FSM Online Internship Completion Report
on

Predicting Tool Wear and Surface Roughness for a Lathe Machine

In

Machine Learning in Manufacturing

Submitted by

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Smart Manufacturing Simplified

IITD-AIA Foundation for Smart Manufacturing
[1-June-2023 to 31-July-2023]

Predicting Tool Wear and Surface Roughness for a Lathe Machine

Abstract

Predicting Tool Wear and Surface Roughness plays a pivotal role in machining industry. It also helps in minimizing costs, Surface roughness can affect product quality, predicting it can help you make adjustments to improve it and optimize your cutting parameters and increase your productivity. The predictive model generated by this study will help in predicting the Tool wear and Surface Roughness of the Lathe Machine. The study done is considering the machining parameters such as RPM (Revolutions per minute), Feed of the machine, Depth of the cut, and Ra (Surface Roughness of the Lathe machine). This study demonstrates the value of Data Analysis and Machine Learning in the machining and their role in the industry

Keywords: Tool life optimization, Predictive ML model, quality improvement, process optimization, Surface Roughness prediction, Tool Wear detection, Lathe Machine, manufacturing industry, Rpm, Depth of cut, Surface Roughness, Tool wear.

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Introduction

Lathe Machine is said to be a machining tool that is used primarily for shaping metal or wood. It is said to be one of the oldest machine tools in the production of machine, also known as the Mother of all Machines. Predicting tool wear and surface roughness in machining processes is a complex task that involves numerous factors and variables. Tool wear and surface roughness are critical parameters that affects machining quality, productivity, and cost in the manufacturing industry. By accurately predicting tool wear and surface roughness, operators can optimize cutting parameters and implement proactive maintenance strategies, leading to improved efficiency and reduced downtime. In this study we develop a predictive Machine Learning model to predict tool wear and surface roughness we train and test the predictive model using linear regression models and Random forest model. Model performance metrices such as mean squared error (MAE) are used to evaluating the performance of a machine learning model.

Problem Statement

Develop a machine learning model that can predict tool wear and surface roughness of workpieces produced by a lathe machine. By analysing various process parameters, tool characteristics, and historical data, the model will estimate the tool wear progression and surface roughness for different machining operations. This project aims to optimize tool usage, improve product quality, and enhance overall efficiency in the manufacturing process.

Existing Solution

Methods for predicting Tool Wear and Surface Roughness which includes, For Tool Wear Measurement we use contact measurement etc. For Surface Roughness Measurement we use optical techniques etc. For Data Analysis we use Regression analysis, Neural Network etc.

Several existing approaches and methodologies have been explored to address these prediction challenges:

- Analytical Models: Analytical models are based on mathematical equations and empirical relationships derived from experimental data.
- Empirical Equations: Empirical equations are derived from experimental data and provide a simplified representation of the tool wear and surface roughness phenomena.
- Machine Learning Techniques: Machine learning approaches have gained popularity in recent years for tool wear and surface roughness prediction. These techniques leverage algorithms such as support vector machines (SVM), random forests, neural networks, and gradient boosting to learn patterns and relationships from large datasets.

There are many more methods and previous approaches used to predict the tool wear and surface roughness of a machine.

Proposed Development

The proposed model involves data preprocessing, feature engineering, model training, hyperparameter tuning, and model evaluation. An Inclusive Data Analysis was conducted on the dataset, descriptive statistics, correlation analysis and Data Visualization techniques were employed to explore the relationships between the variables. Multiple machine learning algorithms, such as Support Vector Machines (SVM), Random Forest, Neural Networks, and Gradient Boosting, are employed and compared to identify the most accurate and reliable model.

Libraries that are necessary for data manipulation and visualization, such as Pandas, NumPy, and Matplotlib or Seaborn. NumPy can be used to perform a wide variety of mathematical operations on arrays. Pandas is a Python library used for working with data sets. It has functions for analyzing, cleaning, exploring, and manipulating data. Matplotlib is a comprehensive library for creating static, animated, and interactive visualizations in Python.

Functional Implementation

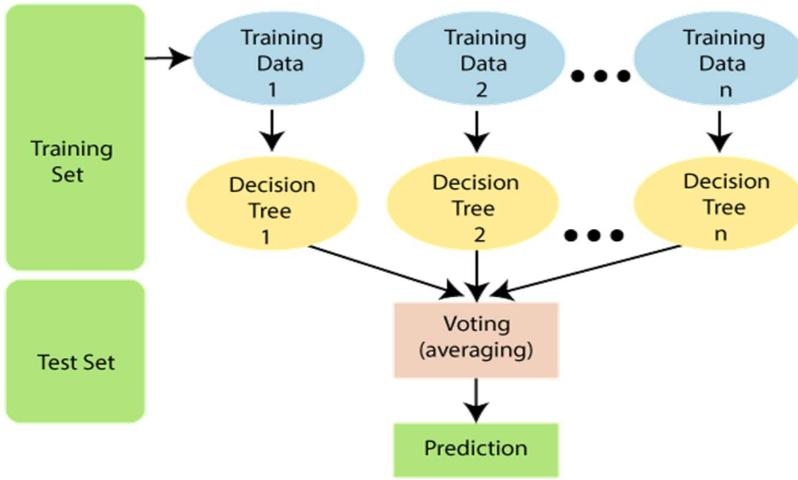
We perform linear regression, Applying Linear regression and Mean squared error on the model. Two separate linear regression models are trained for surface roughness and tool wear prediction. The models are fitted on the training data using the fit method. Predictions are made on the testing set using the predict method, and the mean squared error (MSE) is calculated to evaluate the model's performance. Abstract included basis, machine learning model to be used on the dataset, data analysis and EDA (exploratory data analysis) on the data.

Descriptive Statistics:

	Experiment	Rpm	Feed	Depth	Ra
count	60.000000	60.000000	60.000000	60.00000	60.000000
mean	30.500000	415.000000	0.331667	0.60000	5.418967
std	17.464249	196.386854	0.180129	0.28523	2.148913
min	1.000000	190.000000	0.140000	0.20000	2.037000
25%	15.750000	265.000000	0.140000	0.40000	3.365250
50%	30.500000	385.000000	0.285000	0.60000	5.580000
75%	45.250000	535.000000	0.570000	0.80000	7.029000
max	60.000000	700.000000	0.570000	1.00000	9.411000

Implementation of Random Forest model- A random forest regression model is initialized with RandomForestRegressor(). The model is trained on the training data using the fit() method. Predictions are made on the test set using the predict() method. The model performance is evaluated using the mean squared error (MSE) metric.

The performance of each model is evaluated using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared, and Mean Absolute Percentage Error (MAPE).



Random Forest Algorithm

Final Deliverable

The following section contains the results of Data Preprocessing, Data Analysis, Data visualization, Feature Engineering, Performance Evaluation Metrics, Different Model comparisons.

Results of Data Preprocessing

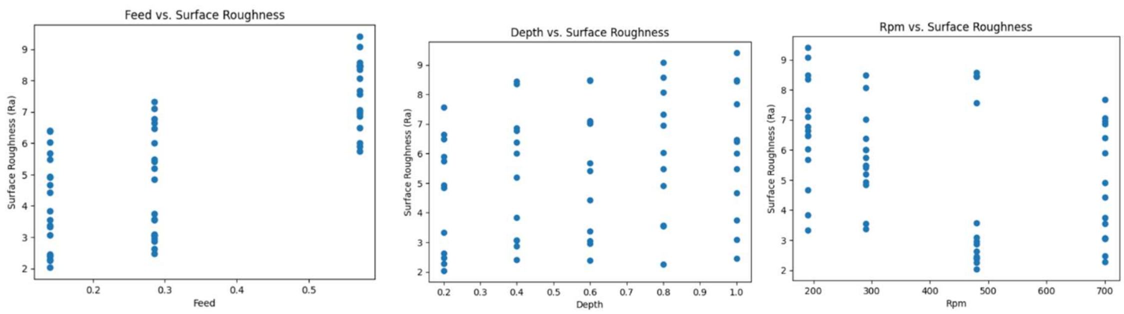
```
Shape of the dataset: (60, 5)

Number of rows: 60
Number of columns: 5
```

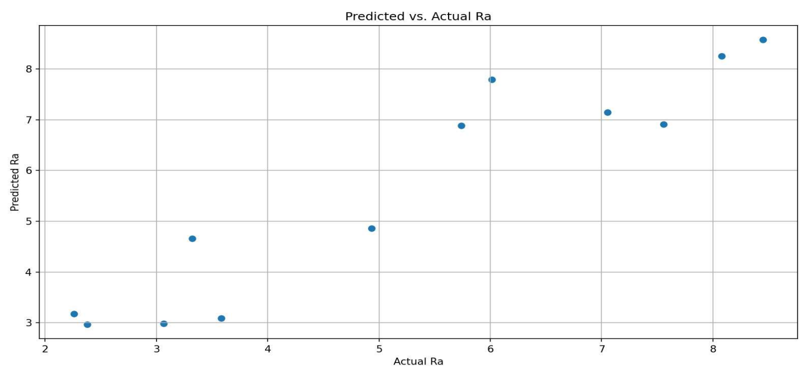
```
Experiment      int64
Rpm             int64
Feed          float64
Depth         float64
Ra            float64
dtype: object
```

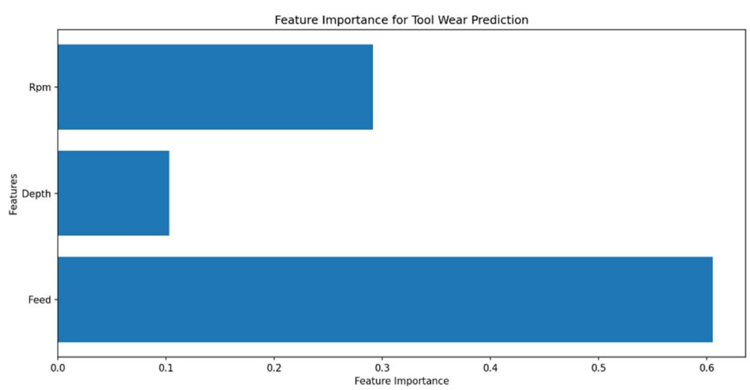
```
Experiment    0
Rpm           0
Feed          0
Depth         0
Ra            0
dtype: int64
```

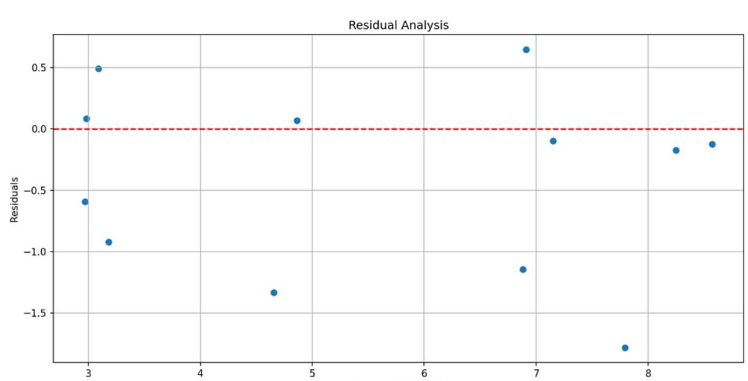
```
   Experiment  Rpm  Feed  Depth     Ra
0           1  190  0.14    0.2  3.324
1           2  190  0.14    0.4  3.843
2           3  190  0.14    0.6  5.671
3           4  190  0.14    0.8  6.025
4           5  190  0.14    1.0  4.664
```

Results of Data Visualization









Results of Evaluation metrices performed on the dataset-

Random Forest model

```
Model Evaluation:
R-squared (Test): 0.8541254416847537
Mean Squared Error (Test): 0.6829179039008436
Root Mean Squared Error (Test): 0.8263884703339245
```

Regression Model

```
REGRESSION MODEL:
Mean Squared Error: 1.3886596104682034
R-squared: 0.7033756090297445
```

Innovation in Implementation

We have build a Predictive Machine learning model that predicts the tool wear and surface roughness for a lathe machine using machine learning techniques is a rapidly evolving field with immense potential. It offers a data-driven approach to optimize machining processes, enhance product quality, and reduce costs. The ability to accurately forecast tool wear and surface roughness empowers manufacturers to make informed decisions, improve operational efficiency, and stay competive in the ever-revolving manufacturing landscape.

A parameter grid is defined, specifying different values for the hyperparameters you want to tune. A Random Forest regressor is initialized. Grid Search Cross-Validation is performed using GridSearchCV() with the specified parameter grid and the desired scoring metric. The best hyperparameters are obtained using best_params_. A new Random Forest model is initialized with the best hyperparameters. The model is trained on the training data using fit(). Predictions are made on the test set using predict(). The model performance is evaluated using mean squared error (MSE) and R-squared metrics.

```
Best Hyperparameters: {'max_depth': 5, 'min_samples_split': 5, 'n_estimators': 100}
Mean Squared Error: 0.8500774699269403
R-squared: 0.8184193520904682
```

Scalability to Solve Industrial Problem

Predicting tool wear and surface roughness is of paramount importance in the machining industry for several compelling reasons. In this study we develop a predictive Machine Learning model to predict tool wear and surface roughness we train and test the predictive model using linear regression models and Random forest model. Future Directions and Potential Applications of the project include Real-Time Monitoring and Control Predicting, tool wear and surface roughness in real-time and adjusting cutting parameters automatically. Industry 4.0 Implementation Integrating predictive maintenance with industry 4.0 technologies for better manufacturing efficiency. Online Tool and Surface Roughness Databases Creating reliable databases for tool wear and surface roughness data for better research and development.

References

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