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HSS Tool Life Prediction Using XGBoost for Al 6061

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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.

The various milling processes performed by different milling cutters may be classified under different headings.

1. Milling on the outskirts
2. Milling the face

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.

Tool life is very important for manufacturing processes in industries.Milling tools are discarded while their life still remains.

The purpose of this study is to determine how these parameters affect the ability to forecast tool life in milling operations using Xgboost Regressor and combinations of signal processing algorithms for cutting force signals-based real-time estimates of tool wear in face milling.

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 using a tool of 15 mm diameter, cutter mill with 5 cutter inserts. CC The chemical composition of the investigated Al 6061 alloy is given in Table.

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. 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-

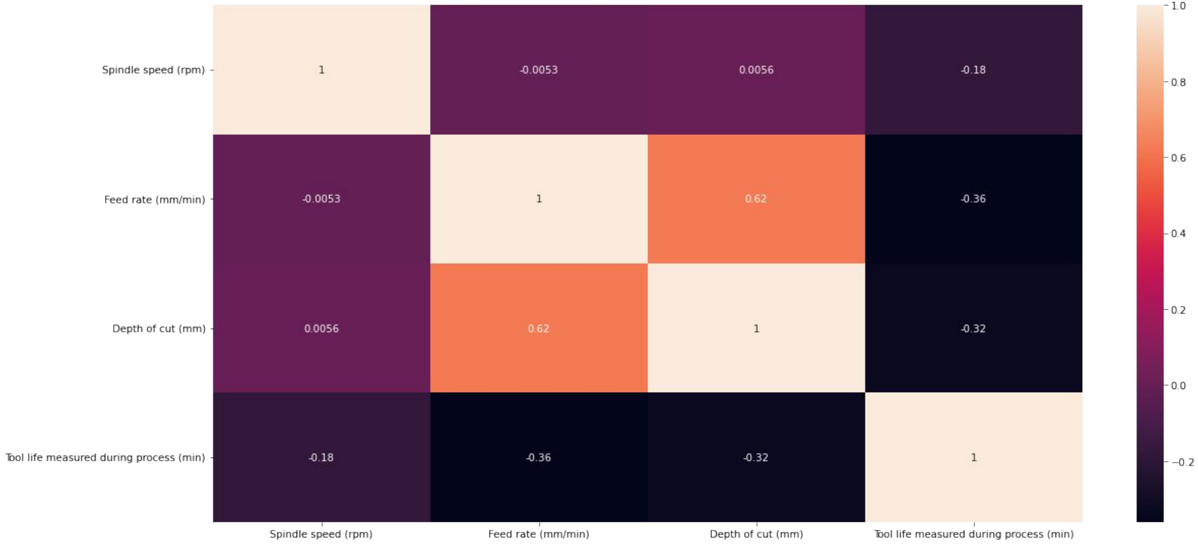
Dataset of 200 points is semi-synthesised from the experiment,so as to remove bias and improve accuracy.. Data points are splitted into train and test (validation),90% data is given for training and 10% is given for validation.Data is then scaled because the parameters which have smaller values do not imply that they are less significant.

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.

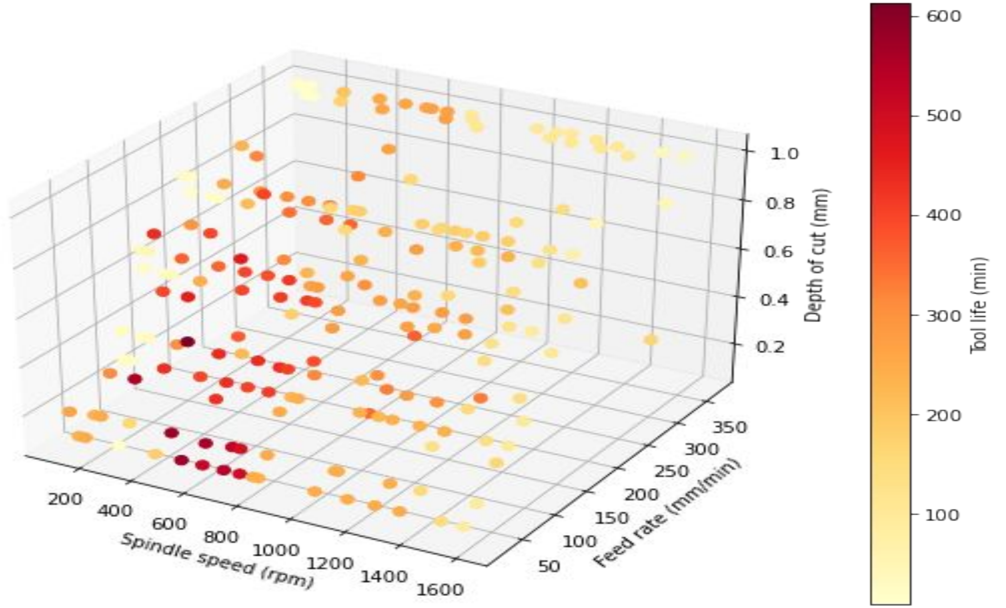
Various data visualization graphs have been plotted to get proper proper correlation between the parameters as shown in heatmap.



2] XGBoost Regressor-

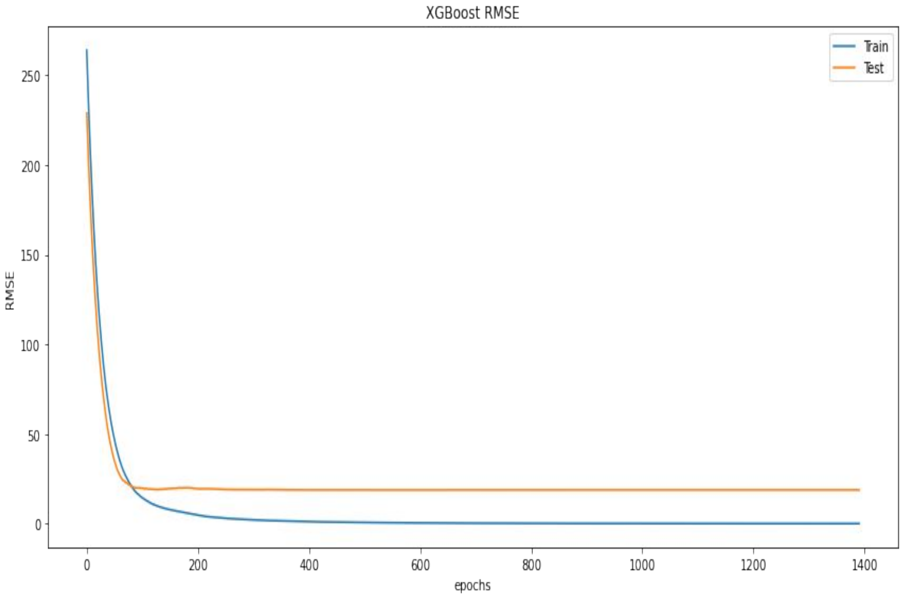
XGBoost is a distributed gradient boosting library that has been developed to be very effective, adaptable, and portable. It uses the Gradient Boosting framework to implement machine learning algorithms.For regression predictive modeling, XGBoost is an effective gradient boosting solution.

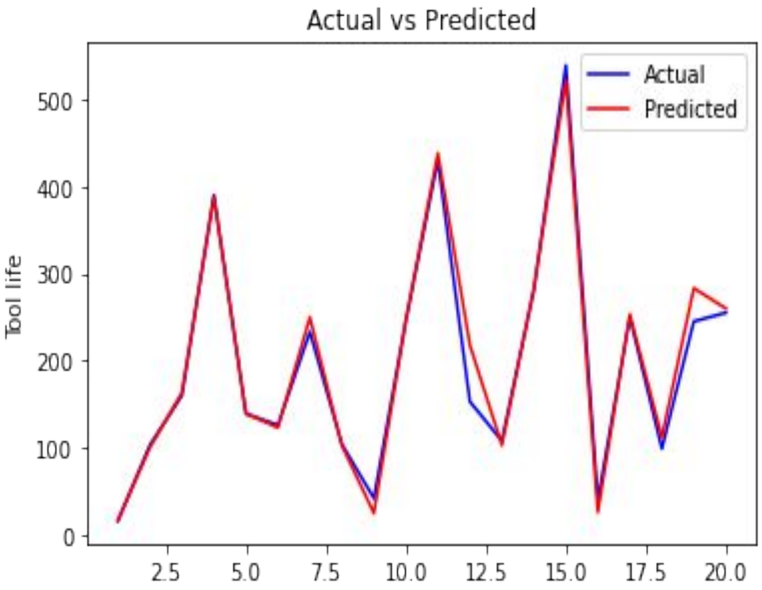
XGBoost minimizes a regularized objective function (in other words, the regression tree functions). Adding new trees that forecast the residuals or errors of earlier trees, which are then integrated with earlier trees to produce the final prediction, is how the training process is carried out iteratively.



Result and Analysis-

Root mean squared error is applied as evaluation metrics. .The obtained Root Mean Squared (RMS) error and Accuracy 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.





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.

References-

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Thank You!