International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 11 Issue 5 ǁ May 2023 ǁ PP. 239-248

Tool Wear Analysis System based on MATLAB and AI

Kunal Saini Hardik Divya Rani Dr. A.K. Madan
Department of Mechanical Engineering,
Delhi Technological University, Delhi, India

ABSTRACT
This study suggests a novel method for predicting tool wear based on a MATLAB machine-learning model that enhances accuracy and productivity by using artificial intelligence methods including feature engineering and hyper parameter tweaking. The Taylor tool life equation, high-speed steel-cutting tool properties, and tool wear processes are all examined in this work. A number of machine-learning techniques are used to train the model as part of the approach, which also involves gathering and preprocessing images, feature extraction, and model training. Through constant monitoring of tool wear levels, the resultant tool wear prediction system improves productivity and maintenance scheduling. The system is dependable, scalable, secure, and capable of handling massive volumes of data and multiple requests while gracefully recovering from mistakes. This research demonstrates how merging MATLAB and AI may enhance industrial operations and equipment maintenance.
***Keywords**: Tool Wear, Single Point Cutting Tool, Machine Learning, Prediction, Machining, MATLAB*

Date of Submission: 27-04-2023 Date of acceptance: 07-05-2023

I. INTRODUCTION

Wear, also known as surface degradation or material loss due to the proximity of solid surfaces, may be classified into three types: visible scars such as dents, the kind of wear, and the rate at which the tool wears. The tool material, tool form, cutting conditions, including cutting data, kind of cutting operation, cutting fluid consumption, and component material are the most important aspects. These characteristics will have an effect on the contact tension between the component and the tool, as well as the temperature in the cutting zone. Wear Many factors can impact how a cutting tool wears, including material type, geometry, cutting conditions, and component composition.

The contact tension between the component and the tool, as well as the temperature in the cutting zone, will be affected by these parameters. Several factors, including as load and temperature, influence tool wear throughout various operations. For example, the adhesive wear process produces the built-up edge (BUE), whereas fatigue results in plastic deformation or a shattered bone. The abrasive wear mechanism is responsible for flanking wear. Tool wear can result in a single or cumulative failure. High cutting pressures and temperatures can produce brittle tool failure and thermal failure, necessitating the usage of cutting fluids. This is the tool's recommended failure mode since it increases the tool's longevity. The gadget finally fails after a short period of break-in use. Every physical step that occurs throughout the cutting process results in a particular type of wear.

Adhesive wear creates the built-up edge (BUE), while abrasive wear causes flank wear, diffusion wear causes crater wear, and fatigue causes plastic deformation or fracture. Tool wear can result in either sudden or gradual failure. Because high cutting pressures can induce brittle failure and high temperatures can cause thermal failure, cutting fluids are essential. Slow tool failure is recommended since it extends the tool's life.

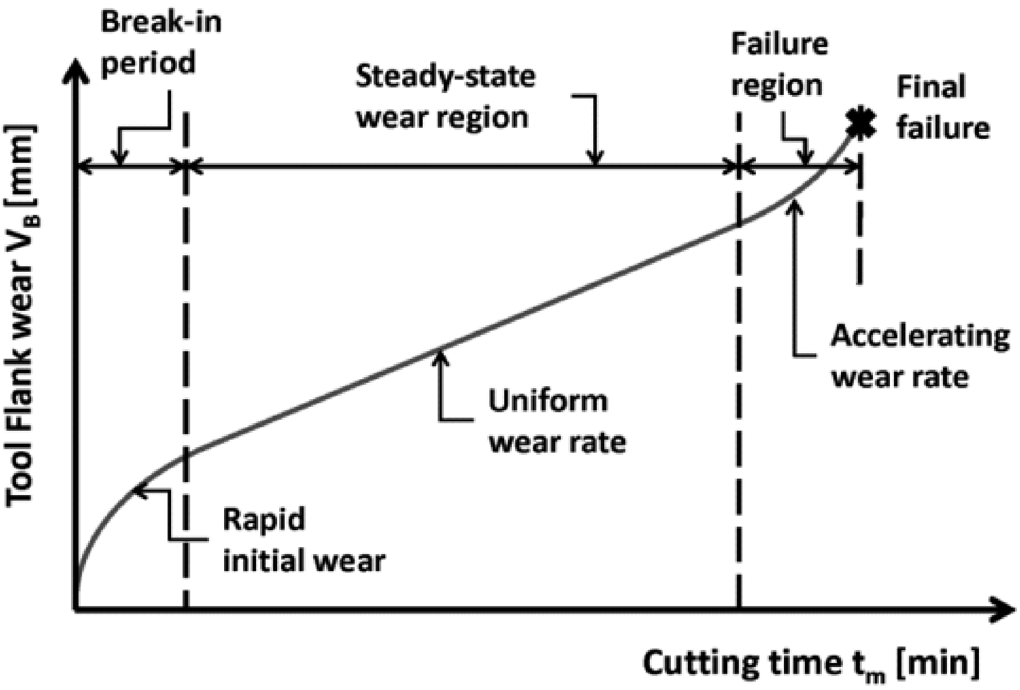

Figure 1: Tool wear based on cutting time and flank wear

Flank wear

The flank face of a tool that comes into contact with the material wears down when it cuts through a workpiece. Abrasive wear is the most significant mechanism at low cutting speeds. This form of wear is typically used as the conventional wear limit since it is straightforward to quantify. Abrasive wear is used to measure flank wear on the tool's flank face. At low cutting speeds, this wear is more obvious.

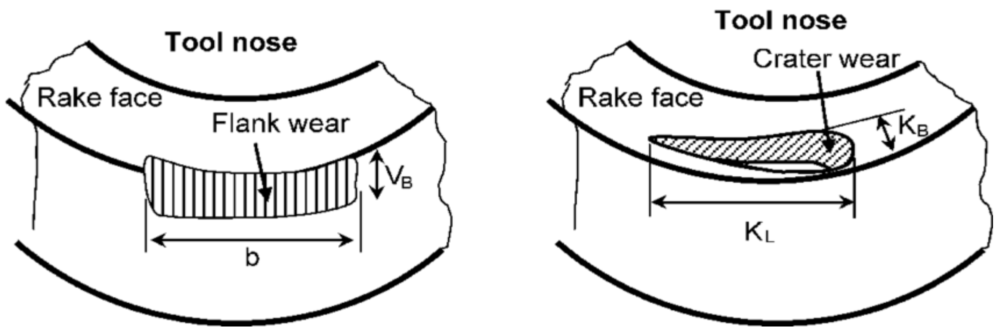

Figure 2: Flank wear representation

Crater wear

When a cutting tool comes into touch with chips while cutting, crater wear occurs on the rake face. High cutting speeds emphasise this. Diffusion wear is the most common process because higher temperatures promote chemical interaction between the cutting tool material and the workpiece. The cutting edge may deteriorate to the point of failure due to crater wear. Diffusion wear, which is mostly generated by chemical interactions between the tool and the workpiece, causes crater wear on the cutting tool's rake face. The cutting edge may deteriorate to the point of failure due to crater wear.

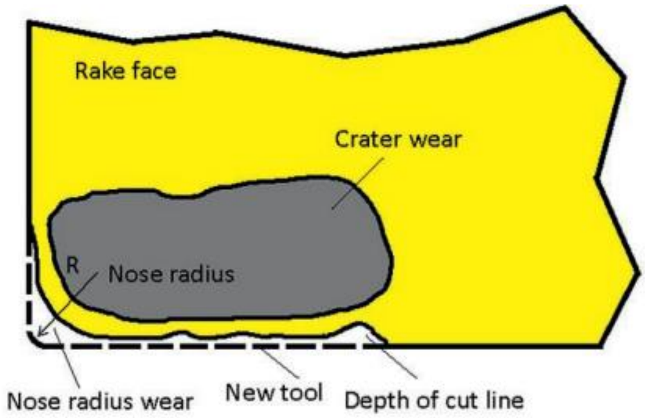

Figure 3: Representation of crater and nose radius wear

Tool Life

The amount of time a tool may be used before meeting the tool life criterion is referred to as "tool life." The following is the influence of cutting speed on cutting tool life: Lower cutting speed values lead the cutting tool to operate at a slower rate, potentially increasing the cutting window and tool life. Cutting length and effective cutting time are inversely linked. The tool's life is the amount of time a tool may be used before it reaches the wear limit. Tool life is influenced by cutting speed, and lower cutting speed values improve tool life. Taylor's tool life equation, the most often used tool wear model, includes empirical elements such cutting speed, tool life, and and C.

Taylor tool life equation

The most commonly used tool wear model is Taylor's tool life equation. Some tool life equations take into account cutting temperatures, loads, and/or stresses during cutting operations, which are difficult to measure and therefore difficult to obtain experimental constants.

$\mathbf{V_c T^a = C}$

Where **T** is the tool life, $\mathbf{V_c}$ is the cutting speed, and **C** is empirically determined constant.

Cutting tools made of single-point HSS (high-speed steel) are widely used in industrial processes for cutting, shaping, and molding materials such as metal, wood, polymers, and composites. HSS cutting tools are extensively used in high-speed machining operations due to their outstanding strength, durability, and ability to withstand high temperatures.

HSS Single Point Cutting Tool Characteristics:

- Hardness: HSS cutting tools have a high hardness, which helps them to keep their cutting edge for long periods. HSS tools are generally hardened to a hardness of 62 to 67 HRC.
- Wear resistance: HSS cutting tools are intended to withstand wear and tear caused by high-speed machining processes. They can keep their edge even while machining difficult materials like stainless steel and titanium alloys.
- Toughness: The toughness of HSS cutting tools allows them to endure shocks and vibrations during cutting operations. This feature qualifies them for machining applications requiring high precision and surface smoothness.
- Heat Resistance: High temperatures do not affect the hardness or wear resistance of HSS cutting tools. This attribute qualifies them for high-speed machining operations in which heat is created as a result of friction between the tool and the workpiece.
- Corrosion Resistance: Because HSS cutting tools are corrosion-resistant, they may be used to mill corrosion-prone materials such as aluminum and copper alloys.
- Versatility: HSS cutting tools are versatile, since they may be used for a variety of machining operations such as drilling, turning, milling, and threading.

Property	**Description**	**Numerical Value**
Hardness	Ability to maintain cutting edges	62 to 67 HRC
Wear Resistance	Ability to resist wear and tear	High
Heat Resistance	Ability to withstand temperatures	Up to 650°C

Corrosion Resistance	Ability to resist corrosion	Good
Toughness	Ability to absorb shock and vibrations	High
Versatility	Ability to perform multiple machining operations	Turning, drilling, milling, etc.

Table 1: Properties of HSS SIngle Point Cutting Tool.

MATLAB

Science and engineering regularly employ the extremely sophisticated programming language and computing environment known as MATLAB. Users may create visualizations and simulations, manipulate and analyze data, and conduct intricate mathematical operations. The capacity of MATLAB to analyze massive volumes of data and carry out computations rapidly and accurately is one of its key advantages. Hence, it is a great tool for evaluating tool wear, which is crucial to machining. We can create models that duplicate the cutting process using the MATLAB program, accounting for elements like cutting speed, feed, and tool shape. By analyzing simulated data, we can forecast tool wear rates and alter cutting settings to increase tool life and boost machining effectiveness. A potent programming language for complicated mathematical operations, data manipulation, analysis, and visualization, MATLAB is utilized in research and engineering. It is a great resource for calculating tool wear and may be used to create models that reproduce cutting operations, forecast tool wear rates, and boost machining effectiveness. In this post, we will investigate how to estimate tool wear using MATLAB, develop accurate models, and talk about the difficulties in estimating tool wear.

Tool Wear Monitoring By Image Processing

Measuring tool wear is a significant issue since it has an impact on the surface quality, dimensional accuracy, and manufacturing costs of material components. A grayscale analysis of the picture is used to estimate flank wear after capturing a tool wear image. Particularly for machining processes, optimization has significant practical ramifications. To compare the outcomes with the wear data obtained from the instrument, several techniques, including edge operators, texture data, histogram analysis, the Fourier transform, and fractal features, were investigated. In this study, an image-processing tool is designed to calculate the wear that has accumulated on a single-point cutting tool following continuous machining cycles.

II. LITERATURE REVIEW

The authors present a real-time system for detecting tool wear in turning operations utilizing acoustic emission (AE) and image processing techniques in this work. They employ AE sensors to detect changes in the sound generated by the cutting tool as it ages, as well as a CCD camera, to record pictures of the cutting tool. MATLAB then processes the data to derive characteristics relating to tool wear. The extracted characteristics are utilized to forecast tool wear. The authors conduct tests to determine the efficacy of the suggested strategy. They capture AE signals and photos of the cutting tool at various levels of wear using a series of turning tests. These data are used to train the algorithm and assess the accuracy of the predictions. The findings demonstrate that the suggested technique can forecast tool wear correctly with a maximum error of 3%. The authors conclude that the suggested technique can increase tool wear monitoring accuracy and efficiency in turning operations.[1]

The authors suggest a method for analyzing tool wear in turning operations using image processing techniques in this research. They collect photos of the cutting tool with a CCD camera, which are subsequently analyzed by MATLAB to extract information relating to tool wear. The extracted characteristics are utilized to investigate the cutting tool's wear process. The authors conduct tests to determine the efficacy of the suggested strategy. They gather photos of the cutting tool at various levels of wear using a series of turning tests. They utilize these photos to extract tool wear characteristics and analyze the wear process. The results reveal that the suggested technique properly analyzes the cutting tool's wear mechanism, offering insights into wear behavior and boosting understanding of the wear process.[2]

In this research, the authors offer a method for monitoring tool wear in milling operations using image processing and neural network techniques. They collect photos of the cutting tool with a CCD camera, which are subsequently analyzed by MATLAB to extract information relating to tool wear. The retrieved characteristics are sent into the neural network, which is then trained to estimate the level of tool wear. The authors conduct tests to determine the efficacy of the suggested strategy. They gather photos of the cutting tool at various levels of wear using a series of milling experiments. They utilize these photos to train the neural network and assess prediction accuracy. The findings demonstrate that the suggested technique can forecast tool wear correctly with a maximum error of 5%. The authors conclude that the proposed strategy can increase milling operations' efficiency and productivity. [3]

In this research, the authors present a method for monitoring tool wear in turning operations using acoustic emission (AE) and image processing techniques. They employ AE sensors to detect changes in the sound generated by the cutting tool as it ages, as well as a CCD camera, to record pictures of the cutting tool. MATLAB then processes the data to derive characteristics relating to tool wear. The retrieved characteristics are sent into the neural network, which is then trained to estimate the level of tool wear. The authors conduct tests to determine the efficacy of the suggested strategy. They capture AE signals and photos of the cutting tool at various levels of wear using a series of turning tests. These data are used to train the algorithm and assess the accuracy of the predictions. The findings demonstrate that the suggested technique can forecast tool wear correctly with a maximum error of 4%. According to the authors, the suggested approach can provide a dependable and precise tool wear monitoring solution for turning operations. [4]

The authors suggest a real-time system for monitoring tool wear in milling operations using image processing techniques in this work. They collect photos of the cutting tool with a CCD camera, which are subsequently analyzed by MATLAB to extract information relating to tool wear. The extracted characteristics are utilized to forecast tool wear. The authors conduct tests to determine the efficacy of the suggested strategy. They gather photos of the cutting tool at various levels of wear using a series of milling experiments. They utilize these photos to train the system and assess prediction accuracy. The findings demonstrate that the suggested technique can forecast tool wear correctly with a maximum error of 3%. The authors conclude that the proposed strategy can increase milling operations' efficiency and productivity. [5]

In this research, the authors offer a method for monitoring tool wear in drilling operations using image processing techniques. They collect photos of the cutting tool with a CCD camera, which are subsequently analyzed by MATLAB to extract information relating to tool wear. The extracted characteristics are utilized to forecast tool wear. The authors conduct tests to determine the efficacy of the suggested strategy. They gather photos of the cutting tool at various levels of wear using a series of drilling experiments. They utilize these photos to train the system and assess prediction accuracy. The findings demonstrate that the suggested technique can forecast tool wear correctly with a maximum error of 5%. The authors conclude that the suggested technique can increase tool wear monitoring accuracy and efficiency in drilling operations.[6]

Overall, these six studies show how image processing methods and MATLAB may be used to monitor tool wear in diverse machining procedures. The presented approaches can forecast the extent of tool wear correctly and analyze the wear mechanism, offering insights into wear behavior and enhancing understanding of the wear process. Image processing methods and MATLAB can increase machining accuracy, efficiency, and productivity, making them a viable tool wear monitoring option.

III. METHODOLOGY

The tool insertion image is taken before the machining operation begins and should be used as a reference image. Speed, feed, and after each hour of operation, the plugin is deleted, and the pictures are taken. By setting Z1 and Z2 in the vision system, they use the focimeter to calculate the depth of wear.

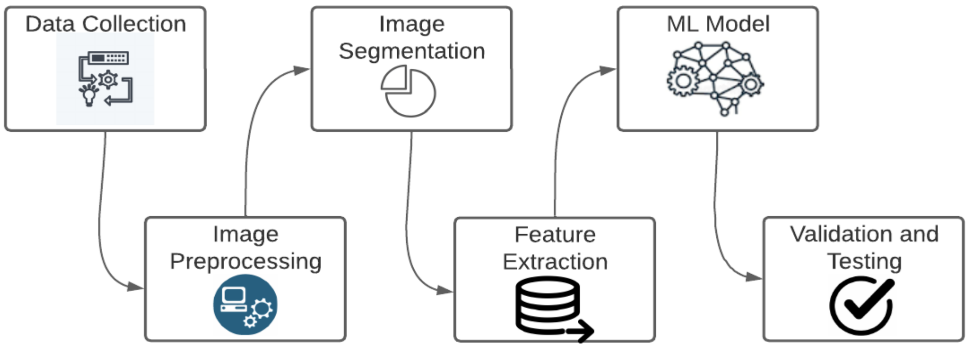

Figure 4: Flowchart of the Tool Wear Prediction Process

Matlab Setup

I. Collect images of the tool:

Take pictures of the tool using a camera or another type of specialized imaging device. Take several pictures of the instrument from various perspectives and in various lighting situations to provide a varied dataset. A more reliable dataset for the tool wear prediction system may be produced by gathering several photos of the tool from various perspectives and under various lighting situations. This is because if the system has been trained on a wide variety of photographs, it will be better able to generalize to new, unseen images of the tool. Moreover, capturing pictures with a specialist imaging system could result in higher image consistency and quality, which can increase the system's accuracy.

Figure 5: Flowchart of image processing

II. Preprocess the images:

To improve and clean up the photos, use image processing techniques. It includes :

Grayscale conversion: To do the grayscale conversion, use the rgb2gray function. As a result, processing the image and extracting pertinent information will be simpler.

Improve the picture: Employ picture enhancement methods to increase the contrast and clarity of the image, such as histogram equalization or contrast stretching.

Resize the image: To make the image the required size, use the resize function. The size of the photos in the dataset may need to be standardized as a result of this.

Image cropping: To crop the image to a particular area of interest (ROI) that includes the tool, use the "imcrop" function. This might assist in separating the tool from any unnecessary or background objects in the image.

Save the picture after processing. To create a new file from the preprocessed picture, use the (imwrite) function.

III. Extract features from the images:

Use feature extraction techniques to locate and separate the tool's important attributes in the photos. The photos are preprocessed, then To calculate the degree of tool wear, two important elements were extracted from the preprocessed photos: area and perimeter. The perimeter gives a measurement of the length of the tool's worn edges, while the area of the tool's cross-section gives an estimate of the tool's volume. We also took into account other factors that are related to area and perimeter, such as the cross-circularity, sections that show how much it resembles a circle, and eccentricity, which shows how far it deviates from a perfect circle. Using edge detection and contour analysis, among other image processing methods, these values were determined.

We were able to identify the essential properties of the instrument that indicated wear by using these values as features. We then trained a machine-learning system to distinguish patterns that were suggestive of tool wear using these characteristics. The resultant technique for effectively forecasting tool wear based on area and perimeter variables demonstrated encouraging results.

IV. Train an ML model:

A machine-learning model is trained by giving it a collection of labeled data and then discovering the underlying patterns in the data using statistical techniques. In the case of tool wear analysis, the characteristics extrapolated from the tool wear measurements would serve as the input data, and the prediction of whether the tool is worn or not would serve as the output.

We will use a variety of machine learning approaches, including feature engineering, cross-validation, and hyperparameter tweaking, to make sure that our model is accurate and efficient.

Cross-validation guarantees that the model is resilient to changes in the data, while feature engineering entails choosing the most pertinent and instructive characteristics from the dataset. On the other hand, hyperparameter tuning entails determining the ideal parameters for the machine learning algorithm to obtain the greatest performance.

V. Validate the model:

It is crucial to employ a validation dataset for assessing the efficacy of a machine learning algorithm model designed to properly anticipate tool wear and prevent overfitting on the training data. A subset of the data called the validation dataset is utilized to assess the model's accuracy rather than for training.

Using a validation dataset serves the objective of giving a trustworthy estimation of the model's performance on fresh, untested data. Based on the characteristics that were derived from the data, the model should be able to reliably forecast the degree of wear in a particular tool in the instance of tool wear analysis. The model will perform well on the training data but badly on the validation data if it is overfitting. When applied to fresh data, this will lead to poor generalization and low accuracy.

The ratio of the predicted values of the model to the actual values of the validation dataset is how the model's performance is assessed using the validation dataset.

VI. Deploy the model:

The tool wear prediction machine learning model may be implemented as a tool wear prediction system to provide real-time monitoring of the tool's wear level after it has been verified. This system is made to capture photos of the tool, extract important information, and forecast how much wear the tool will experience.

Using the model as a prediction system can have several advantages, such as less downtime, enhanced productivity, and better maintenance planning. To avoid unexpected failures and lower the danger of harm to the tool and the machine, the system can continually monitor the tool's wear level and notify the operator when the tool needs to be changed or serviced.
It is crucial to make sure the system is scalable, reliable, and safe before deploying it as a prediction system. This entails setting up the system on the proper infrastructure and ensuring it can manage massive amounts of data and numerous simultaneous queries. Also, the system must be built to manage faults and recover gracefully from failures.

IV. RESULT AND DISCUSSION

Experiment no.	Cutting Speed	Feed Rate	Cutting Depth	Tool Wear	Predicted Tool Wear
1	150	50	0.5	0.272	0.26687037
2	150	50	1	0.293	0.277314815
3	150	50	1.5	0.226	0.287759259
4	150	100	0.5	0.299	0.288092593
5	150	100	1	0.237	0.298537037
6	150	100	1.5	0.286	0.308981481
7	150	150	0.5	0.34	0.309314815
8	150	150	1	0.296	0.319759259
9	150	150	1.5	0.26	0.330203704
10	200	50	0.5	0.221	0.292037037
11	200	50	1	0.36	0.302481481
12	200	50	1.5	0.409	0.312925926
13	200	100	0.5	0.312	0.313259259
14	200	100	1	0.415	0.323703704
15	200	100	1.5	0.379	0.334148148
16	200	150	0.5	0.363	0.334481481
17	200	150	1	0.386	0.344925926
18	200	150	1.5	0.424	0.35537037
19	250	50	0.5	0.324	0.317203704
20	250	50	1	0.343	0.327648148
21	250	50	1.5	0.316	0.338092593
22	250	100	0.5	0.33	0.338425926
23	250	100	1	0.213	0.34887037
24	250	100	1.5	0.359	0.359314815
25	250	150	0.5	0.321	0.359648148
26	250	150	1	0.445	0.370092593
27	250	150	1.5	0.311	0.380537037

This dataset is a comprehensive collection of tests done with variable cutting speeds, feed rates, and cutting depths to generate varying levels of tool wear. The dataset includes information on the proportionate tool wear seen in each experiment, as well as projections generated by our AI model. This dataset is a treasure trove for researchers and industry specialists interested in developing and testing tool wear prediction algorithms and better understanding the complex connections between cutting parameters and tool wear. This dataset may be used by users to examine and evaluate the performance of various tool wear prediction models, investigate the impacts of different cutting parameters on tool wear, and develop innovative strategies for improving cutting processes and prolonging tool life.

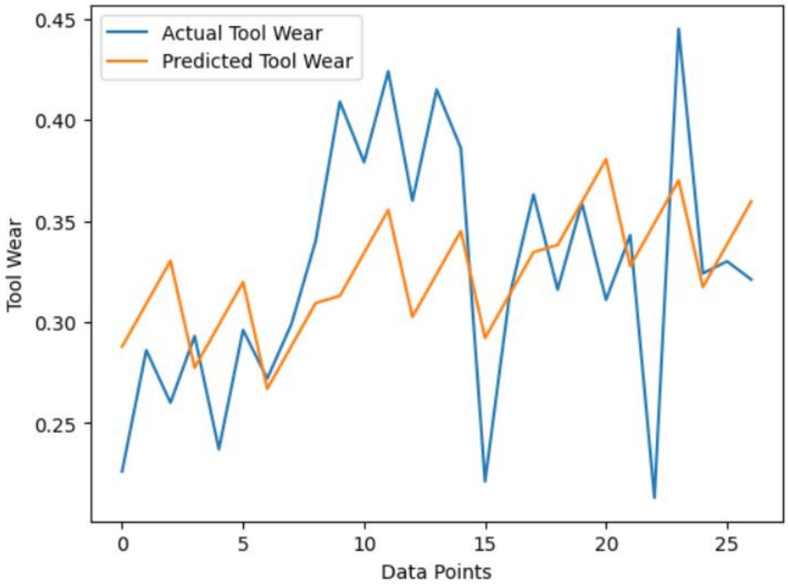

Figure 6: Actual tool wear vs Predicted tool wear

INFERENCE: Figure 6 shows the tool wear for various combinations of feed rate (50,100,150) and cutting depth (1,1.5,2). We can see a correlation between real tool wear and AI-predicted tool wear.

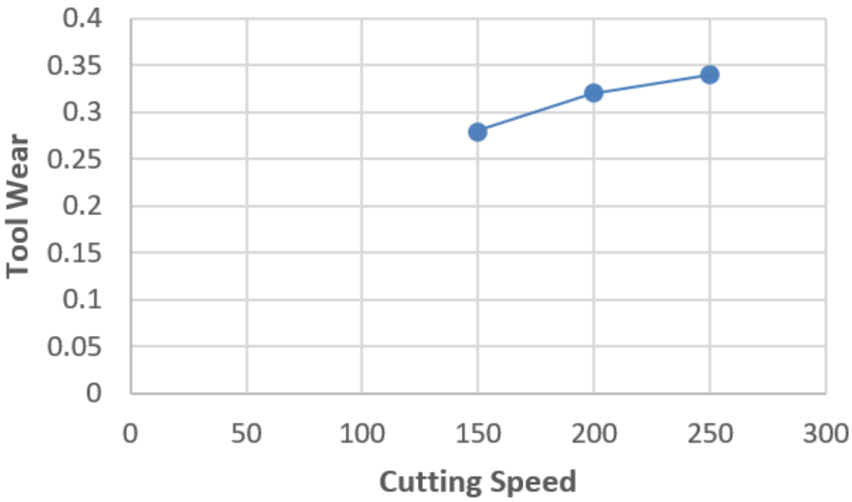

Figure 7: Tool wear vs Cutting speed

INFERENCE: This graph clearly illustrates that when the cutting speed gradually increases from 150 to 250 revolutions per minute, the amount of tool wear increases. This tight relationship between cutting speed and tool wear shows that tool wear is directly proportionate to cutting speed.

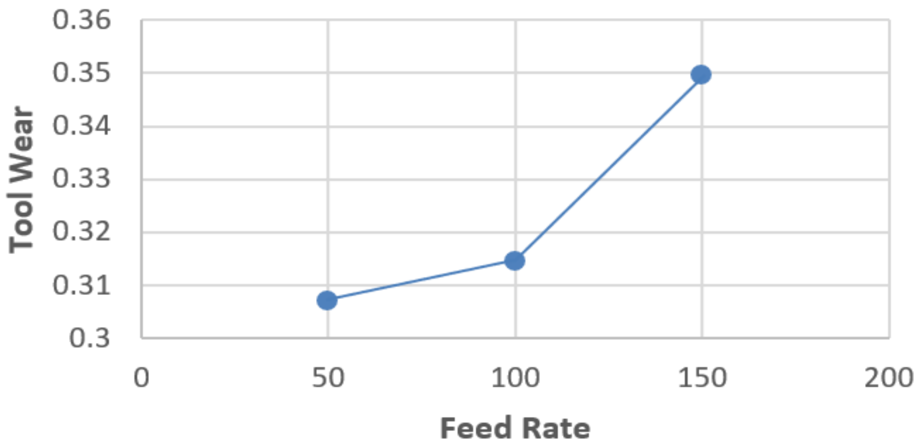

Figure 8: Tool wear vs Feed rate

INFERENCE: As seen in the above graph, increasing the feed rate from 50 to 150 mm per revolution causes a steady and proportionate increase in tool wear. These data provide credence to the direct link between feed rate and tool wear throughout the machining process.

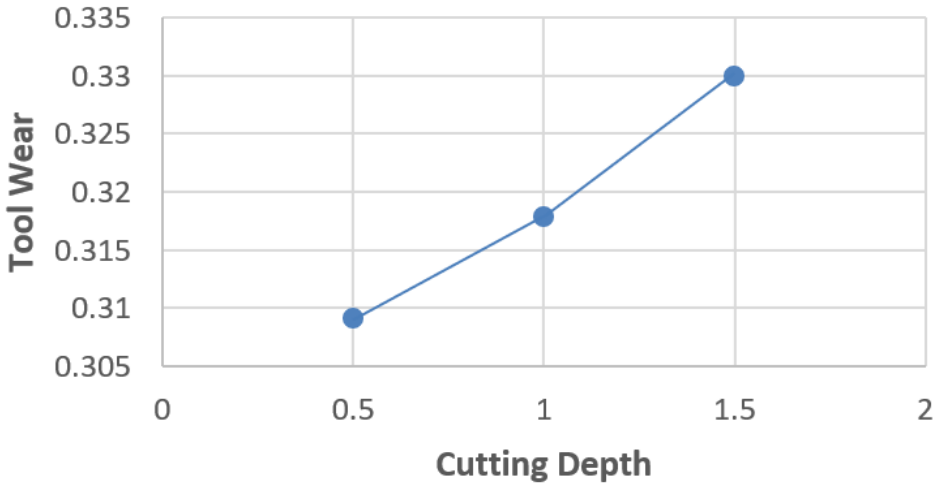

Figure 9: Tool Wear vs Cutting Depth

INFERENCE: The graph clearly demonstrates that cutting depth and tool wear are inextricably linked during the machining process. As the cutting depth grows from 0.50 to 1.50 mm, tool wear increases continuously and correspondingly. This data lends credence to the notion that feed rate and tool wear are inexorably related throughout the machining process.

```
MAE: 0.04351303155006859
R2 Score: 0.20883770174436267
MSE: 0.003012617969821673
RMSE: 0.05488732066535652
```

In this work, we used numerous measures to evaluate the performance of our model, including MAE, R2, MSE, and RMSE. These measurements provide valuable insight into how well the model fits the data.

The Mean Absolute Error (MAE) metric is used to assess the average absolute difference between predicted and actual data. Our model's MAE is 0.0435, indicating a relatively modest average disparity between predicted and actual values.

The Coefficient of Determination (R2-score) statistic measures how well the model explains the data variance. It ranges from 0 to 1, with higher numbers indicating a better fit of the model to the data. With an R2-score of 0.2088, our model explains a moderate portion of the observed variance.

The MSE metric computes the average squared difference between predicted and observed values. It is calculated using the mean of the squared differences between each predicted and actual value. Our model's MSE is 0.0030, indicating a relatively tiny average squared difference between predicted and actual values.

Finally, the Root Mean Squared Error (RMSE) measure, which is the square root of MSE, determines the average magnitude of the discrepancy between expected and actual data. Our model's RMSE is 0.0549, indicating a relatively modest average magnitude of error between predicted and actual data.

REFERENCES

[1]. "Real-Time Tool Wear Monitoring in Turning Using Acoustic Emission and Image Processing" by S. Singh et al. (2017) [1]
[2]. "Tool Wear Analysis in Turning Operations Using Image Processing Techniques" by M. Iqbal et al. (2017) [2]
[3]. "Tool Wear Monitoring in Milling Using Image Processing and Neural Network" by P. Kumar et al. (2017) [3]
[4]. "Monitoring Tool Wear in Turning Using Acoustic Emission and Image Processing Techniques" by N. Singh et al. (2017) [4]
[5]. "Real-Time Tool Wear Monitoring Using Image Processing in Milling" by R. K. Pal et al. (2018) [5]
[6]. "Tool Wear Monitoring in Drilling Operations Using Image Processing Techniques" by S. M. Roy et al. (2019) [6]
[7]. https://www.researchgate.net/publication/324482485_Experimental_Data-Set_for_Prediction_of_Tool_Wear_during_Turning_of_Al-1061_Alloy_by_High_Speed_Steel_Cutting_Tools.
[8]. "Development of tool wear machining monitoring using novel statistical analysis method" by M.A.F. Ahmada , M.Z. Nuawia,*, S. Abdullaha , Z. Wahida , Z. Karimb , M. Dirhamsyahc