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RESEARCH PAPER

Towards an ensemble machine learning framework for accurate prediction of WAAM bead geometry

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Abstract

Wire Arc Additive Manufacturing (WAAM) has gained significant attention as an efficient technique for producing large-scale metallic structures with high material utilization and enhanced deposition rates. Despite its advantages, accurately predicting bead geometry remains challenging due to the highly nonlinear interactions between process variables and deposition behavior. In this study, an AI-based regression framework is proposed to predict bead geometry in stainless-steel WAAM processes using key input parameters, including voltage, current, wire feed rate, and travel speed. An experimental WAAM dataset was employed to train and evaluate several machine learning regression models, including Random Forest Regressor (RF), Support Vector Regressor (SVR), and Extreme Gradient Boosting Regressor (XGBoost). Model performance was analyzed using evaluation metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). Among the developed models, XGBoost achieved the highest prediction accuracy, with an R^2 of 0.9560, indicating a strong correlation between predicted and actual bead geometry measurements. In addition, feature importance analysis identified wire feed rate as the most significant parameter influencing bead geometry. The proposed ensemble learning-based framework successfully models the nonlinear dynamics of the WAAM process while minimizing reliance on traditional trial-and-error methods. This work advances intelligent manufacturing, predictive process optimization, and smart WAAM technologies in accordance with Industry 4.0 principles.

1. Introduction

Additive manufacturing (AM) has transformed modern manufacturing by enabling the fabrication of complex geometries with reduced material wastage, shorter production cycles, and enhanced design flexibility. Among various metal additive manufacturing technologies, Wire Arc Additive Manufacturing (WAAM) has emerged as a promising and cost-effective technique for fabricating large-scale metallic components with high deposition rates (Zhou et al., 2024). WAAM uses an electric arc as the heat source and metallic wire as the feedstock to deposit layers, layer by layer, to fabricate components. Due to its ability to efficiently produce medium- to large-scale structures, WAAM has gained considerable attention in the aerospace, automotive, marine, oil and gas, and heavy engineering industries (Petro et al., 2025). Despite its advantages, achieving stable and consistent bead geometry during the WAAM process remains a major challenge. Bead geometry characteristics, such as bead width and height, significantly influence the dimensional accuracy, surface finish, deposition quality, and mechanical properties of the fabricated component. The bead morphology is highly dependent on multiple process parameters, including voltage, current, wire feed rate, and travel speed. Variations in these parameters can alter heat input, molten pool dynamics, cooling behavior, and material transfer mechanisms, resulting in

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defects such as poor fusion, irregular deposition, porosity, residual stresses, and dimensional inaccuracies (Le-Hong et al., 2023).
Therefore, precise prediction and control of bead geometry are essential for ensuring process stability and improving the quality and reliability of WAAM-fabricated parts. Conventionally, optimization of WAAM process parameters has relied heavily on experimental trial-and-error approaches. Although these methods provide practical understanding of process behavior, they require extensive experimentation, increased production time, high material consumption, and high operational cost. Moreover, the complex nonlinear relationship between process parameters and bead geometry makes traditional analytical and empirical modeling approaches insufficient for accurate prediction and intelligent process control. As WAAM systems continue to evolve toward automated and large-scale industrial manufacturing, conventional optimization techniques become increasingly inefficient and difficult to implement in real-time manufacturing environments (Dias et al., 2026).
Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have opened new opportunities for intelligent process modeling and smart manufacturing applications. Machine learning techniques can effectively capture nonlinear relationships between input process parameters and output responses using experimental datasets, enabling accurate prediction, process optimization, and adaptive control. Several researchers have explored ML-based approaches for defect prediction, process optimization, and bead geometry estimation in additive manufacturing systems. (Kim et al. 2024) applied machine learning techniques for predicting deposition bead geometry in WAAM, while Sharma (Sharma et al., 2023) utilized ML algorithms for forecasting process parameters in WAAM applications. Similarly, Chander et al. (2024) conducted a comparative analysis of machine learning models for bead geometry prediction and demonstrated the potential of data-driven frameworks in additive manufacturing environments. Among various machine learning approaches, ensemble learning techniques such as Random Forest and Extreme Gradient Boosting (XGBoost) have demonstrated excellent predictive capability, robustness, and generalization performance in manufacturing applications. These models can efficiently handle nonlinear interactions among processes, improve prediction accuracy, and provide feature-importance analysis to identify dominant process parameters. Integrating ensemble learning with WAAM can significantly reduce reliance on costly trial-and-error while enabling intelligent, data-driven manufacturing systems aligned with Industry 4.0 objectives. In this work, an AI-based ensemble learning approach is developed to estimate bead geometry in WAAM processes using key operational parameters, including voltage, current, wire feed rate, and travel speed. To achieve accurate prediction, several machine learning regression techniques, namely Random Forest Regressor, Support Vector Regressor, and XGBoost Regressor, are trained and analyzed. The performance of these models is assessed through evaluation measures including MAE, RMSE, and coefficient of determination (R^2). In addition, feature importance analysis is conducted to identify the relative contributions of individual process parameters to bead geometry characteristics. The overall objective of the proposed framework is to advance intelligent, robust, and data-driven WAAM systems for next-generation manufacturing environments.

2. Literature Review

Wire Arc Additive Manufacturing (WAAM) has emerged as an important metal additive manufacturing technique for producing large-scale components with improved deposition efficiency and reduced fabrication costs. Despite these advantages, achieving uniform and stable bead geometry during deposition remains a significant challenge. The geometry of the deposited bead is strongly influenced by the complex interrelationship among process parameters such as voltage, welding current, wire feed rate, and travel speed. Variations in these parameters directly affect heat input, molten pool behavior, and material deposition characteristics, thereby influencing the overall quality of the fabricated structure (Le-Hong et al., 2023). Conventional methods for optimizing WAAM process parameters primarily rely on repeated experimental trials and manual analysis. Such approaches require substantial time, material consumption, and operational cost. In recent years, Artificial Intelligence (AI) and Machine Learning (ML) techniques have attracted considerable attention as effective alternatives for predictive modeling, process optimization, and intelligent manufacturing applications. Several researchers have explored the use of ML algorithms to estimate bead geometry and improve deposition quality in WAAM processes. For instance, Mbodj et al. (2021) employed machine learning-based approaches for bead geometry prediction, whereas Sharma et al. (2023) investigated ML techniques for forecasting process behavior in additive manufacturing environments.
Various AI-based models, including Decision Tree (DT), Random Forest (RF), Artificial Neural Network (ANN), and XGBoost, have been studied to predict bead morphology and process performance in WAAM systems (Chandra et al., 2024). These studies demonstrated the capability of data-driven approaches to capture nonlinear process behavior more effectively than traditional analytical techniques. Likewise, Shah and Fuse (2024) used machine-learning classification algorithms, including Decision Tree, Random Forest, and K-Nearest Neighbor (KNN), to predict bead width and height in stainless steel WAAM applications. Although existing studies have reported encouraging outcomes, many investigations are primarily limited to classification-oriented approaches and a restricted set of machine learning techniques. To address these limitations, the present work introduces an AI-driven ensemble learning framework based on regression models, including Random Forest Regressor, Support Vector Regressor, and XGBoost Regressor, for accurate bead geometry prediction in WAAM systems. In addition, feature importance analysis is conducted to determine the relative impact of individual process parameters on bead formation and deposition behavior.

3. Methodology

3.1 Dataset Description and Statistical Analysis

The dataset used in this study comprised 50 experimental samples collected to predict bead geometry in the WAAM process. The input features included four key process parameters: voltage (V), current (A), wire feed rate (m/min), and travel speed (mm/min). The corresponding output responses were bead width (mm) and bead height (mm). Prior to model training, the dataset underwent preprocessing to maintain data quality and consistency. All records contained numerical floating-point values, and no missing data were observed. After preprocessing, the input and target variables were separated, and the dataset was partitioned into training and testing sets using an 80:20 split ratio. Accordingly, 40 samples were allocated for model training, while the remaining 10 samples were reserved for performance evaluation and testing. Table 1 presents the statistical summary of the WAAM dataset used for regression modeling.

Table 1: Statistical summary of the WAAM dataset.

Parameter	Mean	Std	Min	Max
Voltage (V)	25.102	4.499	18.3	31.9
Current (A)	207.774	54.969	126.3	299.5
Wire Feed Rate (m/min)	6.153	2.599	2.07	9.96
Travel Speed (mm/min)	474.176	157.477	204.0	782.8
Bead Width (mm)	6.214	1.549	3.06	9.18
Bead Height (mm)	2.688	1.054	0.82	4.65

The observed variation in process parameters and output responses indicates nonlinear behavior in the WAAM process, making the dataset suitable for machine-learning-based predictive modeling. Multiple regression models, including RF, SVR, and XGBoost, were implemented in Python with the scikit-learn library to predict bead geometry.

3.2 Machine Learning Models

In the present study, three regression-based machine learning models, namely RF, SVR, and XGBoost, were implemented for predicting bead geometry in WAAM systems. These models were selected for their strong ability to capture complex nonlinear relationships between process parameters and output responses.

3.2.1 Random Forest Regressor (RF)

Random Forest is an ensemble learning algorithm that generates multiple decision trees during the training phase and produces the final prediction by averaging the outputs of individual trees. The model improves prediction performance and reduces overfitting using bootstrap aggregation and random feature selection techniques. Owing to its robustness and efficient handling of nonlinear data, RF has been widely applied in manufacturing and regression-based prediction problems (Breiman, 2001). Figure 1 illustrates the working framework of the Random Forest algorithm, in which bootstrap sampling generates multiple training subsets, and independent decision trees learn distinct patterns from the data. The predictions from these trees are aggregated, improving model robustness, reducing variance, and supporting reliable predictive performance.

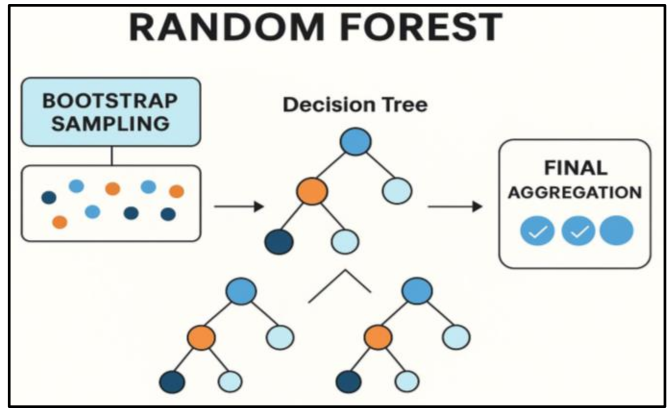

Figure 1: Architecture of Random Forest Regressor

3.2.2 Support Vector Regressor (SVR)

Support Vector Regression is a supervised machine learning technique used for predicting continuous output values. SVR attempts to identify an optimal regression hyperplane while maintaining a predefined error margin. The model is effective for nonlinear regression problems and minimizes prediction errors by maximizing the margin between data points and the regression boundary (Awad & Khanna, 2015).

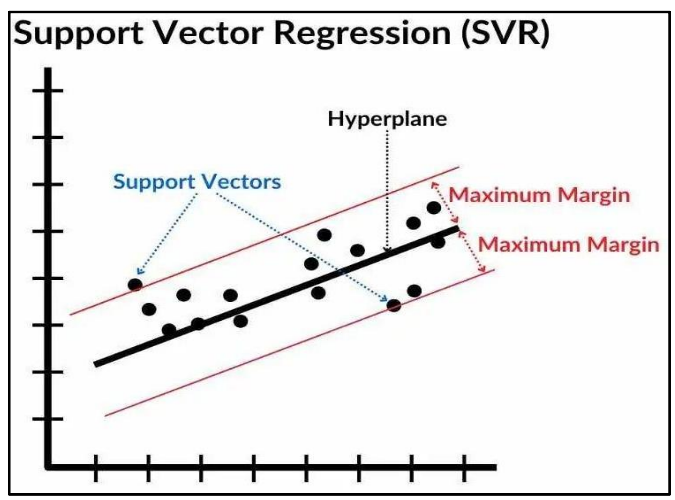

Figure 2: Architecture of Support Vector Regressor

Fig. 2 presents the architecture of the Support Vector Regressor (SVR), illustrating the fitted hyperplane and corresponding maximum-margin boundaries. Data points located within or influencing these margins serve as support vectors and determine the regression function. This formulation enables SVR to model nonlinear relationships while maintaining controlled prediction error and improved generalization.

3.2.3 Extreme Gradient Boosting Regressor (XGBoost)

XGBoost is an advanced ensemble boosting algorithm based on gradient boosting decision trees. The model sequentially constructs multiple trees, with each new tree attempting to minimize the residual errors of the previous ones. XGBoost offers high prediction accuracy, regularization capability, computational efficiency, and robustness against overfitting, making it well-suited for intelligent manufacturing and predictive modeling applications (Chen & Guestrin, 2016). Figure 3 depicts the architecture of the XGBoost regressor, in which multiple decision trees are trained sequentially on the dataset and progressively focus on correcting prediction errors from earlier learners. The outputs of individual trees are combined to generate the final prediction, enabling efficient learning, improved accuracy, and strong generalization across complex regression problems.

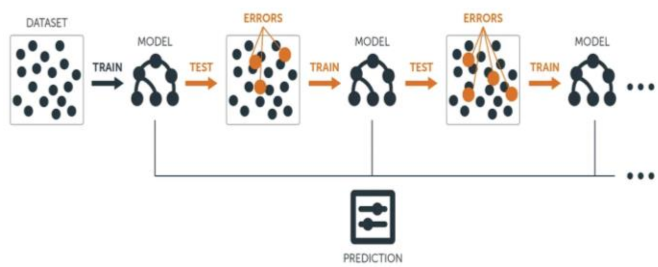

Figure 3: Architecture of XGBoost Regressor

The developed regression models were evaluated using statistical performance metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). Furthermore, feature importance analysis was conducted to investigate the influence of process parameters on bead-geometry prediction in WAAM systems.

4. Results and Discussion

The developed machine learning regression models were assessed using several statistical evaluation measures, namely MAE, MSE, RMSE, and the coefficient of determination (R^2). For model validation, the dataset was partitioned into training and testing subsets using an 80:20 split, with 40 samples used for training and the remaining 10 for testing and performance analysis.

Table 2: Performance comparison of regression models

Model	MAE	MSE	RMSE	R^2 Score
Random Forest Regressor	0.3899	0.2121	0.4606	0.9137
Support Vector Regressor	0.5504	0.6294	0.7933	0.7714
XGBoost Regressor	0.2945	0.1103	0.3321	0.9560

Table 2 summarizes the comparative predictive performance of the three regression models using MAE, MSE, RMSE, and overall score. XGBoost achieves the strongest performance, with the lowest error values and the highest score, followed by Random Forest. SVR exhibits comparatively larger prediction errors and the lowest overall score among the evaluated models. The results indicate that the XGBoost Regressor outperformed the other regression models, achieving the highest R^2 score of 0.9560 and the lowest prediction error. The superior performance of XGBoost can be attributed to its ensemble boosting mechanism, which effectively captures the nonlinear relationship between WAAM process parameters and bead geometry characteristics. The Random Forest Regressor also demonstrated strong predictive capability with an R^2 value of 0.9137, whereas the Support Vector Regressor achieved comparatively lower prediction performance with an R^2 score of 0.7714.

4.1 Actual vs Predicted Bead Width Analysis

The actual-versus-predicted bead width plot shows strong agreement between experimental and XGBoost-predicted values. The predicted values closely follow the actual bead width measurements across the testing dataset, indicating excellent prediction capability and strong generalization performance of the developed ensemble learning framework. The minimal deviation between the actual and predicted values confirms the robustness and reliability of the proposed AI-driven regression model for predicting WAAM bead geometry.

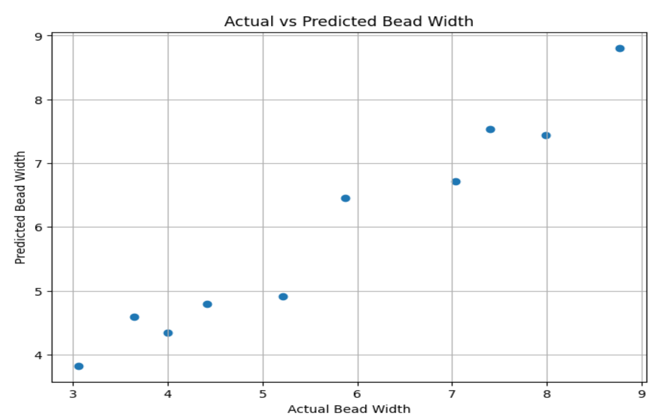

Figure 4: Actual versus predicted bead width using XGBoost Regressor

Figure 4 compares the experimentally measured bead width with values predicted by the XGBoost regressor. The close clustering of data points around the ideal agreement trend indicates strong predictive capability, demonstrating that the developed model can effectively capture the relationship between process parameters and bead width with satisfactory accuracy.

4.2 Feature Importance Analysis

Feature importance analysis was conducted to examine the contribution of individual process parameters toward bead geometry prediction. The analysis indicated that Wire Feed Rate (WFR) had the greatest impact on bead geometry, making it the most influential input. This strong influence can be attributed to its direct effect on the material deposition rate and molten pool generation during the WAAM process. Current was identified as the second most significant parameter due to its role in controlling heat input and metal melting behavior. In comparison, travel speed and voltage made relatively small contributions to the prediction of bead geometry characteristics. The feature importance analysis demonstrates the capability of ensemble learning techniques to identify dominant process variables in intelligent manufacturing systems. Such insights can support process optimization, adaptive control, and real-time monitoring in smart WAAM environments.

Unlike the existing study, which used classification algorithms such as Decision Tree, Random Forest, and K-Nearest Neighbor for binary prediction of bead geometry classes, the proposed work adopted a regression-based framework for continuous prediction of bead geometry. Advanced ensemble learning models, including Random Forest Regressor, Support Vector Regressor, and XGBoost Regressor, were implemented to capture the nonlinear relationship between WAAM process parameters and bead geometry responses.

The proposed XGBoost model achieved superior predictive performance, with an R^2 score of 0.9560, demonstrating stronger predictive capability than the classification accuracy of 87.8% reported in the existing study. Furthermore, the present work incorporated feature-importance analysis, thereby enabling a better understanding of the influence of process parameters on bead geometry formation. The comparison clearly demonstrates that the proposed AI-driven regression framework offers improved prediction accuracy, enhanced process understanding, and greater suitability for intelligent, smart WAAM manufacturing applications.

Overall, the developed AI-driven ensemble learning framework demonstrated excellent predictive capability for bead geometry estimation in WAAM systems. The proposed XGBoost-based model outperformed Random Forest and Support Vector Regression, highlighting the potential of advanced ensemble learning approaches for intelligent, data-driven additive manufacturing applications.

5. Conclusion

The present study proposes an AI-driven ensemble learning framework for predicting bead geometry in WAAM using process parameters such as voltage, current, wire feed rate, and travel speed. Three regression-based machine learning models, namely RF, SVR, and XGBoost, were implemented and evaluated for bead geometry prediction. The results demonstrated that the XGBoost Regressor achieved the best predictive performance, with the highest coefficient of determination (R^2) of 0.9560 and the lowest prediction error among all investigated models. Feature importance analysis revealed that wire feed rate is the most influential parameter for predicting bead geometry. The proposed AI-driven framework effectively captures the nonlinear relationship between WAAM process parameters and bead geometry characteristics, thereby reducing dependency on conventional trial-and-error experimentation. The presented approach contributes toward intelligent process prediction, smart manufacturing, and Industry 4.0-based WAAM applications.

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