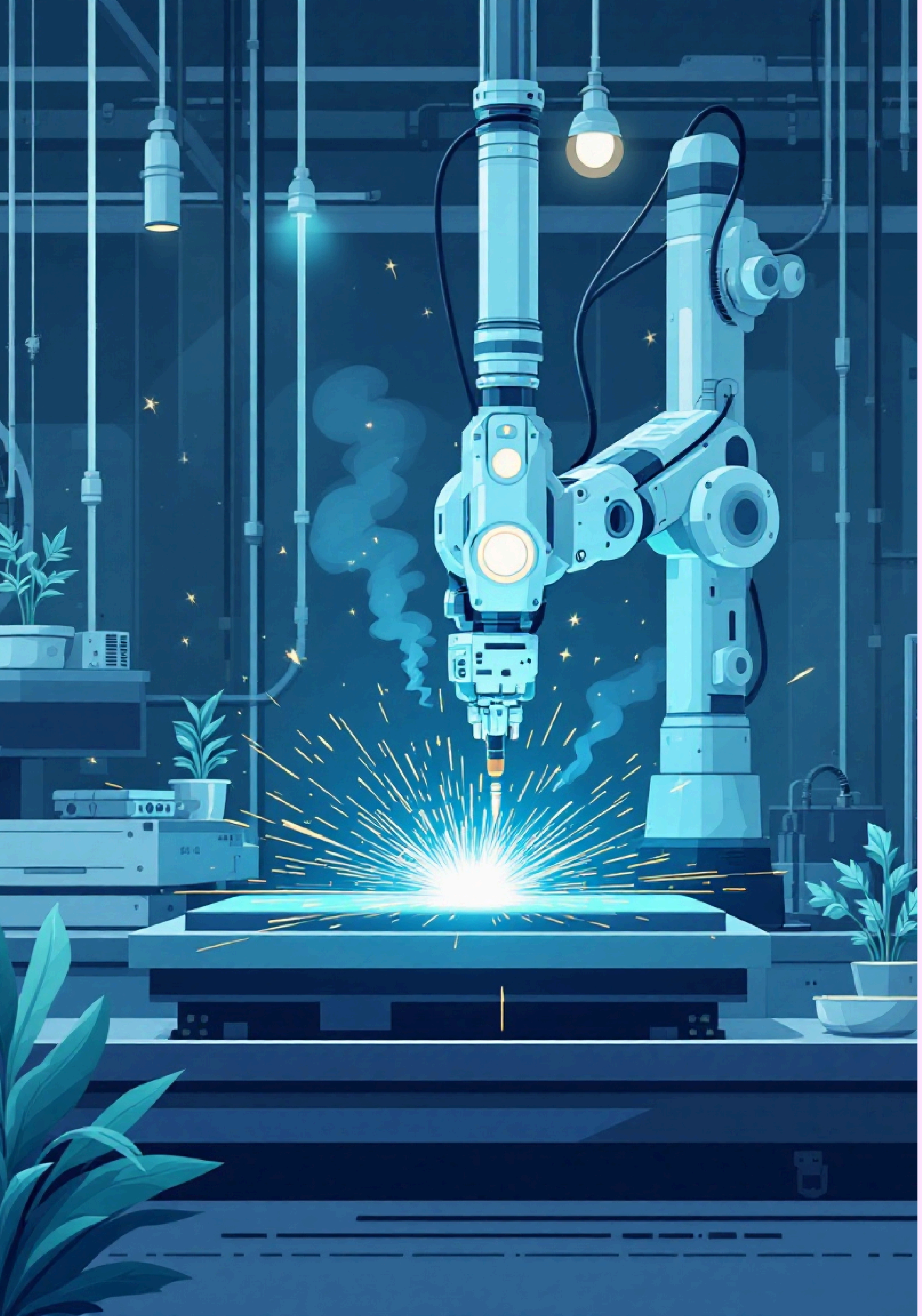


WAAM Bead Geometry Prediction Using Machine Learning & Deep Learning

This study explores a dual-model AI framework using Machine Learning and Deep Learning to predict bead height and stability in Wire Arc Additive Manufacturing (WAAM).

Outline

- Introduction
- Challange of WAAM
- Dataset Overview
- Exploratory Data Analysis (EDA)
- Machine Learning Model (Random Forest)
- Deep Learning Model (Neural Network)
- Comparative Results
- Feature Importance
- Predicting New WAAM Conditions
- Conclusion & Future Work

Introduction

- WAAM = Wire Arc Additive Manufacturing
- Produces metal beads layer by layer
- Bead geometry affects stability, quality, defects
- Manual tuning of parameters is time-consuming
- Goal: Predict bead height & stability using AI
- Models used:
    - Random Forest (Machine Learning)
    - Neural Network (Deep Learning)

THE CHALLENGE OF WAAM

WIRE ARC ADDITIVE MANUFACTURING (WAAM) OFFERS HIGH DEPOSITION RATES AND COST-EFFECTIVENESS FOR LARGE-SCALE METAL COMPONENTS.

HIGH DEPOSITION RATES

Efficient for large components in aerospace, automotive, and maritime industries.

COST-EFFECTIVE

Lower equipment costs compared to other AM technologies.

BEAD INSTABILITY

Nonlinear interactions among process parameters lead to inconsistent bead geometry.

Dataset Description

FEATURE	VALUES
TOTAL SAMPLES	229
INPUTS	VOLTAGE, WFS, TRAVEL SPEED, CTWD
MEASURED OUTPUTS (13 SAMPLES)	SZ1–SZ13 BEAD HEIGHT READINGS PER EXPERIMENT
COMPUTED OUTPUTS (2)	AVERAGE (MEAN BEAD HEIGHT), VARIANCE (BEAD STABILITY)
VOLTAGE RANGE	9.7 – 30.7 V
WFS RANGE	50 – 650 MM/MIN

FEATURE	VALUES
TRAVEL SPEED RANGE	75 – 635 MM/MIN
CTWD RANGE	5 – 26 MM
AVERAGE RANGE	0.87 – 5.15 MM
VARIANCE RANGE	0.01 – 0.92
DATASET SOURCE	LABORATORY WAAM EXPERIMENTS (CASE WESTERN RESERVE UNIVERSITY, OHIO USA (CWRU))

Dual-Model Framework

We compare Machine Learning (Random Forest) and Deep Learning (Neural Networks) for WAAM bead geometry prediction.

MACHINE LEARNING

Random Forest Regressors

- Ensemble learning method
- Robust to outliers
- Provides feature importance

$$\hat{y} = \frac{1}{N} \sum_{i=1}^{N} T_i(x)$$

y: : final predicted output
N: number of decision trees
Ti: prediction made by the i-th tree for input
x: input feature vector

DEEP LEARNING

Fully Connected Neural Networks

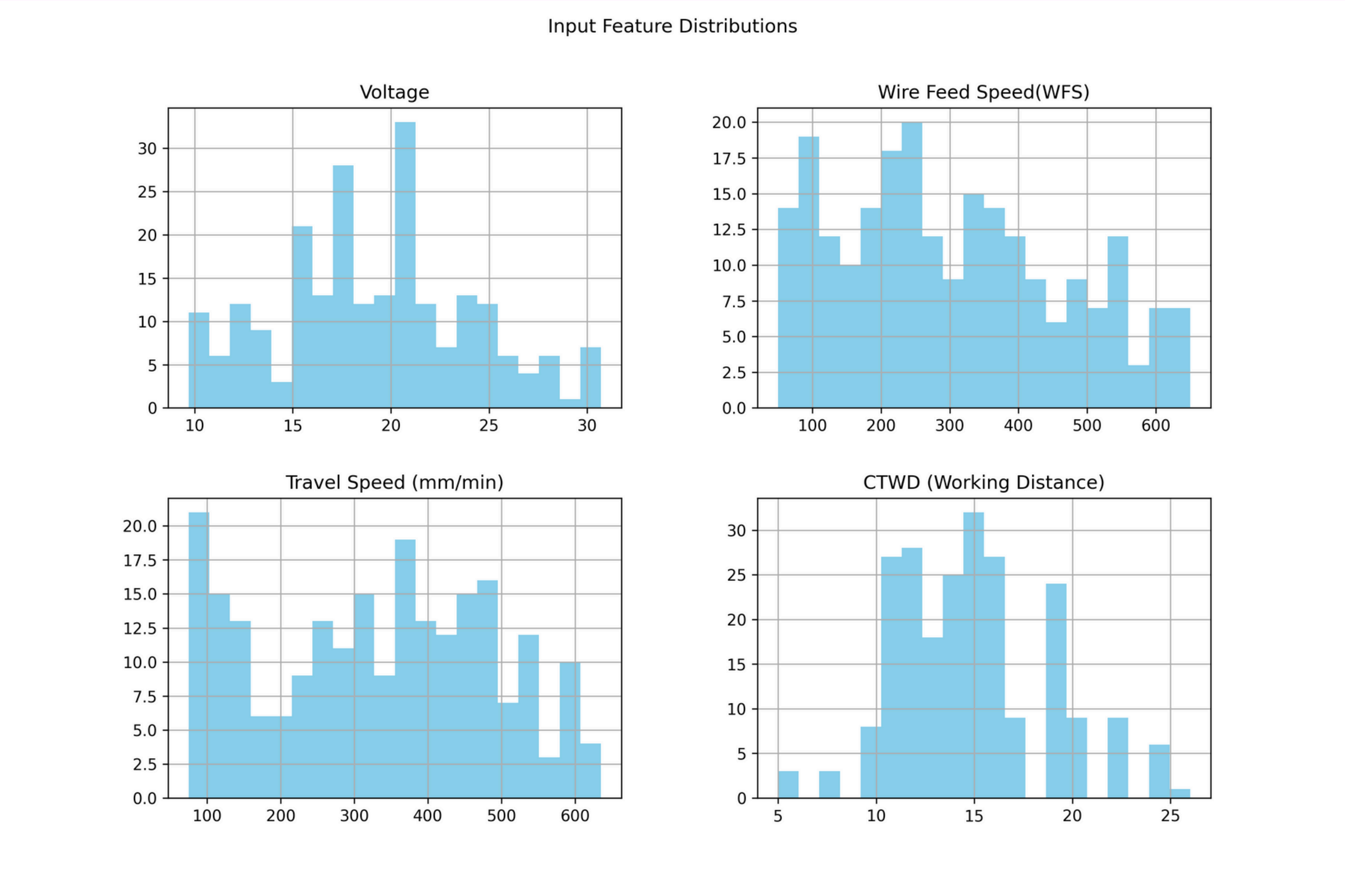
- Captures complex nonlinearities
- Learns hierarchical features
- Requires large datasets

$$h = \sigma(Wx + b)$$

$$\hat{y} = f(x) = \sigma_L(W_L\,(\sigma_{L-1}(W_{L-1}(\ldots\sigma_1(W_1x + b_1)) + b_{L-1})) + b_L)$$

x: : Input vector
W: Weight Metrics
b: Bias Vector
σ: Activation Function
h: Output of the Layer

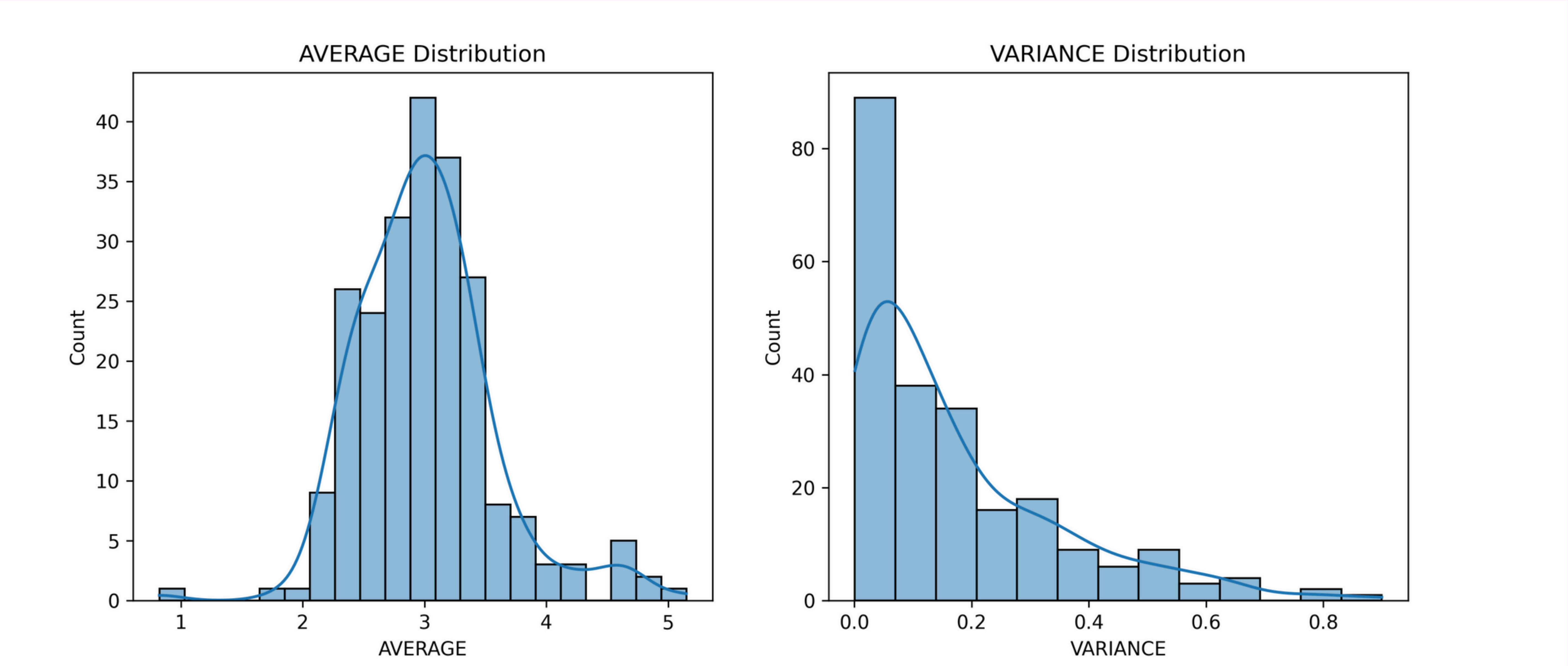
EDA: Input Feature Distributions



- Voltage mostly between 12–22 V
  - The voltage values range from about 10 to 30 volts.
  - The distribution is fairly spread out, meaning different voltage settings were tested.
- WFS
  - WFS ranges from about 50 to 600 mm/min.
  - The distribution is wide with many mid-range values.
  - Variations influence bead height and bead formation.
- Travel Speed show wide ranges
  - Travel speed varies from 80 to 600 mm/min.
  - There are multiple clusters in the mid-range.
  - High speeds → thin, low bead height
  - Low speeds → thick, tall bead height
- CTWD concentrated between 10–20 mm
  - CTWD values range from 8 mm to 25 mm.
  - Most values fall between 12–18 mm.
  - CTWD affects arc stability and melting behavior.

plots showing how each WAAM process parameter is distributed

EDA: Target Distributions



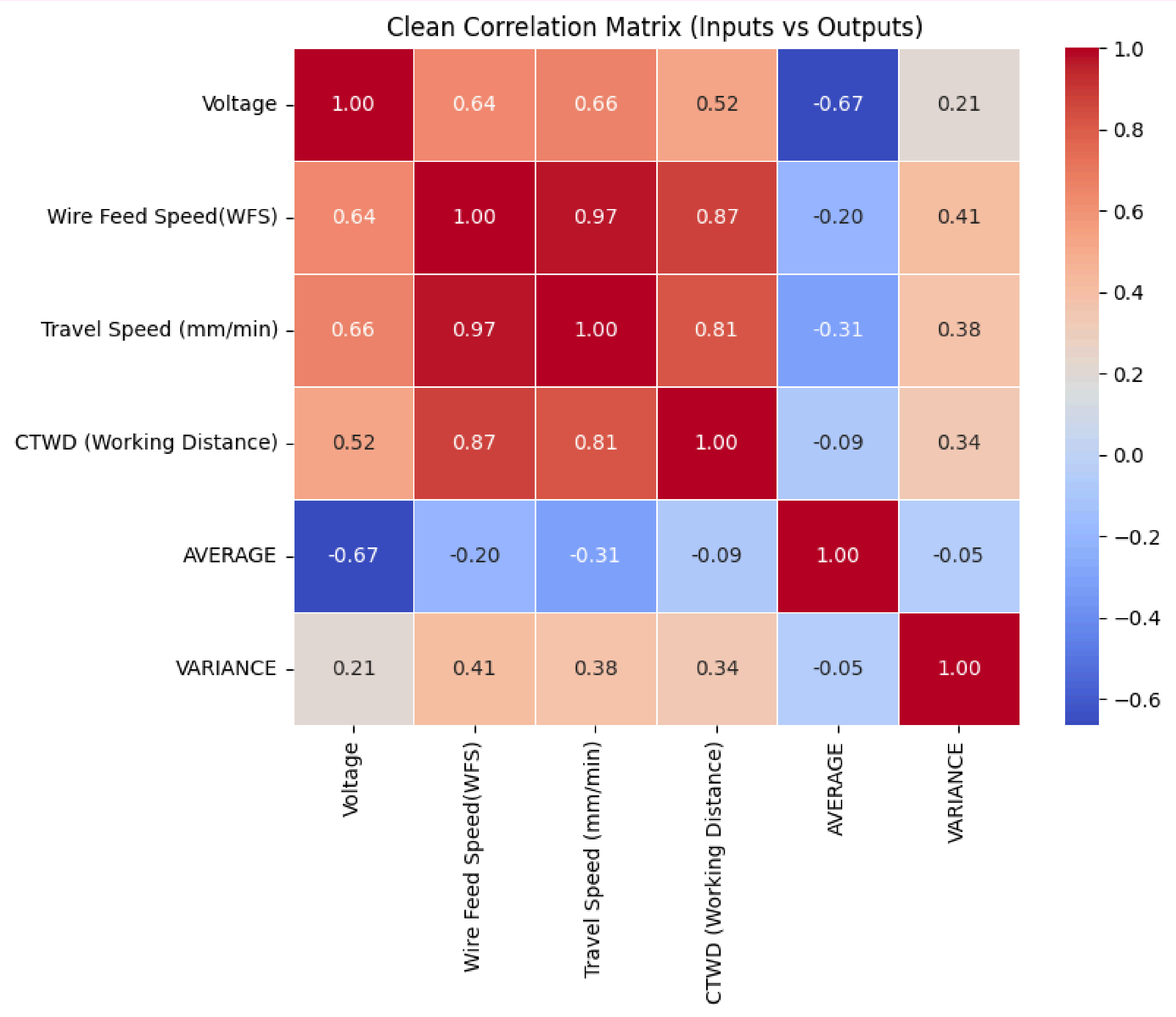
Observations:

The values of AVERAGE (bead height) form a bell-shaped curve, meaning:

- Most bead heights fall between 2.5 mm and 3.5 mm
- Very few beads are below 2 mm or above 4 mm
  - The distribution looks close to normal (Gaussian)
  - This is good for machine learning — models tend to learn better from well-behaved, smooth distributions.

- The values of VARIANCE are heavily skewed to the right.
- Most beads have low variance (0.0 – 0.2)
- A few beads have very high variance (up to 0.8)
  - Many prints were stable
  - Some prints were unstable

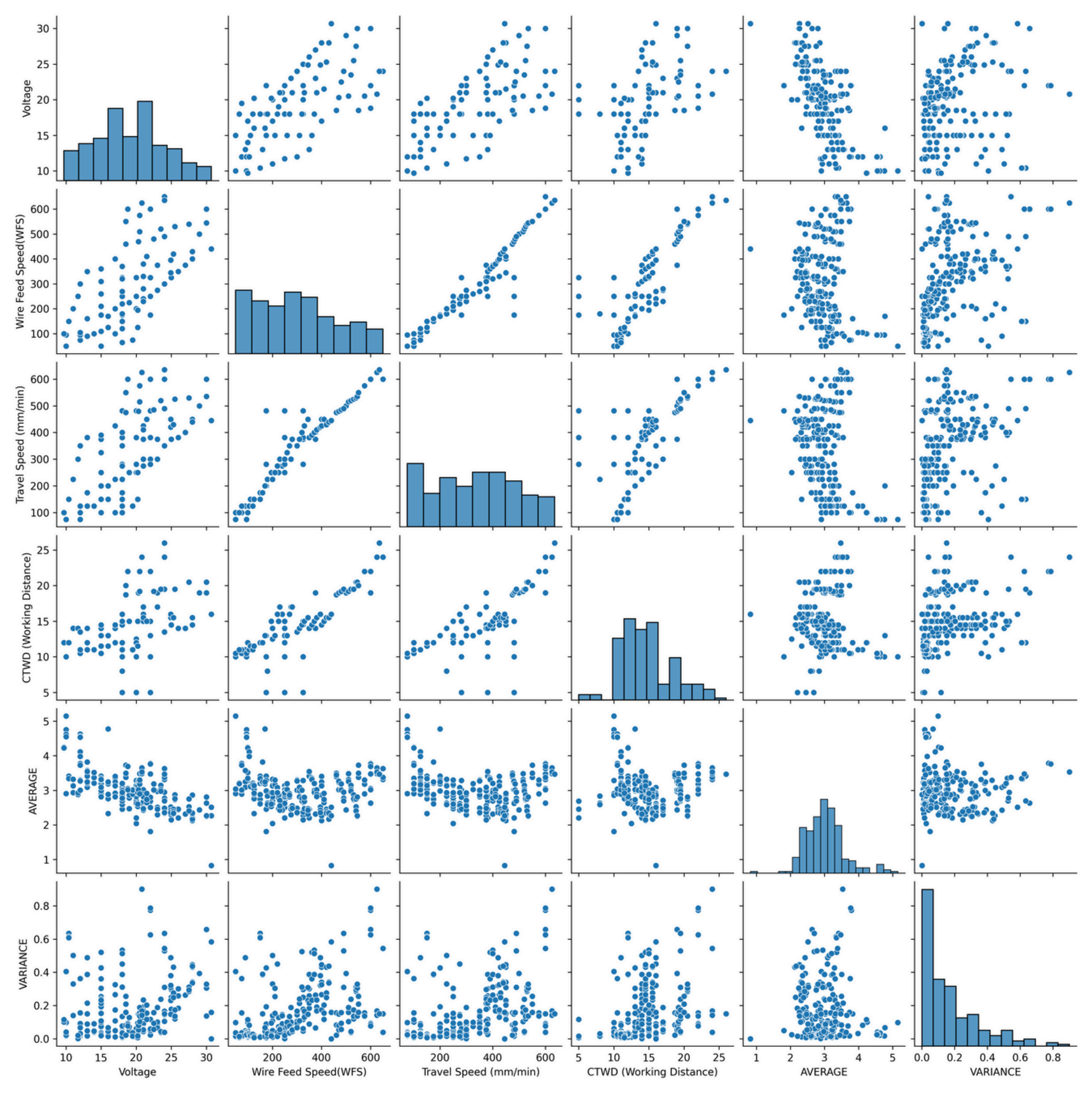
Correlation Heatmap



Input	Correlation → AVERAGE	Result
Voltage	-0.67 (strong negative)	Higher voltage *reduces* bead height. More heat → metal spreads out.
WFS	-0.20 (very weak)	Wire feed has almost no direct effect on bead height.
Travel Speed	0.31 (weak negative)	Faster travel → less material deposited → slightly lower bead height.
CTWD	-0.09 (very weak)	Working distance barely affects bead height directly.

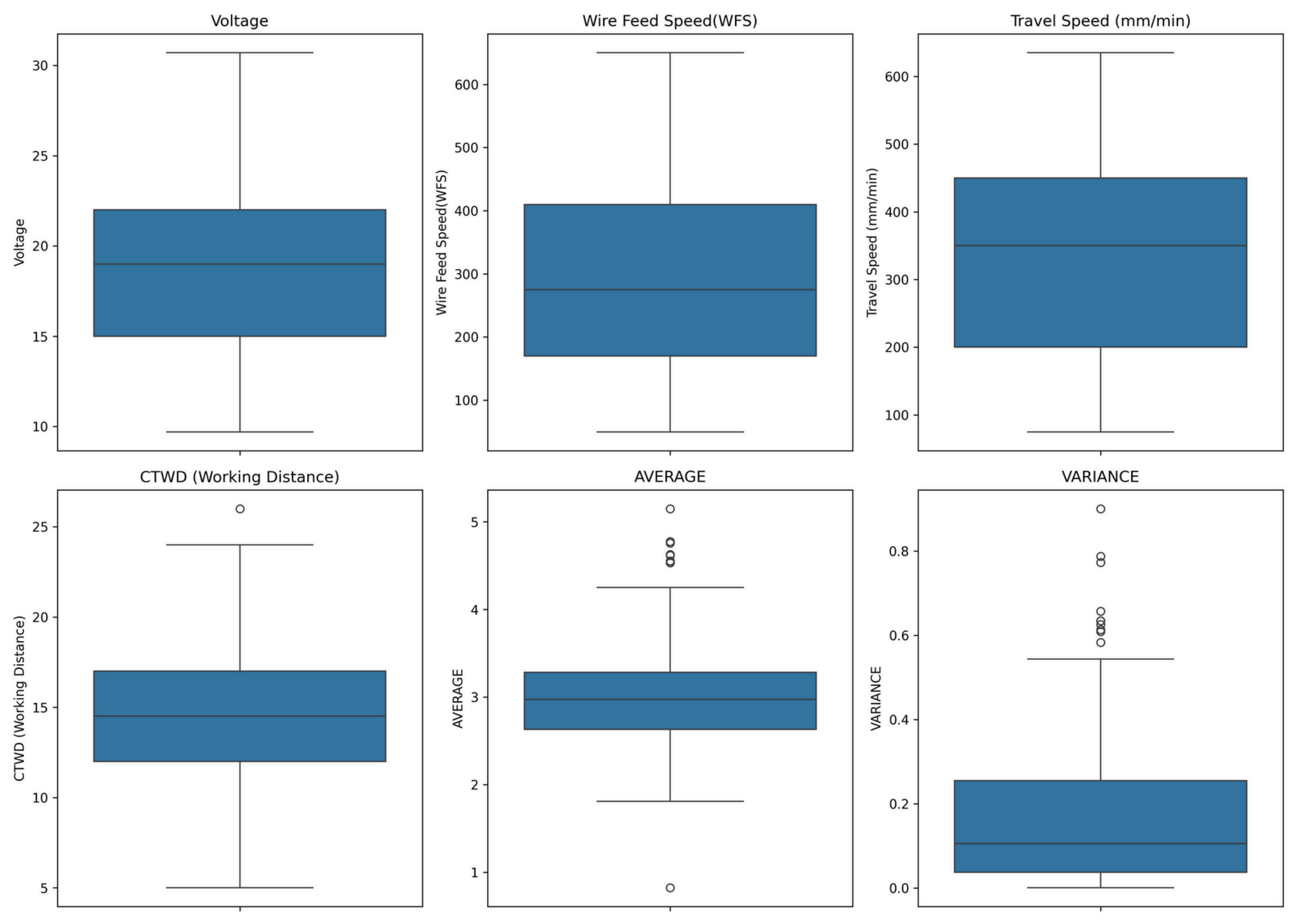
- Voltage is the strongest predictor of bead height — and it reduces the height
- Bead Stability (VARIANCE) is influenced by WFS, Travel Speed, and CTWD more than voltage.

Pairplot (Feature Interactions)



- Diagonal histograms show the distribution of each variable.
- Strong linear patterns appear only between WFS and Travel Speed.
- Voltage has a clear negative effect on bead height (AVERAGE).
- CTWD has no strong pattern with any output → weak influence.
- VARIANCE plots are messy, meaning bead stability is hard to predict.

Boxplots (Outlier Detection)



Boxplots help us understand and prepare the dataset before building machine learning models. These show how each parameter varies across the experiment. Travel Speed and WFS have the widest variation, while Voltage and CTWD are more controlled. The output AVERAGE is fairly stable, but VARIANCE has many outliers, showing that bead stability is unpredictable and harder to model

Voltage

- Most voltage values lie between 17–23 V (the box).
- A few values go down to 10 V and up to 30 V.
- The spread is moderate, showing normal experimental variation.
- No major outliers — voltage is fairly stable.

Wire Feed Speed (WFS) Boxplot

- The median value is around 300–350 mm/min.
- Minimum values go down to about 100, and max up to 600+.
- The height of the box is large → wide variation in WFS was tested.
- Some mild outliers exist.

Travel Speed

- Median is around 350–400 mm/min.
- Wide range: 100 to about 650 mm/min.
- No large extreme outliers, but there is high variability.

CTWD (Contact Tip–Work Distance) Boxplot

- Median is around 15–17 mm.
- Range is narrower (about 5–25 mm).
- A couple of outliers appear at the top.

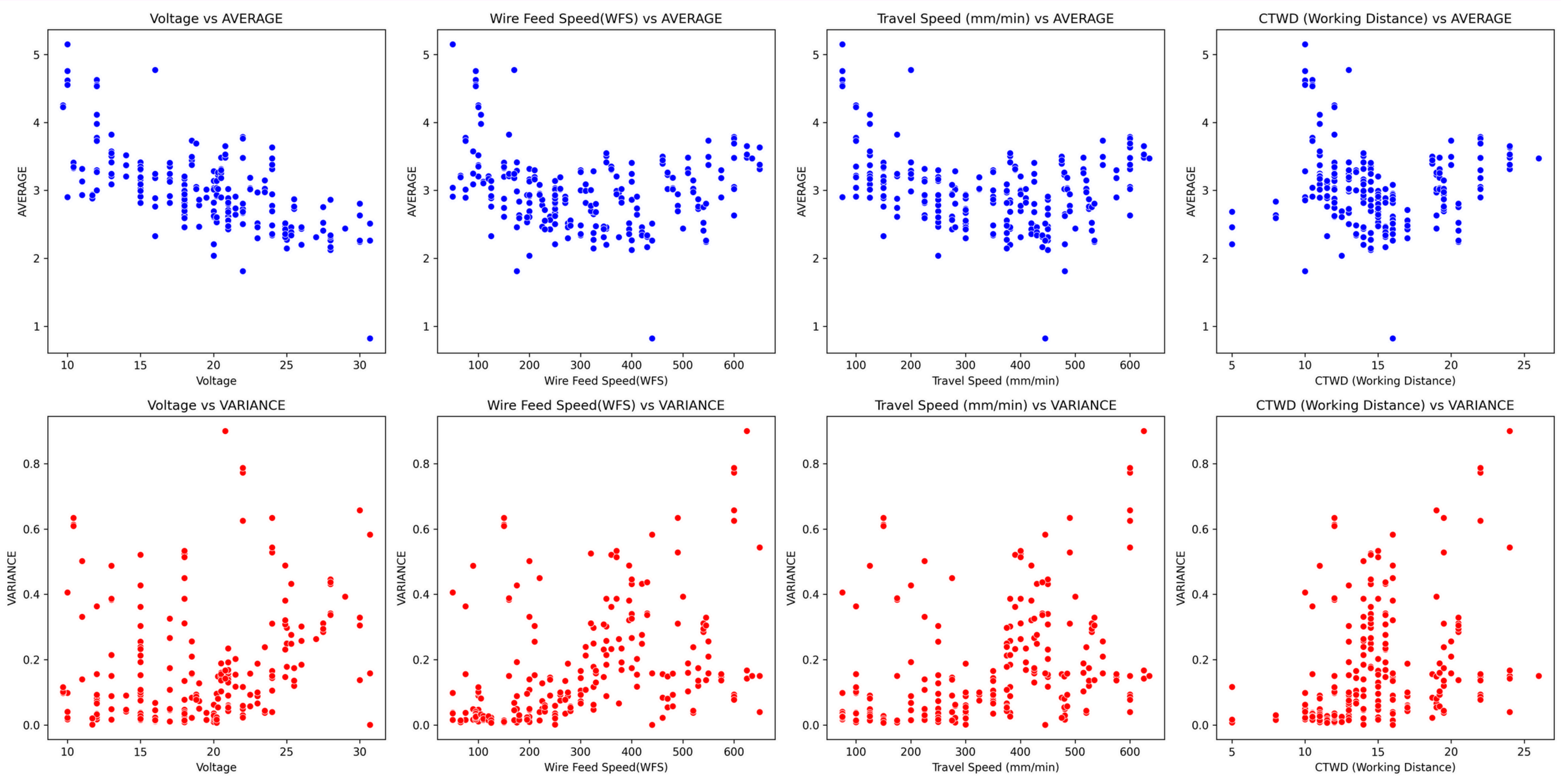
AVERAGE (Bead Height) Boxplot

- Median bead height is around 3 mm.
- Several high outliers, showing occasional tall beads.
- Distribution is reasonably tight, but a few extreme values exist.

VARIANCE (Bead Stability) Boxplot

- Median is around 0.15–0.20.
- Wide span from 0.02 up to 0.9.
- Many outliers → bead stability varied significantly between experiments.

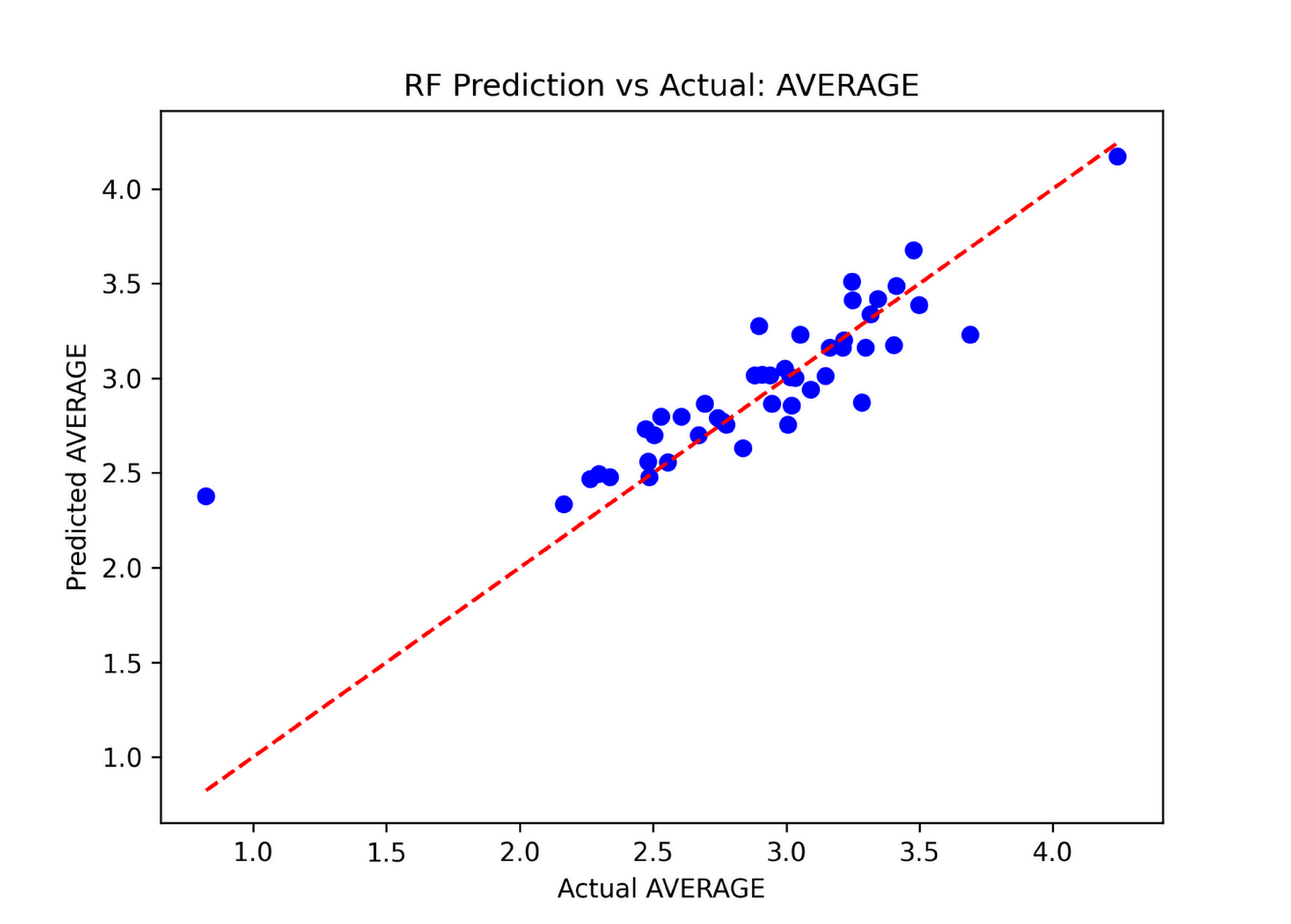
Relationship Plot



These plots show how each WAAM setting affects bead height and bead stability.
For bead height, wire feed speed and travel speed have the strongest relationship, while voltage and CTWD have weaker effects.
AAlso Voltage has a moderate effect.

For bead stability, voltage, WFS, and travel speed introduce more variation.
The scattered nature of these plots shows why we need machine learning — the relationships are not linear.

RF Results: AVERAGE



Machine Learning Model

- Random Forest Regressor
- RF trained separately for AVERAGE and VARIANCE
- 300 trees; optimized hyperparameters
- Robust to noise and nonlinear interactions
- Performs strongly for tabular WAAM data

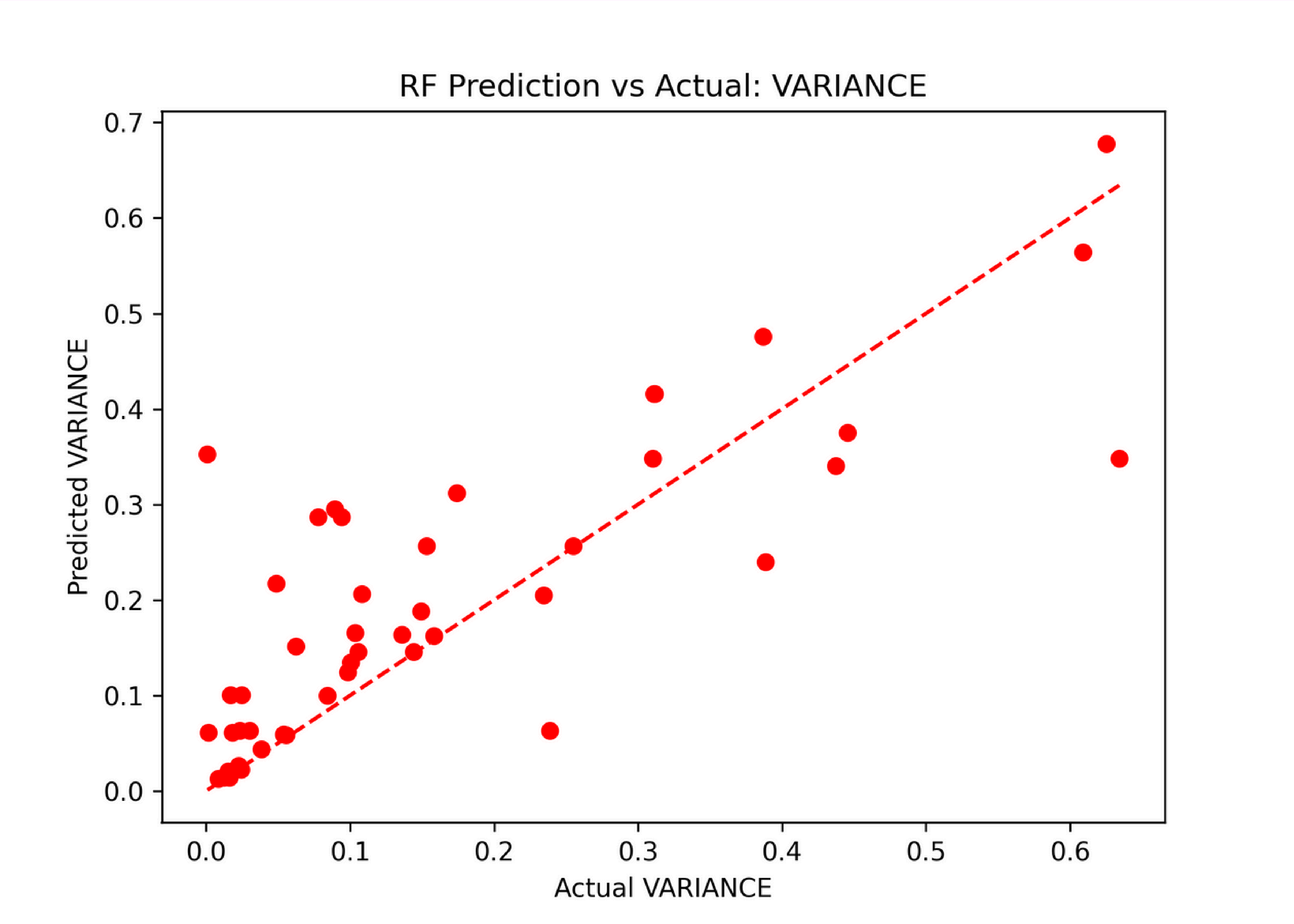
This plot compares the Random Forest predictions with the actual bead height values.
The blue points closely follow the red diagonal line, which means the predicted values are very close to the real values.
This shows that the Random Forest model learned the relationship between WAAM parameters and bead height accurately.

Metrics:

- RMSE ≈ 0.288
- MAE ≈ 0.169
- R^2 ≈ 0.685

Very good predictive accuracy.

RF Results: VARIANCE



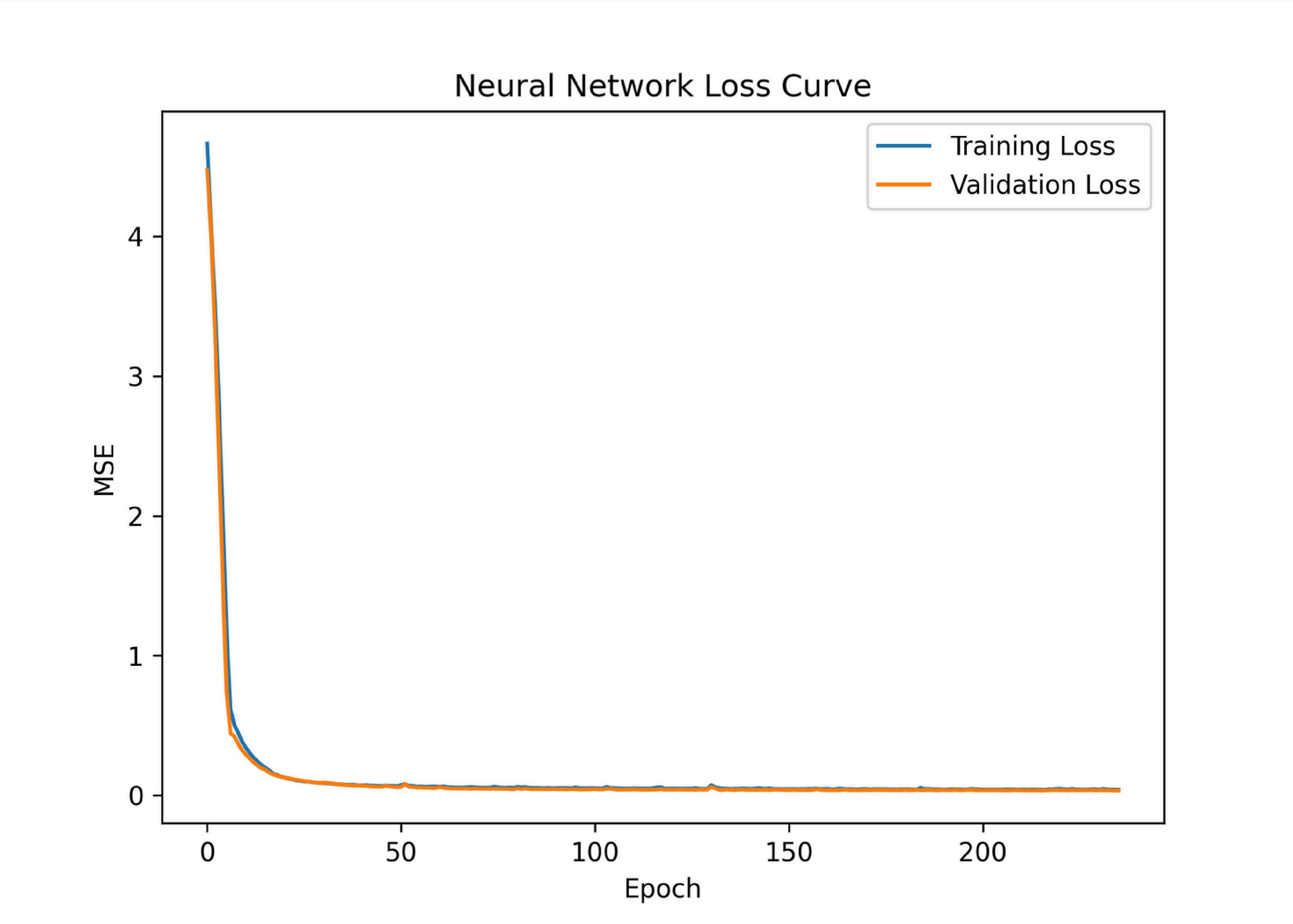
This plot compares our model's prediction of bead stability to the real experimental values.
Because bead stability is naturally noisy in WAAM, the points scatter more, but they still follow the upward trend of the perfect-prediction line.
With an R^2 of about 0.60, the model is performing well on a very difficult target.

Metrics:

- RMSE ≈ 0.183
- MAE ≈ 0.074
- R^2 ≈ 0.603

Harder target but still well modeled.

Neural Network: Loss Curve



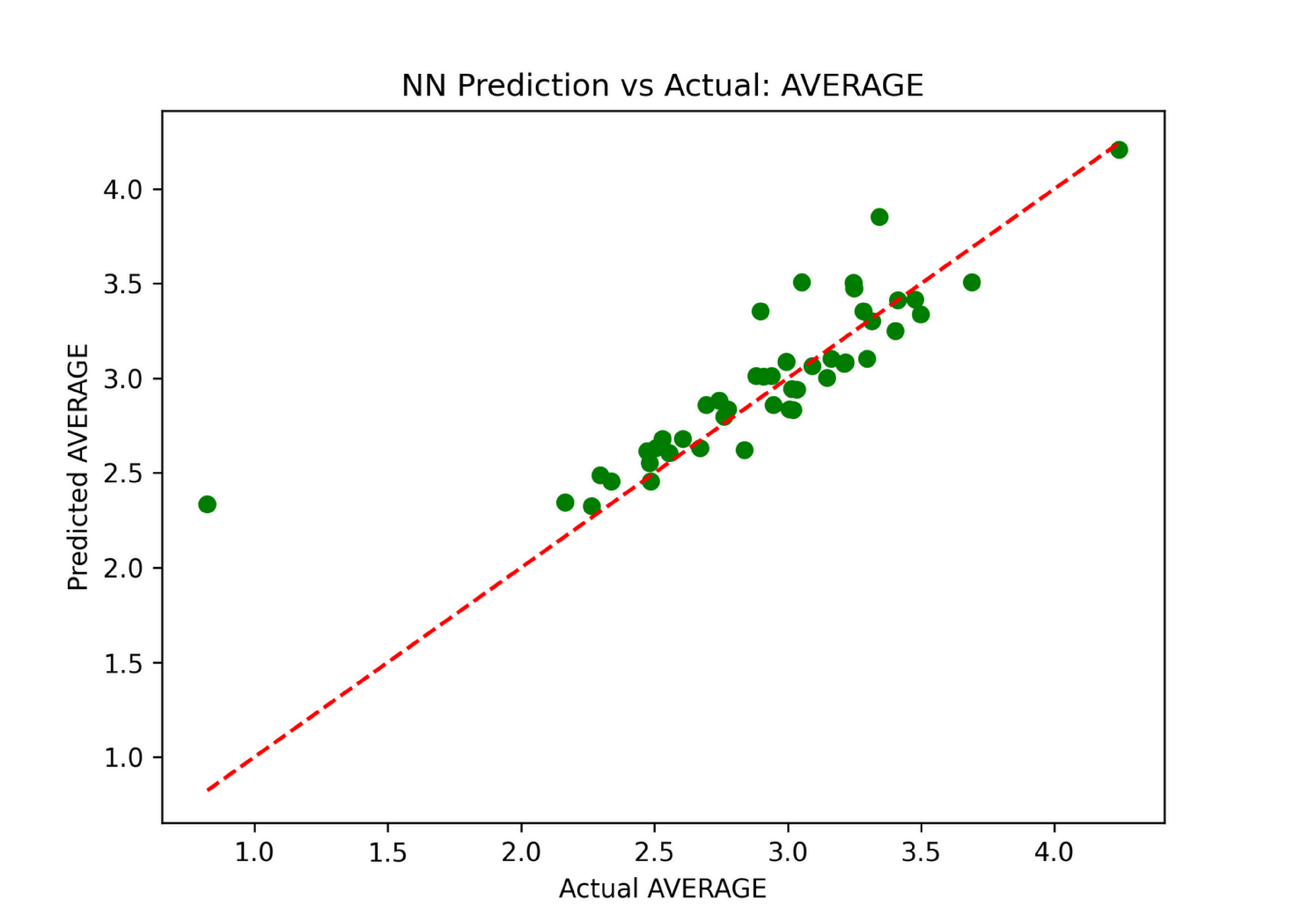
Loss stabilizes after ~150 epochs.

The loss curve shows how well the neural network learns over time. You can see that the error drops very quickly at the beginning, at the first 20 epoch, which means the model is learning the main patterns fast.
After around 150 epochs, the loss becomes flat — this tells us the model has finished learning and is now stable.
Also, the training and validation lines are very close, which means the model is not overfitting and can generalize well to new WAAM conditions."

Deep Learning Model

- Fully Connected Neural Network
- 64 → 32 → 16 → 2 neurons
- ReLU activations
- Adam optimizer
- Early stopping to prevent overfitting
- Predicts both AVERAGE & VARIANCE jointly

NN Results: AVERAGE



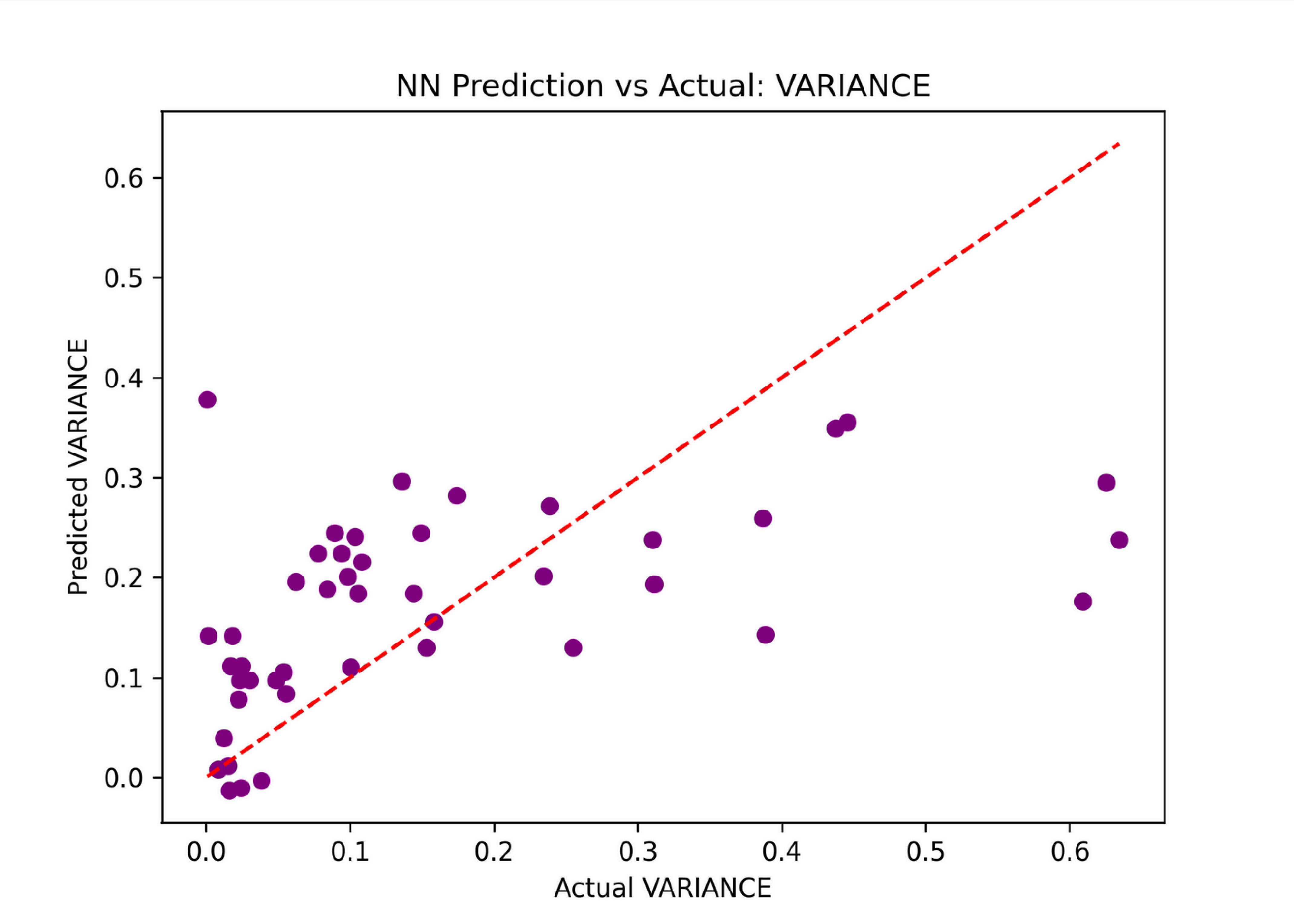
Here, we compare the Neural Network bead-height predictions to the actual experimental values.
Most points fall close to the red line, meaning the NN predicts bead height accurately.
With an R^2 of 0.665 and a small error (RMSE ≈ 0.30), the network captures the underlying WAAM behavior very well—just slightly below the Random Forest in performance

Metrics:

- RMSE ≈ 0.296
- MAE ≈ 0.190
- $R^2 \approx 0.665$

Performance slightly below RF.

NN Results: VARIANCE



Here we evaluate the Neural Network on bead stability prediction.
The points are widely scattered, meaning the NN finds variance harder to model.
With an R^2 of about 0.20, the NN captures only part of the pattern—which is expected because variance is a noisy and unstable response in WAAM. Random Forest handled this better

Metrics:

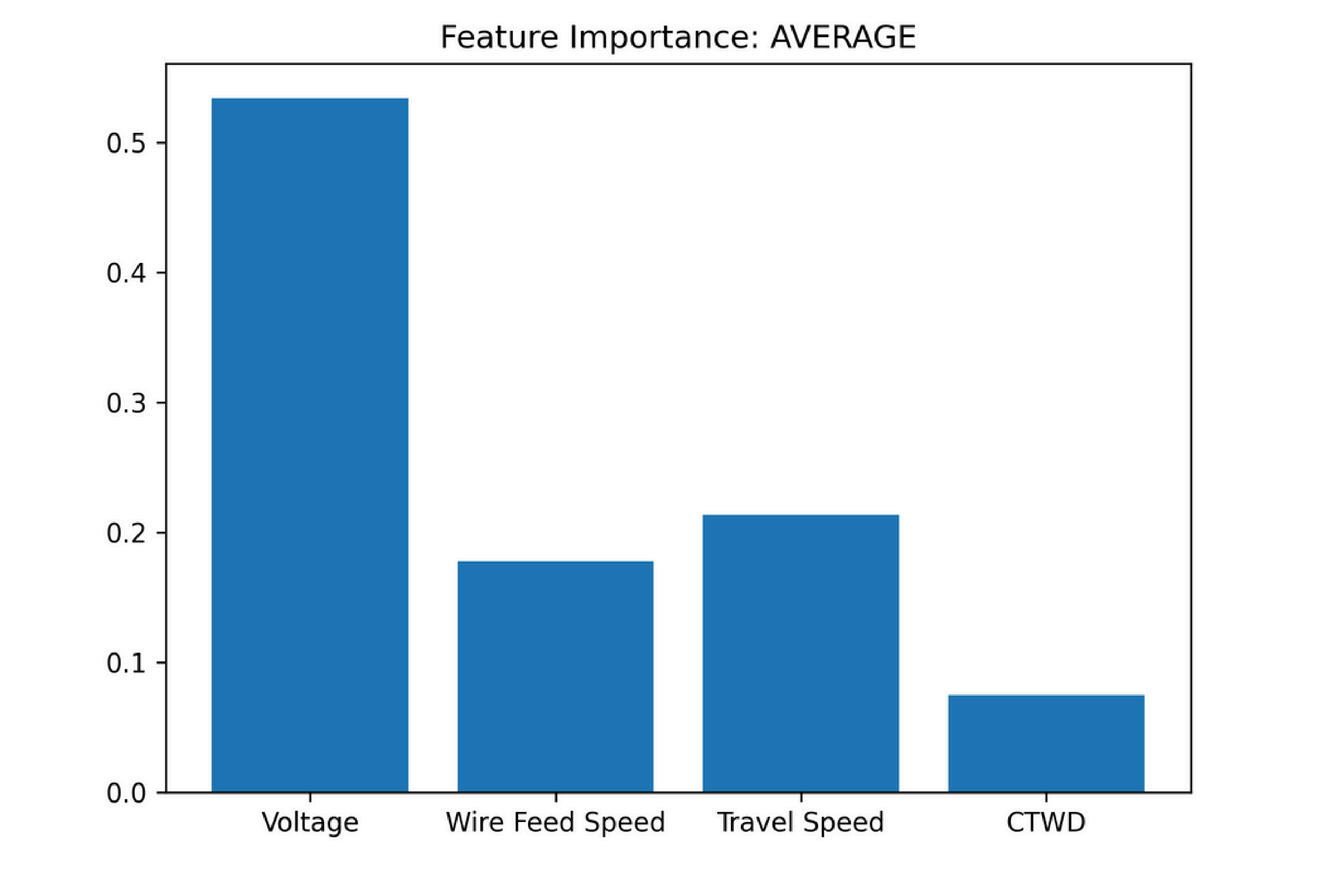
- RMSE ≈ 0.153
- MAE ≈ 0.116
- R^2 ≈ 0.205

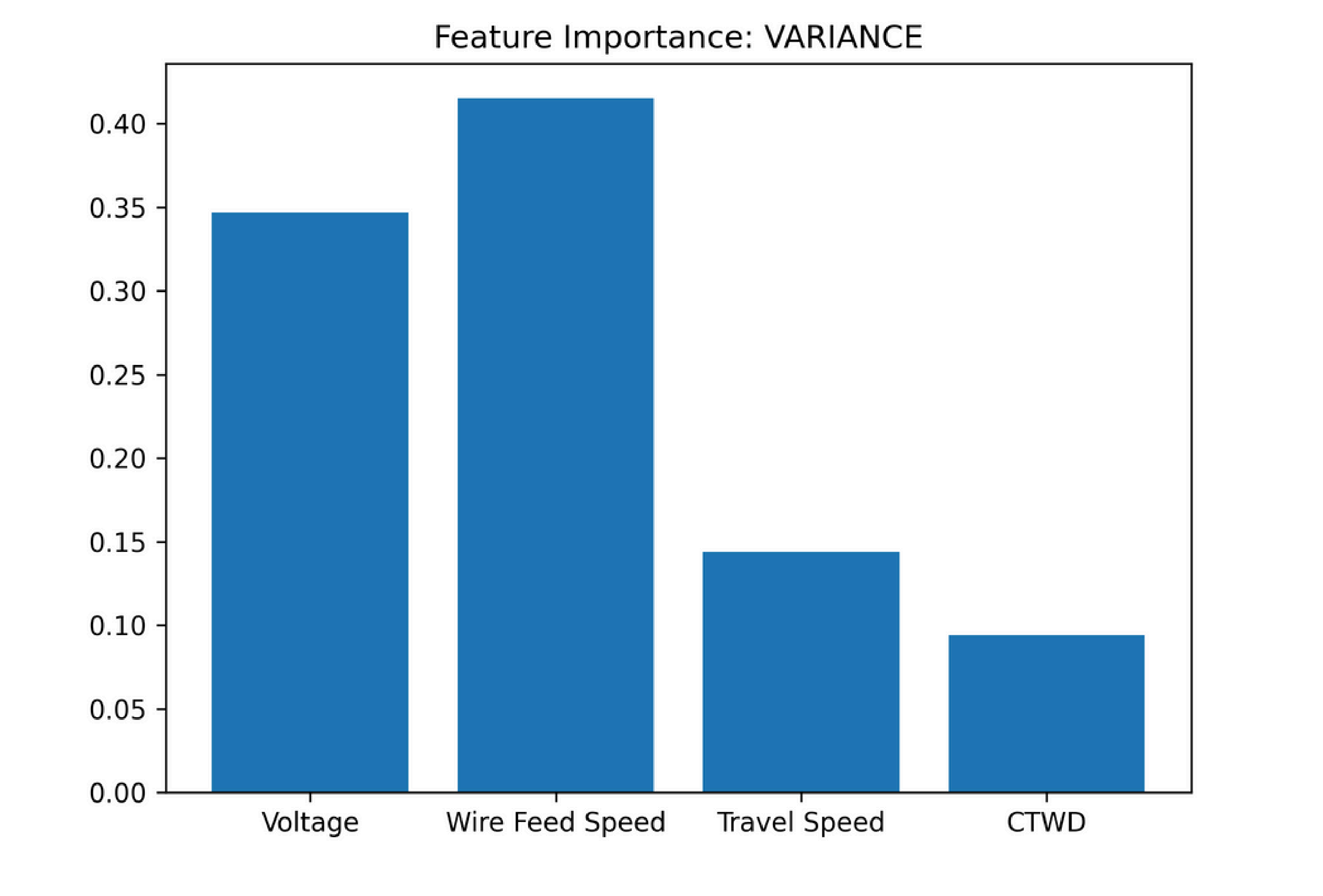
Variance more difficult for NN.

Model Performance: Random Forest vs. Neural Network

MODEL	TARGET	RMSE	MAE	R^2
RF	AVERAGE	0.288	0.169	0.685
NN	AVERAGE	0.296	0.190	0.665
RF	VARIANCE	0.183	0.074	0.603
NN	VARIANCE	0.153	0.116	0.205

Feature Importance (RF)





These plots show which WAAM parameters affect bead height and bead stability.
For bead height, voltage is the most important factor because it controls the amount of metal melted. Travel speed and wire feed speed have moderate influence, while CTWD has a small effect.

For bead stability (variance), wire feed speed and voltage are the most influential. Any fluctuations in these parameters cause instability in the melt pool, leading to an uneven bead. Travel speed and CTWD matter but to a lesser extent.

Voltage and WFS are dominant predictors.

Predicting New Conditions

Sample input:

- Voltage = 20
- WFS = 300
- Travel Speed = 400
- CTWD = 14

Predictions (RF & NN):

- Predicted AVERAGE ≈ 2.7
- Predicted VARIANCE ≈ 0.09

When we input new WAAM parameters like voltage = 20, WFS = 300, travel speed = 400, and CTWD = 14, the model predicts what the bead will look like.
It tells us the bead height will be about 2.7 mm, and the bead variance will be about 0.09, meaning the bead is expected to be smooth and stable.
This allows us to test new conditions without printing metal, which saves cost, time, and material

Conclusion

- ML/DL can accurately model WAAM bead geometry
- RF outperformed NN
- VARIANCE is harder to predict due to high noise
- The model can assist real-time WAAM parameter tuning
  - Suggest the best WAAM settings (voltage, speed, WFS, CTWD)
  - Improve consistency in manufacturing
  - Reduce material waste and defects

VARIANCE is harder to predict due to high noise
Bead stability (variance) changes a lot during WAAM due to:
heat fluctuations
arc instability
molten metal turbulence
wire feed vibration
These random changes make VARIANCE naturally noisy

Future Work

- Reinforcement Learning for adaptive WAAM control
- Larger dataset for improved generalization
- Incorporate temperature, arc behavior, bead width
- Deploy model into actual WAAM controller

In the future, this work can be expanded by using reinforcement learning to make WAAM self-adjusting, collecting a larger dataset for better model performance, incorporating more process variables like temperature and arc behavior, and finally deploying the model into a real WAAM controller for intelligent automated printing."

THANK YOU

Any Questions?