# Predictive Modeling of Tool Wear Using Machine Learning


## Abstract

This project presents a machine learning approach to predict tool wear in manufacturing processes, aiming to enhance production efficiency and tool longevity. Utilizing synthetic data and advanced modeling techniques, the project explores the impact of various factors, such as cutting speed, feed rate, and material properties, on tool wear. Key steps and findings are summarized below:

- Data Simulation and Feature Engineering:
  - Generated synthetic data for tool wear prediction based on 1000 samples.
  - Key features include cutting speed, feed rate, tool geometry, environment factors, and material type.
  - Enhanced model input by encoding material types with a hardness factor, representing varying impacts on tool wear.

- Modelling Approach:
  - Employed a Random Forest Regressor with hyperparameter tuning via GridSearchCV.
  - Conducted train-test split and feature scaling to ensure standardized inputs.

- Evaluation Metrics:
  - Assessed model performance with Mean Squared Error (MSE) and R-squared (R2) metrics.
  - Analyzed differences between actual and predicted tool wear, grouped by material type.
  - Achieved a high predictive accuracy, validated through metrics and visualizations.

- Visualization and Analysis:

- Generated bar plots to compare mean actual vs. predicted tool wear by material.
- Created scatter plots of actual vs. predicted values to assess model performance.

- Explainable AI Integration:

- Applied SHAP (SHapley Additive exPlanations) for global feature importance analysis.
- Leveraged LIME (Local Interpretable Model-Agnostic Explanations) for local interpretability, enabling insights into individual predictions.

Conclusion:

This project demonstrates the potential of machine learning for predictive maintenance in manufacturing, providing valuable insights into factors affecting tool wear. The integration of SHAP and LIME facilitates transparency, supporting model reliability and actionable insights for industrial applications.

## References:


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