“HSS Tool Life Prediction Using XGBoost for Al 6061”

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Importance of Problem

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. 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 study provides an overview of tool life prediction in CNC machines that are widely used in the industry and are the best option for most milling tasks.

Current Status

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.

In most industries ,predictive methods for tool life detection using XGBoost are not practiced.Traditional methods like manual investigation of surface burr are used for detection tool life.

Scope of Investigation

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. Second, we describe, train, and compare the explanatory performance of an explainable model and an explanatory interface. This study 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 study and an outlook on future work in this field is given.

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.

The experimental setup consists of a CNC machine on which experiments were carried out at the Vishwakarma Institute of Information Technology. The experiments were conducted in a vertical axis CNC machine using a tool 15 mm diameter cutter mill with 5 cutter inserts. The Taguchi design of experiment method was carried out which involves reducing the variation in a process through the robust design of experiments. The overall objective of the method is to produce high-quality products at a low cost to the manufacturer. 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.

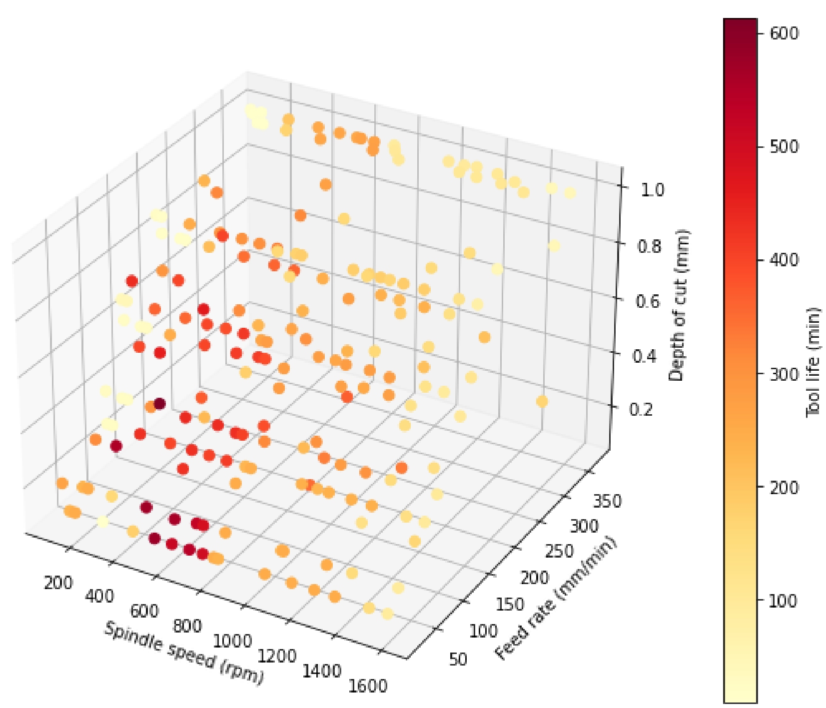

Fig. 1 Correlation between the parameters as shown in heatmap

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.

Expected Outcomes:

Current 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 .

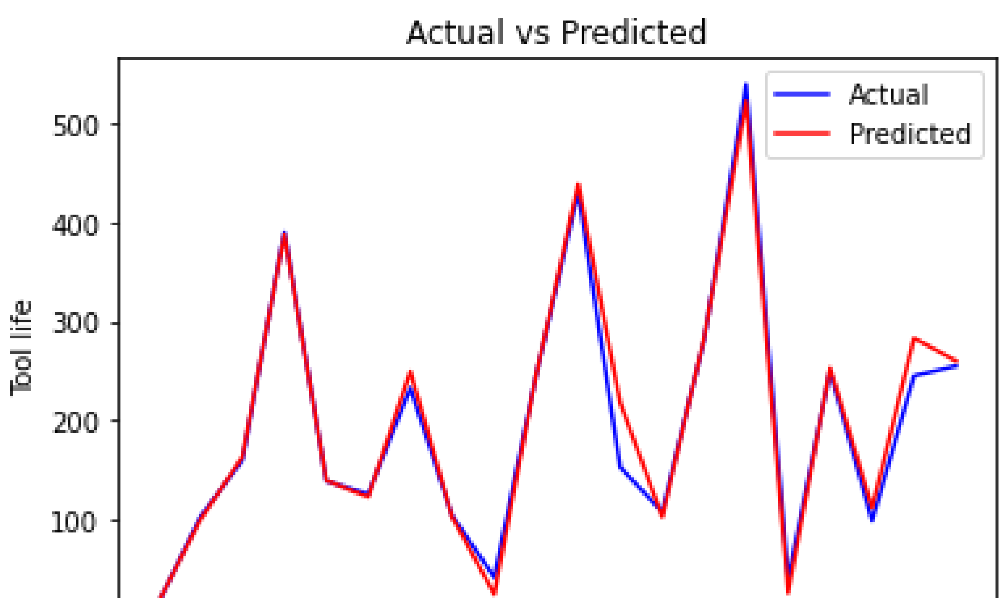

Fig. 2 Actual vs Predicted Tool Life

In future it can be used to sync with SCADA systems to get an accurate number of tools required for certain machined jobs and also optimize parameters to get minimum tool wear and maximum tool life.
It can be used in industries to keep ample amounts of tool stock for inventory management and also help in pitching quotations to customers.

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