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Development of ML Model for Tool Life Prediction

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Abstract - This project aims to study the tool life of cutting tools in CNC machines using machine learning techniques. By analysing parameters like cutting speed, feed rate, depth of cut, and material properties, the model predicts tool life based on experimental data. This results in increased productivity, reduced downtime, and enhanced machining efficiency. It also explores predictive maintenance and quality control in industrial areas. Machine learning algorithms, such as regression and classification models, are evaluated for predicting tool life. The study's findings demonstrate how machine learning may be used to accurately predict the life of CNC tools, giving manufacturers the ability to plan preventative maintenance procedures. Machining operations can be managed to reduce production disruptions and tool replacement costs by anticipating wear and breakdown of the tools.

***Key Words*:** Machine vision, image processing, metrology, inspection, automation

1.INTRODUCTION

Digitalization significantly impacts human life, reducing human efforts and increasing productivity. It improves living standards, comfort, and economic growth by fostering innovation and forming new sectors. This benefits society by creating jobs, new enterprises, and increased money.

Tasks are automated, procedures are streamlined, and productivity is increased by technology. Businesses may be able to increase revenues and maybe lower customer expenses as a result of this efficiency. Automation and robots increase productivity, accuracy, and consistency in the manufacturing and other industries. Both output and labor expenses may be decreased as a result. In the discipline of mechanical engineering, machine learning has multiple benefits that improve multiple areas of design, analysis, and operations.

Taylor's tool life equation is used to calculate the tool life, however there are now a number of digital methods available. One technique for predicting the tool life of cutting tools is machine learning, which makes use of a variety of algorithms, including random forests and support vector machines. Preventative tool replacement or maintaining is intended to reduce downtime and maximize production efficiency. Tool life prediction is done by various aspects. There are several ways to predict the tool life, including data-driven, analytical, and empirical approaches. Which tool life prediction method is best depends on the complexity of the machining process, the required level of accuracy and the available data. Tool life prediction is an essential component of manufacturing process optimization, cost reduction, and consistent product quality, regardless of the approach taken.

2.LITERATURE SURVEY

Jaydeep Karandikar has proposed that[1]the time it takes for wear to reach critical threshold—also known as the time to tool failure—is unknown since wear data is gathered from the shopfloor. Every tool wear data point represents a single point on tool wear vs. cut time curve, providing information about whether or not tool has failed. Tool life is therefore approached as classification problem. Support Vector Machines and logistic machine learning classification algorithms are the two chosen for evaluation since tool life as a function of cutting speed is continuous and monotonically decreasing. The goal of "machine learning" research is to make computers capable of learning without the need for explicit programming. Formally, if a computer program performs better on tasks in T as measured by P after experiencing E, then it is said to have learned from experience E with relation to a class of tasks T and performance measure P.This is another definition of machine learning. When it comes to tool life classification, wear data gathered from the shop floor provides experience E. The job T is to identify the tool as failed or not failed, and the accuracy of the classification serves as the performance measure P.

Robin Oberléa,Sebastian Schorrb et.al.[2] have proposed that with a limited amount of labeled data sets, Random Forest Regression Algorithm was able to predict tool wear with a high degree of accuracy. Due to the small amount of data and fact that tool wear is a random process variable, some forecasts differed more from the actual tool wear.

One can enhance accuracy and resilience of the model by implementing the subsequent strategies:

- Gathering more data, particularly in the final minutes of cutting, to strengthen the model's resilience.
- Capturing more cutting process signals or looking at different kinds of tool wear to discover possibly more trustworthy data.

In summary, it is not an easy task to strike a balance between obtaining right kind & quantity of data to enhance model's predictions & minimizing the amount of time and resources required, but this effort managed to do so. [2] Machine learning approaches exhibit a high level of maturity and have potential applications in the manufacturing sector. This study examines the relationship between process performance and parameters, enabling production system optimization.The life of a production tool can only be roughly estimated using conventional methods of analysis. In light of this, this study presents an industrial use case for machine learning to forecast lifespan of particular cutting tools. As a result, it is possible to more precisely estimate each manufacturing tool's life and optimize its operating duration.

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Vedant Parwal and B.K Rout[3]have proposed that a way to create a machining supervision system that tracks the tool life cycle. The suggested approach is adaptable to various operating environments and may be configured to work with any type of machining system that carries out various tasks or gathers various process data. This technique predicts how many operations the cutting tool will withstand given the tool wear probability, thereby reducing the delay during a tool change over operation. The suggested technique uses mean feature levels and dataset cleaning to remove random noise that may have been present. The Boruta algorithm, which integrates the advantages of wrapper & filter approaches, is used for feature selection. Adjusting thresholds gives the user a simple way to decide between an aggressive and conservative monitoring strategy. Medium-sized and larger manufacturing units can employ these kinds of supervisory systems to stop production, ensuring that it never stops. This lowers the overall tool cost per prodcut of produce and result in a strong tool management system. As sensor technologies progress, a great deal of data is captured during machining process. Frequently, only specific sections of data are helpful in explaining the selected issue. It is possible for the features necessary to fully describe the outcome to be left out of the model, leading to models that are less accurate. For this reason, feature selection is crucial to the creation of models.

3. PROPOSED DESIGN

3.1 What is an algorithm?

An algorithm is defined as a set of principles governing calculations or problem-solving procedures. It serves as a compilation of instructions or directions outlining, in a step-by-step manner, the process for achieving desired results. Notably, algorithms are agnostic to programming languages, representing straightforward guidelines applicable across various languages to accomplish specific objectives.

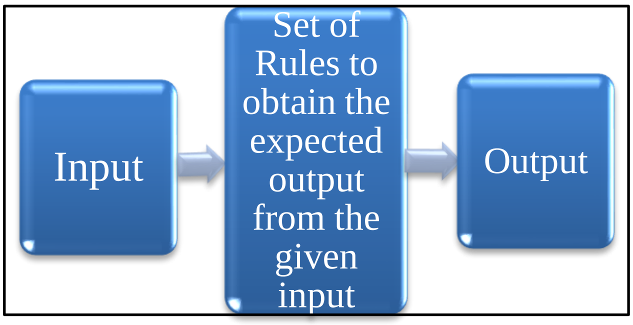

Fig3.1 Typical Algorithm

Not all computer instructions can be classified as algorithms. To qualify as such, certain criteria must be met by these instructions:

• Clear & Unambiguous: Algorithm ought to be absolute & clear. Its steps all lead to same meaning and be very obvious.

• Well-Defined Outputs: The algorithm needs to specify the output it will produce and make sure it is well-defined.

• Finiteness: The method needs to be finite, meaning it cannot run into an endless loop.

3.2 How to create a model ?

A critical stage in the creation of machine learning systems is preparation of machine learning model. It consists of a number of actions meant to prepare the model and data for deployment, validation, and training. Firstly step in process is data collection, which involves gathering pertinent data that has been properly categorized. The next step is data preprocessing, which includes operations like data splitting to produce distinct sets for training, validation, and testing, data cleaning to manage missing values and outliers, and feature engineering to choose or generate pertinent features.

The next step after preparing the data is to choose an appropriate machine learning model or algorithm. This decision is based on the sort of work at hand, such as regression, classification or another task and the characteristics of the data. Following model selection, the trained dataset was used for training model, enabling it to identify patterns & generate predictions.

Model validation is an iterative process; if the model doesn't meet the desired criteria, adjustments to the architecture, hyperparameters, or data preprocessing are made, followed by a return to the training and evaluation phases. If the model passes validation, it proceeds to the testing phase, where it's assessed on a separate test dataset to ensure its generalizability to new, unseen data.

In the end, models that satisfy the requirements and exhibit strong performance can be used in real-world settings, where they can forecast fresh data. Given that data distributions might change over time, it is imperative that the model be continuously maintained and monitored to guarantee that its performance is still acceptable under dynamic real-world settings. Thus, model preparation lays the groundwork for effective machine learning model building, where accurate predictions and real-world application depend on high-quality data and a ready-made model.

4. DETAIL DESIGN

In this section, the detailed calculations and data used as base of the ML model is described.

4.1 Theoretical calculations

Taylor's tool life equation,

$$VT^n = C$$

Here,
V= Cutting speed
T=Tool life in minute
n = Constant
C= constant

Considering,

$$\text{Cutting speed}(V) = \frac{\pi DN}{1000}$$

Here,
D= workpiece diameter
N= Spindle speed

Sample calculations:

(1)For threading on part
Tool material: Carbide tool
Workpiece material: MS

Reading taken from experimentally
D= 9.7 mm
N= 550 rpm
Taking,
n = 0.3
C= 150
Considering,

$$\text{Cutting speed}(V) = \frac{\pi DN}{1000}$$

$$= \frac{\pi * 9.7 * 550}{1000}$$

= 1676 m/min

Now using Taylor's tool life equation,

$$VT^n = C$$

$$16.76 * T^{0.3} = 150$$

$$T = \left(\frac{150}{16.76}\right)^{\frac{1}{0.3}}$$

Tool life ($\boldsymbol{T}$) = $\boldsymbol{1498\ min}$

From above calculation we got tool life of threading tool theoretically, which was used further for validation purpose.

Material of tools used to collect datset for analysis is carbide and workpice material is Mild Steel.

In following table sample values from dataset and theoretically calculated values of tool life mention

Table -1:Sample Dataset

OPERATION	SPINDEL SPEED (rpm)	CUTTING SPEED (m/min)	FEED (mm/rev)	DEPTH OF CUT (mm)	TOOL LIFE (IN MIN)
THREADING	550	16.7519	3	0.15	1491
THREADING	500	15.229	2.5	0.14	2048
TURNING	1650	51.81	0.2	0.15	464
TURNING	1600	50.24	0.3	0.15	534
TURNING	1700	53.38	0.4	0.15	405
BORING	1250	125.6	0.6	1.75	1000

5. PROJECT IMPLEMENTATION

To fulfill the intended goals, we've established the experimental framework and conducted trials to evaluate the developed algorithm. This section provides comprehensive insights into the experimental arrangement, methodology, and the observed outcomes. Multiple trials have been conducted using the CNC machine.

5.1Experimental Setup

In Fig 5.1 shows flow pattern of experimental setup or of procedure.

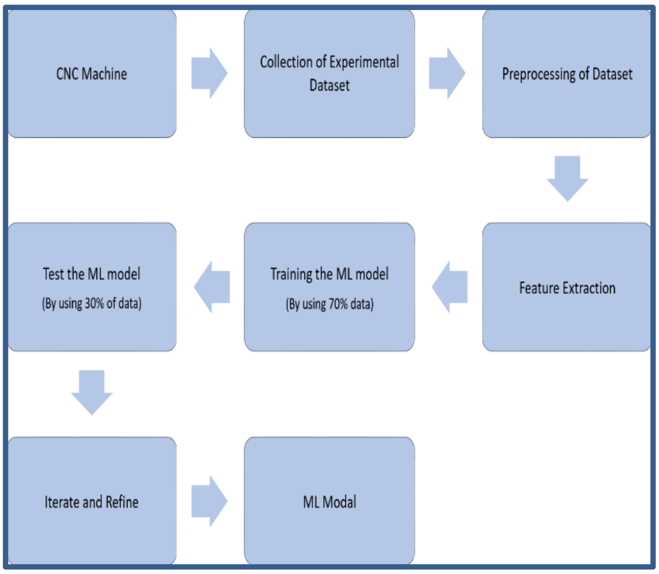

Fig 5.1 Experimental Setup

5.2 Modular Testing

Since using programing ml model created and by training and testing data with various algorithms (such as Linear regression, Decision tree regressor, Random forest regressor, Gradient boosting regressor, Ada boost regressor, Kneighbors regressor, SVR, XGB regressor, MLP regressor) we had evaluated model performance training and testing with various metric techniques like Mean absolute error(MAE), Mean squared error(MSE), R^2 score.

Table -2: R^2 score values of various models training and testing got from code

Algorithms	R^2 (train)	R^2(test)
Linear regression	0.6291	0.6097
Decision tree	1	1
Random forest	1	1
Gradient Boosting	1	1
Adaboost	0.9939	0.9942
KNN	1	1
SVR	0.2464	0.2278
XGB	1	1
MLP	0.0406	0.0202

Values of performance got from output of code and considering properties of above mention algorithms it was concluded that ada boost is best fitted algorithm for this model.

6.RESULTS

After performing the testing and validation part, some results are obtain in the form of graphs and tables. In this section the results from the ML algorithms are discussed in detailed.

In fig 6.1 Graph which is plotted between speed and tool life shows that spindle speed is directly affecting on life tool. From graph it was concluded that tool life is inversely proportional to spindle speed.

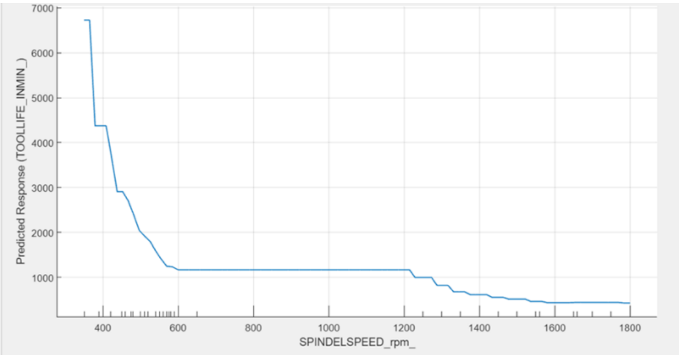

Fig 6.1 Spindle Speed vs Tool life Graph

Output got from model prediction of tool life is 1973 min & actual tool life which is calculated experimentally and theoretically is 2048 min as shown in fig 7.2.

```
output
array([1973.390625])
df['tool_life'].loc[1]
2048
```

Fig 6.2 Output of model

From above output values it was found that model gives about 97% accurate values of tool life

7.CONCLUSIONS

In summary, the analysis revealed a direct correlation between spindle speed and tool life. Specifically, the examination indicated that an increase in spindle speed corresponds to a decrease in the tool's lifespan. Results collected from ml analysis shows accuracy of predicting tool life from given input values is upto 96% to 97%. Which is excellent value of accuracy. By the use of ada boost it was achieved.
Machine learning models play a pivotal role in streamlining manufacturing operations by accurately forecasting tool wear and potential failures, thereby minimizing production interruptions and unplanned downtimes.Machine learning models, with their ability to continuously adapt and learn from evolving scenarios, refine tool life predictions with enhanced accuracy over time. This perpetual learning process empowers models to accumulate vast amounts of operational data and insights, ultimately elevating tool performance and predictive capabilities to unprecedented levels.

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