Intelligent prediction of machine tool performance in micro turning using textured inserts

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KEYWORDS

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Tool Wear,
Surface Roughness.

ABSTRACT

Intelligent machine tools can adapt to modifications in the machining environment while performing operations. An intelligent prediction of machine tool condition is an essential aspect in the manufacturing sector of Industry 4.0. Micro components of titanium alloys have huge applications in aerospace, optical and biomedical industries. In this study, machine learning (ML) based models are developed to forecast the performance of a micro-turning machine tool while working with plain and variously patterned textured micro inserts. The micro-turning experiments are performed on Ti6Al4V alloy and the cutting force, surface roughness and tool flank wear are measured for every machining pass. Supervised ML models are trained in order to predict the cutting force, flank wear and surface roughness with cutting parameters and the type of cutting inserts. In the comparison of developed ML models, Extreme Gradient Boost (XGBoost) performs best in prediction with the accuracy of 98.53% and runs in 40.67 milliseconds.

1. Introduction

In this era of Industry 4.0, the advancement of intelligent machine tools is becoming highly significant to enhance the productivity and quality of manufacturing industries. Miniaturization of mechanical components is much needed in the field of manufacturing, aerospace, biomedical and optical industries. Mechanical micro-turning is one of the significant processes for manufacturing the axisymmetric micro components at great precision level. Micro turning requires high speed in machining, due this maximum cutting speeds, very high temperature produced at the tool and workpiece interface, which can lead to tool failure, increase in cutting forces and poor surface quality. The temperatures during the machining will be reduced by applying the coolants like vegetable oils and synthetic oils, which pose an environmental hazard.

Textured cutting tools are suggested to use for machining to reduce the usage of coolants. The texturing on the surface of the cutting tool enhances the tribological features at the tool-chip interface and maximises heat dissipation during the machining operations. Therefore, it helps in improving machining quality and prolonged tool life (Sabino et al., 2020). Titanium alloys are widely used in aerospace, biomedical, optical and automobile industries because of its excellent mechanical properties such as outstanding wear and corrosion resistance, high strength to weight ratio. But machining of titanium alloys is a challenging task because of its low thermal conductivity, less elastic modulus and high chemical reactivity with the cutting tool material (Pramanik, 2014). PCD and coated carbide tools are performing better while machining as they do not react with Ti alloy and avoid the diffusion of ingredients from work materials (Hartung et al., 1982). In micro turning of Ti alloys with coated carbide inserts, the surface roughness decreases with increase in cutting speed due to thermal softening. The depth of cut and uncut chip thickness to be more than the edge radius of the cutting inserts, otherwise ploughing happens instead of shearing and it results in poor surface quality (Jagadesh & Samuel, 2014). Improved surface finish and less cutting forces will be achieved by setting the feed and depth of cut is equal to nose and edge radius of the cutting inserts respectively (Aslantas & Çiçek, 2018). Flank and Crater wear are the dominant failures of tools in micro turning of Ti alloys (Aslantas et al., 2020).

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Devraj et al. (2021) studied the effectiveness of micro dimple pattern inserts in the turning process by varying the pattern in terms of dimple size, dimple depth and pitch between the dimples. They discovered that the dimple's width affects localised stress and chip formation, the dimple's depth affects friction, and pitch affects lubrication and chip breakage (Devaraj et al., 2021). Vasumathy and Meena, (2017) investigated the effectiveness of the line pattern textured WC-Co inserts by changing the orientation of the lines in pattern while turning AISI31. They found that the length of the tool-chip contact and lubrication are greatly influenced by the lay angle.

Development of intelligent prediction models to forecast the state of the machine tools in order to further improve the machining quality and the precision levels to meet advancements in Industry 4.0. Recently a much research has been reported on development of machine learning and deep learning models for predicting the machine tool condition during machining. Wang et al., (2017) developed Deep Brief Network (DBN) for prediction of MRR from the rotational speed and pressure in polishing operation. The developed model is verified with the PSO algorithm and concluded that the model is effective (Wang et al., 2017). Cheng et al. (2020) established an intelligent support vector regression model to determine the tool wear from the vibration signal, surface texture and cutting force. The model was trained using the time-domain, time-frequency, and frequency-domain features of cutting force and vibration signals as well as the grey characteristics from surface roughness. Rajesh and Samuel, (2022) developed ML models such as Radial based function, Decision trees, MLPNN and Random Forest (RF) models to predict the tool wear and average surface roughness based on the cutting parameters and concluded that the RF model predicts better among the other models.

Lin et al. (2020) established an ANN model with 93.14% to determine the surface roughness utilising the vibration signal and process parameters on the milling machine. Liu et al. (2018) introduced a systematic architecture for a cyber physical machine tool development. In this architecture, intelligent algorithms are integrated with machine tool, real time data and machining process through several networks. Aghazadeh et al. (2018) established a milling process tool wear monitoring system with spectral subtraction algorithm from the spindle current. Several advanced ML models including Bayesian, Gaussian, Support Vector, decision tree and nearest neighbour regression algorithms are modelled for the prediction of tool failure . Gouarir et al. (2018) proposed an adaptive control system based on convolutional neural networks to predict the tool wear. They created an adaptive control system that continually modifies the optimal spindle speed and feed rates based on data from the force sensor to improve the tool life.

This work presents the performance of various textured cutting inserts in micro turning of Ti6Al4V. Also presents the ML based models to predict the cutting force, surface quality and tool wear based on the process parameters and type of cutting inserts. Experimental data from the micro-turning process using various textured inserts is used to train ML-based models. A series of ML models: Decision tree, Random Forest (RF), XGBoost and AdaBoost are developed. The training and prediction accuracies of the models are compared.

2. Experimental

2.1. Experimental Details

A Table top micro turning machine shown in Figure 1, is utilised to carry out the experiments. The machine tool consists of an iron bed of size 600 x 600 mm, mounted on an antivibration optical table. An air-cooled bearing spindle of 24,000 rpm is mounted on the base, which is controlled by a variable frequency drive (VFD) with the resolution of 6 rpm. X-Y stage with the 1µm precision and 4mm per second maximum speed is installed to control the feed and depth. A Kistler dynamometer is fixed under the tool with the help of a tool post to measure the cutting forces during machining operation. This dynamometer with Piezoelectric sensor has the capability of measuring the force from 1N to 200N.

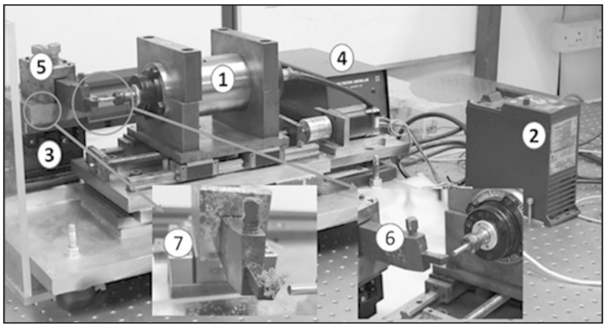

Fig. 1. Micro turning machine - 1. Spindle, 2. VLT drive, 3. X-Y stage, 4. Micro motion controller, 5. Tool post, 6. Tool holder, 7. Mini dynamometer.

2.2. Cutting tool

The tool holder is mounted on the X-Y stage with the help of a tool post to accommodate the cutting insert. Coated carbide cutting inserts with nose radius of 200µm and 400µm (CCMT060202LF KC5010 &CCMT060204LF KC5010) are utilized for the experiments. The edge radii of all the inserts utilised in the present work are 20 µm. These inserts are textured with various patterns, including line and square, using a Femtosecond laser as shown in the figure 2. Textures are designed in AutoCAD and the designs are imported to the Kyla software which is used to operate the femtosecond laser. The table 1 shows the parameters that are established during the Laser machining process.

The line patterns are fabricated with the line pitch of 100 µm. In squared pattern texture, both the size and pitch of the squares are 100 µm. The shape and dimensions of the textures are illustrated in the magnified images of the cutting inserts as shown in figure 3. Each experiment has been performed with new cutting insert.

2.3. Work material

Ti-6Al-4V alloy of 5mm diameter and 50mm length samples are used for the experiments and ER 11 collet is used to hold the workpiece in the spindle.

2.4. Cutting force measurement

Cutting force was measured during each pass of the machining process using a Kystler mini dynamometer with aid of Dynoware software. Applying the drift allowance and operating the amplifier for three hours prior to data collection

Table 1
Laser parameters for fabrication of textures.

Parameters	Range
Wavelength	1030 nm
Power	20W
Pulse energy	40 µJ
Pulse duration	800 fs
Repetition rate	2 MHz
Beam quality, M^2	<1.2
Scanning Speed	10 mm/s

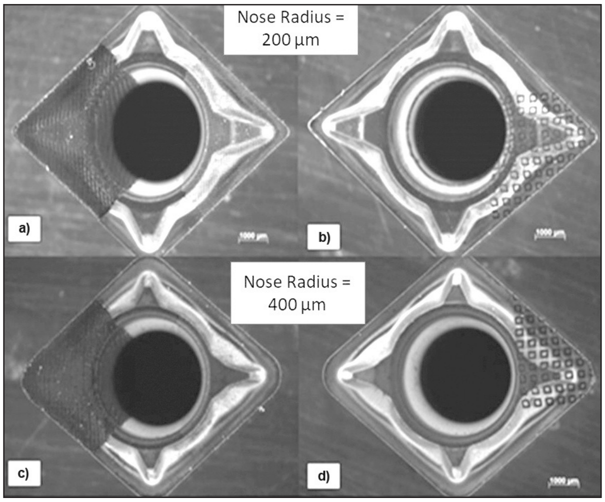

Fig. 2. Cutting inserts,
a). Line texture on 200µm nose radius insert,
b). Square texture on 200µm nose radius insert,
c). Line texture on 400µm nose radius insert,
d). Line texture on 400µm nose radius insert.

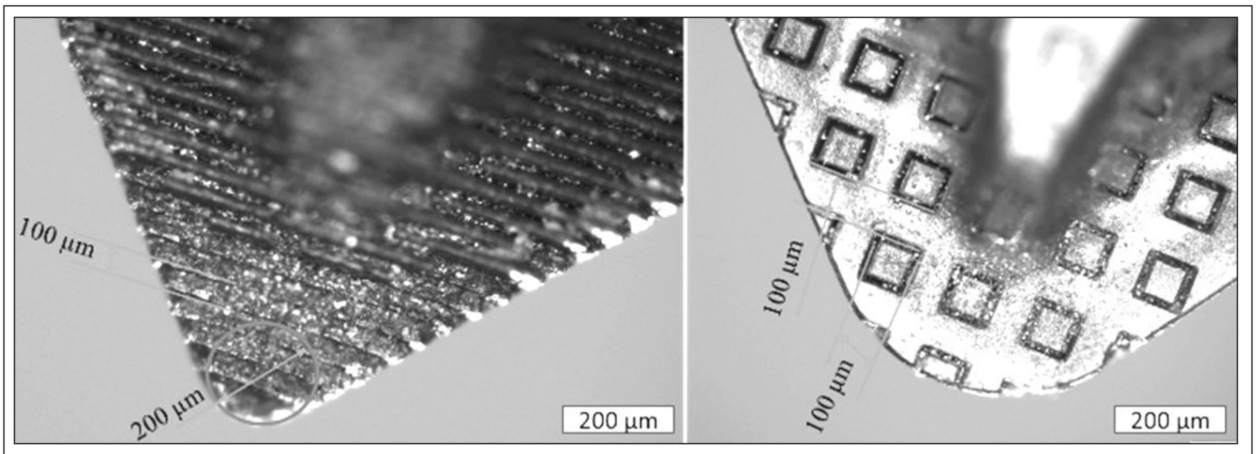

Fig. 3. Magnified view of the line and square pattern textured inserts.

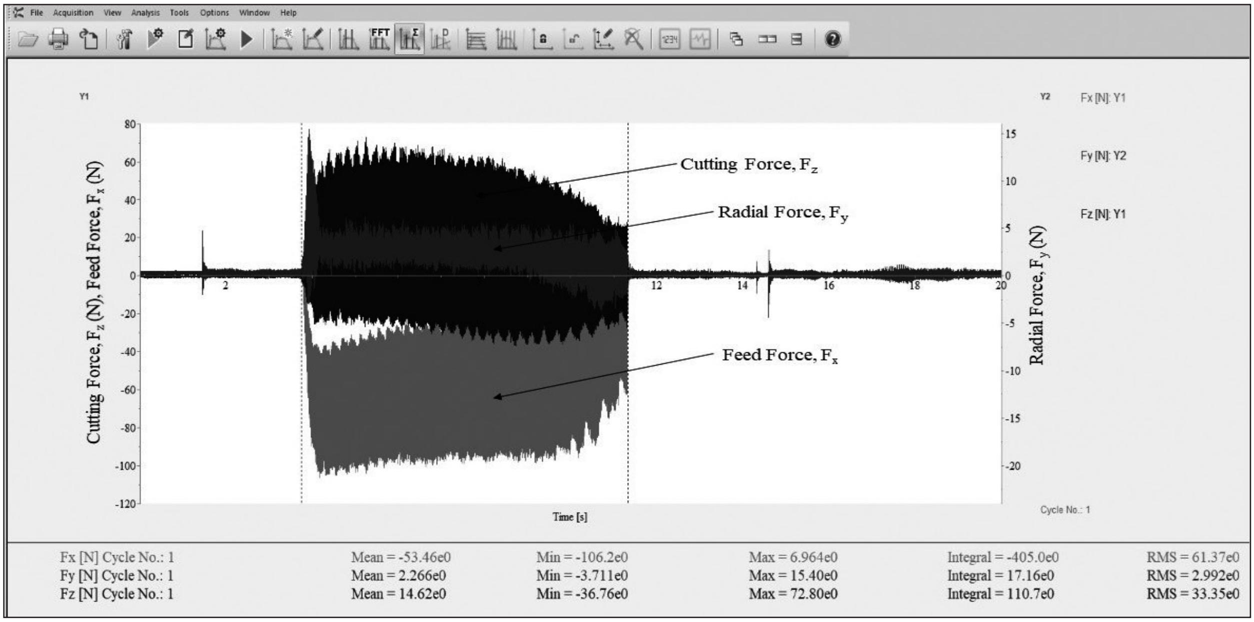

Fig. 4. Cutting force measurement.

allowed the drift to be eradicated. As seen in Figure 4, six modules determine the RMS value of the cutting force and are utilised to measure the cutting force generated during machining.

2.5. Surface roughness measurement

A contact type surface roughness tester Mahr surf M400 with stylus radii of 2µm is utilized for measuring the average surface roughness (Ra) of machined sample. The readings have been taken at three distinct locations on the surface of each sample after each pass and the average of those readings was considered as actual Ra of the sample as shown in Fig.5.

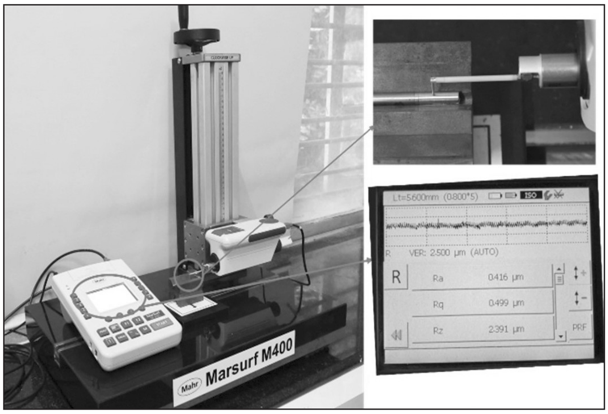

Fig. 5. Surface roughness measurement using mahrsurf M400.

2.6. Tool wear measurement

Tool flank wear width is measured from the images of cutting tool tip taken by the inverted Microscope GX 200 as shown in Figure. 6. The image magnification range for this microscope is 5X to 200X.

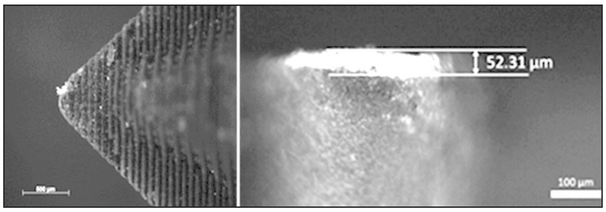

Fig. 6. Tool wear on cutting tip.

3. Machine Learning Models

The potential of computers to solve problems without external instructions is known as machine learning (ML). In the industrial sector, machine learning models are used for machine tool prognosis and diagnosis to avoid the breakdown in supply chain, increase the product quality and product quality and reduce cost (Silva et al., 2018). In previous research many ML models are created for the prediction of machine tool condition. In this research work, A few well-performing ML regression models like Decision Tree, Random Forest, XGBoost, and AdaBoost are developed and are described below.

3.1. Decision tree

Regression and classification problems can both be solved using decision trees. Regression based decision tree is created by binary recursive partitioning, where the data divides into small batches or branches as the technique evaluates each branch to take the decision. The decision tree algorithm prevents the overfitting and performs better even though the data is too large. Hence the decision tree algorithms are widely used in development of Tool Monitoring Systems and adaptive machine tool control systems. In this work, a decision tree regressor with a cost entropy function is employed and tree pruning is utilizer to avoid over-fitting.

3.2. Random forest (RF)

Random forest is an assembly of multiple independent decision trees, where several decision trees function parallelly together to take the final decision. In this approach the data bootstraps using randomly chosen sub samples for each iteration of building tree. RF models are able to reduce the overfitting by merging multiple weak learners which underfits because they employ a subset of training data. Hence, the algorithm is effectively employed in the development of machine tool prediction and classification models, including chatter recognition, tool wear classification during machine operation based on vibration signals, and prediction of machining quality, etc. In this work a random forest model is employed by setting the maximum depth in number of trees, mean squared error, minimum samples leaf is 1, minimum samples split is 2 and other parameters are default.

3.3. Extreme gradient boosting - XGBoost

XGBoost is a very effective ML algorithm for classification and regression problems, which works priorly on the basis of decision trees. It was firstly implemented in 2016 by Chen and Guestrin to increase the speed and efficiency of gradient boosted decision trees (Chakraborty & Bhattacharya, 2021). The XGBoost algorithm combines weak prediction of multiple decision trees, which is trained with subsets of data and increases its predictive ability but it will not work satisfactorily with unlabelled data. XGBoost models have several useful applications in the manufacturing industry, including the creation of an adaptable and efficient framework for real-time prediction in machine tools. Because, the algorithm performs much better than artificial neural networks with small dataset, which may normally result in the model being overfit. In this algorithm the decision of each tree depends on previous tree results. In this work model is trained with xgboost library, set seed 123, split ratio 2/3, nrounds 100 and other parameters default.

3.4 AdaBoost

The AdaBoost technique also combines a series of weak learners, but in this case, data will be divided up into different subgroups and given equal weight to train the decision trees, whereas series of weak learners combine to improve the overall performance. The weight of a sample of faulty prediction by previous tree will be boosted so that the subsequent tree focuses on correct prediction.The algorithm has been utilised in the manufacturing industry for both classification and regression tasks including predicting machine quality based on process parameter, predicting tool life with the help of vibration signal, and classifying various machining defects, etc.

4. Results and Discussion

All the experiments are carried out on an in-house build table top micro turning machine. The experiments are designed by varying the size of tool nose radius, design of texture pattern, feed rates, depth of cuts by keeping the cutting speed constant as shown in table 2.

A Kystler mini dynamometer was used to obtain the cutting force while machining, surface roughness was measured on Mahrsurf M400 and inverted microscope images are utilised to

Table 2
Experimental designs.

Experimental Designs				
Nose Radius (µm)	**Texture Type**	**Speed (m/min)**	**Feed (µm)**	**Depth (µm)**
200 400	No Texture Line Pattern Square Pattern	157	10 20 30	10 20 30

Table 3
Accuracy and rub time of ML models.

ML Models	**Prediction Score (%)**	**Run Time (ms)**
Decision Trees	84.5	10.03
Random Forest	86.08	79.45
XGBoost	98.53	40.67
AdaBoost	94.65	195.16

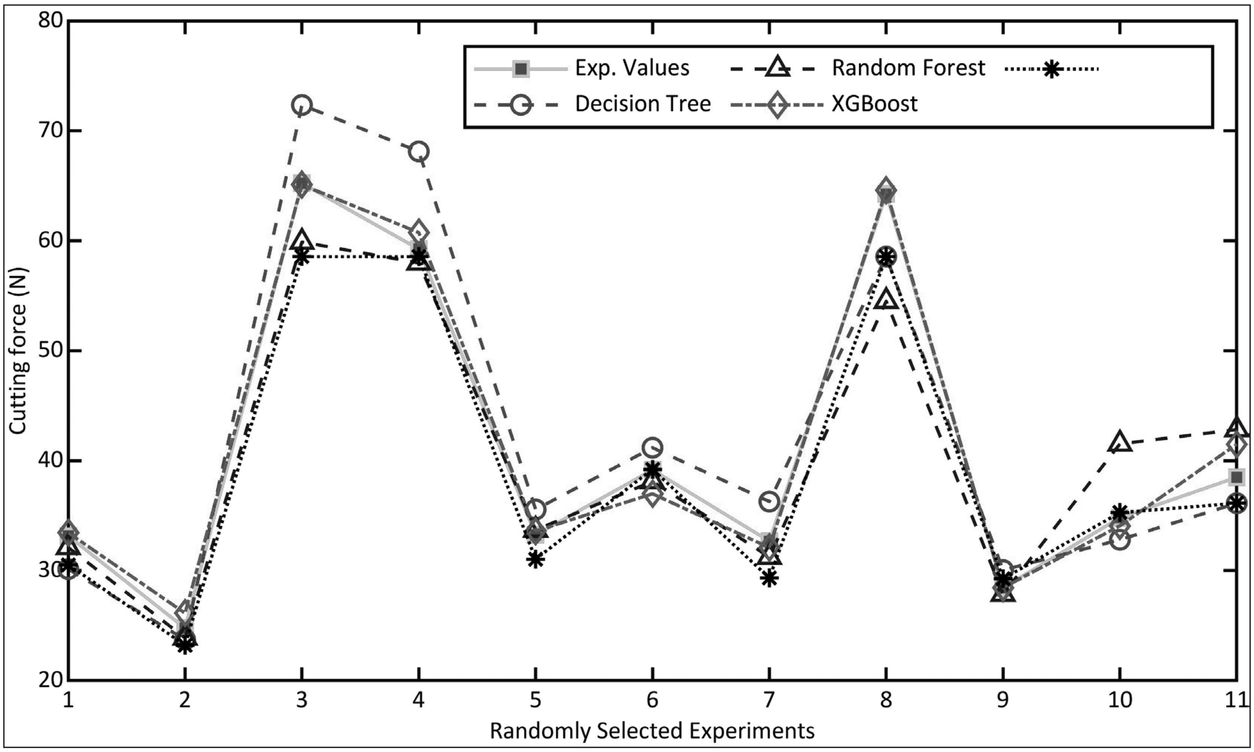

Fig. 7. Cutting force prediction with various ML models.

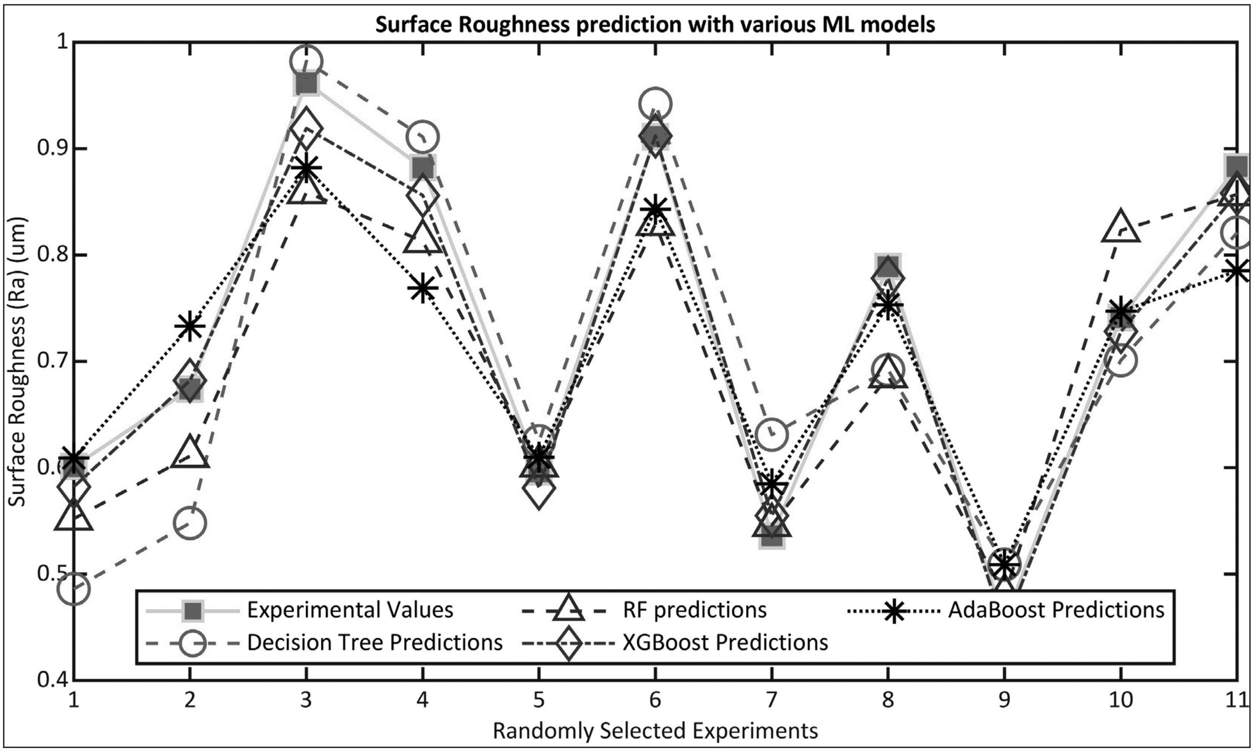

Fig. 8. Surface Roughness (Ra) prediction with various ML models.

determine tool wear. The process parameter data and the obtained performance parameter data was cleansed in order to train the ML models. The Pareto principle is used to split the data, that is 80% for testing and 20% for validation.

To effectively evaluate the model, the data was split so that none of the training data contained any of the testing data. Cutting force, surface roughness, and tool wear are employed as output data to train the ML models while process parameters,

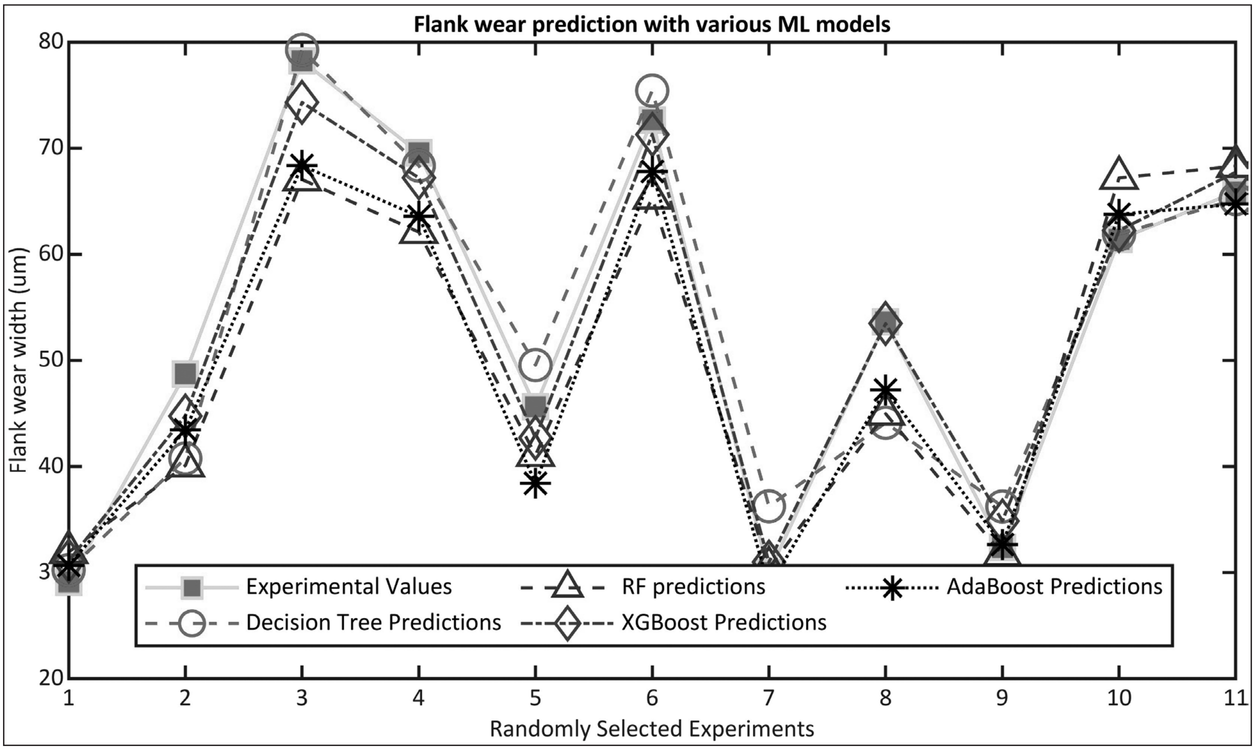

Fig. 9. Tool wear prediction with various ML models.

tool size, and texture design are used as input. These machine learning models were created using Python software, which was installed on a PC that had Windows 11, an i7 processor, and 16 GB of RAM. The performances of these ML models are evaluated in terms of prediction score and run time as listed in the table 3.

The cutting force, surface roughness and tool wear are predicted by utilising the developed ML models from randomly chosen Input variables from the experimental data set. The predicted values and the experimental values are plotted to visualize the performance of the ML models as shown in figure 7, figure 8 and figure 9.

5. Conclusions

This research initially studied the effect of textured inserts in micro turning of Ti6AL4V alloy, later four effective machine learning models namely Decision Trees, Random Forest, XGBoost and AdaBoost are developed for the prediction of cutting force, surface roughness and tool wear based on the type of texture, tool nose radius and cutting parameters. It was observed that reduced cutting forces, improved surface finish and less tool wear while machining with line textured inserts. The prediction performance and run time of the ML models are investigated and compared among them.

It is found that XGBoost and AdaBoost models performed better in prediction with score of 98.53% and 94.65% respectively. AdaBoost model took 195.16 milliseconds to run whereas XGBoost run in 40.67 milliseconds. Considering the importance in computational time and accuracy associated with other ML models, XGBoost model is best in prediction quickly.

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