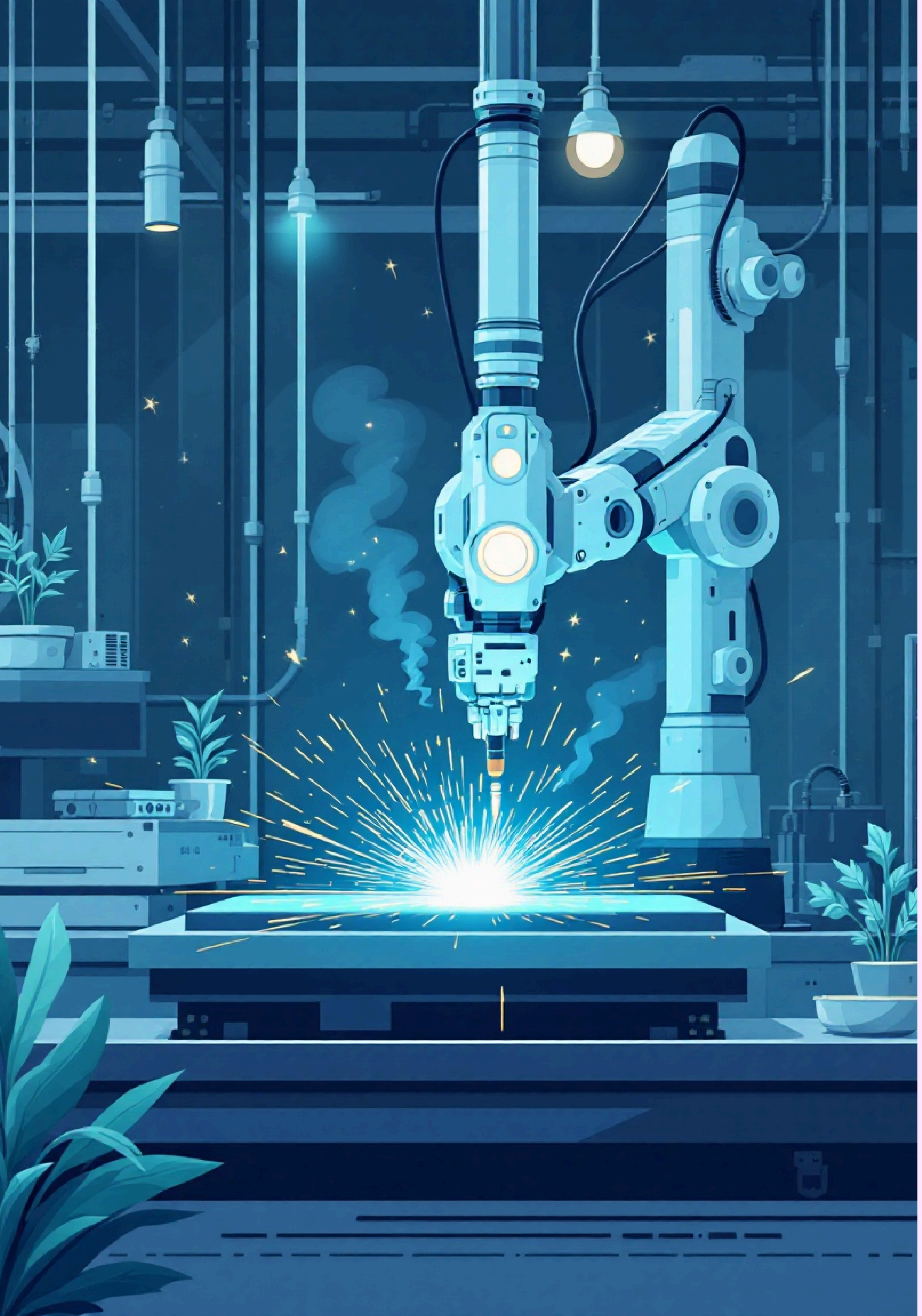


WAAM Bead Geometry Prediction Using Machine Learning & Deep Learning

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
- WAAM Process & Problem Statement
- 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
- 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

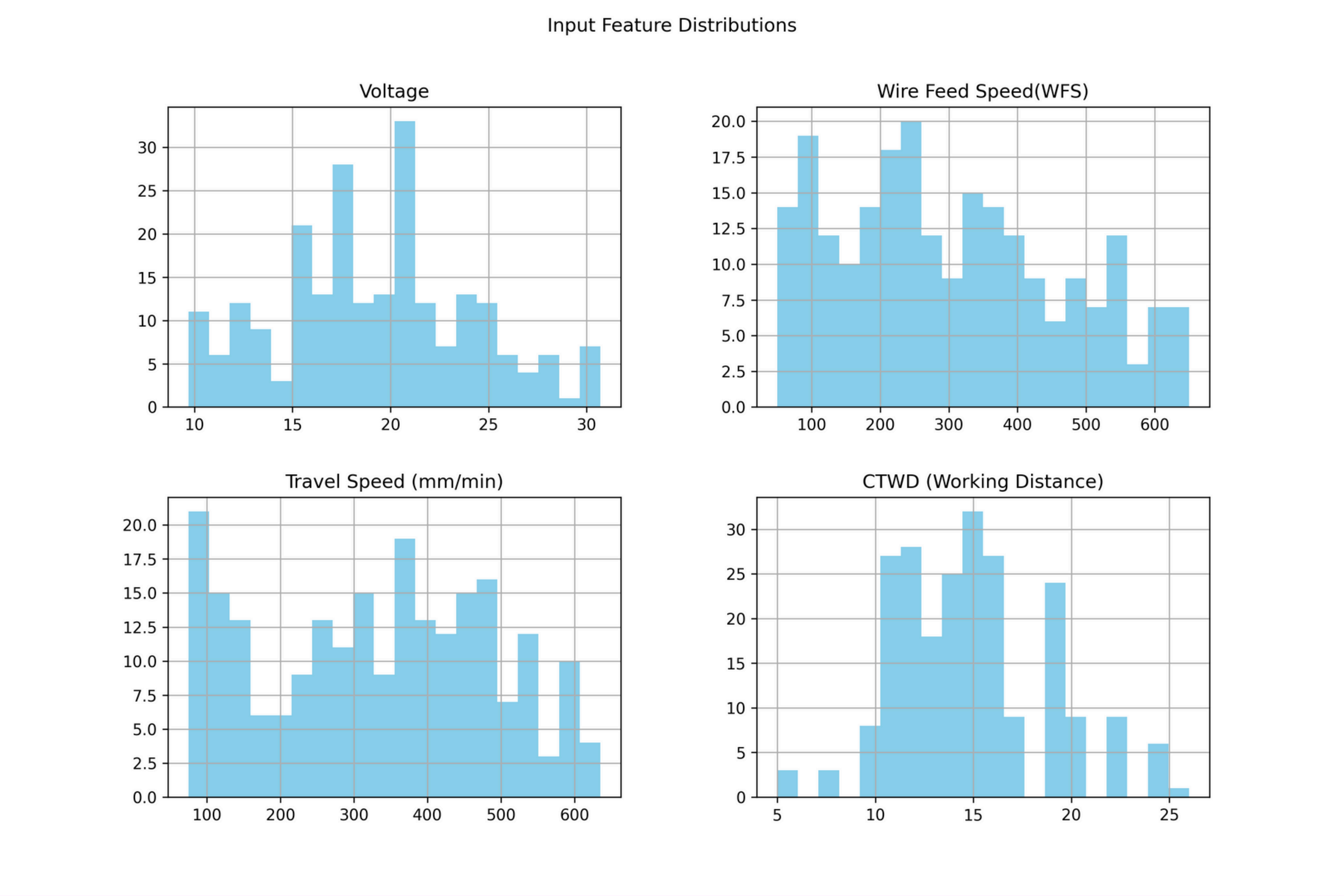
- Ensemble learning method
- Robust to outliers
- Provides feature importance

DEEP LEARNING

Fully Connected Neural Networks

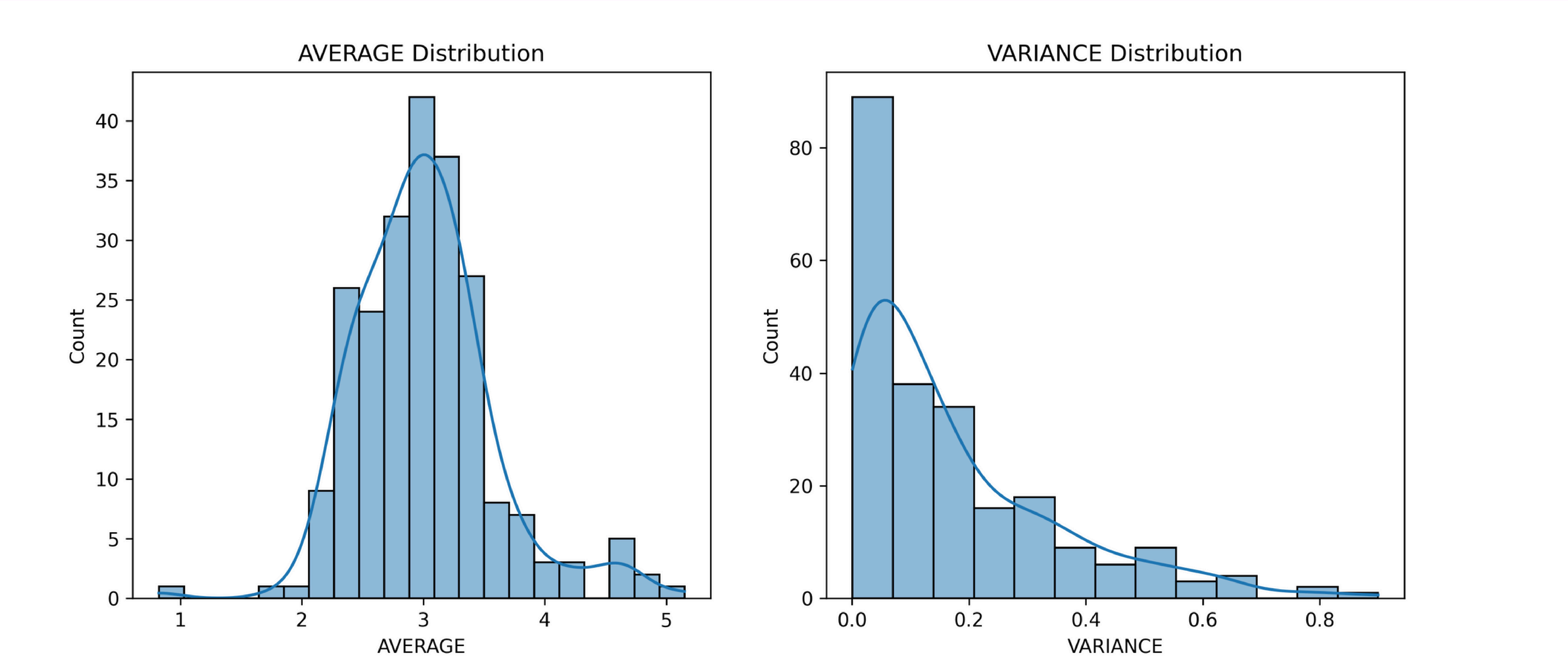
- Captures complex nonlinearities
- Learns hierarchical features
- Requires large datasets

EDA: Input Feature Distributions



- Voltage mostly between 12–22 V
- WFS and Travel Speed show wide ranges
- CTWD concentrated between 10–20 mm

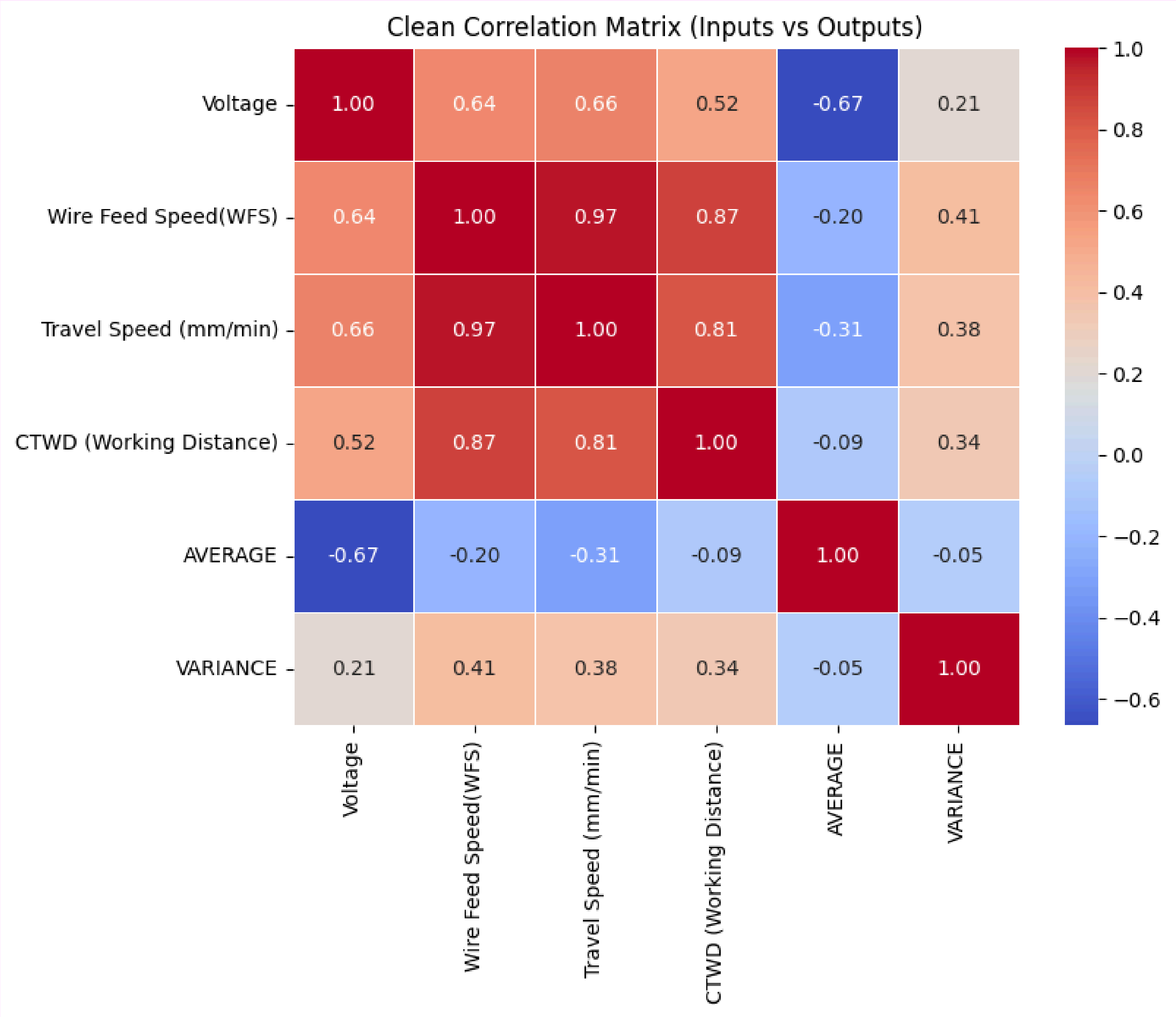
EDA: Target Distributions



Observations:

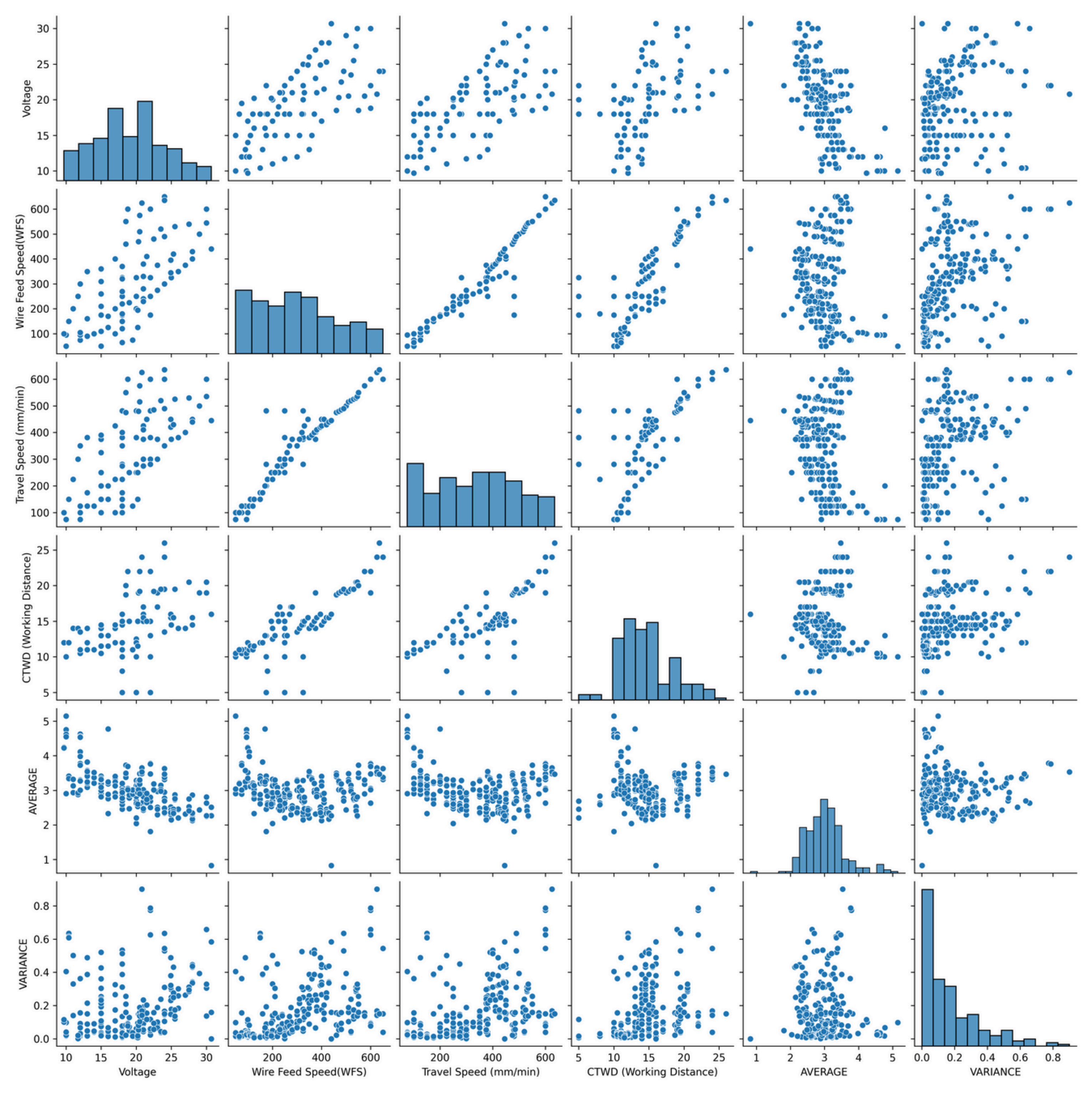
- AVERAGE roughly normal
- VARIANCE positively skewed → more instability cases

Correlation Heatmap



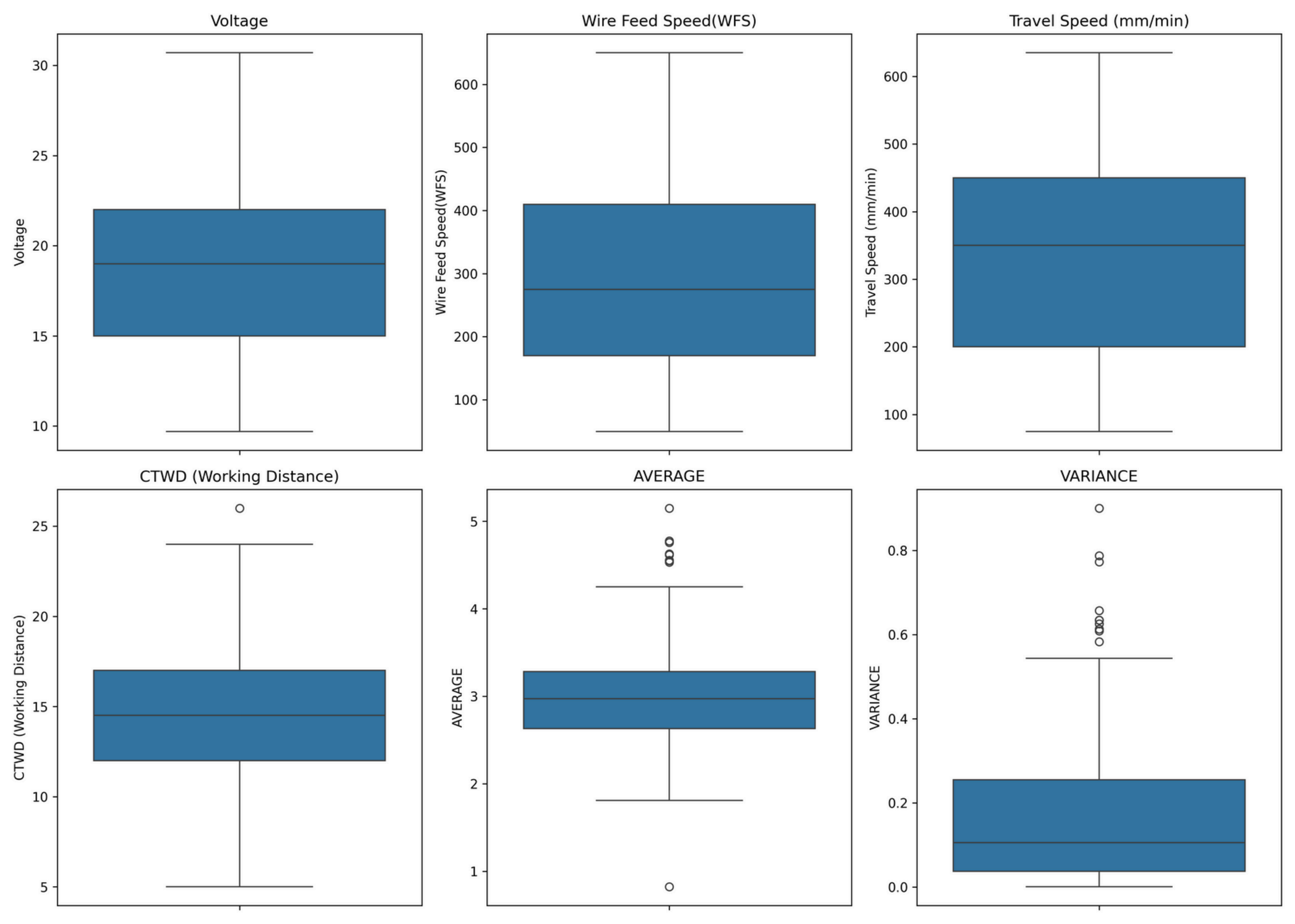
- Voltage & WFS strongly correlated
- WFS has notable correlation with AVERAGE
- VARIANCE has weak linear correlation → nonlinear model required

Pairplot (Feature Interactions)



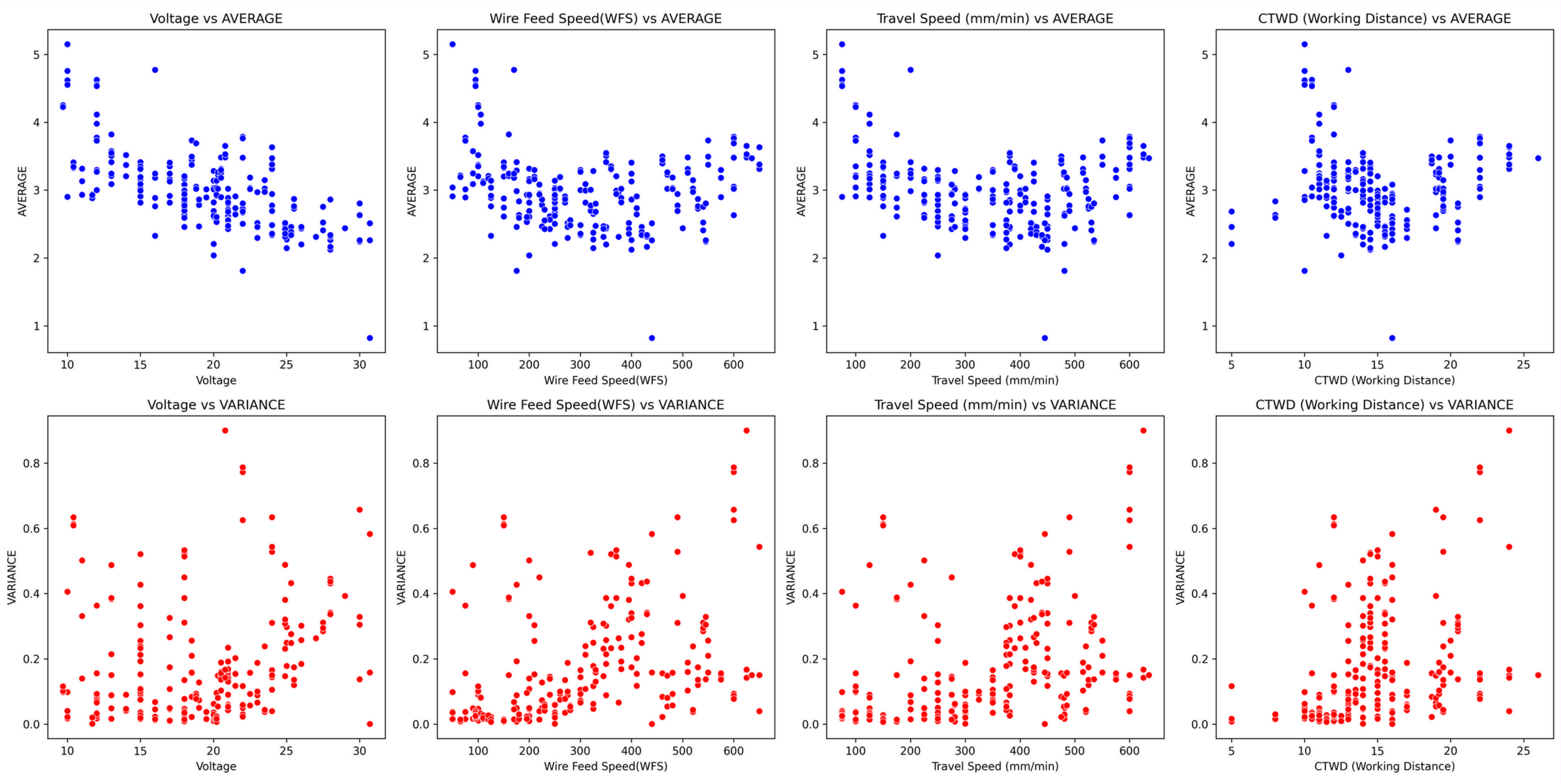
Shows multivariate interactions between inputs & outputs.

Boxplots (Outlier Detection)



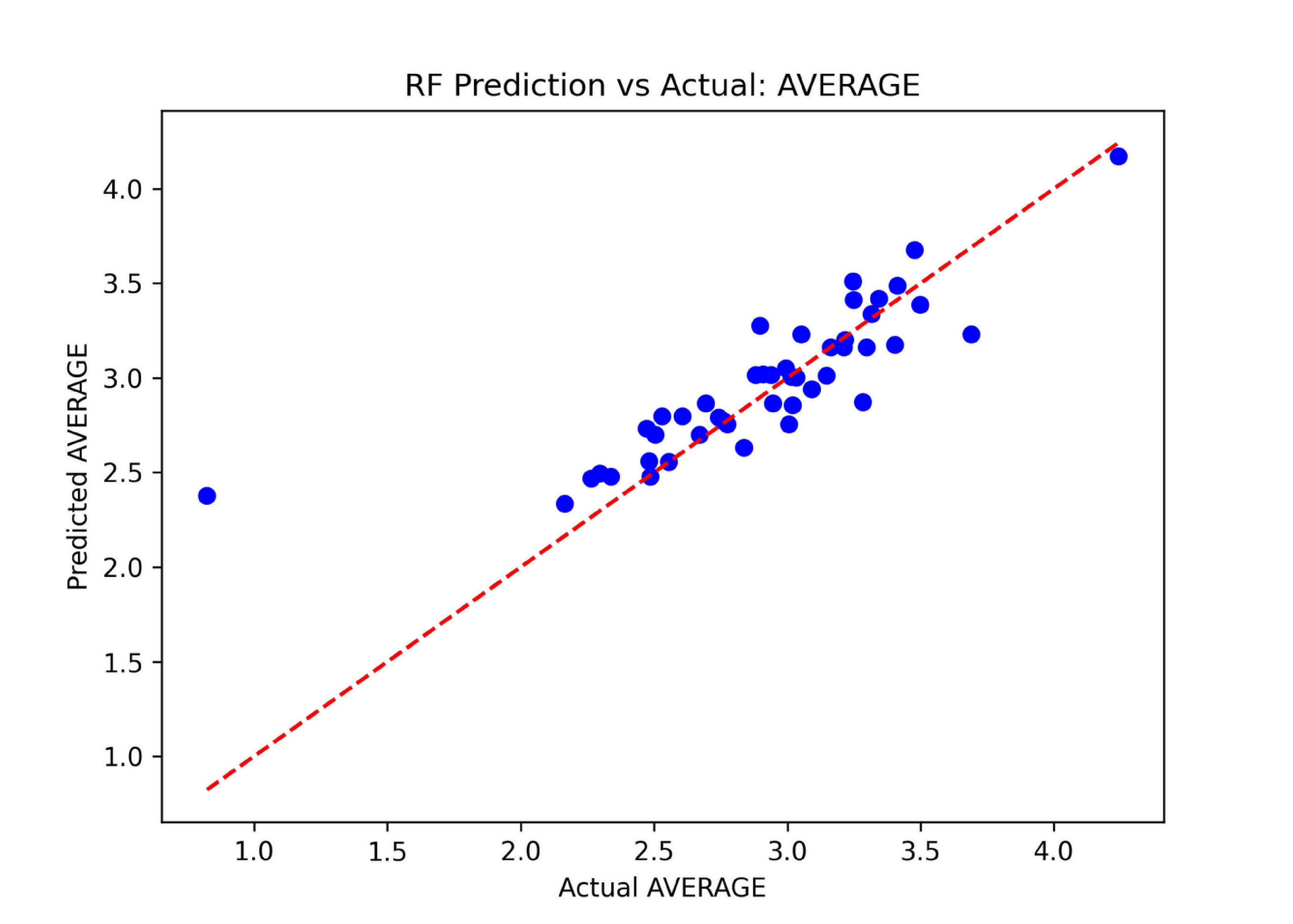
Outliers exist in WFS and VARIANCE.

Relationship Plot



Top row: Inputs → AVERAGE
Bottom row: Inputs → VARIANCE

RF Results: AVERAGE



Metrics:

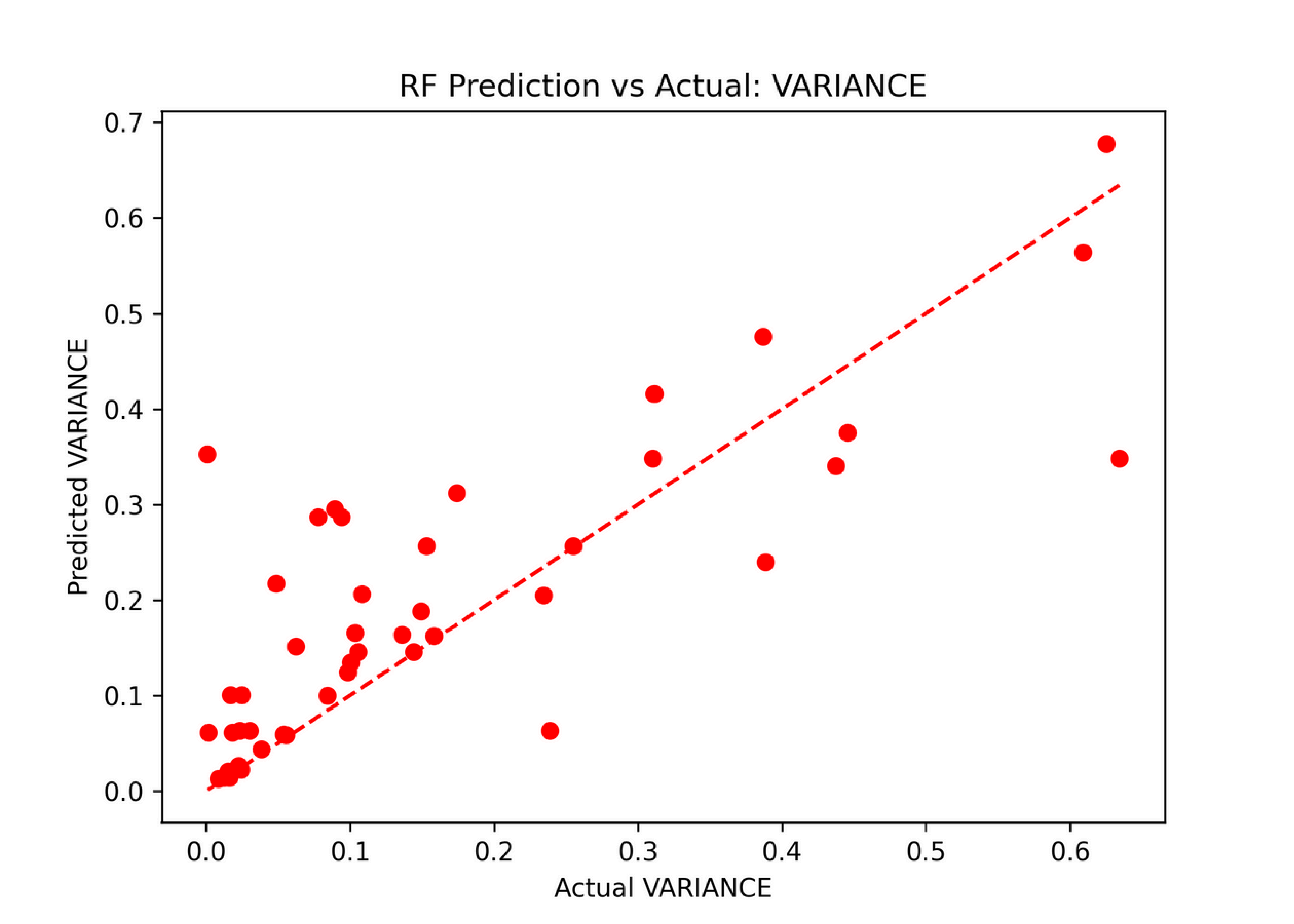
- RMSE ≈ 0.288
- MAE ≈ 0.169
- R^2 ≈ 0.685

Very good predictive accuracy.

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

RF Results: VARIANCE

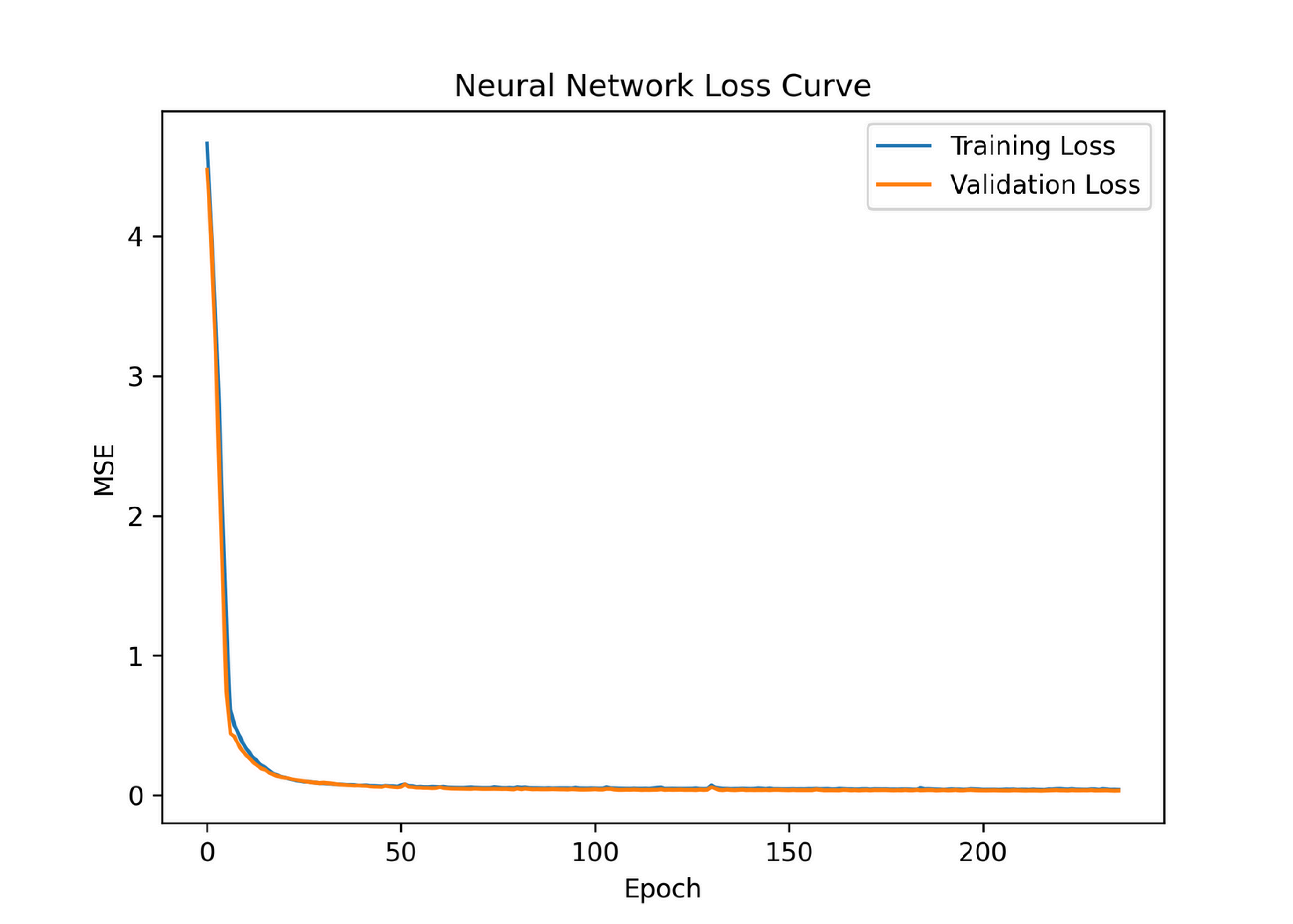


Metrics:

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

Harder target but still well modeled.

Neural Network: Loss Curve

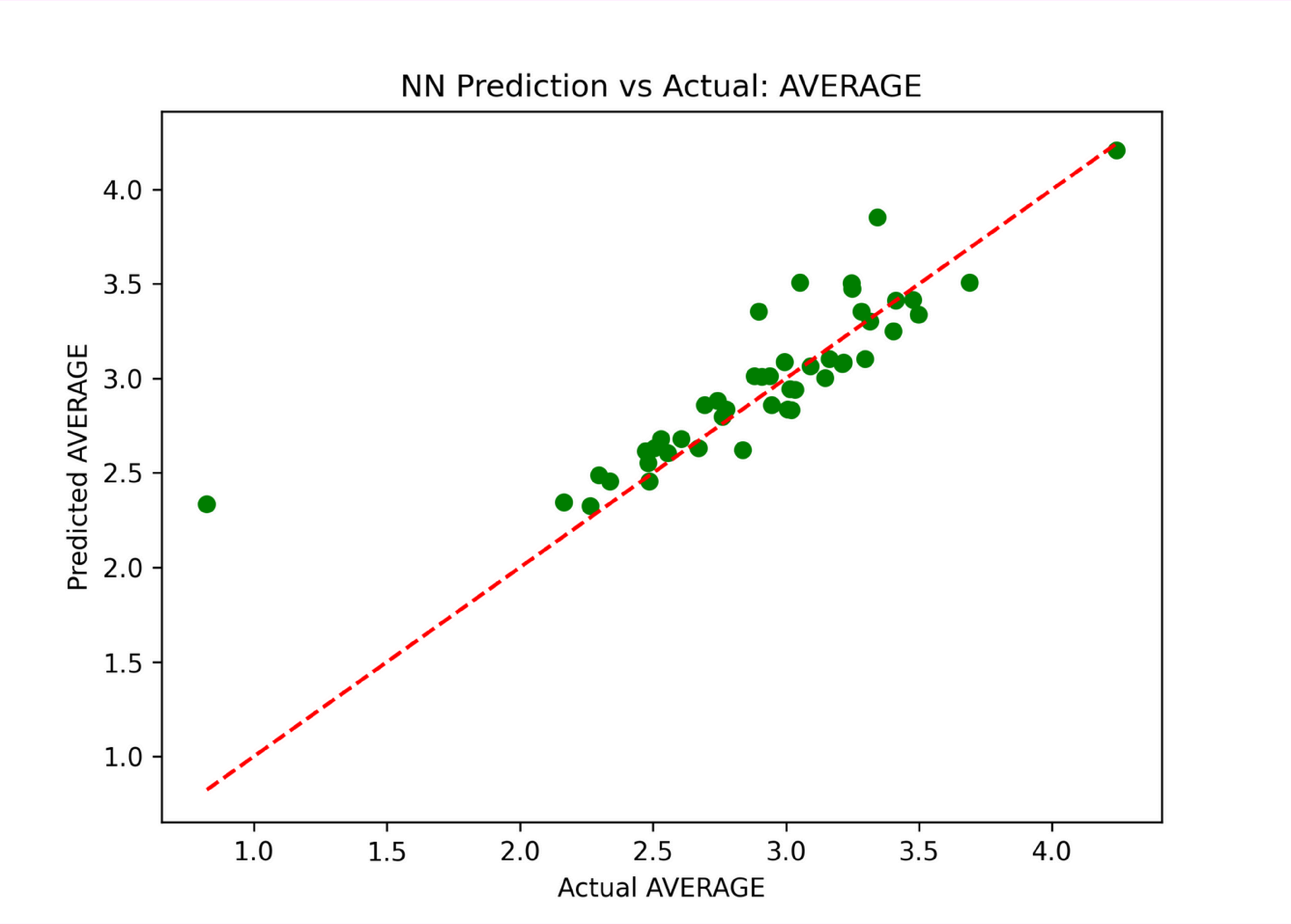


Loss stabilizes after ~150 epochs.

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

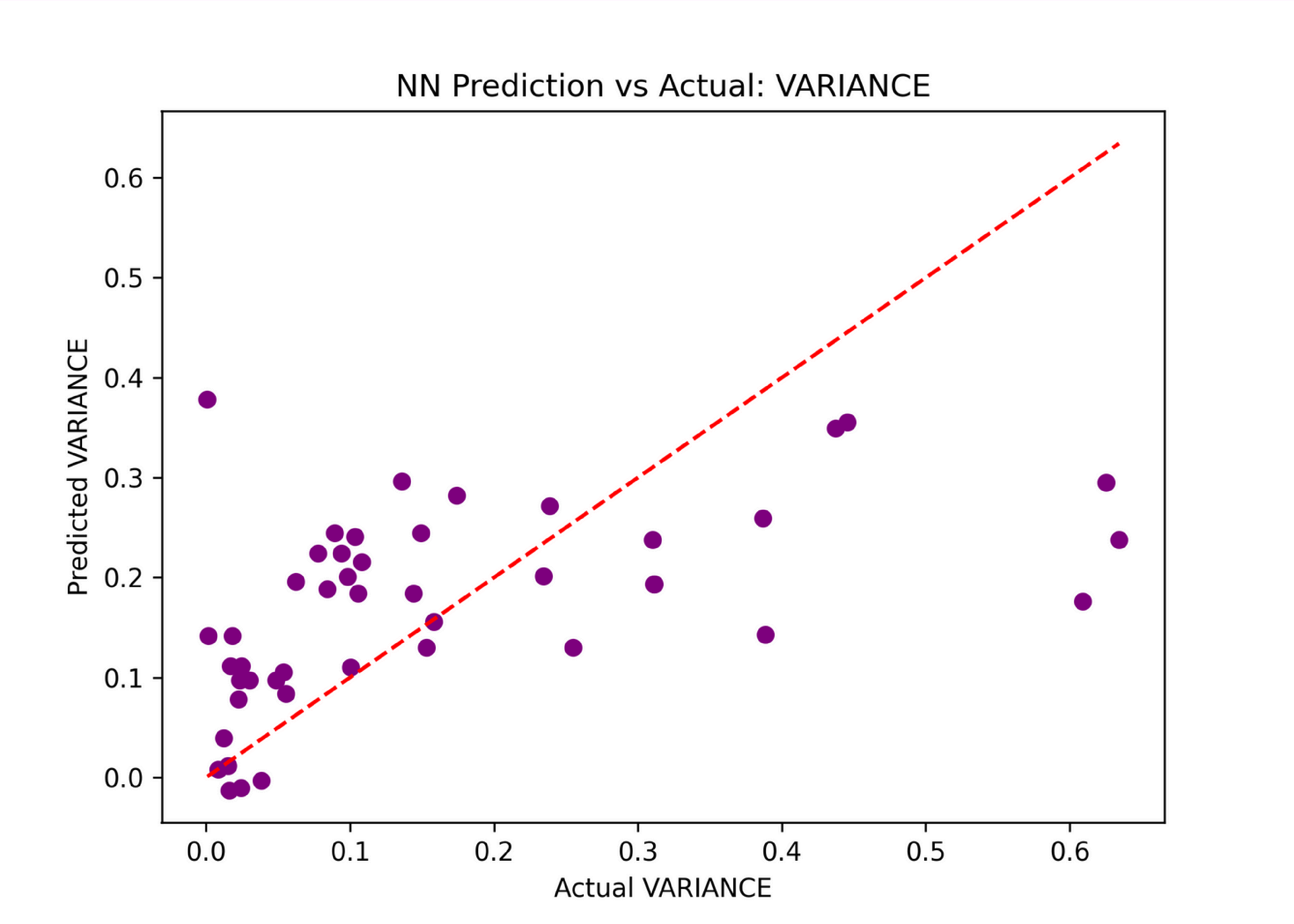


Metrics:

- RMSE ≈ 0.296
- MAE ≈ 0.190
- R^2 ≈ 0.665

Performance slightly below RF.

NN Results: VARIANCE



Metrics:

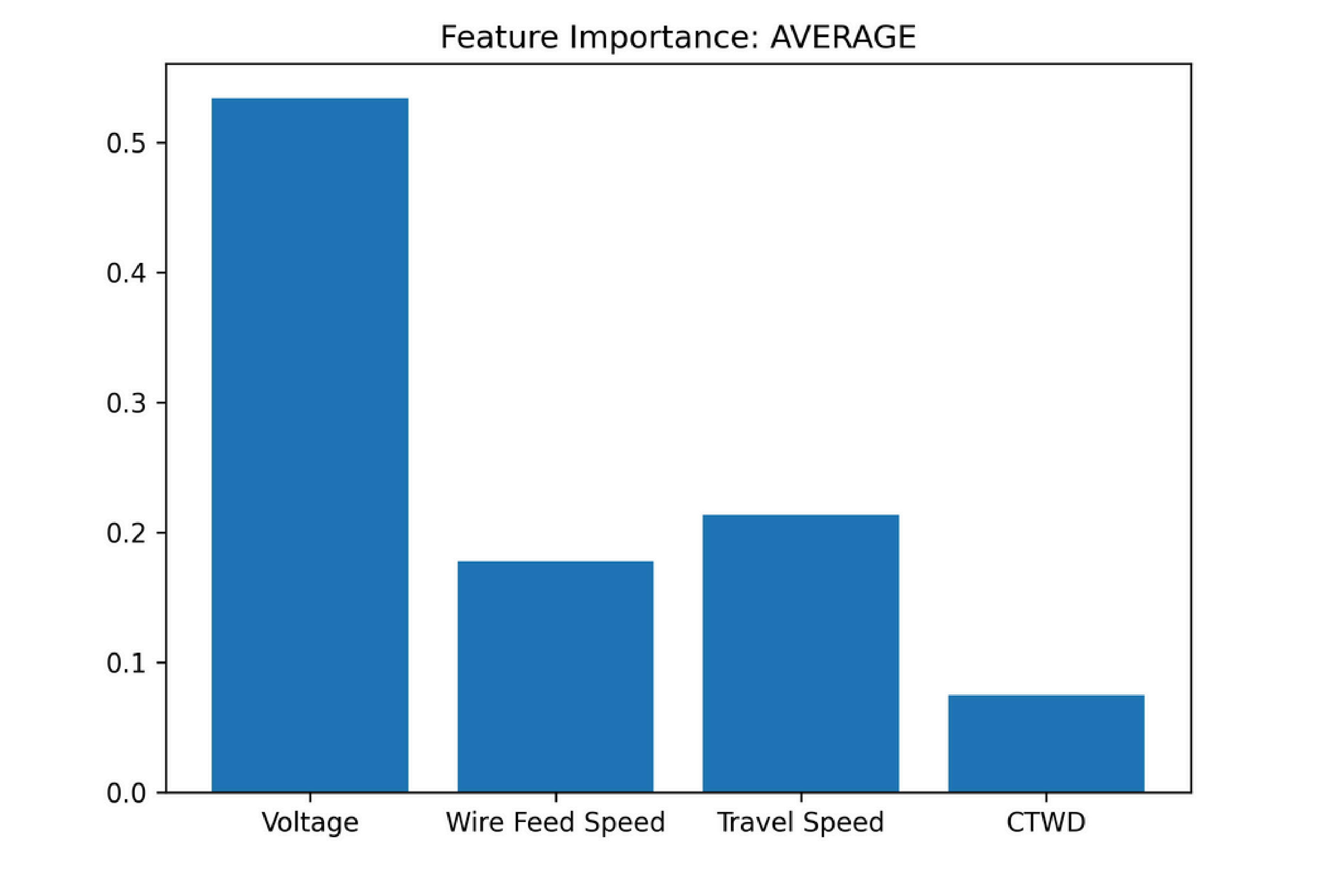
- RMSE ≈ 0.153
- MAE ≈ 0.116
- R^2 ≈ 0.205

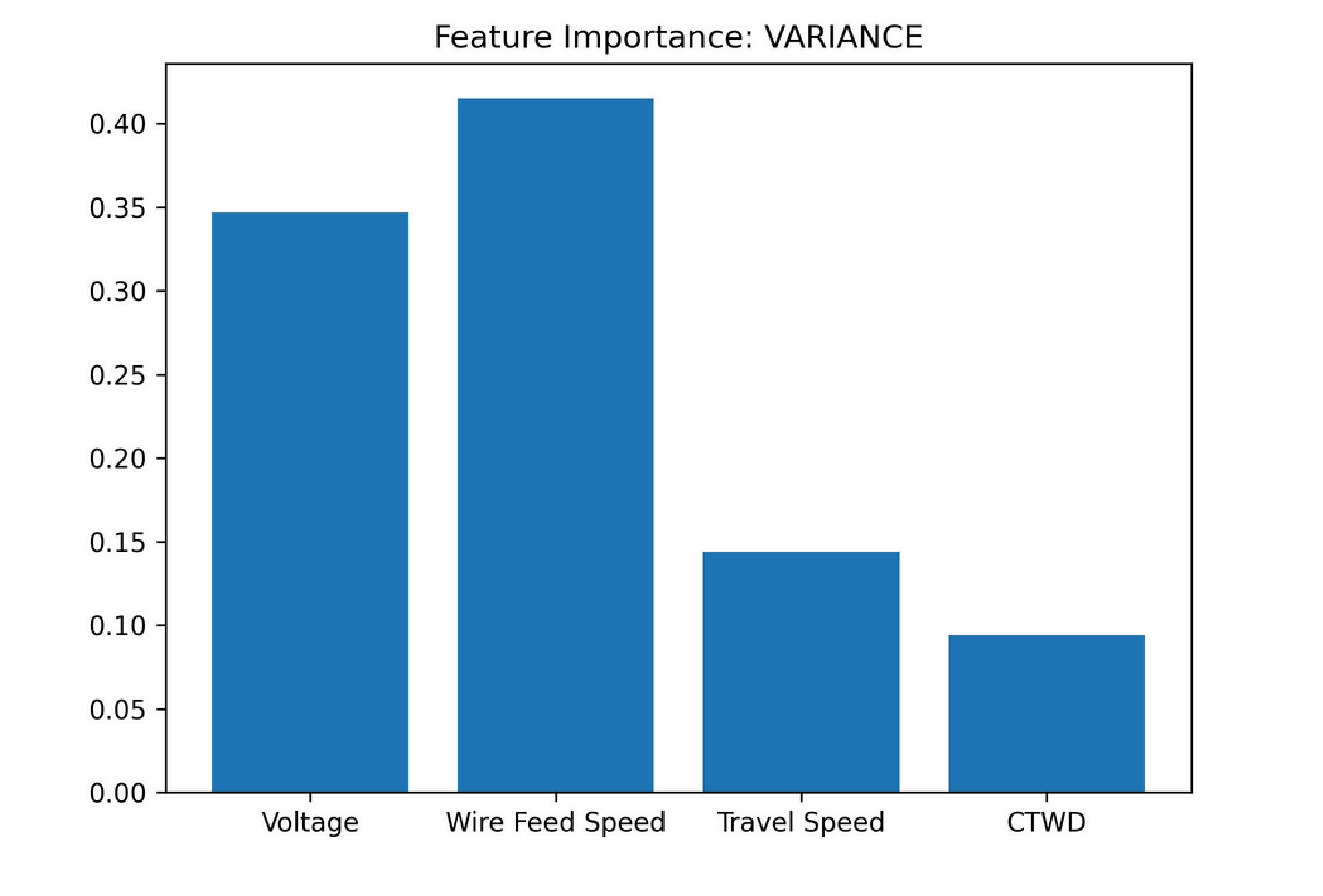
Variance more difficult for NN.

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)





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

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

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

THANK YOU

Any Questions?