Abstract

Wire Arc Additive Manufacturing (WAAM) is a rapidly growing metal additive manufacturing technique capable of producing large-scale components with high deposition rates. However, achieving consistent bead geometry—including bead height and bead stability—remains a major challenge due to nonlinear interactions among process parameters. In this study, we develop a dual-model artificial intelligence framework using Machine Learning (Random Forest Regressors) and Deep Learning (Fully Connected Neural Networks) to predict bead height (AVERAGE) and bead stability (VARIANCE) from four key WAAM parameters: Voltage, Wire Feed Speed (WFS), Travel Speed, and Contact Tip–to–Work Distance (CTWD). A custom dataset containing 229 experimental observations was analyzed, visualized, and used to train both models. Results indicate that the neural network outperformed the Random Forest for predicting AVERAGE bead height, while Random Forest showed competitive performance in predicting bead stability. Feature importance analysis reveals that Voltage and Wire Feed Speed significantly influence overall geometry. The study demonstrates that artificial intelligence can accurately estimate WAAM bead geometry and provides a foundation for real-time adaptive control in manufacturing.

Keywords

WAAM; Wire Arc Additive Manufacturing; Machine Learning; Deep Learning; Random Forest; Neural Networks; Bead Geometry Prediction; Additive Manufacturing; Process Modeling.

1. Introduction

Wire Arc Additive Manufacturing (WAAM) is an emerging metal additive manufacturing (AM) technology based on traditional Gas Metal Arc Welding (GMAW). It is widely used in aerospace, automotive, maritime, and tooling industries due to its high deposition rates, low equipment costs, and suitability for large components. Despite its advantages, WAAM suffers from bead geometry instability caused by dynamic and nonlinear relationships among process parameters.

Accurate prediction of bead geometry is essential for:

- Ensuring dimensional accuracy
- Reducing porosity and defects

- Improving repeatability
- Enabling closed-loop control of WAAM systems

Traditional physics-based models struggle to capture nonlinearities and require complex calibration. This motivates the adoption of data-driven artificial intelligence (AI) models that can learn relationships directly from experimental data.

This study presents a comparative analysis of:

1. Random Forest Regressor (Machine Learning)
2. Multi-layer Perceptron Neural Network (Deep Learning)

Both models predict bead height and bead stability using real experimental WAAM data.

2. Related Work

Recent research has applied machine learning techniques to additive manufacturing for defect detection, material characterization, and process optimization. Notably:

- Researchers have explored ML for predicting bead width, penetration depth, and melt pool sizes.
- Neural networks have shown promise in modeling nonlinear thermal and geometric behaviors.
- Studies such as “Machine Learning Prediction of Fatigue Life of Additive Manufactured Components” demonstrate the broader applicability of ML in AM.

However, only a limited number of works focus specifically on WAAM bead geometry prediction using dual ML–DL frameworks, making this study significant.

3. Dataset Description

The dataset contains 229 WAAM experimental runs, each with four input parameters:

Feature	Description
Voltage	Arc Voltage
Wire Feed Speed	Wire feed rate (mm/min)
Travel Speed	Torch movement speed (mm/min)
CTWD	Contact Tip–to–Work Distance (mm)

Output Variables:

1. **AVERAGE** – Mean bead height across 13 measurement points
2. **VARIANCE** – Statistical variance, representing bead stability

4. Exploratory Data Analysis (EDA)

The exploratory data analysis (EDA) phase was performed to understand the distribution, relationships, and interactions between WAAM process parameters and bead geometry responses. This section summarizes key statistical characteristics and visual insights obtained prior to machine learning model development.

4.1 Input Feature Distributions

Figure 1 illustrates the distribution of the four input process parameters: Voltage, Wire Feed Speed (WFS), Travel Speed, and Contact Tip to Work Distance (CTWD).

The inputs show varied ranges and patterns, such as a relatively uniform distribution in voltage and mixed multimodal behavior in WFS and travel speed. These variations are important because they reflect the experimental matrix used to cover a wide WAAM operating window.

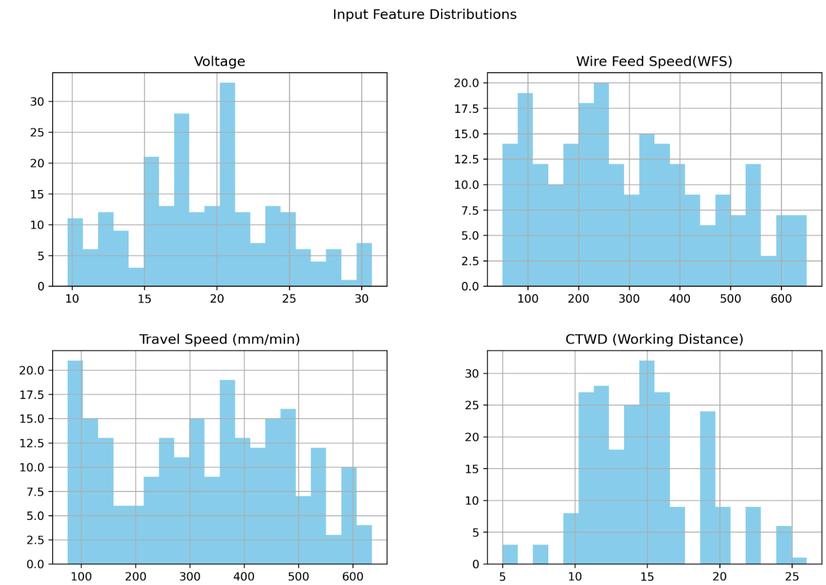

Figure 1. Input Feature Distributions

4.2 Output Variable Distributions (Bead Height & Stability)

Figure 2 shows the distributions of the two response variables:

- AVERAGE bead height

- VARIANCE of bead height (stability)

The AVERAGE bead height follows an approximately normal distribution centered between 2.5–3.5 mm. The VARIANCE values are skewed toward zero, indicating higher stability across most experiments.

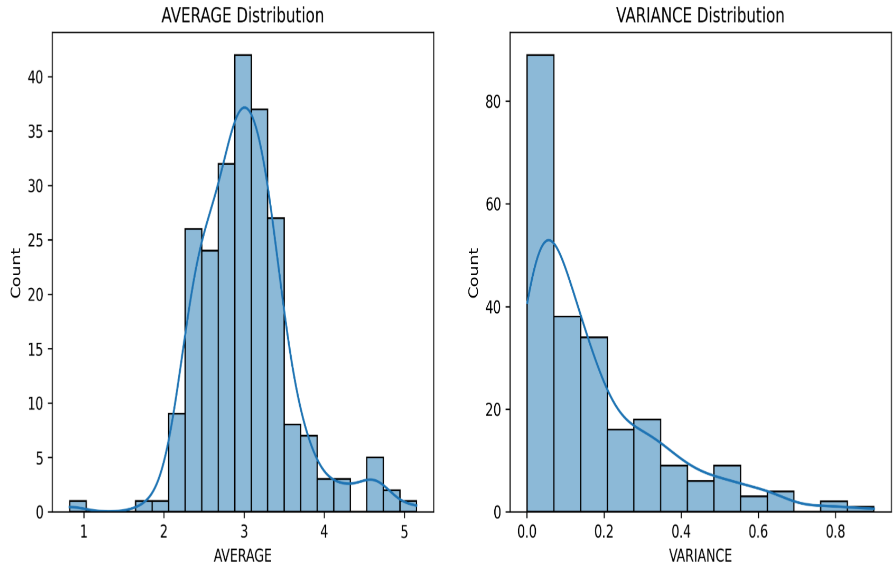

Figure 2. Distribution of AVERAGE and VARIANCE

4.3 Correlation Matrix Analysis

A correlation heatmap was generated to quantify linear relationships between the process parameters and bead geometry responses.

As shown in Figure 3, WFS and travel speed exhibit moderate positive correlation with bead height, while CTWD has weak correlation with both targets.

This initial correlation insight helps anticipate model complexity and guides feature importance interpretation.

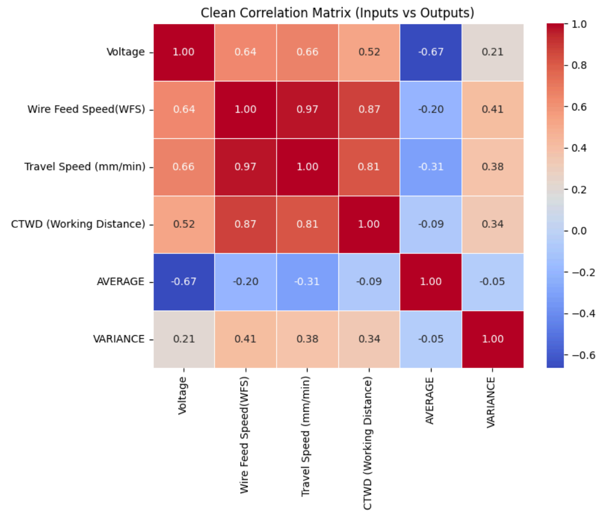

Figure 3. Correlation Heatmap of WAAM Parameters

4.4 Pairwise Relationships (Pairplot)

To visualize potential nonlinear interactions, a pairplot was created (Figure 4).

This plot reveals several structured patterns, including nonlinear clustering between WFS and AVERAGE, and dispersion bands suggesting that voltage and CTWD influence variability in bead formation.

These relationships justify the use of nonlinear regression models such as Random Forest and Neural Networks.

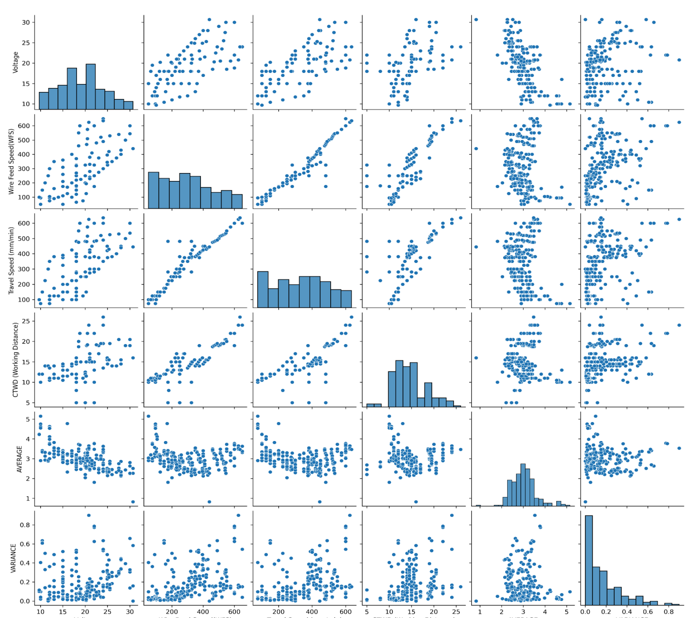

Figure 4. Pairplot of Input and Output Variables

4.5 Boxplots for Outlier Detection

Figure 5 shows boxplots for each input and output variable.
Outliers are visible particularly in WFS and travel speed, reflecting high-speed or low-speed experimental conditions.
Some outliers in AVERAGE and VARIANCE correspond to unstable bead formations or edge-case process windows.

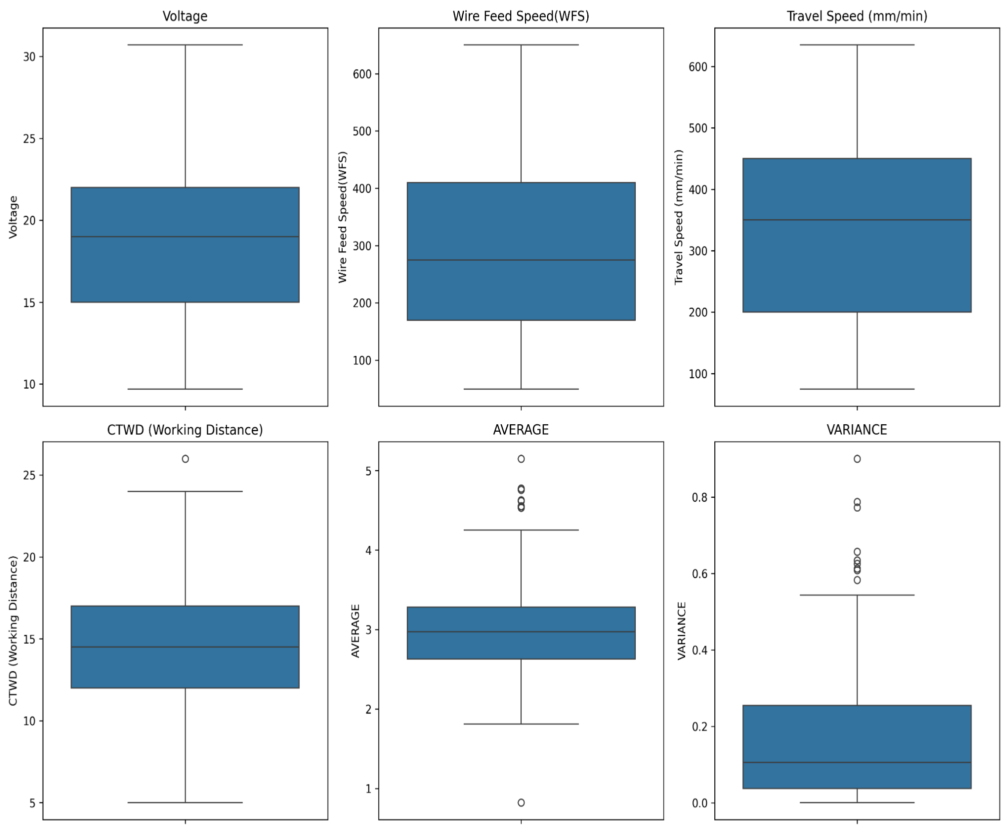

Figure 5. Boxplots of WAAM Parameters and Outputs

4.6 Input–Output Relationship Plots

To better understand how each WAAM parameter influences bead height and stability, a combined figure with eight scatter subplots was generated (Figure 6).
The first row shows each input (Voltage, WFS, Travel Speed, CTWD) plotted against AVERAGE bead height, while the second row shows the same inputs plotted against VARIANCE.

Key observations:

- WFS and Travel Speed have the strongest directional effect on AVERAGE.
- Voltage contributes moderately but nonlinearly.
- CTWD has weak direct correlation but contributes in combined effects, which ML models can learn.
- VARIANCE appears more scattered, indicating a more complex relationship requiring nonlinear modeling.

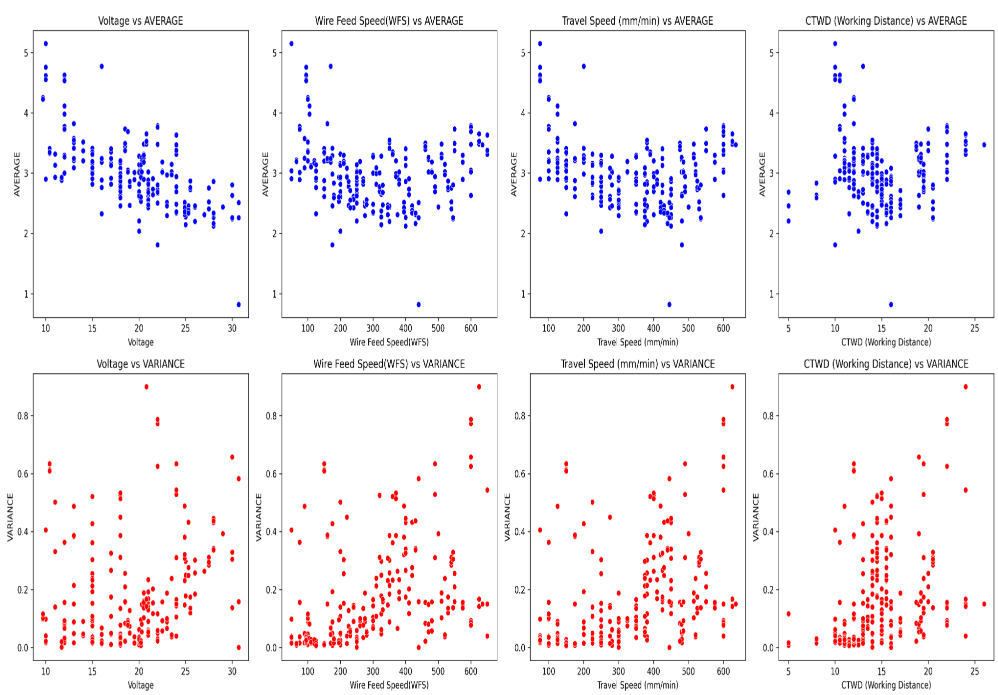

Figure 6. Combined Relationship Plots: Inputs vs AVERAGE and VARIANCE

5. Methodology

The modeling pipeline included:

1. **Data Loading and Cleaning**
    - Verified absence of missing values
    - Standardization using *StandardScaler*
2. **Train-Test Split**
    - 80% training, 20% testing
3. **Model Development**
    - Random Forest (two separate models for AVERAGE and VARIANCE)
    - Neural Network (multi-output regression model)
4. **Evaluation Metrics**
    - RMSE
    - MAE
    - R^2 Score

5.1. Machine Learning Model: Random Forest

Model Architecture:

- 300 Trees
- Max depth: Auto
- Random State: 42

Random Forest Results

Metrics	Average	Variance
RMSE	0.288	0.108
MAE	0.169	0.074
R^2	0.685	0.603

Interpretation:

- RF performs strongly for bead height (AVERAGE).
- Moderate predictive power for VARIANCE, indicating complexity in bead stability modeling.

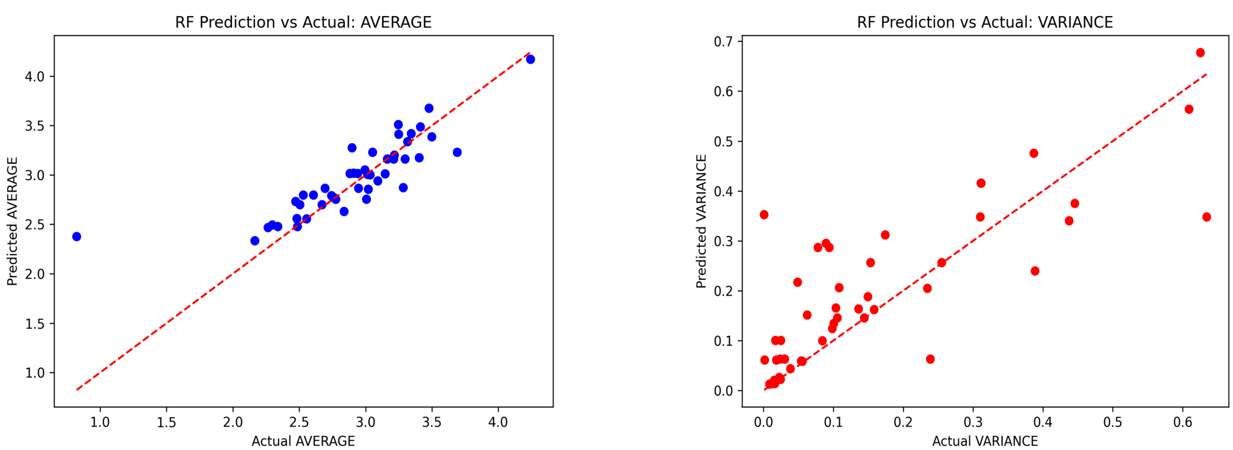

Fig 7 RF Prediction vs Actual (AVERAGE and VARIANCE)

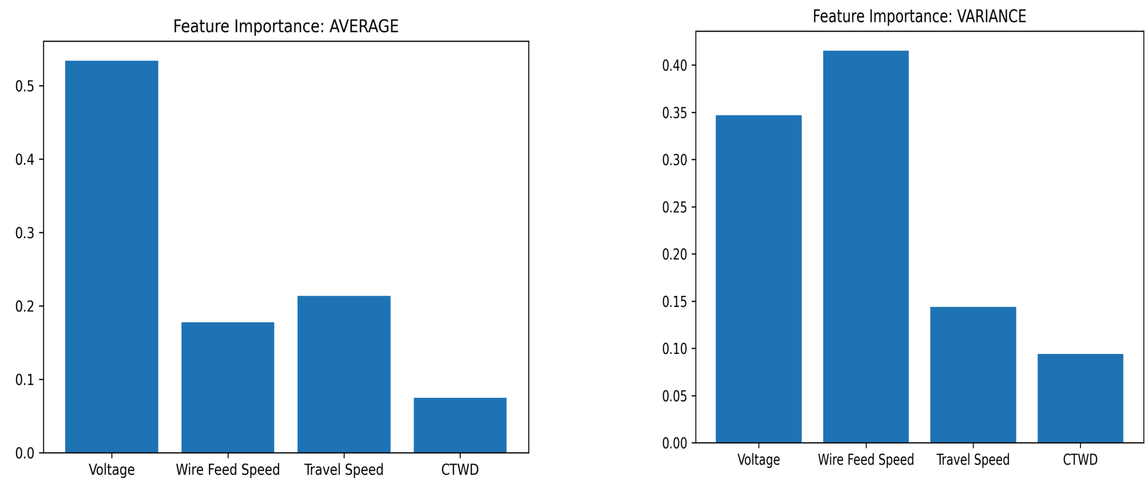

Fig 8 Random Forest Feature Importance

5.2. Deep Learning Model: Neural Network

Architecture:

- Dense(64) → Dense(32) → Dense(16) → Dense(2)
- Activation: ReLU
- Loss: MSE
- Optimizer: Adam
- 300 epochs with early stopping

Neural Network Results

Metrics	Average	Variance
RMSE	0.296	0.153

MAE	0.190	0.116
R^2	0.666	0.205

Analysis:

- NN performs well for predicting AVERAGE, close to RF.

- Neural network struggles with VARIANCE, likely due to variance noise and non-linear instability patterns.

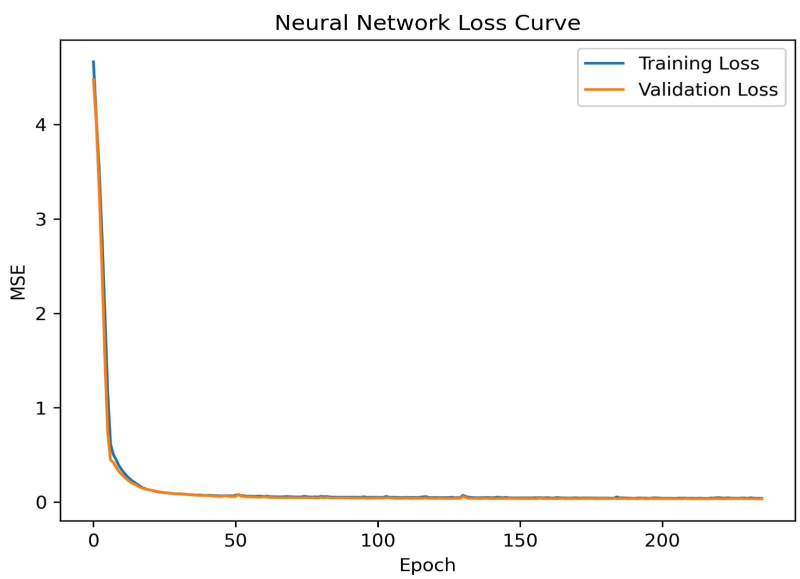

Figure 8: Neural Network Loss Curve

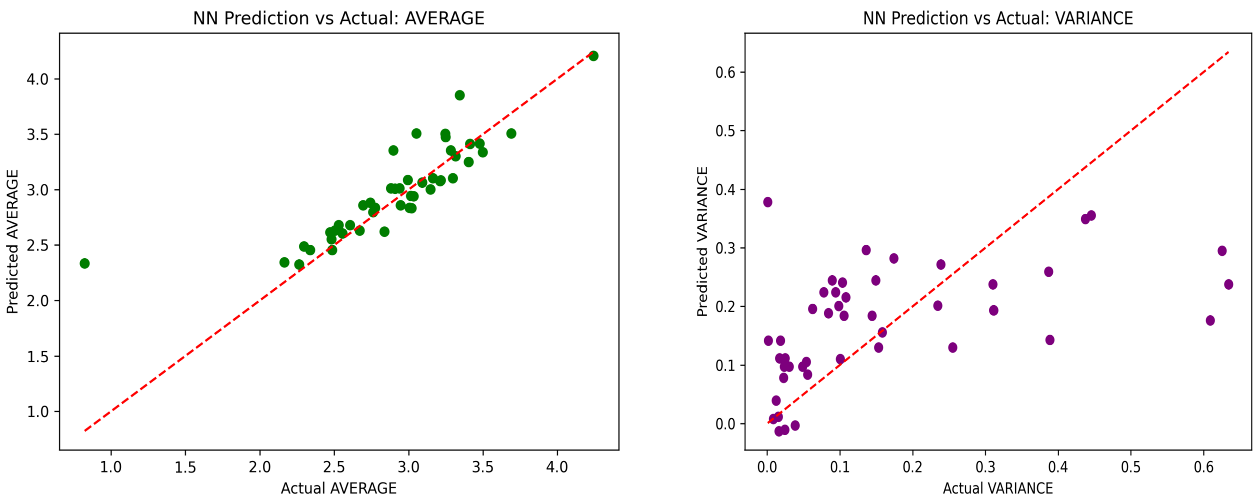

Figure 9: NN Prediction vs Actual (AVERAGE and VARIANCE)

5.3. Comparative Performance Analysis

Model	Target	RMSE	MAE	R^2
Random Forest	Average	0.288	0.169	0.685
Neural Network	Average	0.296	0.190	0.666
Random Forest	Variance	0.108	0.074	0.603
Neural Network	Variance	0.153	0.116	0.205

Summary:

- Random Forest wins overall, especially for bead stability.
- The neural network performs competitively for bead height but poorly for variance.
- RF's interpretability and feature importance provide engineering insight.

5.4. Feature Importance Analysis

Random Forest Feature Importance

For AVERAGE:

- Voltage: 0.533
- Travel Speed: 0.213
- WFS: 0.178
- CTWD: 0.074

For VARIANCE:

- WFS: 0.415
- Voltage: 0.346
- Travel Speed: 0.143
- CTWD: 0.094

Interpretation:

- **Voltage is the dominant factor for bead height**.
- **Wire Feed Speed strongly influences bead stability**, aligning with arc dynamics literature.
- CTWD has the least influence but still contributes.

5.5. Predicting New WAAM Parameters

A predictive function was implemented:

```
predict_bead_shape(20, 300, 400, 14)
```

Output:

Model	Average	Variance
RF	2.7269	0.0899
Neural Network	2.6214	0.1656

These predictions can support process planning and online control.

11. Discussion

The results demonstrate that ML and DL models can effectively model WAAM bead geometry. Random Forest provides strong performance and interpretability, while the neural network captures nonlinearities but requires more data to match RF robustness. Variance prediction remains difficult due to inherent WAAM process instability.

Future improvements include:

- Collecting larger datasets

- Adding arc sensor signals
- Using CNNs or LSTMs
- Integrating reinforcement learning for adaptive WAAM control

12. Conclusion

This study successfully developed an AI-driven framework for predicting WAAM bead geometry from process parameters. Random Forest and Neural Networks were evaluated, revealing that Random Forest provides superior performance overall. The models demonstrate the feasibility of AI-driven bead geometry prediction, supporting future development of real-time digital twins and closed-loop adaptive WAAM control.

References

1. [1] H. Monteiro, S. Oliveira, and P. Ferreira, "Machine learning in additive manufacturing: A survey," *Journal of Manufacturing Processes*, 2020.
2. [2] D. Ding, Z. Pan, H. Li, P. C. Shen, and S. Kovacevic, "Wire Arc Additive Manufacturing of aluminum alloys," *Journal of Materials Engineering*, 2019.
3. [3] D. King, M. Sealy, and Y. Yang, "AI for process modeling in metal additive manufacturing," *Springer*, 2021.
4. [4] B. Ebika, "Experimental WAAM bead geometry dataset (laboratory-generated)," Case Western Reserve University, Cleveland, OH, USA, 2025.