

# 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).



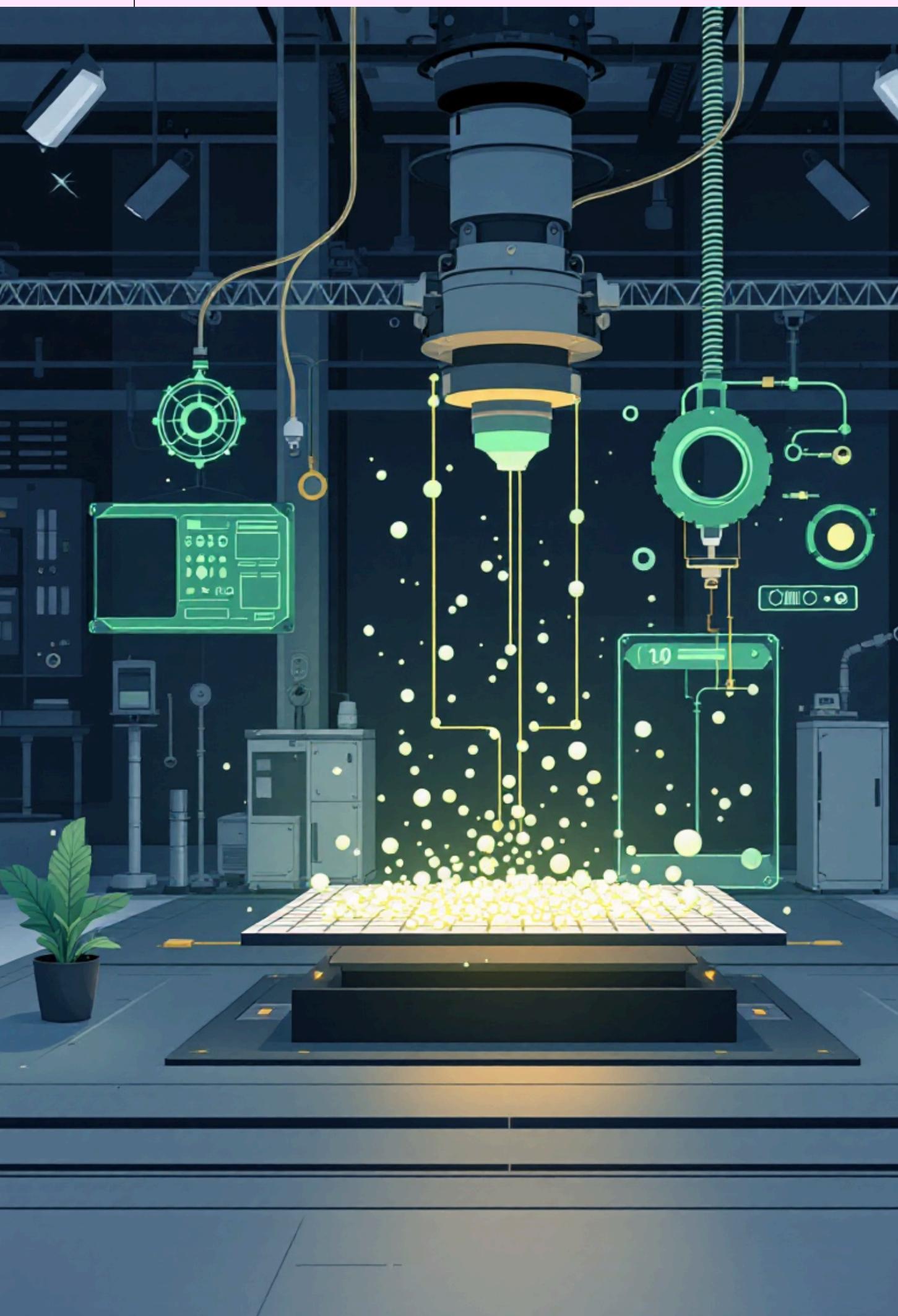
## Outline

- Introduction
- WAAM Process & Problem Statement
- Dataset Overview
- Exploratory Data Analysis (EDA)
- Machine Learning Model (Random Forest)
- Deep Learning Model (Neural Network)
- Comparative Results
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- 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

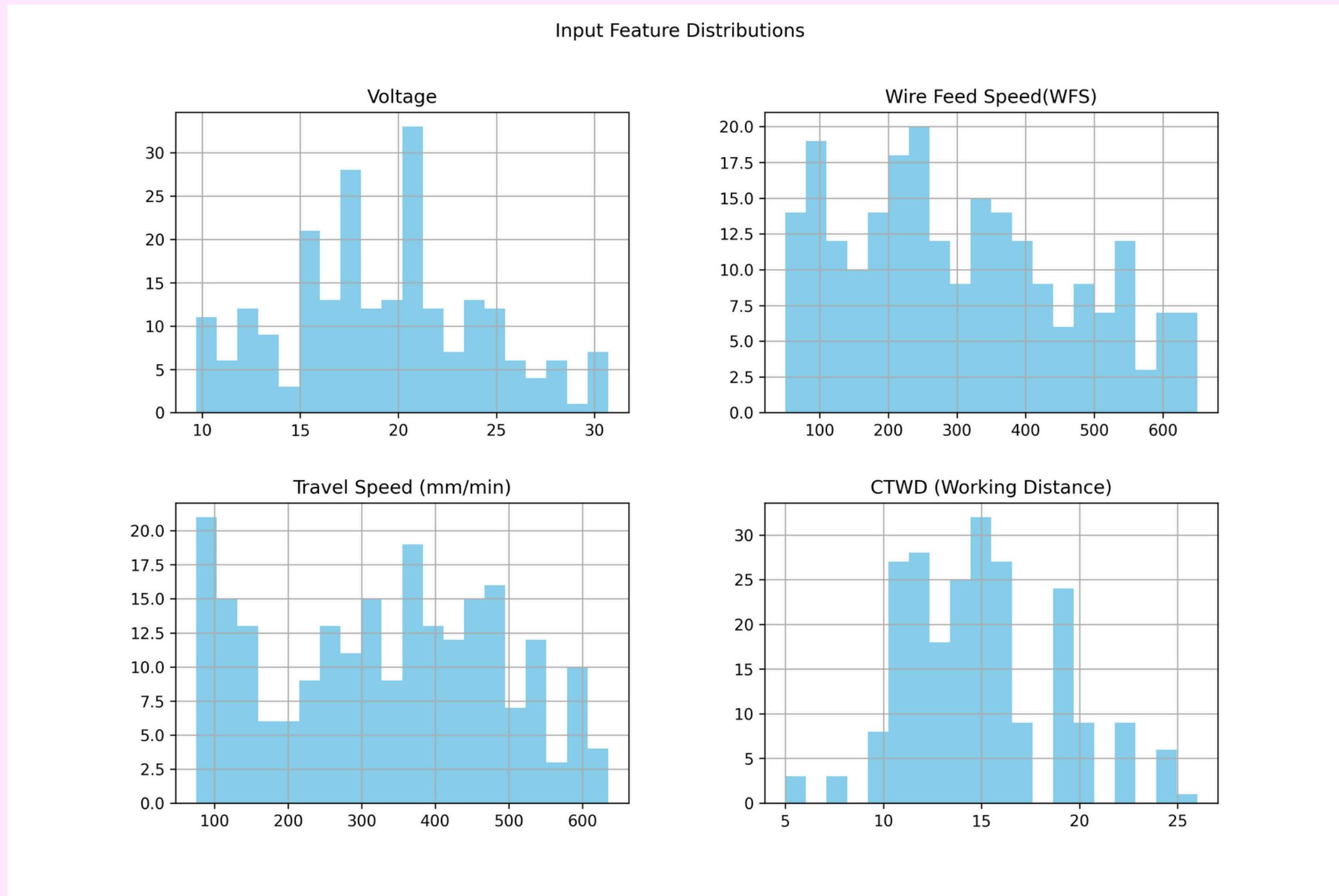
- Ensemble learning method
- Robust to outliers
- Provides feature importance

## DEEP LEARNING

### Fully Connected Neural Networks

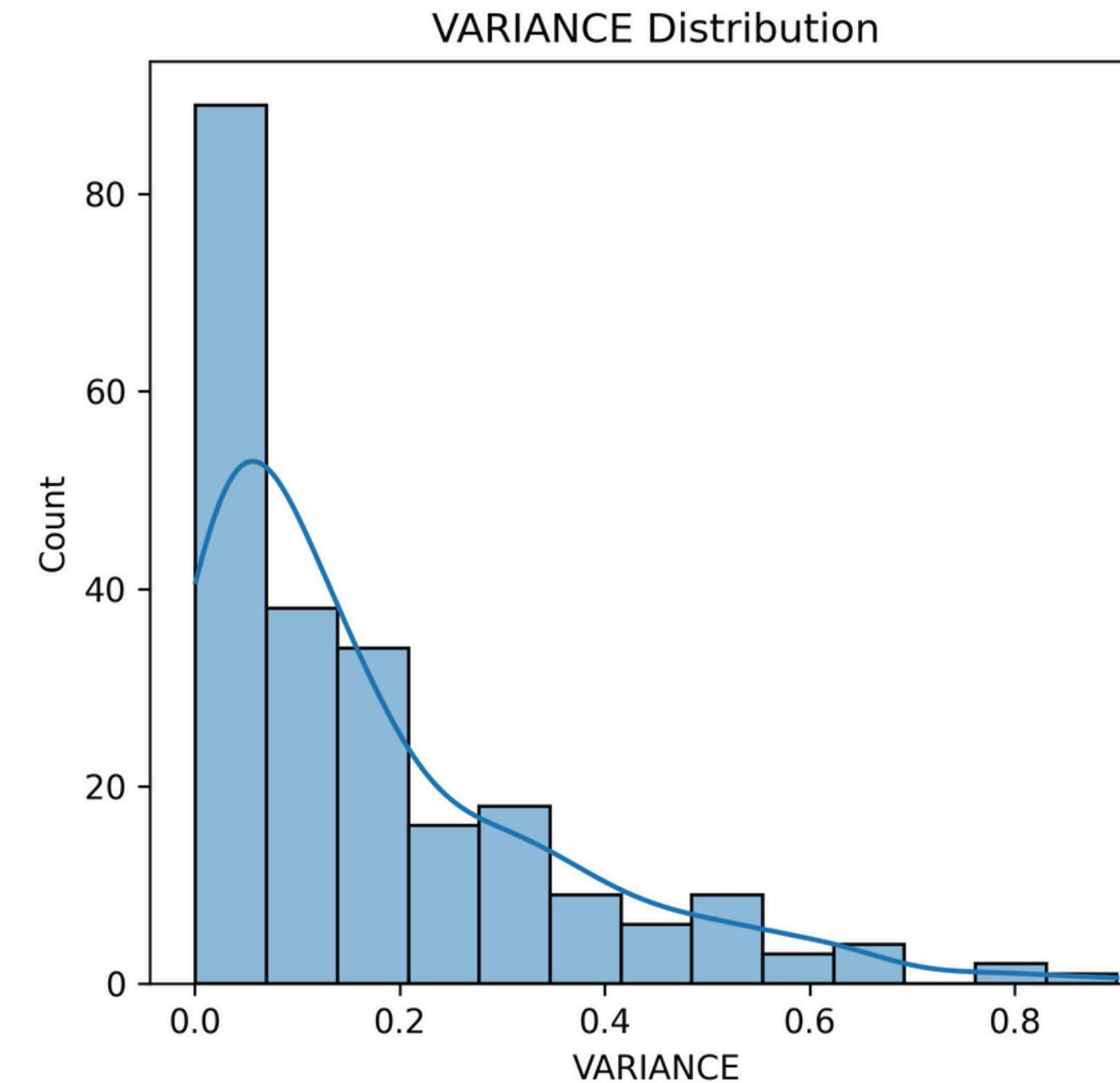
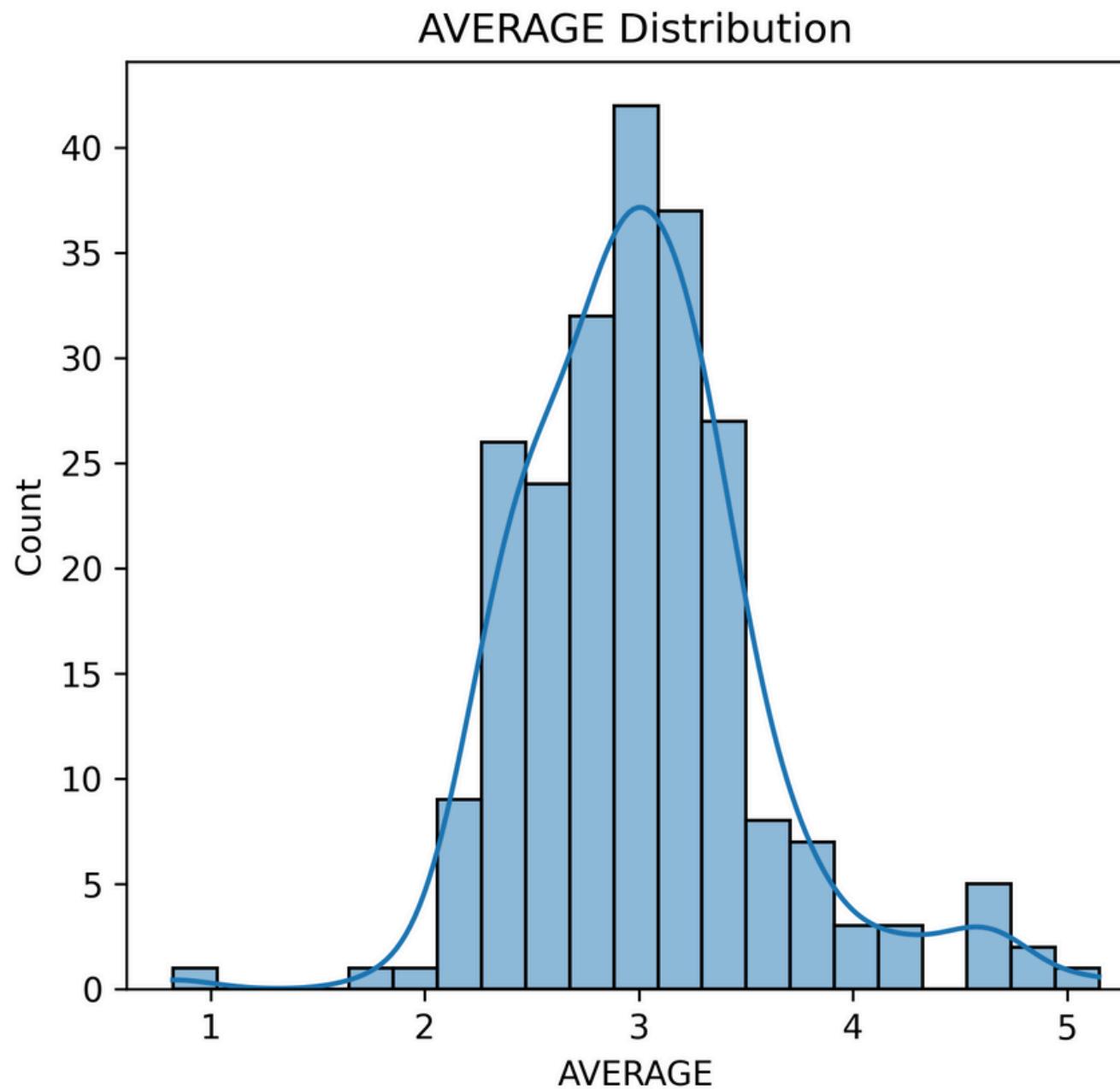
- Captures complex nonlinearities
- Learns hierarchical features
- Requires large datasets

# EDA: Input Feature Distributions



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

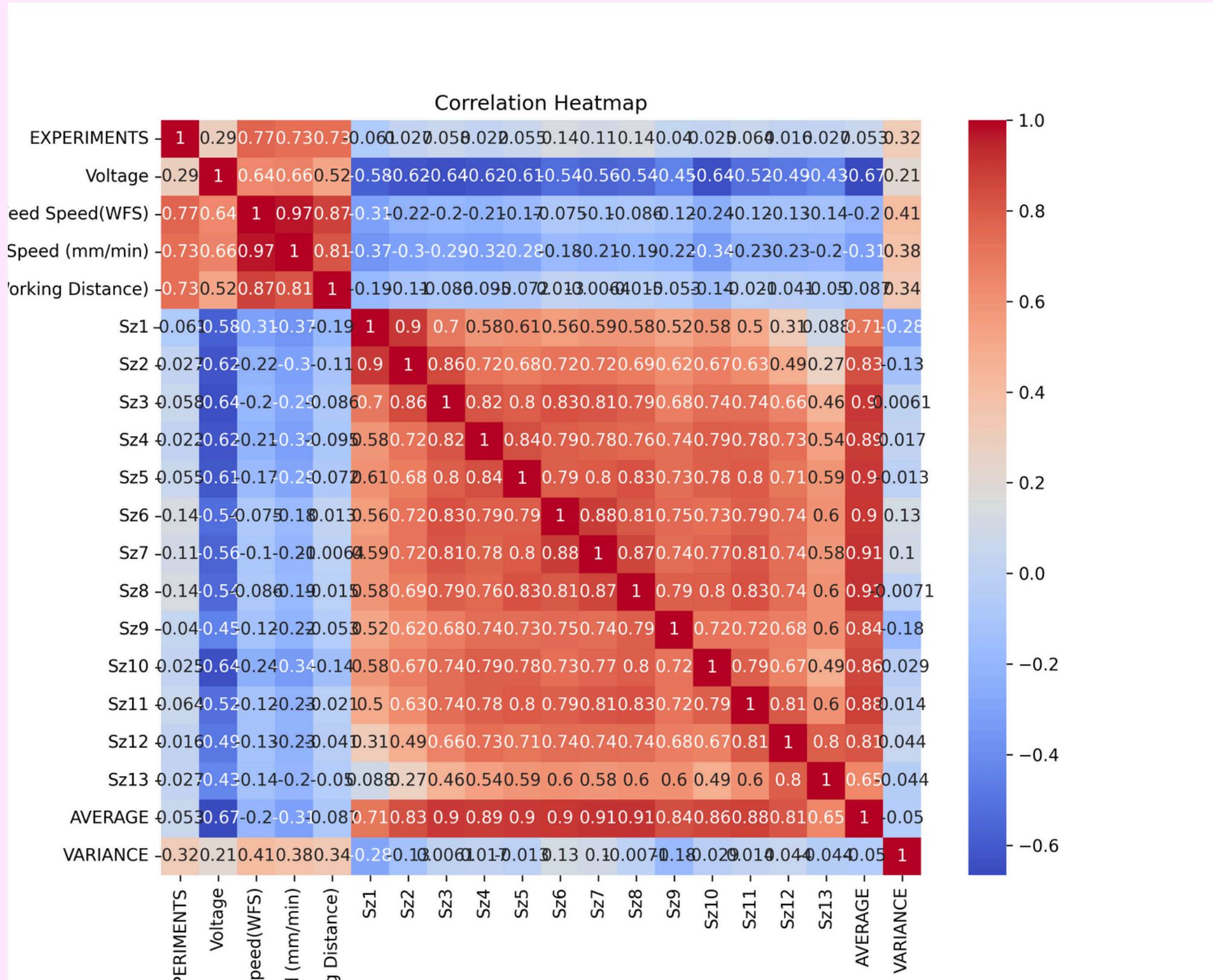
# EDA: Target Distributions



## Observations:

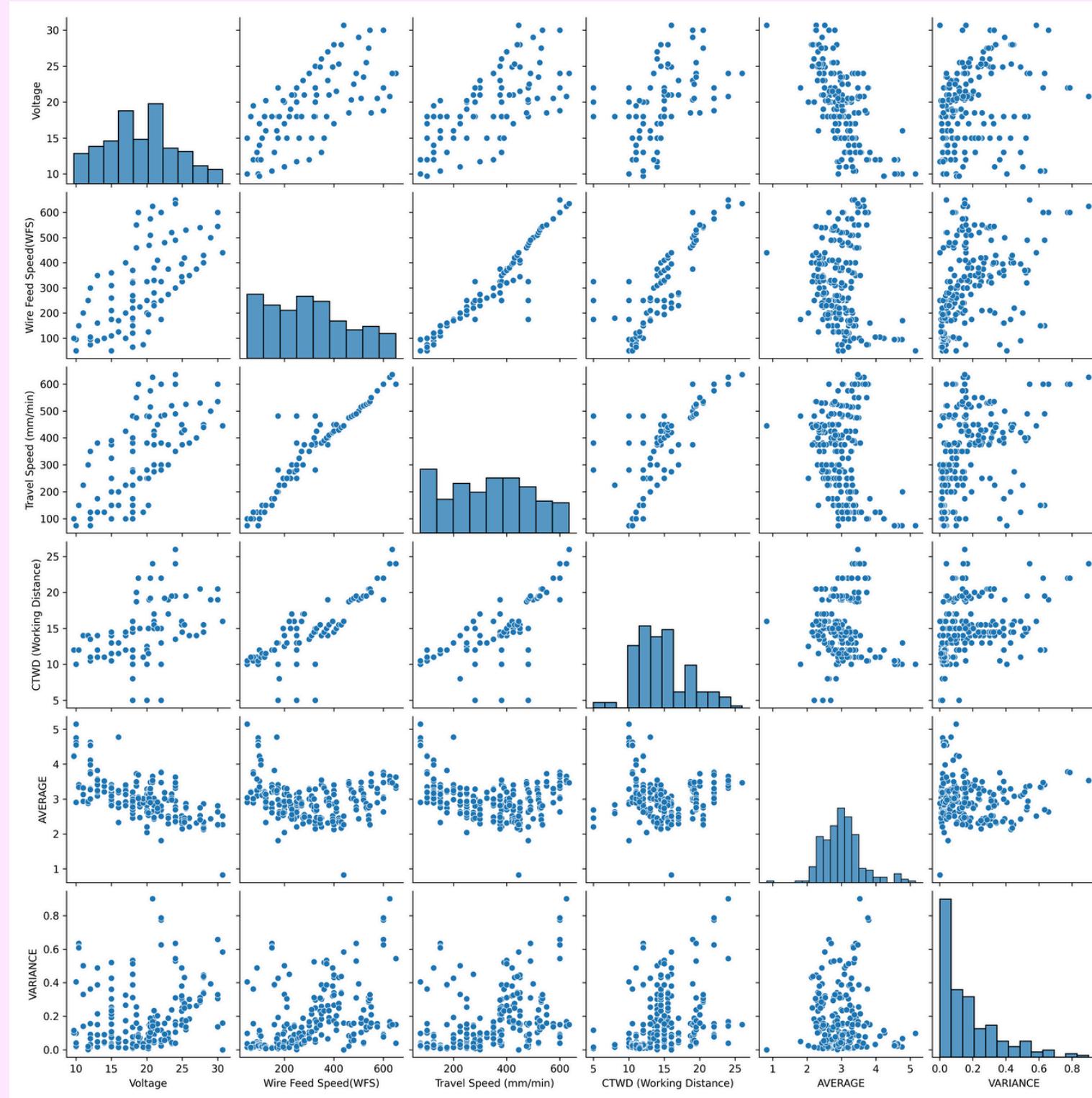
- AVERAGE roughly normal
- VARIANCE positively skewed → more instability cases

# Correlation Heatmap



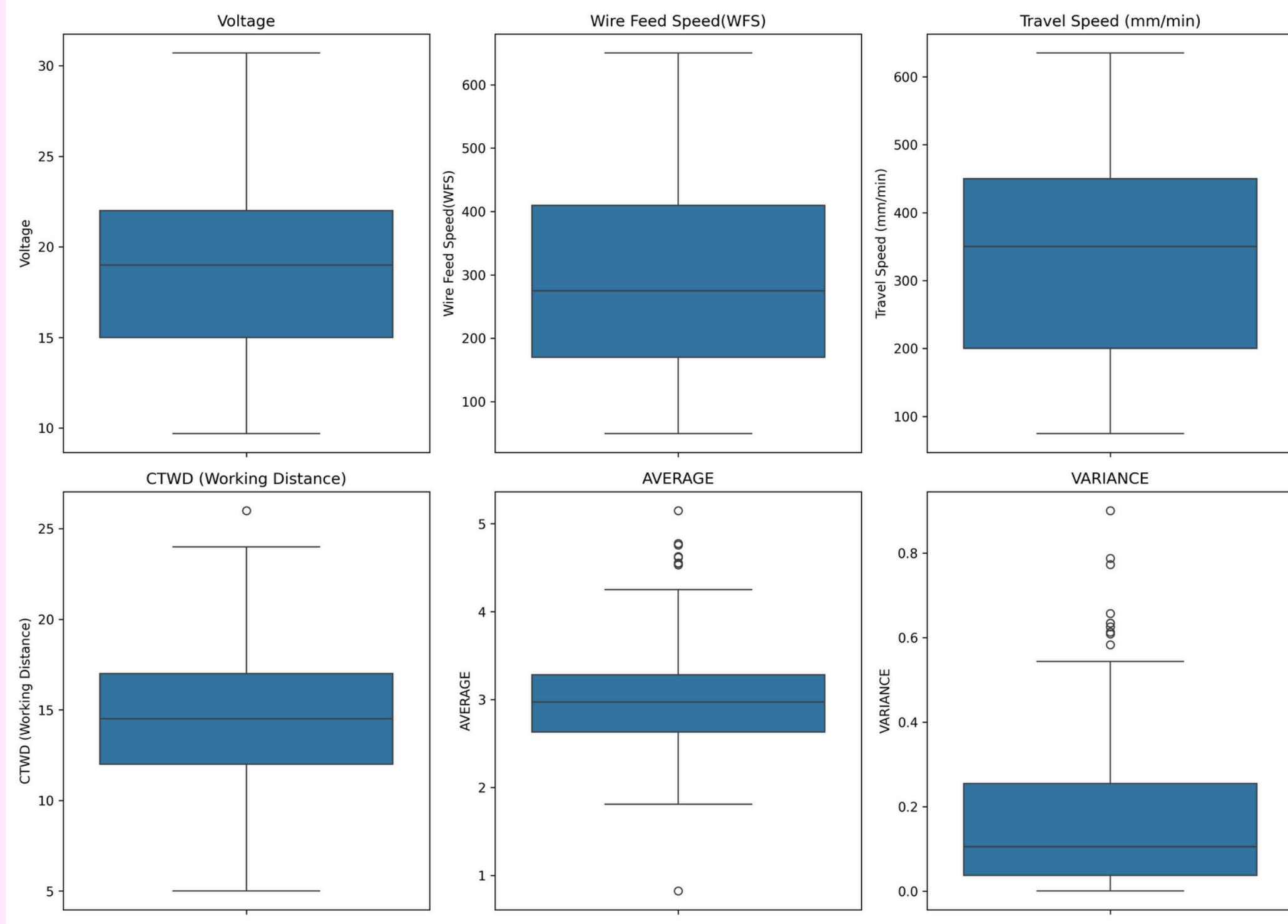
- Voltage & WFS strongly correlated
- WFS has notable correlation with AVERAGE
- VARIANCE has weak linear correlation → nonlinear model required

# Pairplot (Feature Interactions)



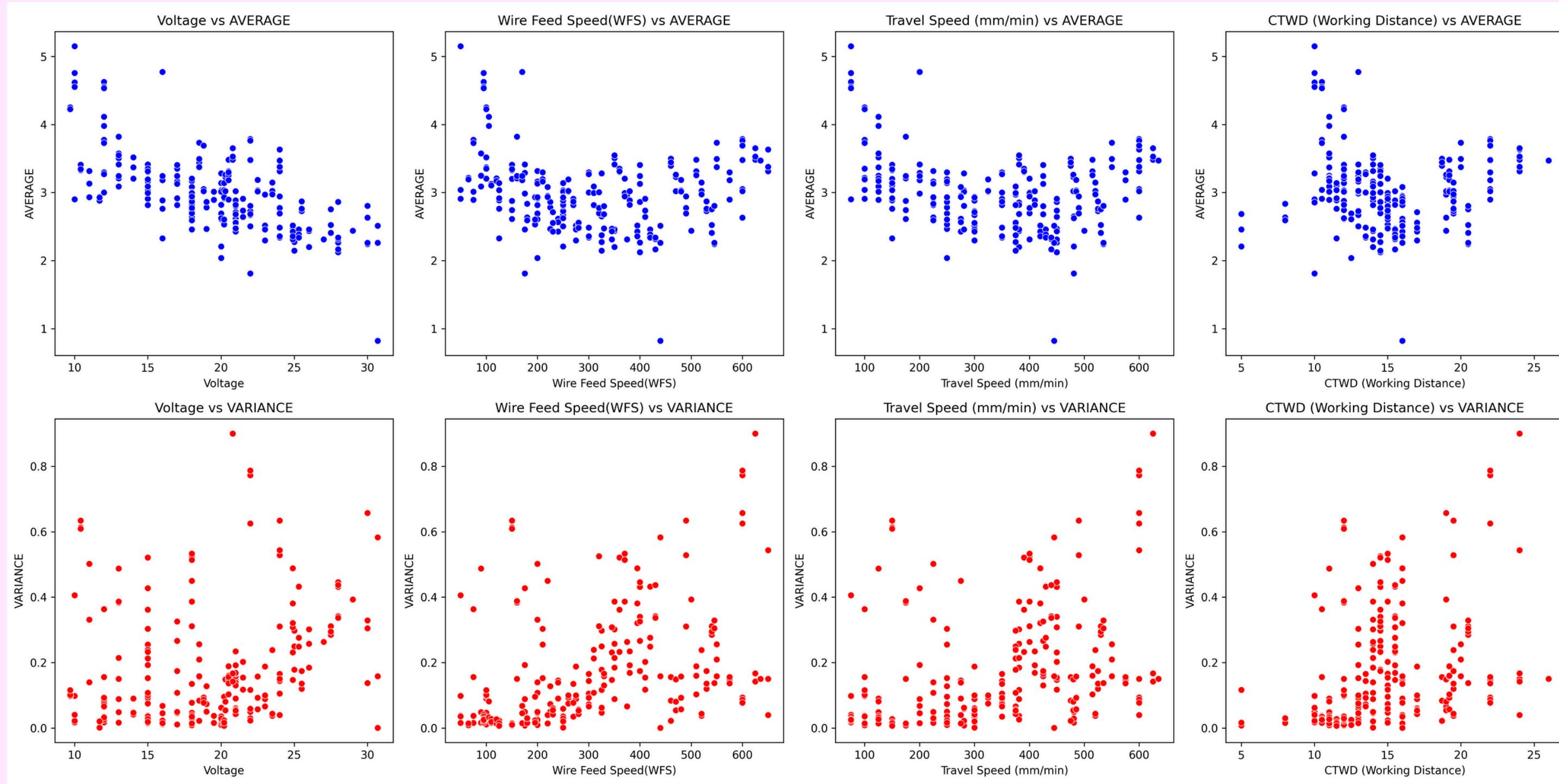
Shows multivariate interactions between inputs & outputs.

# Boxplots (Outlier Detection)



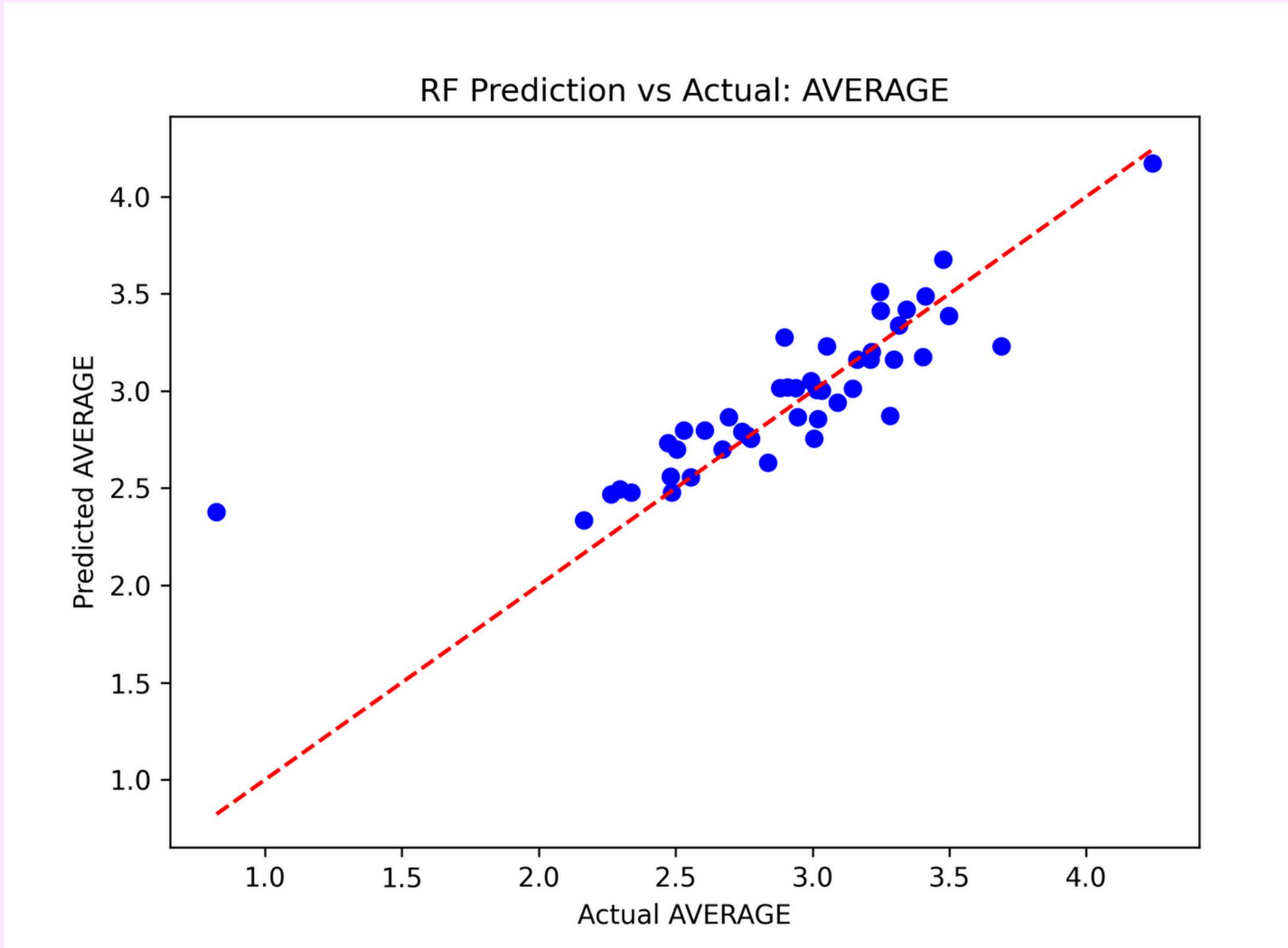
Outliers exist in WFS and VARIANCE.

# Relationship Plot



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

# RF Results: AVERAGE



## Metrics:

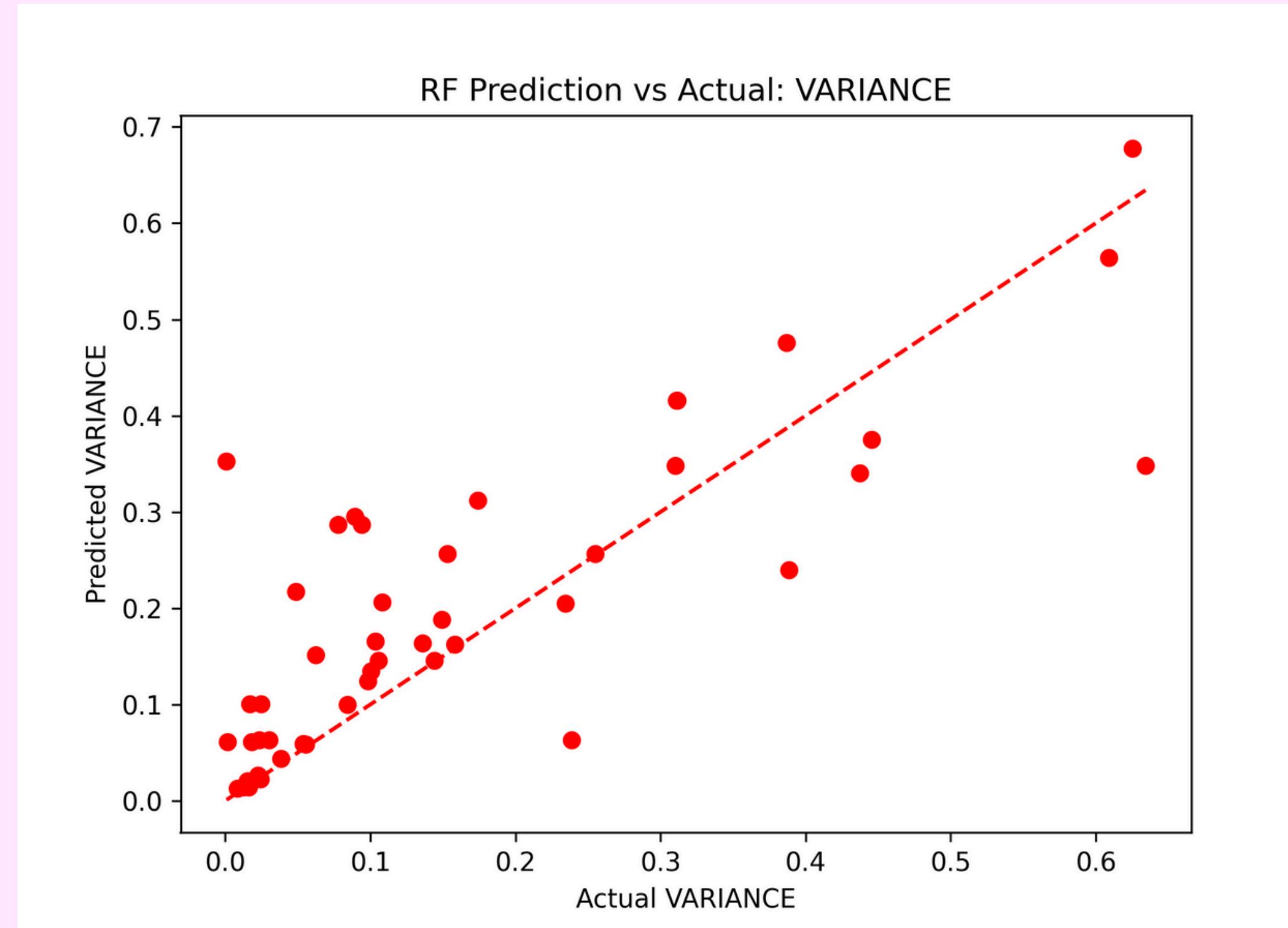
- RMSE  $\approx 0.288$
- MAE  $\approx 0.169$
- $R^2 \approx 0.685$

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

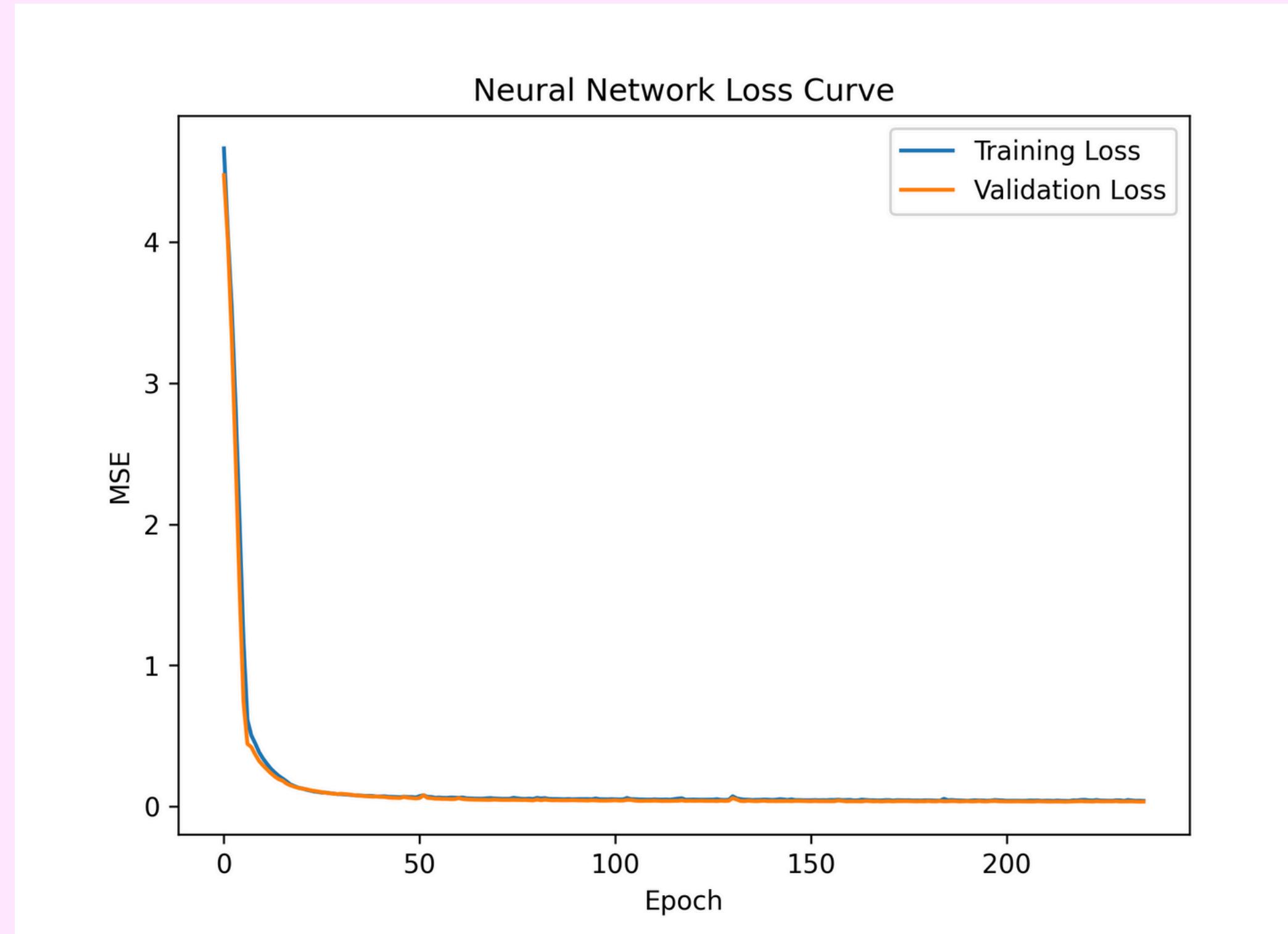


## Metrics:

- RMSE  $\approx 0.183$
- MAE  $\approx 0.074$
- $R^2 \approx 0.603$

Harder target but still well modeled.

# Neural Network: Loss Curve

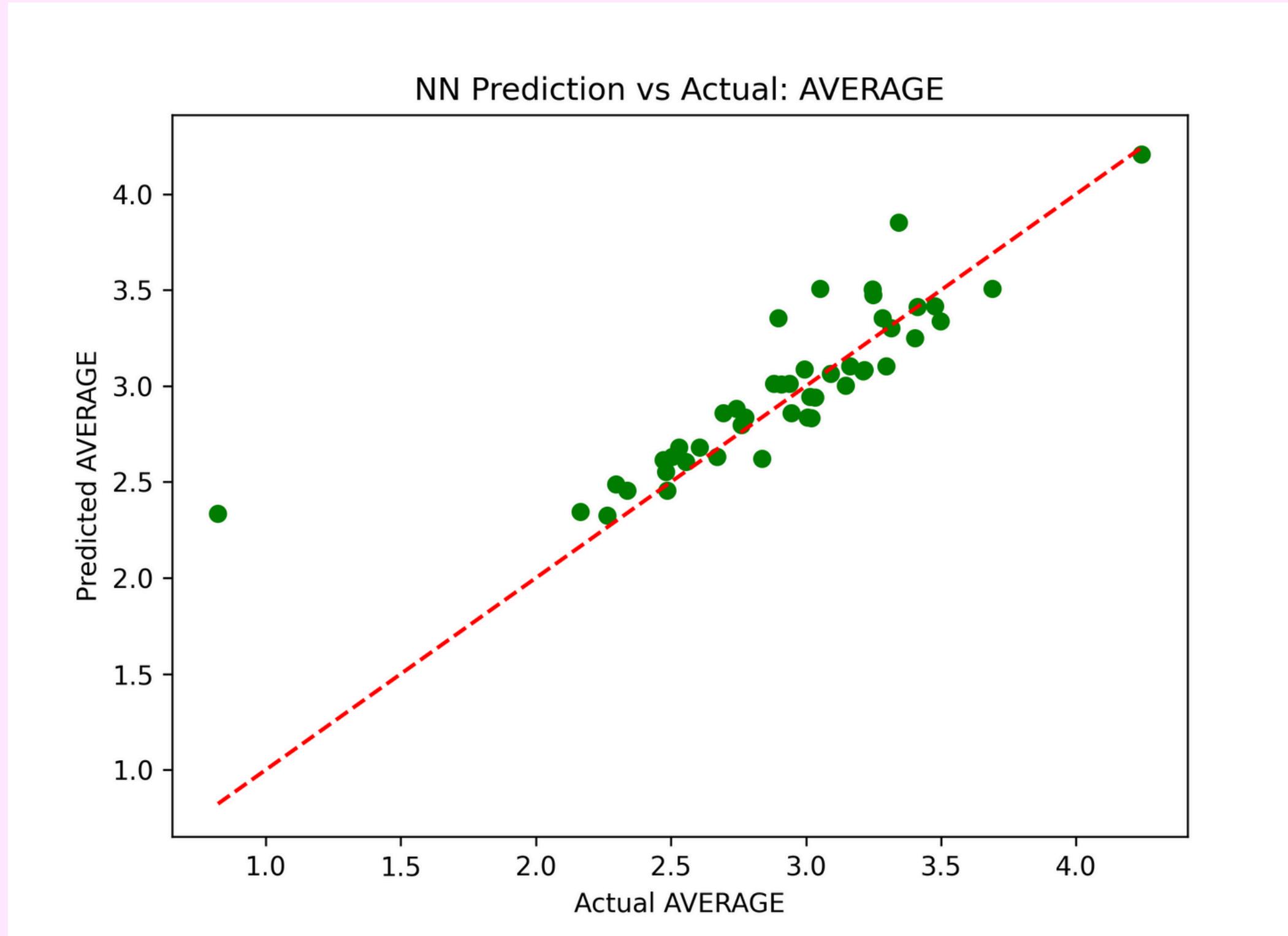


Loss stabilizes after ~150 epochs.

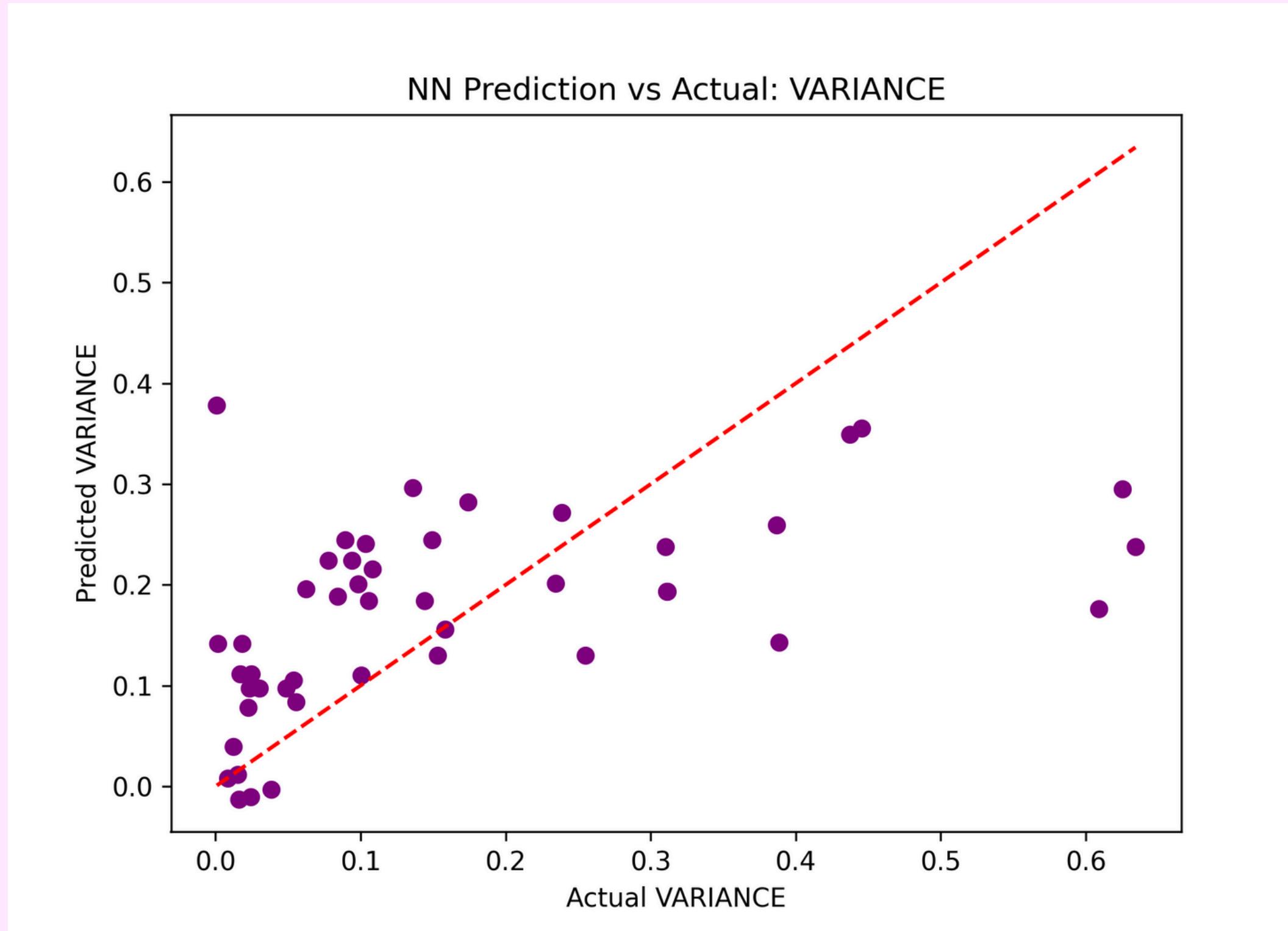
## Deep Learning Model

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

# NN Results: AVERAGE



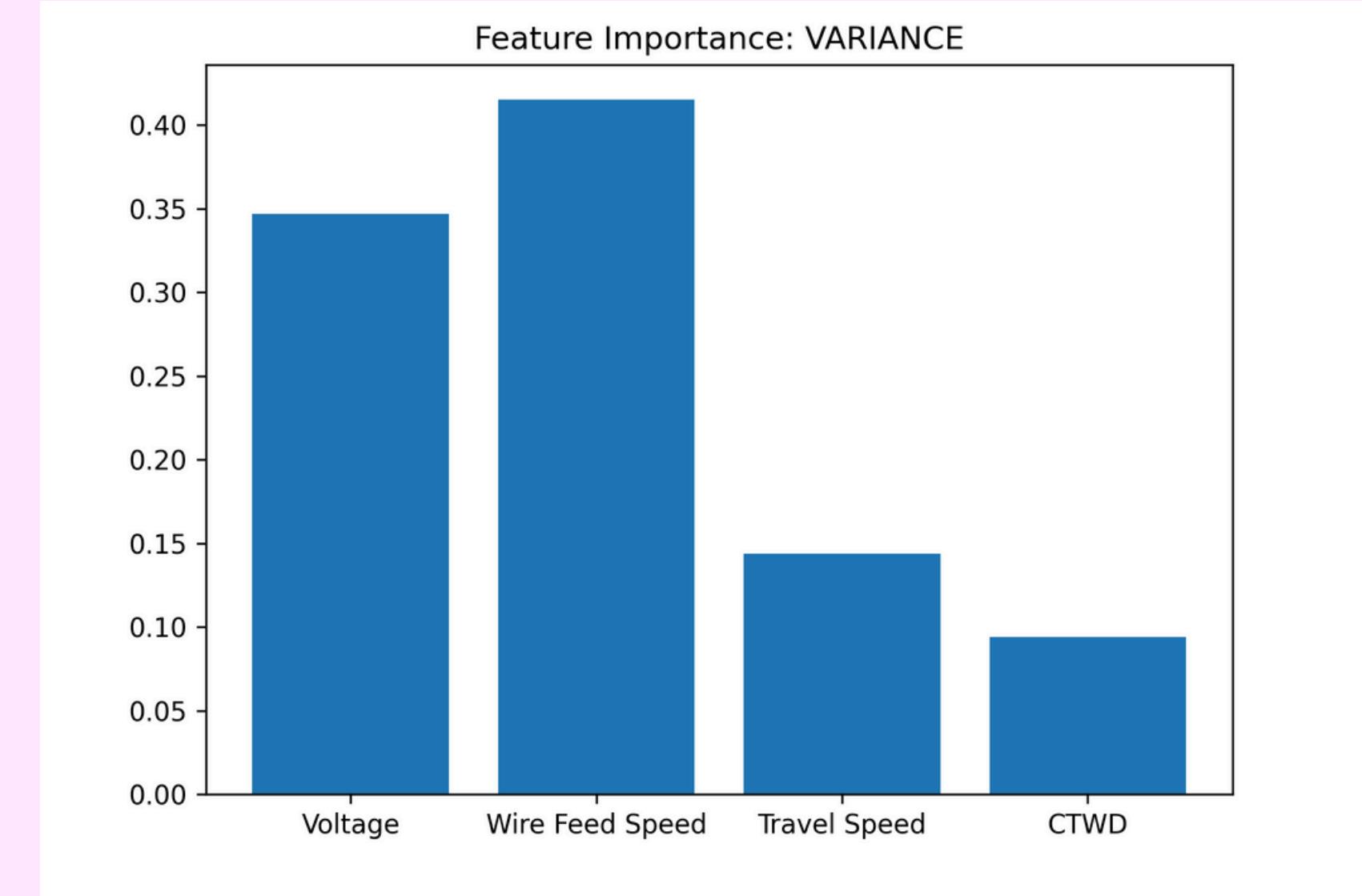
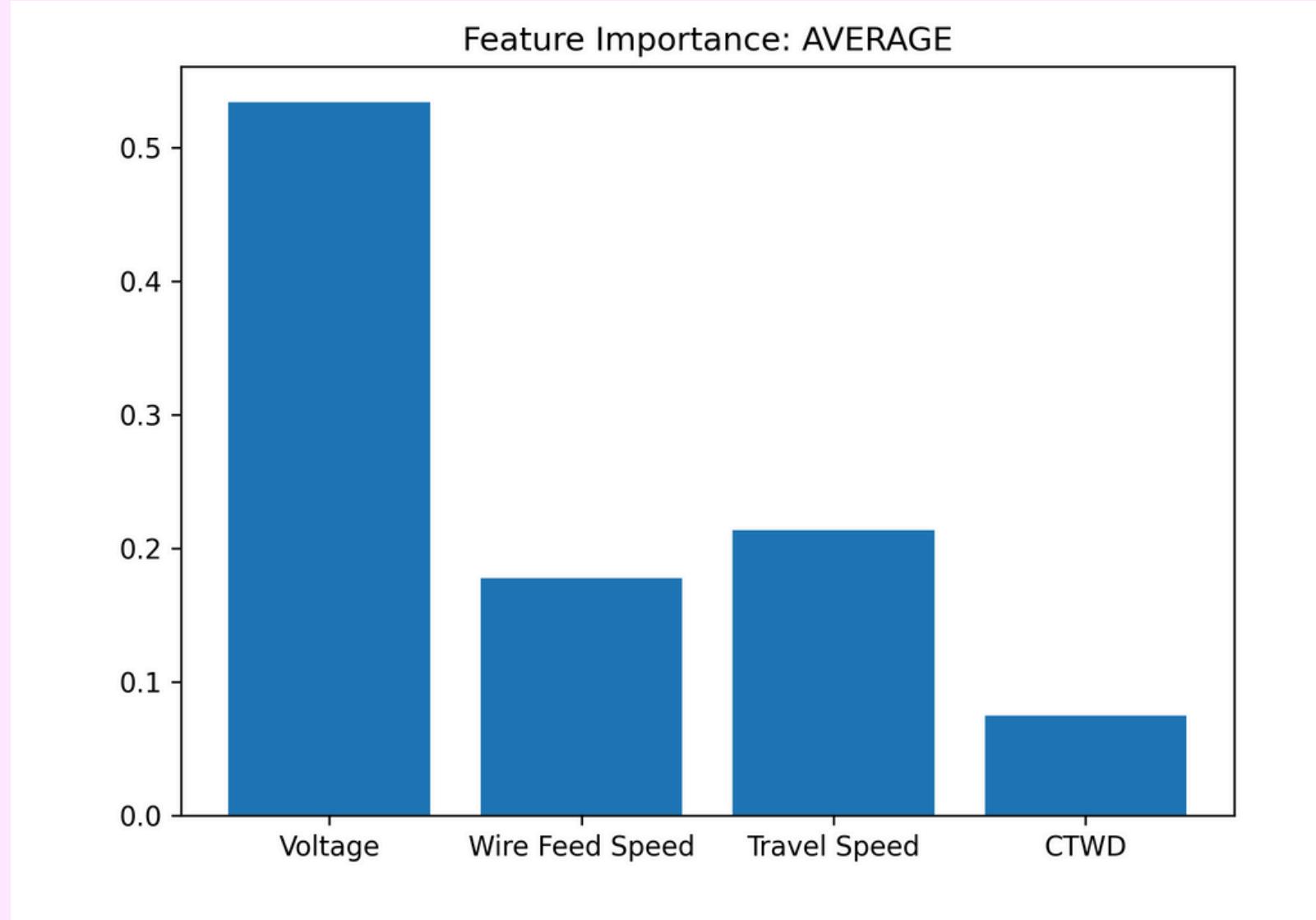
# NN Results: VARIANCE



# Model Performance: Random Forest vs. Neural Network

MODEL	TARGET	RMSE	MAE	R <sup>2</sup>
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  $\approx 2.7$
- Predicted VARIANCE  $\approx 0.09$

## 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?