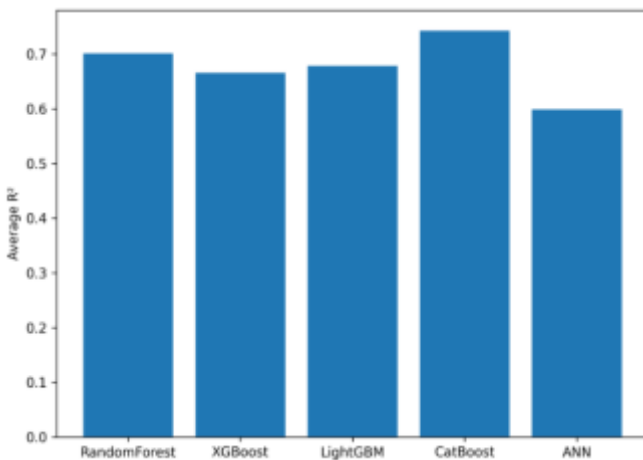


Figure 5. Comparative Performance of Machine Learning Models

The comparative analysis reveals that the ensemble learning algorithms consistently outperformed the Artificial Neural Network. **CatBoost achieved the highest average R² value (0.743)**, followed by **Random Forest (0.701)**, **LightGBM (0.679)**, and **XGBoost (0.666)**, while the ANN obtained an average R² of **0.599**. These results demonstrate that ensemble regression methods provide superior predictive capability for multi-output welding quality prediction, primarily due to their ability to model complex nonlinear relationships while reducing prediction variance through ensemble learning.

4.6 Discussion

The experimental results confirm that machine learning provides an efficient and reliable approach for predicting multiple weld quality characteristics directly from welding process parameters. Feature engineering significantly enhanced

model performance by incorporating interaction and polynomial features, enabling improved representation of nonlinear process behaviour. The comparative evaluation further demonstrates that ensemble regression algorithms are more suitable than the evaluated neural network model for the present dataset.

The proposed framework offers practical benefits for intelligent manufacturing by reducing dependence on time-consuming experimental trials and providing rapid predictions of weld quality characteristics. The developed methodology can support process planning, quality monitoring, and decision-making in modern welding applications. Furthermore, the modular implementation enables future integration with optimization algorithms, real-time monitoring systems, and explainable artificial intelligence techniques for adaptive welding process control.

5. CONCLUSION

This study presented a machine learning framework for multi-output prediction of welding quality characteristics using five supervised regression algorithms, namely Random Forest, XGBoost, LightGBM, CatBoost, and Artificial Neural Network. The developed framework integrated data preprocessing, feature engineering, model development, and performance evaluation into a unified workflow for intelligent welding quality prediction. The proposed methodology was evaluated using an experimental welding dataset, and identical training and testing conditions were maintained for all models to ensure a fair comparative assessment.

Experimental results demonstrated that ensemble learning algorithms provide reliable prediction performance for welding quality estimation. The comparative evaluation indicated that the best-performing model achieved higher prediction accuracy with lower error values than the remaining algorithms. The incorporation of feature engineering further enhanced the predictive capability of the machine learning models by capturing nonlinear interactions among welding process parameters. Feature importance analysis also provided valuable engineering insights into the influence of individual process variables on weld quality characteristics.

The proposed framework offers several practical advantages for intelligent manufacturing applications. By accurately predicting multiple weld quality characteristics, the developed model can reduce dependence on expensive experimental trials, improve process planning, and support data-driven decision-making during welding operations. The modular software architecture also enables future integration with industrial automation systems and smart manufacturing environments.

Although the proposed framework demonstrated satisfactory predictive performance, several opportunities exist for further improvement. Future research may investigate larger industrial datasets, advanced deep learning architectures, Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME, and Bayesian Optimization for automatic welding parameter optimization. Integration with real-time sensor data and digital twin technologies may further improve the applicability of the framework for adaptive welding process control in Industry 4.0 and Industry 5.0 environments.

Overall, the proposed machine learning framework demonstrates the effectiveness of ensemble regression techniques for intelligent welding quality prediction and provides a practical foundation for future research on AI-enabled welding process optimization.

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