HSS Tool Life Prediction Using XGBoost for Al 6061

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Abstract-

Tool life is very important for manufacturing processes in industries.Milling tools are discarded while their life still remains.Cutting speed, feed rate, and depth of cut are the three primary parameters typically used in the milling process; 25 identical HSS tools of 15mm diameter are used in this experiment . The purpose of this study is to determine how these parameters affect the ability to forecast tool life in milling operations using Xgboost Regressor.In this experiment Taguchi DOE was used for performing machining operations.The Xgboost Regressor model predicts excellent tool life with train accuracy of 0.999999997088664 and test accuracy of 0.9801597248618984.

Literature review-

This review discusses the development of monitoring and control technologies used in the machining process and performs a thorough analysis of their state-of-the-art during the previous ten years.And also indicates tuning of parameters feed, speed, depth of cut, to drastically increase performance of a machine tool in terms of part tolerances, surface quality, operating cycle time and its life.Burr and Chip Formation can be controlled by regulating feed rate is also discussed in this paper.[1] This research presents combinations of signal processing algorithms for cutting force signals-based real-time estimates of tool wear in face milling. The collected characteristics are used in the first stage to create multiple linear regression models for certain cutting situations. At the second stage, the first-stage models are combined, in accordance with proven theory, into a single tool wear model, including the effect of cutting parameters. The three chosen strategies show improvements over those reported in the literature, in the case of training data as well as test data used for validation—for both laboratory and industrial experiments.In order to assess tool wear during face milling operations, the study introduces combinations of signal processing techniques, including DWT, TDA, Isotonic regression, and exponential smoothing. In order to lessen the impact of random process changes and fixed faults, features are calculated robustly.[2] The purpose of that research was to use artificial neural networks and Taguchi design of experiments to determine how these parameters affect the prediction of tool life in milling operations. Using test specimens, machining experiments were carried out under various cutting circumstances. The findings of the experiments and the projected model had a very excellent agreement. For the train and the test, the estimated and experimental data were correlated by 0.96966 and 0.94966, respectively.[3]Matsubara and Ibaraki discuss monitoring and control schemes of cutting force and torque. Sensors to measure cutting force and torque, as well as their indirect results, are reviewed. [4]In this paper, Stephen Maztka discusses, two methods which provide an explanation for the classification result of a complex classifier are evaluated on synthetic predictive maintenance dataset. Evaluated on a synthetic predictive maintenance dataset.Also they described, train and an explainable model and an explanatory interface and evaluated its performance.[5] This paper presents a stochastic approach to tool wear prediction, based on the particle filter. Effectiveness of the developed method is demonstrated through tool wear experiments using a ball nose tungsten carbide cutter in a CNC milling machine. The performance of the developed method received good results.[6]Three tool wear indices have been developed using statistical and time series techniques.Using a particular thresholding scheme, 22 milling tests have been presented. Results were effective in minimizing the effects of changes in the cutting conditions.[7] XGBoost model with the default features of the XGBoost module was executed,a brief overview of the XGBoost model was studied and various concepts like estimators, overfitting etc. and its effects on accuracy were discussed.[8]Ghosh used neural network-based sensor fusion to estimate tool wear during CNC milling.[9]This review aimed to present an overall analysis of the recent advances in machining processes using ML. The literature presents several studies and research with promising results. The proposed approaches are based on the same methods. This point may represent a limit to identify a common rule to implement the ML approach. A number of practical studies show promising results—in particular, for milling and turning machining.[14]

Introduction-

Milling is the machining process of removing unwanted material from a workpiece by feeding in a direction that is at an angle with the tool's axis. It encompasses a wide range of operations. The various milling processes performed by different milling cutters may be classified under different headings.

1. Milling on the outskirts 2. Milling the face

To maintain their profit, the world is constantly looking for cost-cutting solutions with shorter lead times. It has long been recognised that cutting conditions such as feed rate, cutting speed, and depth of cut should be chosen to optimize the economics of the machining operation as measured by productivity, total manufacturing cost per component, or other appropriate criteria. In terms of economics, tool life estimation is a more essential issue that is affected by numerous circumstances such as speed, feed, and depth, as well as tool geometry, tool material, cutting fluid, and workpiece material.

The importance of cutting tools cannot be overstated in any machining system. Most of the time, the quality of the end product is determined by the quality of the cutting tools. The cutting tool's quality and performance have a direct impact on the machining systems and overall productivity. This paper provides an overview of tool life prediction. CNC machines are widely used in the metalworking industry and are the best option for most milling tasks.

Given the rarity of publicly available predictive maintenance datasets, we offer and supply a semi-synthetic, yet realistic, predictive maintenance dataset for use in our evaluation and by the community in this publication. Second, we describe, train, and compare the explanatory performance of an explainable model and an explanatory interface. This paper is organized as follows: In section II we describe our experiment setup, in section III we explain predictive methodology , train our classifiers and measure their performance. Section IV evaluates the explanations provided by an explainable model and an explanatory interface. Section V concludes this paper and an outlook on future work in this field is given.

Experimental Setup-

A. CNC machine

Experiments were carried out at the Vishwakarma Institute of Information Technology on CNC machine as shown in Fig 1. The experiments were conducted in a vertical axis CNC machine (Lokesh Make) using a tool 15 mm diameter cutter mill with 5 cutter inserts as shown in Fig 2. Milling bit was of HSS (Miranda Make). CC The chemical composition of the investigated Al 6061 alloy is given in Table 1.

Chemical composition (Maximum) of AL 6061

Element	Mg	Si	Fe	Cu	Cr	Zn	Ti	Mn	Others
%wt	1.20	0.15	0.80	0.40	0.35	0.25	0.15	0.15	0.15

Specification of Al 6061 workpiece

Sr No.	Parameters	Value
1	Yield Strength	110 MPa
2	Ultimate Tensile Strength	210 MPa
3	Young’s Modulus	69 GPa
4	Elongation	10-16%

B. The Taguchi design of experiments method -

The **Taguchi method** involves reducing the variation in a process through robust design of experiments. The overall objective of the method is to produce high quality products at low cost to the manufacturer. Taguchi developed a method for designing experiments to investigate how different parameters affect the mean and variance of a process performance characteristic that defines how well the process is functioning. The experimental design proposed by Taguchi involves using orthogonal arrays to organize the parameters affecting the process and the levels at which they should be varied. Instead of having to test all possible combinations like the factorial design, the Taguchi method tests pairs of combinations. This allows for the collection of the necessary data to determine which factors most affect product quality with a minimum amount of experimentation, thus saving time and resources. G-code was written for CNC keeping Taguchi DOE in mind

Table 1. Random Values of Experiment

Sr No.	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	Actual Tool life measured during process (min)
1	1480	182	0.9	126
2	740.0	136.0	0.6	390
3	1450.0	98.0	0.6	139
4	125.0	24.0	0.1	233
5	1100.0	346.0	1.0	104
6	1290.0	26.0	0.2	246
7	520.0	90.0	0.3	430
8	1290.0	345.0	1.0	108
9	1180.0	95.0	0.4	281
10	680.0	24.0	0.1	539
11	125.0	120.0	0.7	40
12	280.0	182.0	0.9	250
13	600.0	360.0	1.0	255

Predictive Methodology-

1.]Dataset and Preprocessing-

Dataset of 200 points is semi-synthesised from the experiment,so as to remove bias and improve accuracy.Data is in the range of 100-1600 rpm for spindle speed,22-370 mm/min for feed rate ,0.1-1 mm for depth of cut and 9-612 min for tool life. Data points are splitted into train and test (validation),90% data is given for training and 10% is given for validation.Data is then scaled because the parameters which have smaller values do not imply that they are less significant.Data is scaled using python library sklearn.preprocessing and from which StandardScaler has been used.

The standard score of a sample *x* is calculated as:

$$z = (x - u) / s$$

where *u* is the mean of the samples, and *s* is the standard deviation of the samples.

Various data visualization graphs have been plotted to get proper proper correlation between the parameters as shown in heatmap Fig. 2 and as well density of data points shown in Fig. 1
Fig. 1 Shows the 3D visualization of dataset and redirects the efficient zone shown by dark red scatter points for which the range is 360-740 rpm for spindle speed,50-200 mm/min for feed rate and 0.2-0.7 mm for depth of cut.

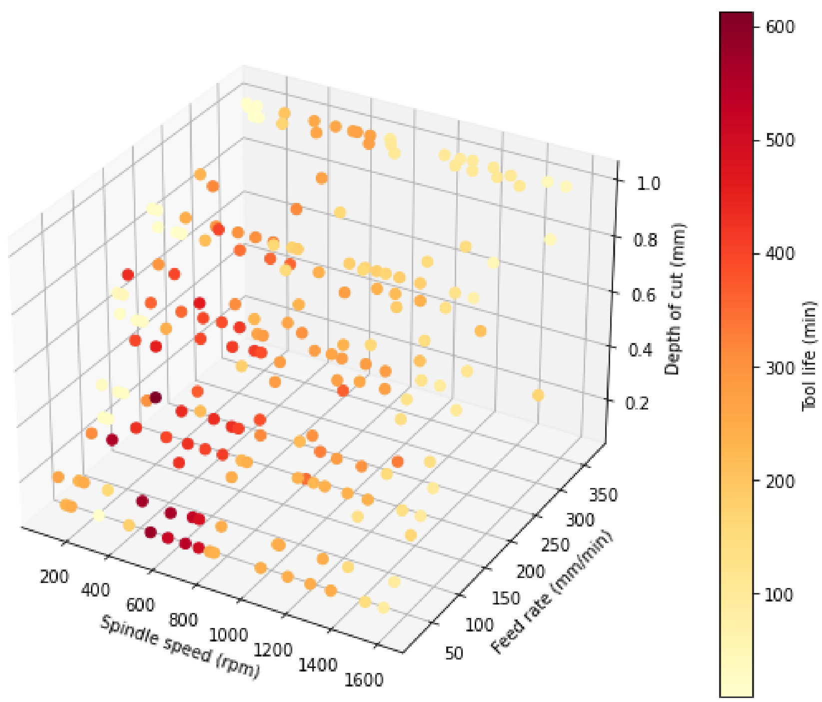

Fig. 1

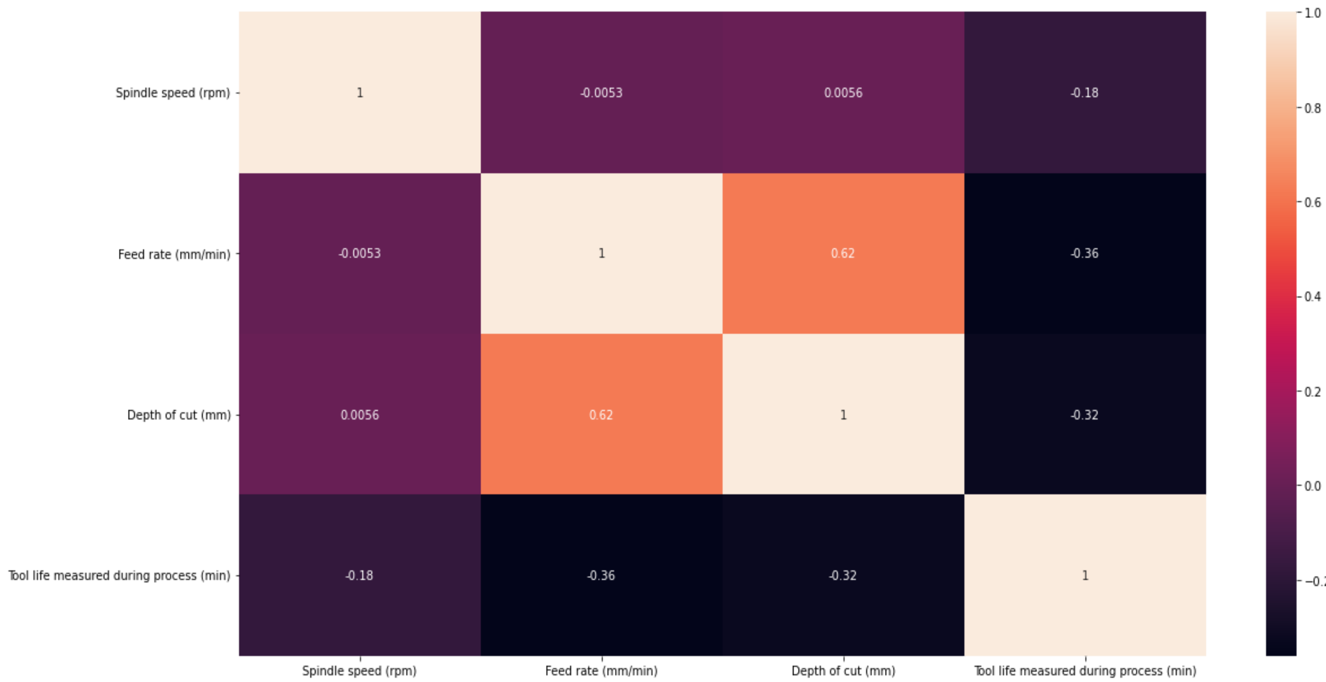

Fig. 2

2.]XGBoost Regressor-

XGBoost is a distributed gradient boosting library that has been developed to be very effective, adaptable, and portable. It uses the Gradient Boosting framework to implement machine learning algorithms.For regression predictive modeling, XGBoost is an effective gradient boosting solution.

Regression trees, which transfer an input data point to one of their leaves that provides a continuous score, are the weak learners. With a convex loss function (based on the difference between the predicted and target outputs) and a penalty term for model complexity, XGBoost minimizes a regularized objective function (in other words, the regression tree functions). Adding new trees that forecast the residuals or errors of earlier trees, which are then integrated with earlier trees to produce the final prediction, is how the training process is carried out iteratively.Here XGBoost model is hypertuned with n_estimators 1391 (Number of gradient boosted trees,equivalent to boosting rounds or in other words epochs or iteration),eta or learning rate of 0.04 and max_depth 6 (maximum depth of tree).Above hypertuned variables are acquired from trial and error method so as to avoid overfitting.

Result and Analysis-

Root mean squared error is applied as evaluation metrics as shown in Fig. 3.The obtained Root Mean Squared (RMS) error and Accuracy shown in Fig. 4 were 0.00736 and

0.999999997088664 for train respectively , and for test 18.78901 and 0.9801597248618984 respectively.Table 2 shows the effectiveness of XGBoost in forecasting tool life during the milling process.

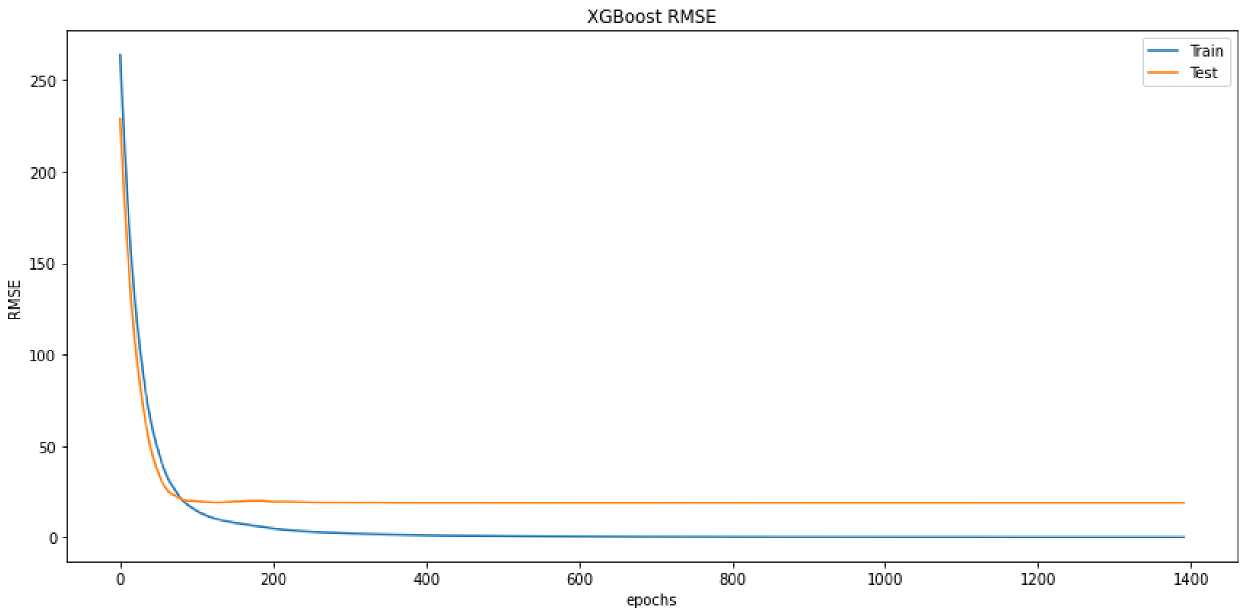

Fig.3

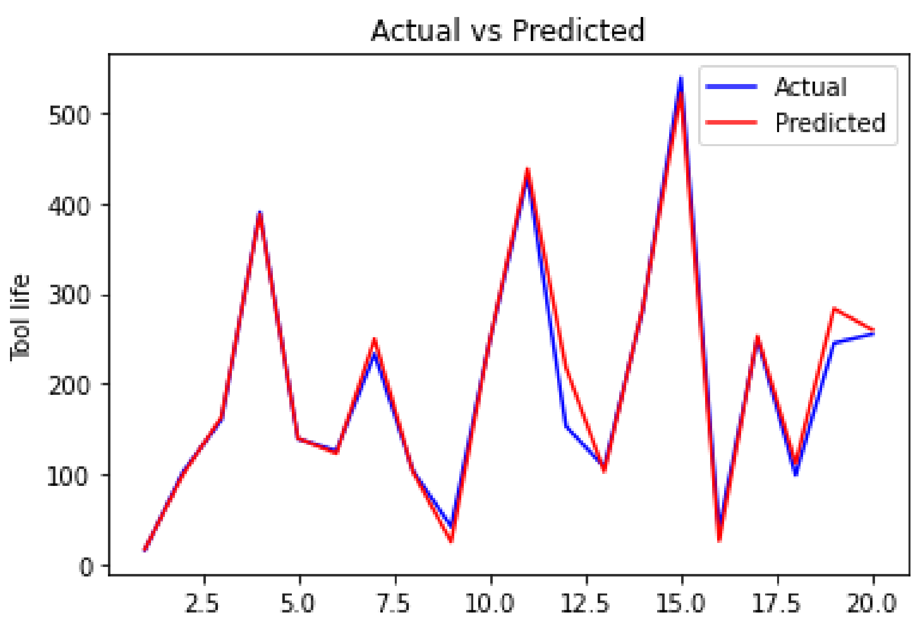

Fig. 4

Table 2. Result of XGBoost and Actual Experimental Values

No	Spindle speed (rpm)	Feed rate (mm/min)	Depth of cut (mm)	Actual Tool life measured during process (min)	Predicted Tool life measured during process (min)	Error %
1	1480	182	0.9	126	123.009	2.374
2	740.0	136.0	0.6	390	387.627	0.608
3	1450.0	98.0	0.6	139	139.550	-0.396
4	125.0	24.0	0.1	233	249.651	-7.146
5	1100.0	346.0	1.0	104	102.649	1.299
6	1290.0	26.0	0.2	246	246.458	-0.186
7	520.0	90.0	0.3	430	438.070	-1.877
8	1290.0	345.0	1.0	108	102.976	4.652
9	1180.0	95.0	0.4	281	282.946	-0.693
10	680.0	24.0	0.1	539	521.881	3.176
11	125.0	120.0	0.7	40	26.118	34.705
12	280.0	182.0	0.9	250	253.123	-1.249
13	600.0	360.0	1.0	255	259.881	-1.914

Conclusion-

This study established an XGBoost for modeling and predicting tool life in CNC milling parts made of aluminum (6061) material. Given the precision attained, it is reasonable to infer that the (DOE) procedure took into account all relevant elements. The current paper's findings can be expanded in three different directions. Building a database using Taguchi (DOE) and various combinations of cutting parameters is the initial stage. Modeling tool life in the second step involves using (XGBoost). Validation is done in the third step by running the experiments. The statistical (RMS) method was applied to create the (XGBoost) model. It was discovered that (XGBoost) prediction closely matches the outcomes of the experiments. Finally, the correlation between the training and test data was determined to be 0.999999997088664 and 0.9801597248618984, respectively, and the root mean squared error for the test and train data was computed to be 18.78901 and 0.00736 respectively . In future it can be used to sync with SCADA systems to get accurate number of tools required for certain machined job and also optimize parameters to get minimum tool wear and maximum tool life.It can be used in industries to keep ample amount of tool stock for inventory management and also help in pitching quotation to customers.

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