Predictive Maintenance of CNC Milling Machine

Tool Wear Estimation using Multi-Sensor Data

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Introduction & Motivation

Why Predictive Maintenance?

Tool wear is critical in CNC milling, affecting product quality, efficiency, and machine downtime. Traditional monitoring is often inaccurate or inefficient.

The rise of Industry 4.0 and IoT sensing allows for continuous, precise monitoring using data analytics.

Problem Statement

Raw sensor signals are noisy and high-dimensional. The challenge is transforming multi-sensor data into meaningful features and building a stable regression model to estimate tool wear.

Project Objectives

Exploratory Data Analysis (EDA)

Identify trends, correlations, and wear-related signal patterns in the machining sensor dataset.

Feature Engineering

Preprocess and extract informative statistical, temporal, and spectral features from force, vibration, and acoustic emission signals.

Model Development

Develop and evaluate a baseline regression model (regularized linear regression) to estimate tool wear from the engineered features.

Literature Survey

Title	Author	Work done	Limitations
Tool wear prediction based on multisensor data fusion and machine learning	Jones, T. & Cao, Y. (2025)	Collected force, vibration, AE data from CNC milling; extracted 28 statistical features; used three-level data fusion (raw, feature, decision); trained RF, XGBoost; best result with (RF+XGBoost) achieving RMSE ≈ 58 μm.	Requires manual feature engineering; not fully end-to-end; ensemble is computationally heavier for deployment in real-time.
Deep learning-based tool wear prediction using multi-scale feature fusion	Xu, X. et al. (2022)	Proposed multi-scale CNN with channel attention mechanism for learning features from multi-sensor signals; improved accuracy by capturing tool wear patterns at multiple scales.	Increased network complexity; computationally more expensive for real-time use.
Tool Wear Prediction Based on Multi-Scale CNN with Attention Fusion	Huang, Q. et al. (2021)	Developed multi-scale CNN with attention-based feature fusion for tool wear regression; showed that combining multi-resolution feature maps improves prediction robustness.	Performance sensitive to kernel size choices; may overfit on small datasets without regularization.
Survey: Deep Learning Models for Predictive Maintenance	Serradilla / Zugasti et al. (2020)	Reviewed CNN, RNN, Autoencoder, VAE-based approaches for predictive maintenance tasks, highlighting benefits of multimodal fusion and hybrid models.	Mostly descriptive; no experimental results; does not give direct implementation details.

Methodology: Data to Prediction

Data Collection

Multimodal measurements (force, vibration, AE) from CNC machine. Tool wear values used as the target variable.

EDA & Understanding

Computed summary statistics, visualized temporal trends, and performed correlation analysis to identify wear-sensitive channels.

Feature Engineering

Extracted time-domain, frequency-domain, and acoustic emission features to convert raw signals into meaningful descriptors.

Model Development

Lasso Regression used for prediction. Evaluated performance using MAE/RMSE and analyzed coefficients for interpretability.

Feature Engineering Categories

Three categories of features were extracted to capture statistical behavior, frequency composition, and acoustic characteristics related to tool wear.

Time-Domain Statistical

Metrics like mean, RMS, standard deviation, skewness, and kurtosis summarize signal energy and shape over time.

Frequency-Domain

Quantify energy distribution using FFT (e.g., dominant frequency, spectral centroid). Captures high-frequency components from chatter.

Acoustic Emission (AE)

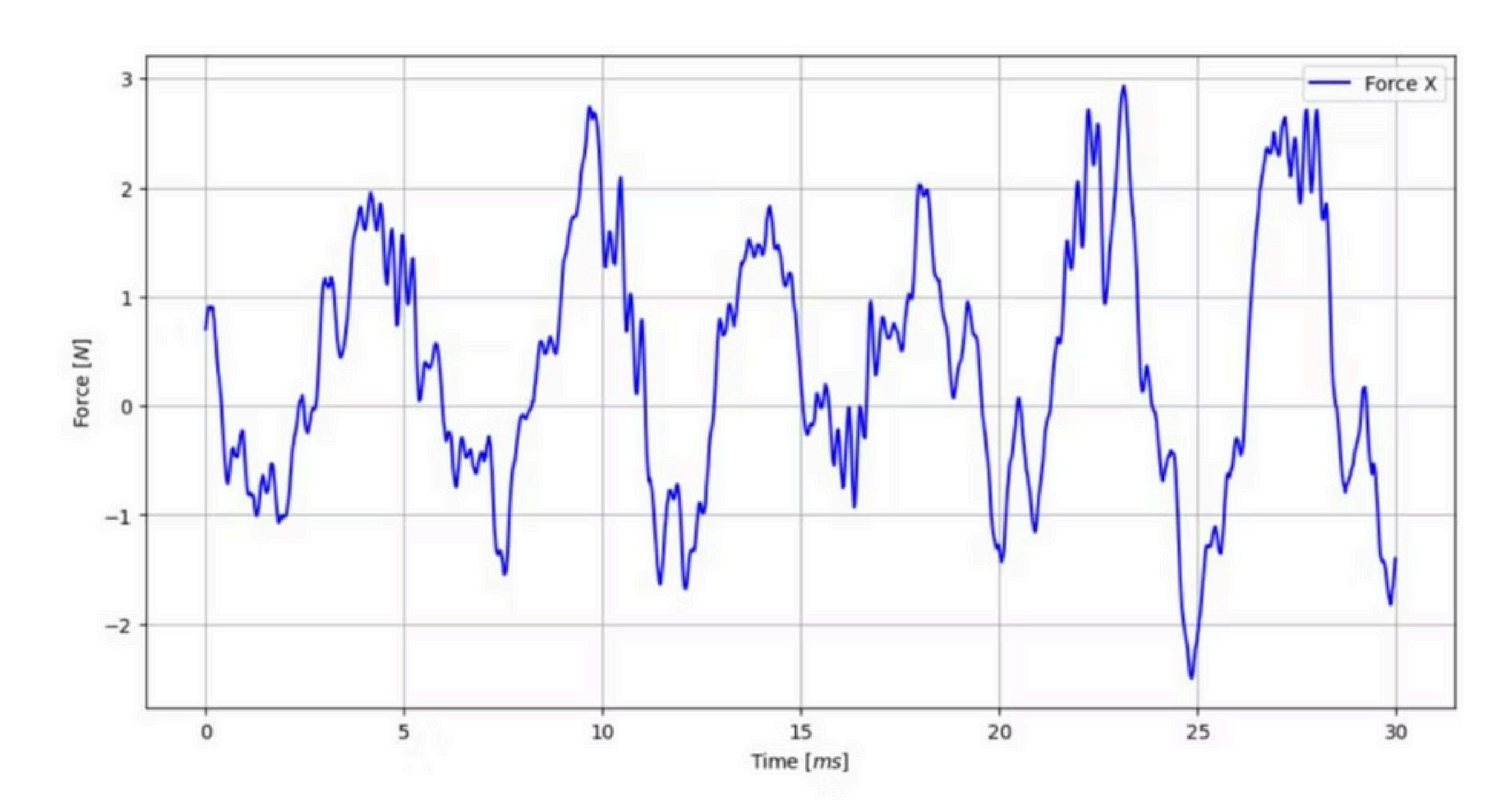
Captures transient events like micro-fractures and cutting instabilities. Features include burst count, RMS, and AE energy.

Results: Sensor Signal Behavior

EDA confirmed that sensor channels carry measurable signatures of wear progression.

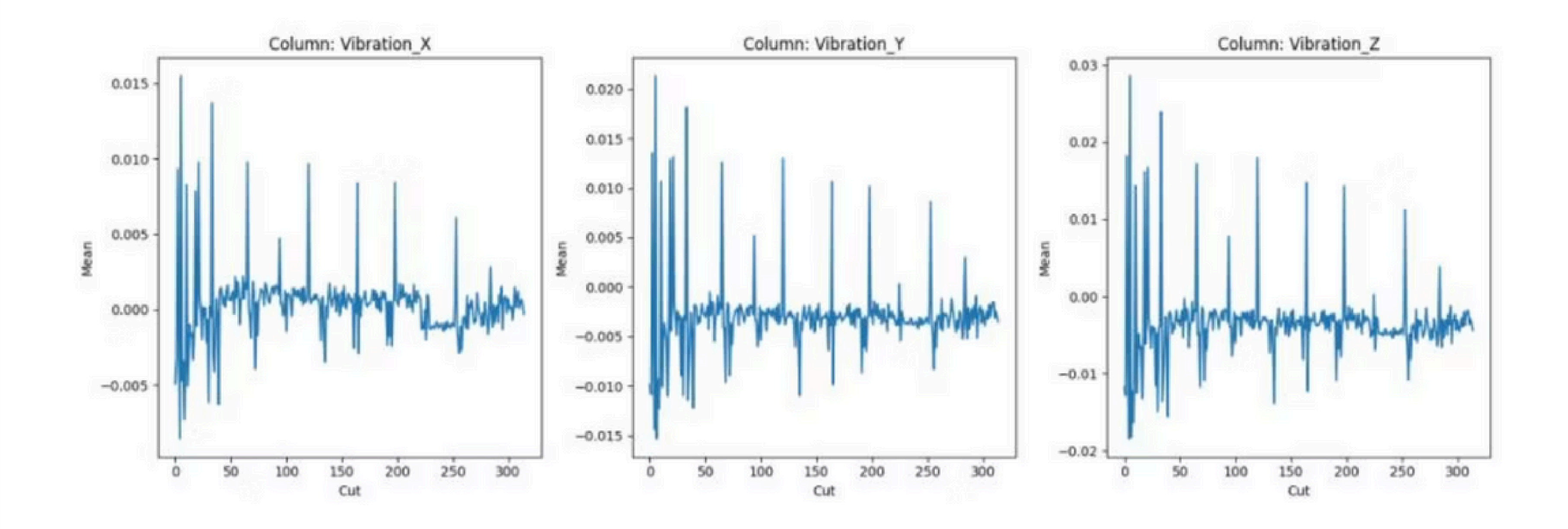
Force Signals

Exhibited increasing mean and peak values as the tool deteriorated, indicating greater cutting resistance.



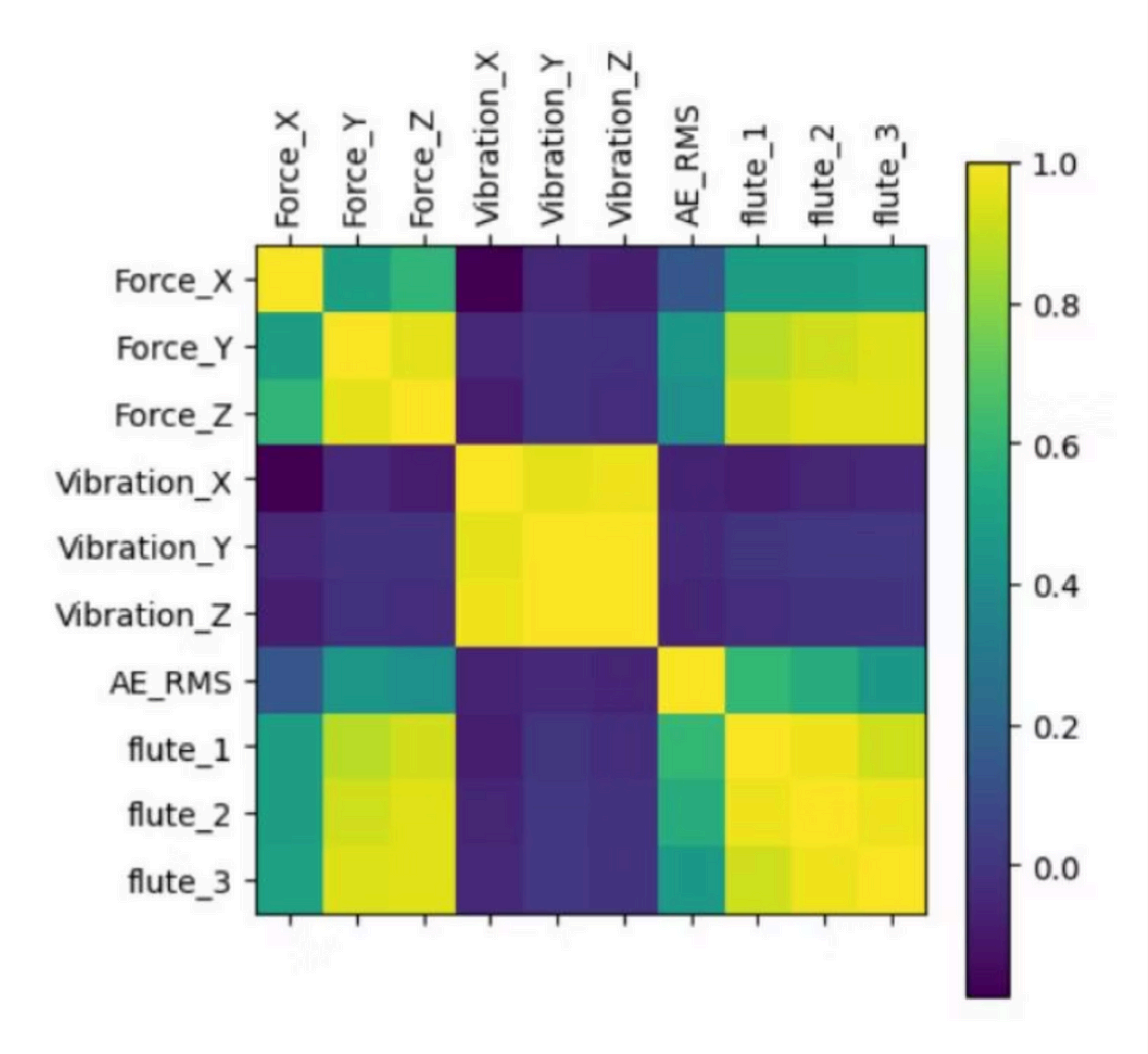
Vibration & AE Signals

- Vibration showed higher variability and pronounced spikes (increased chatter).
- Acoustic Emission displayed more frequent burst events and elevated high-frequency activity (micro-fractures).



Feature Performance and Correlation

The engineered features provided a stable representation of wear-related variations, with strong correlations identified between key features and tool degradation.



Time-Domain

RMS, standard deviation, and peak-to-peak amplitude increased consistently with wear.

Frequency-Domain

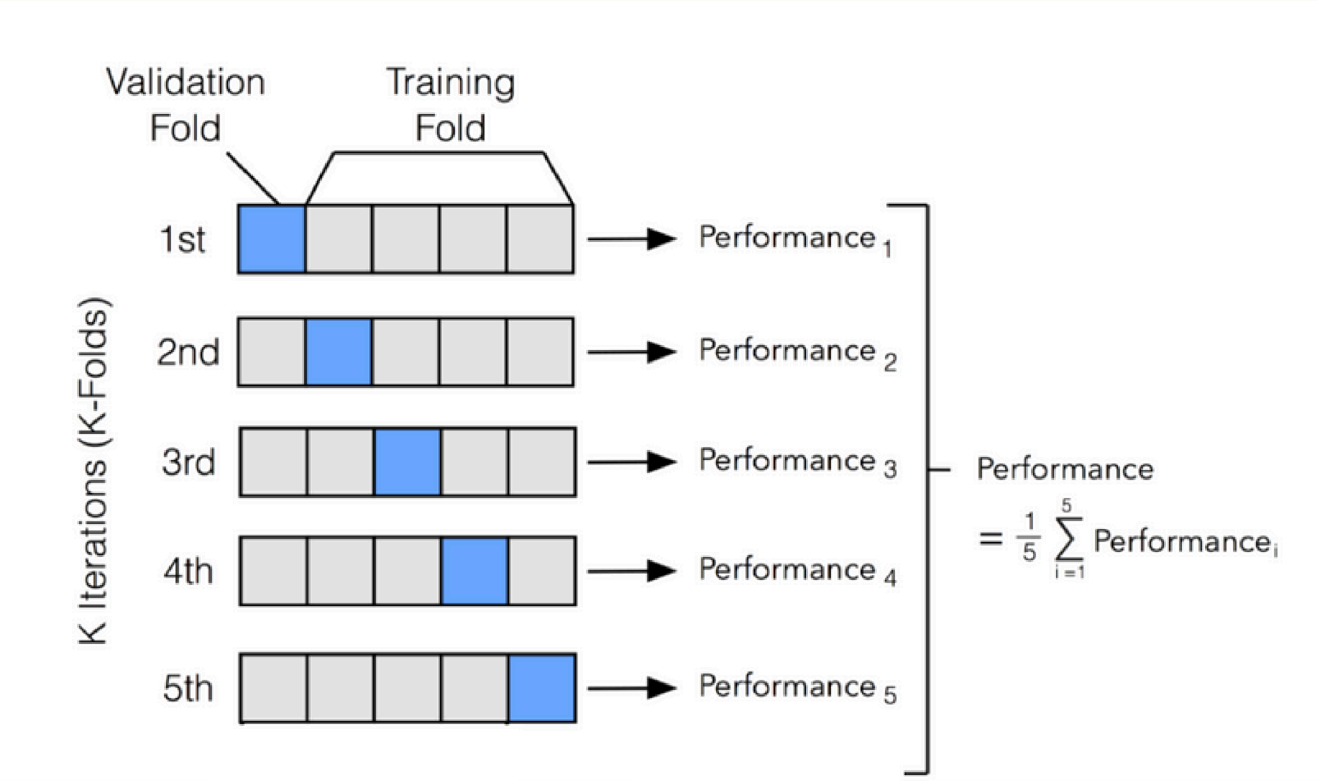
Spectral centroid and band-power captured the energy shift toward higher frequencies.

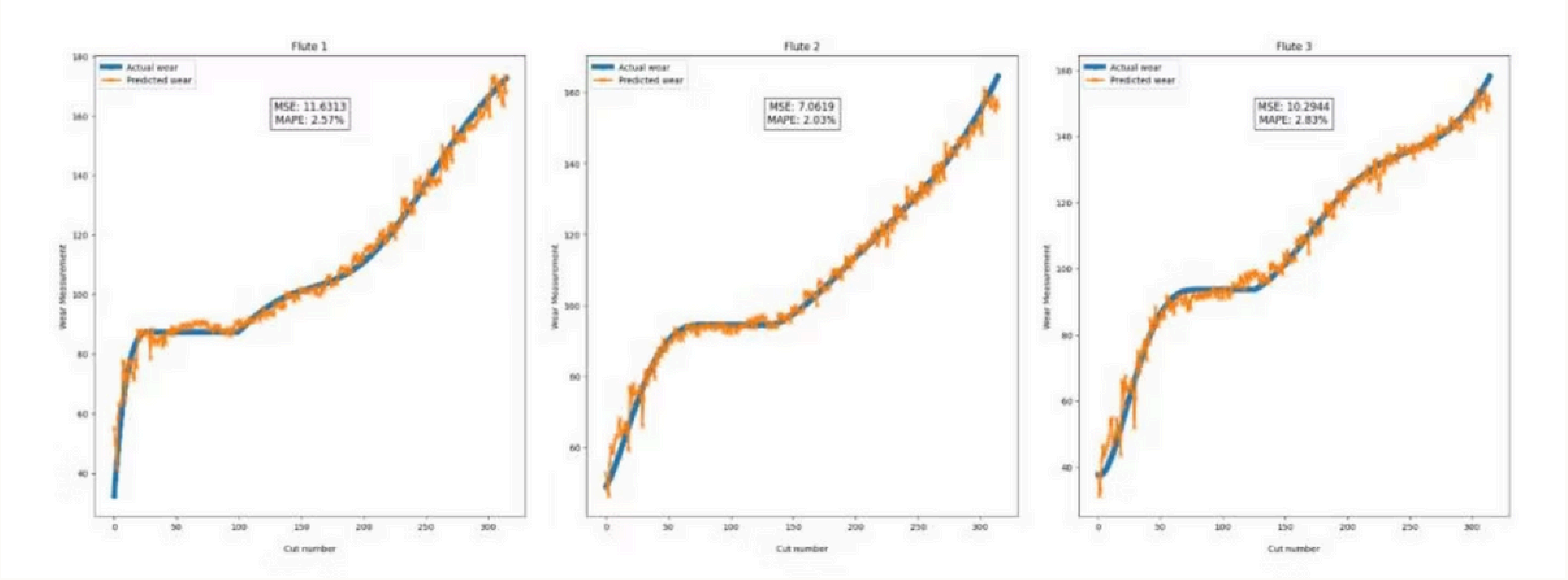
Strongest Indicators

RMS force, vibration variance, spectral centroid, and AE energy were validated as strong indicators of tool condition.

Model Performance: Lasso Regression Baseline

Lasso regression provided an interpretable and stable baseline for tool wear estimation, effectively capturing the dominant wear-related behavior.





1

Stable Prediction

Predicted wear values followed the general trend of the measured data, confirming the model's capability.

2

Regularization Benefit

Lasso effectively removed redundant features, improving generalization and demonstrating a strong baseline.

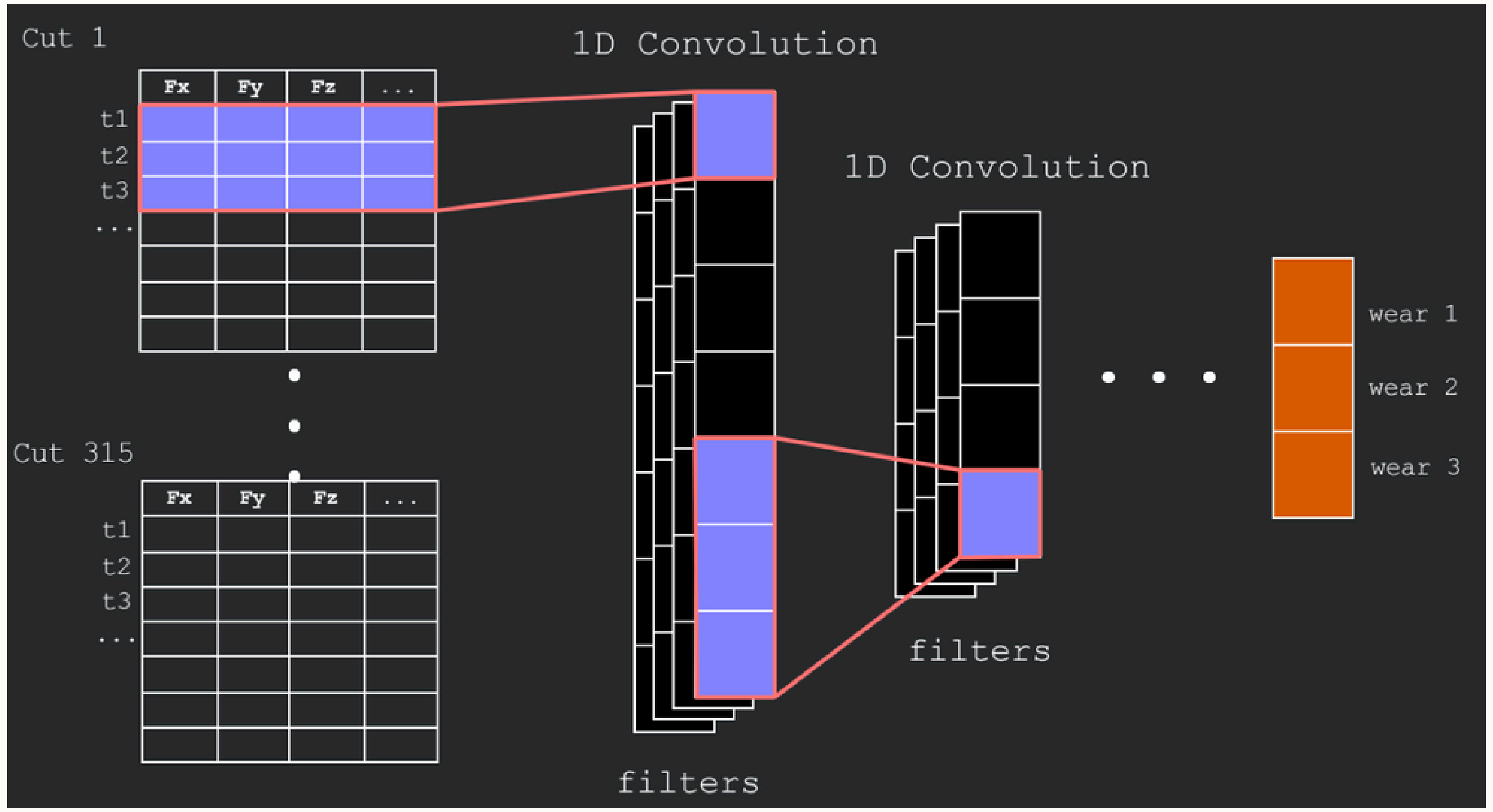
3

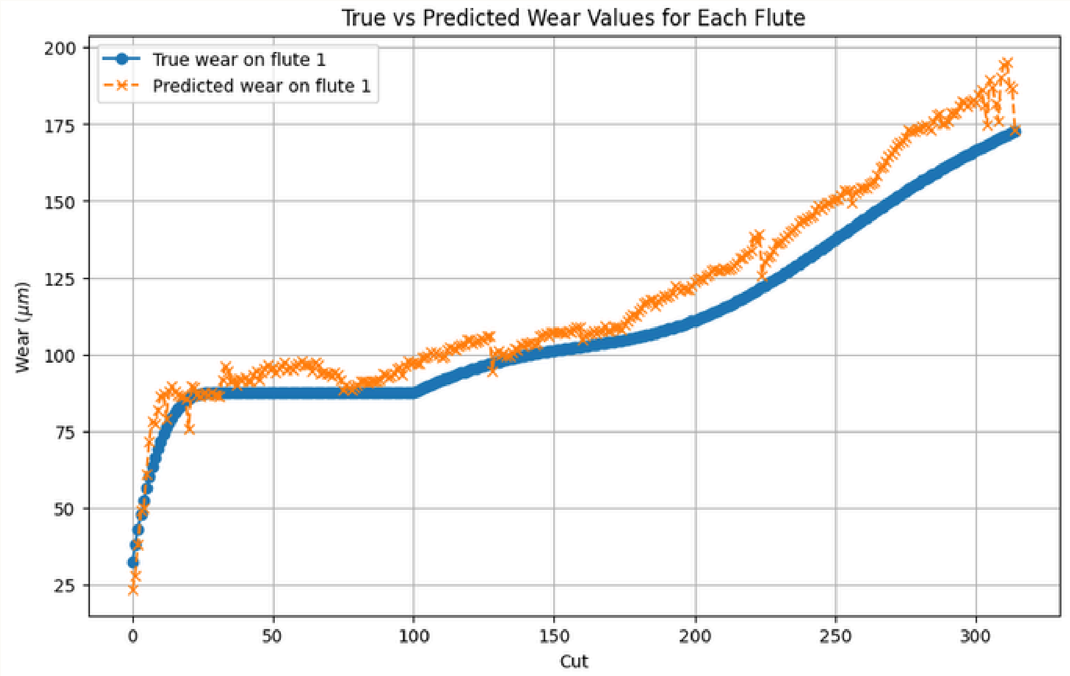
Key Features Identified

Lasso coefficients highlighted force RMS, vibration variance, spectral centroid, and AE energy as the most influential features.

Model Performance: CNN

A 1D convolutional neural network learned temporal representations from multi-channel spindle signals to predict flute wear, producing robust predictions and exporting results for dashboarding.





1

Stable Prediction

Predicted wear curves followed the main trend of measured wear across cuts, confirming the model captures the dominant temporal wear pattern.

2

Representation Learning Benefit

The CNN automatically learned hierarchical temporal features from raw signals (no manual feature engineering), improving predictive power compared to simpler baselines.

3

Temporal & Multi-channel Learning

The 1D convolutions and pooling capture short- and medium-term patterns across channels (force, vibration, AE). Adaptive pooling produces compact per-cut predictions for each flute.

Conclusion

Framework Success

Successfully developed a baseline data-driven framework for tool wear estimation using multi-sensor machining data.

Feature Validation

Engineered features provided informative representations of signal changes, proving more reliable than raw measurements alone.

Interpretability

Lasso regression and CNN confirmed that influential features (Force RMS, AE Energy) align with physical machining phenomena (cutting resistance, micro-fracture activity).

Future Work & Expansion

Advanced ML Models

Explore ensemble methods to capture nonlinear relationships for improved accuracy.

Real-Time Monitoring

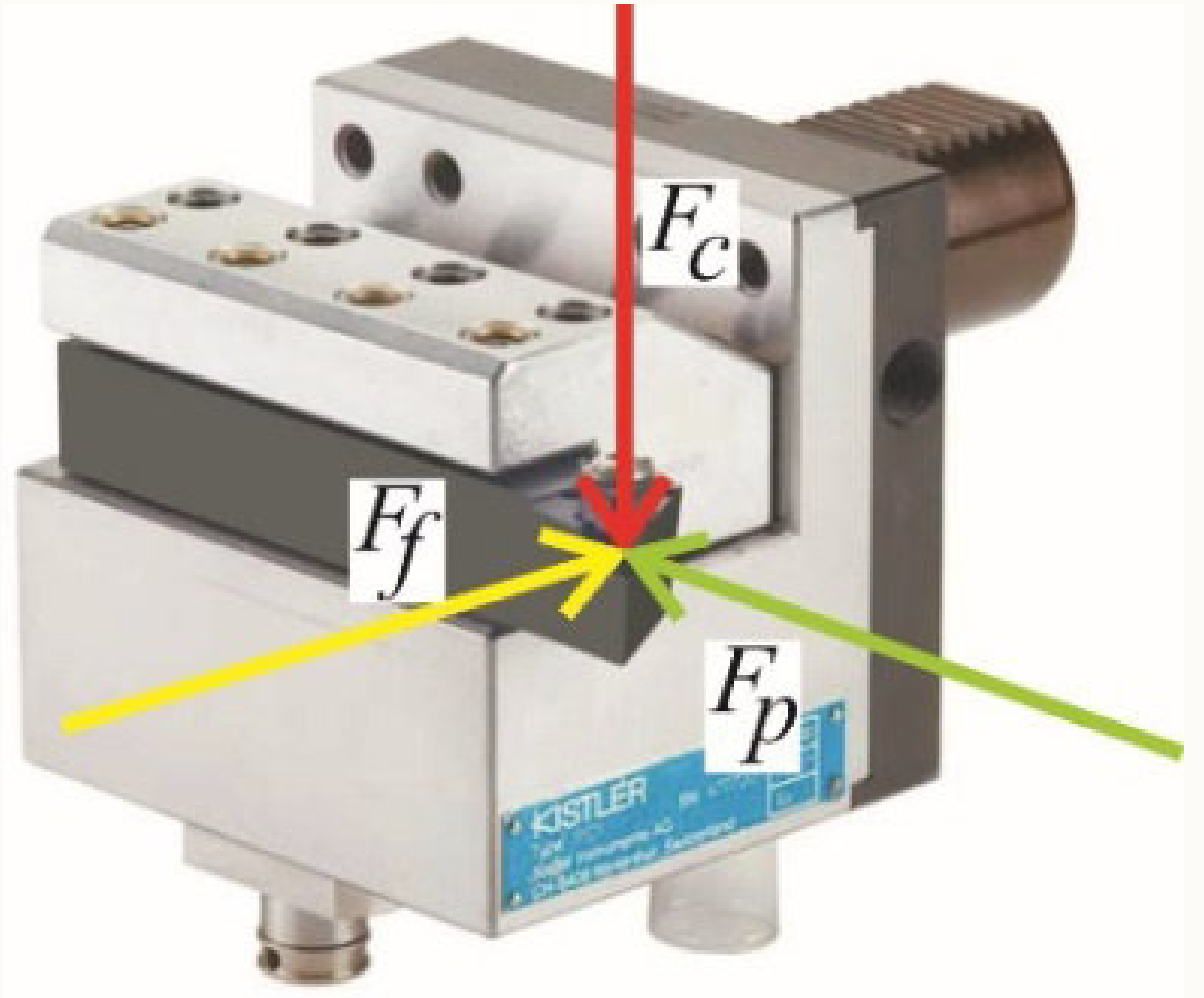
Implement streaming data pipelines and sliding-window feature extraction to support online prediction during machining.

Model Generalization

Expand the dataset to include different tool types, materials, and cutting conditions.

Signal Processing Techniques

Evaluate additional techniques like wavelet features or envelope analysis for more sensitive wear indicators.



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