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A Supervised Machine Learning Model for Tool Condition Monitoring in Smart Manufacturing

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ABSTRACT

In the current industry 4.0 scenario, good quality cutting tools result in a good surface finish, minimum vibrations, low power consumption, and reduction of machining time. Monitoring tool wear plays a crucial role in manufacturing quality components. In addition to tool monitoring, wear prediction assists the manufacturing systems in making tool-changing decisions. This paper introduces an industrial use case supervised machine learning model to predict the turning tool wear. Cutting forces, the surface roughness of a specimen, and flank wear of tool insert are measured for corresponding spindle speed, feed rate, and depth of cut. Those turning test datasets are applied in machine learning for tool wear predictions. The test was conducted using SNMG TiN Coated Silicon Carbide tool insert in turning of EN8 steel specimen. The dataset of cutting forces, surface finish, and flank wear is extracted from 200 turning tests with varied spindle speed, feed rate, and depth of cut. Random forest regression, Support vector regression, K Nearest Neighbour regression machine learning algorithms are used to predict the tool wear. R squared, the technique shows the random forest machine learning model predicts the tool wear of 91.82% of accuracy validated with the experimental trials. The experimental results exhibit flank wear is mainly influenced by the feed rate followed by the spindle speed and depth of cut. The reduction of flank wear with a lower feed rate can be achieved with a good surface finish of the workpiece. The proposed model may be helpful in tool wear prediction and making tool-changing decisions, which leads to achieving good quality machined components. Moreover, the machine learning model is adaptable for industry 4.0 and cloud environments for intelligent manufacturing systems.

Keywords: Tool wear monitoring; Machine learning; Support vector machines; K Nearest neighbour; Random forest; Silicon carbide tool insert; Flank wear; Smart manufacturing; Defence vehicles

1. INTRODUCTION

High Strength Steel (HSS) and advanced High Strength Steel (AHSS) are widely used as structural materials to acquire good mechanical strength for defense vehicles, bomb fragments, and buried charge shielding. In land-based warfare, kinetic energy penetrators, high-density materials such as tungsten are used to acquire kinetic energy to destroy the targets[1]. Machining is a common technique to achieve high precision and accuracy in dimensions to achieve the desired shape and precision of this defense equipment. Turning is a widely used machining technique for cylindrical components in which roundness, thread details, the eccentricity of surface finish strongly influences the behavior of the finished product[2]. The machining behavior and optimization of machining parameters lead to reducing manufacturing time and reduction of wear. EN8 grade is the most common grade of steel used in Bradley Fighting Vehicle, Abrams Tank, and other military vehicles. The machining of steel strongly influences the manufacturing of military vehicles. The machining of EN8 steels with ceramic tool inserts such as Silicon carbide, Titanium nitride-coated tools are widely used in drilling, turning, and other machining operations. Several studies were conducted in cutting tool wear monitoring based on real-time measurements such as cutting forces, the workpiece's surface finish, and vibrations. The tool wear, workpiece vibrations, workpiece surface roughness are predicted using Random forest, K Nearest Neighbor, and Support vector machine learning algorithms in the turning of EN8 steels using TiN coated silicon carbide tool inserts. The machine learning prediction value is very close to the experimental results. The effect of machining parameters on was studied turning of EN8 steel specimen.

The design of experiments was carried out using response surface methodology (RSM). EN8 steel cylindrical workpiece was machined with TiN Coated Silicon carbide tool insert and analysed the effect of machining parameters with surface roughness and flank wear of tool insert. The turning test dataset is applied in the machine learning model. The tool wear prediction accuracy was found more in Random forest machine learning than in other regression machine learning models. The experimental results show that feed rate mainly influences flank wear. Correlation analysis for surface roughness and flank wear was carried out and achieved 96.5 % accuracy. The effect of cutting parameters on the dry turning of EN8 grade steel

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specimen with Titanium nitride coated silicon carbide SNMG tool insert. Flank wear is measured for each trial using a profile projector and the wear.

Tool conditioning monitoring system using machine learning algorithms was developed using SVM, KNN, decision trees, Kernel Bayes, Multi-layer perceptron to forecast the flank wear of the end milling tool using cutting forces. The cutting forces were measured using a milling tool dynamometer and compared the accuracy of algorithms to the real-time wear rate of the end mill tool. The predicted results were compared with the benchmark datasets to validate the accuracy of the algorithms[3]. Turning experiments EN8 steels with silicon carbide tool insert and Titanium Nitride coated tool inserts were carried out to measure the surface roughness, vibrations, and cutting forces. The experimentation exhibited the flank wear was more in silicon carbide tool insert compared to Titanium Nitride coated tool insert[4].

This paper is organised as follows: Section 2 reviews the related work on data acquisition techniques on tool wear investigation in machining operations and the machine learning model on tool wear prediction. Evaluation of the prediction accuracy using MSE, RMSE, and R squared techniques. Section 3 introduces materials and methods which exhibit the experimentation techniques, experimental data acquired from the lathe tool dynamometer, and machine learning model computation framework. Section 4: discusses the effectiveness of the machine learning model and prediction accuracy using R squared, RMSE, and MSE. Section 5: provides the conclusion, includes the contribution of research and scope for future research.

2. RELATED WORK

Dahe, S.V[5] experimented with the tool condition monitoring and classification of wear using Random forest and FURIA (Fuzzy unordered rule induction) and Hoeffding tree statistical learning tools. The study includes feed, speed, and depth of cut, and defective and sharp tool inserts are classified using vibration signals. These extracted features are fed to a machine learning algorithm for wear classification. In this experimentation, the classification accuracy of 93.65 % has achieved using the random forest machine-learning algorithm. Oberlé, R., *et al.*[6] developed a machine learning model to predict the lifetime of the tool inserts. The predicted and actual wear has been compared using regression analysis and achieved an overall accuracy of 93 %. This experimentation is limited to the small amount of labeled data set. The accuracy of the results can be increased by collecting a high number of data. To increase the strength of the data sets and additional signals can be recorded. Schorr, S., *et al.*[7] developed a machine learning model for quality prediction of drilled and reamed bores by random forest technique based on the torque measurements. The accuracy of various machine learning such as CNN, SVR, AN, RF, and ABR has been compared in this experimentation. The learning curves of random forest and Pearson correlation have been exhibited in this study. The Random forest algorithm exhibited a good similarity with the actual and the predicted results. Gouarir, A., *et al.*[8]

A convolution neural network was adopted to predict the tool wear, machining of the stainless steel workpiece with a non-coated ball end mill in dry machining conditions to forecast the tool wear. The dataset has been reinforced using an adaptive control system to communicate continuously with the machine learning model. Cutting forces are measured using force sensors and fed to the machine learning model. The convolution neural network technique exhibits 90 % of prediction accuracy.

Segreto, T., *et al.*[9] implemented a wear assessment tool for turning Inconel 718 nickel alloy. The high dimensionality sensor data was obtained using multiple sensors and fed to an artificial neural network for cutting tool-changing decisions. Using a lathe tool dynamometer, cutting forces from the lathe machine and variations of cutting forces are observed concerning feed, spindle speed, and depth of cut. After pre-processing of signals, features are extracted, and sensor fusion pattern recognition has applied in the supervised neural network. Bergs, T., *et.al*[10] used digital image processing and deep learning techniques in tool wear prediction. The microscopic tool images and cutting force signals from the dynamometer are fed to the deep learning model to make tool-changing decisions. A convolution neural network has been used to train the cutting tool wear classifications model. The machine tool is integrated with the microscope to capture the tool wear images. Sensor data and microscopic images train the datasets.

The industrial environment is maintained with an automated tool wear prediction with 95.6 % accuracy. Ma, J., *et al.*[11] applied deep learning techniques to predict the online tool wear in milling the TC18 Titanium alloys. The combination of convolution neural network, long short term memory network (CNN + BILSTM), and Bidirectional gated recurrent unit (CNN + BIGRU) techniques adopted in milling tool wear prediction. Results achieved less than 8 % of error. Peng B., *et al.*[12] carried out a hybrid approach of deep neural network (DNN) to predict the cutting forces in orthogonal cutting. The cutting forces simulated in the finite element method, values trained in the machine learning model. The conventional model and hybrid machine learning model emphasized the hybrid approach of the machine learning model is more accurate, and the predictions obtained from the deep neural network model are validated using experimental trials. Patange, A.D., *et al.*[13] presented an investigation on the prediction of tool wear using a machine learning model on the vertical machining center. The vibration pattern of the faulty tool and defect-free tools are collected as vibration datasets. The model has been trained to predict the wear of the cutting tools. Statistical features were extracted using a visual basic environment and exhibited in decision trees generated by the J48 algorithm. In a nutshell, experimentation compares the machine learning classifiers and classifies the tool wear condition into six different stages[14].

The related work in tool wear predictions using machine learning algorithms such as Random Forest, KNN, SVR, and deep neural network models exhibits high potential in data-driven techniques. It helps in tool wear prediction and optimizes the machining process to obtain high precision and accuracy with less machining time. However, the prediction accuracy of the machine learning model varies with parameter tuning. For this reason, this paper explored the machine learning models with parameter tuned and evaluated using the statistical approach of Root mean square error (RMSE), R – Squared (R2), and Mean Squared Error (MSE). The back propogation techniques, J48 decision tree techniques, and multilayer perceptron technique results in prediction accuracy of 89.6 %, 77.22 %, and 82.5 % respectively[15]. The proposed random forest regression machine learning model yields 91.82 % of prediction accuracy.

The objectives of the article are summarized as follows:

- Build a machine learning model using Random Forest (RF), Support Vector Regression (SVR), and K Nearest Neighbour (KNN) to predict the tool wear and surface finish of the workpiece to make the tool changing decisions.
- Performance of the proposed machine learning model is compared with various machine learning methods, and statistical analysis is exhibited.

3. MATERIALS AND METHODS

The workpiece used in this investigation is EN8 grade steel, Brinell hardness number is 200-255 BHN. The unalloyed medium carbon steel has higher strength levels compared to bright steel. Due to the enhanced tensile strength, EN8 grade steels are widely used to manufacture shafts, pins, gears, studs. Bolts, keys, etc., can be machined in any condition[16]. The cutting tool inserts material used to machine the EN8 workpiece is the TiN coated silicon carbide tool insert (Sandvik model - SNMG120408). TiN coating of tool inserts achieved through physical vapor deposition method of 5 microns, which allows long time cutting with higher machining speed in stable conditions. On a right-handed SNMG PCLNR2525M12 tool holder, a tool insert was placed. The physical vapor deposition (PVD) coating technique is extensively used for finishing operations, has all-round properties and golden color[17]. The unalloyed EN8 grade steel requires a specific cutting force of 1400-3100 N/mm2. The EN8 steel specimen of diameter 50mm and length of 300 mm is held in the three-jaw chuck. TiN-coated SiC tool inserts are used in the turning tests. The coating thickness of 5 microns was achieved using the PVD technique. The cutting forces acting on three Cartesian coordinates (Fx, Fy, Fz) are measured through a lathe tool dynamometer[18]. The data acquisition system interfaced with the lathe tool dynamometer to measure the cutting forces, as shown in Fig. 1. The surface roughness of the machined workpiece is measured using Mitutoyo 178-923E SJ210 series surface roughness tester with the resolution of the XY resolution was 0.001 mm. The flank wear of the tool insert is measured using a profile projector. The data obtained from the 200 turning tests applied in the machine learning technique to predict the tool wear, Feed rate, and surface roughness leads to reducing flank wear with a good surface finish. The Tool wear pattern and grain structures are observed using scanning electron microscopy for higher and lower feed rates[19].

3.1 Machine Learning Model

Machine learning plays a dominant role in forecasting wear. Machine learning equips the manufacturing industry to produce the components with precision and accuracy. The tool-changing decisions at the right time can be achieved by the machine learning model assisting the manufacturing unit in increasing productivity. The algorithms like linear regression, K-Nearest Neighbour regression, Random forest, Support vector regression leads are widely used to build the machine learning model. The objective of the proposed method is to create the machine learning model using KNN, SVR, and RF using the independent variables of feed, spindle speed, and depth of cut to predict the flank wear, surface roughness, and cutting forces.[20] The prediction of dependent variables, precision and accuracy can make tool-changing decisions. The Random forest, Support vector regression, and KNN Machine learning models are developed. The datasets are trained using Python 3 google compute engine backend with CPU hardware accelerator in google collaboratory. The Numpy, Pandas sci-kit-learn, matplotlib packages in the python library are used for data handling, Pre-processing the dataset, training the models, and data visualization operations[21]. In the turning tests, flank wear, crater wear of the TiN coated SiC tool inserts, and surface roughness of the EN8 steel workpiece is measured for the corresponding feed rate, depth of cut, and cutting speeds. In the machine learning (ML) model, support vector regression (SVR), K–Nearest Neighbour (KNN), and Random forest regression techniques are used to frame the ML model in a google collaboratory environment[22].

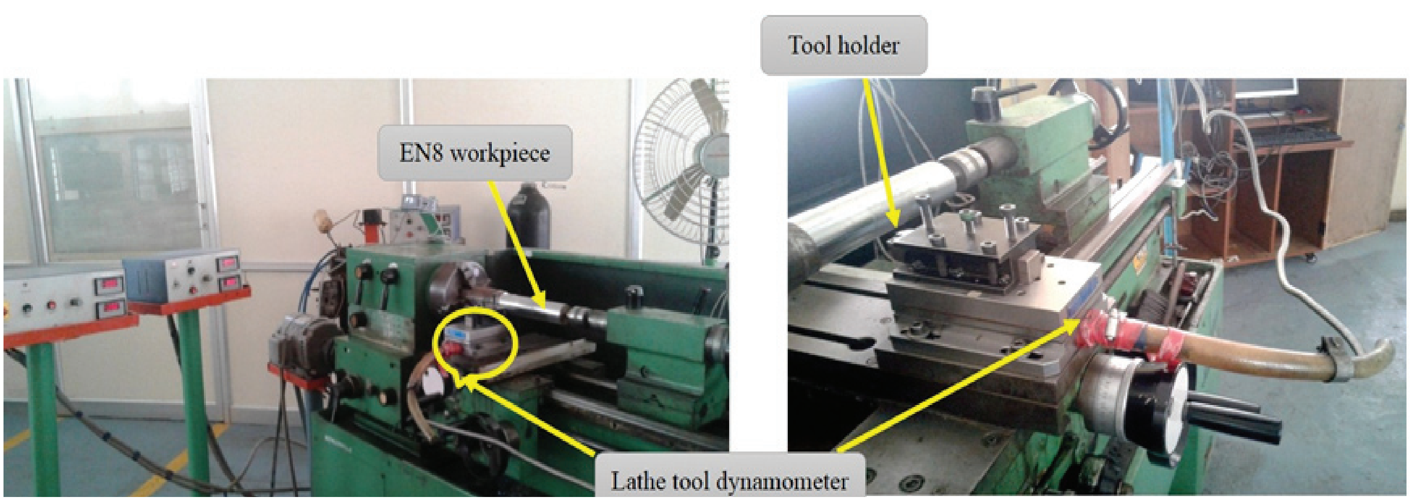

Figure 1. Experimental setup.

3.2 Support Vector Regression (SVR)

Support Vector Machines (SVM) are widely used supervised machine learning algorithms. Vapnik and co-workers developed the original support vector machine[23]. A hyperplane or a set is constructed in the support vector machine and used for classifications regression. The hyperparameter strongly influences the quality of the machine learning model. Kernel, hyperplane, and decision boundaries are the hyperparameters in model building. In the pre-processing stage, feature scaling of the turning data set is acquired to normalize the data within the range[24]. The SVM is fitted to the machining dataset and predicts the new results for the test dataset using the SK-learn library. The prediction framework of SVR is exhibited in figure 3. The prediction accuracy of the test data is evaluated statistically using RMSE, R squared values. The objective of the support vector regression model is to reduce the sum of squared errors. The objective function for ordinary least square (OLS) for simple linear regression is given in Eqn. (1)

$$MIN\sum_{i=1}^{n}(y_i - w_i x_i)^2 \tag{1}$$

where y_i is the target w_i is the coefficient and y is the predictor. Support vector regression is a powerful algorithm in which the acceptable range of errors and flexibility can be determined. The hyperplane in higher dimensions can be determined to fit the data[25]. The flank wear for the respective spindle speed, feed rate, and depth of cut of the machining operations is recorded in the dataset, and a support vector regression model is developed to visualize the acceptable range of errors.

3.3 K–Nearest Neighbour Regression Algorithm

The K nearest neighbor algorithm is used in supervised machine learning classification and regression tasks. The algorithm is based on the number of nearest neighbors. From sklearn packages, nearest neighbor regression fits are developed, neighbour parameters as 5, The Minkowski metric is used and p=2, equivalent to Euclidian distance. Minkowski metric power factor is 1, equal to Manhattan distance (l1) and Euclidean distance (l2), and arbitrary p, lp is used. Test sizes of 20 %, 30 %, and 40 % are varied in the algorithm, predicted results are compared with the experimental data and analyzed statistically by R squared RMSE methods to evaluate the prediction accuracy[26].

3.4 Random Forest Regression Algorithm

The Random forest regression machine learning algorithm is used to train the turning datasets. The predictions from the multiple machine learning algorithms are assembled to make an accurate machine learning model. The schematic predicting technique is exhibited in Fig. 2. The number of trees, number of nodes, number of leaves, number of depth are the hyperparameters considered for tuning the accuracy of the machine learning model. K fold - cross-validation technique is used in the evaluation of predicted results. The regression score is determined and evaluated using R squared and RMSE statistical approach[27].

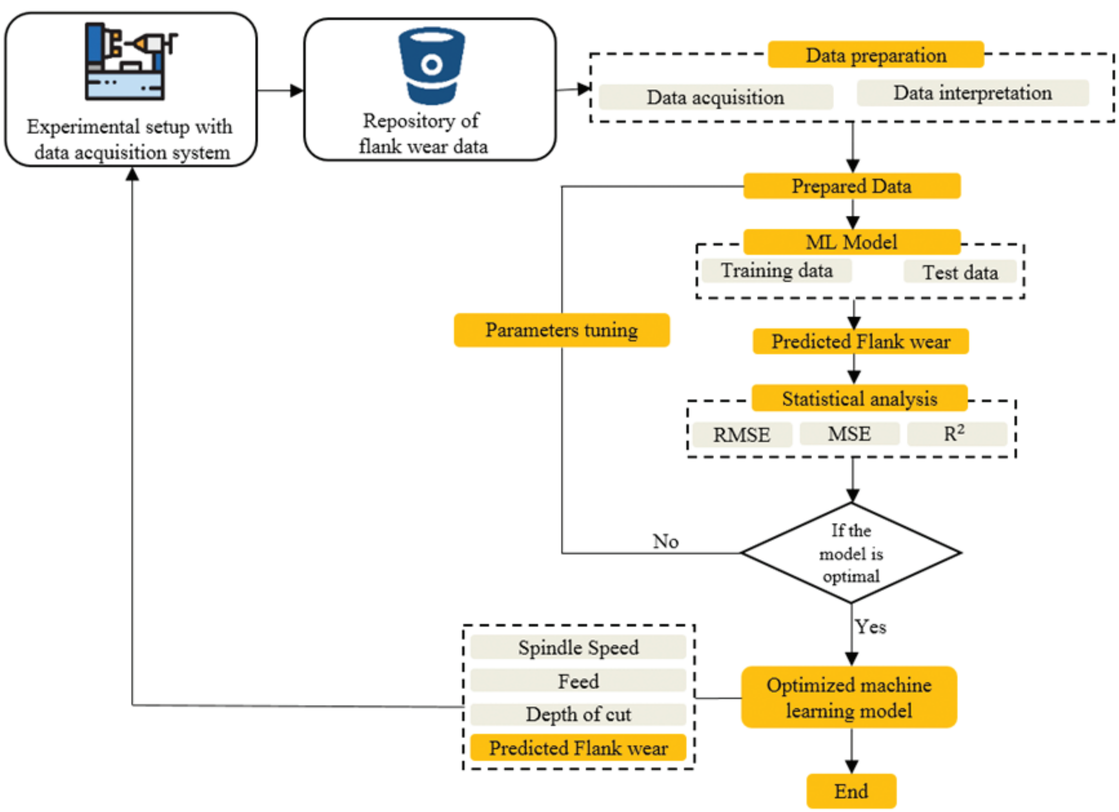

Figure 2. Schematic diagram of proposed model for tool wear prediction.

The data received from the experimentation through data acquisition is stored in the repository, and the dataset is prepared using pre-processing techniques such as scaling and transformations. The prepared dataset is imported to the google collaboratory interactive python notebook. The SVR, RF, and KNN regression is applied to predict the flank wear, surface roughness, and cutting forces in X, Y, and Z directions. Spindle speed, feed rate, and depth of cut are considered predictors, and flank wear, surface roughness, cutting forces are taken as a response[28]. Based on the R2 values obtained in each ML model of RF, SVR, KNN are evaluated. In the RF model, the number of trees, leaves, and child nodes are tuned to achieve maximum R2 values. The tuning iterations are carried out in a google collaboratory python notebook for ten trials. The results are exhibited in the table for RF, SVR, and KNN.

4. EVALUATION OF MACHINE LEARNING MODEL USING R- SQUARED VALUE

The R- Squared values are from 0 to 1, generally stated in percentages from 0 % to 100 %. The values are closer to 1 exhibit a better prediction model. The machine learning model is evaluated in R squared based on squared residuals and squared difference.

$$R^2 = 1 - \frac{SS_{Residual}}{SS_{Residual}} \tag{3}$$

$SS_{Residual}$ is sum of the squared residuals and SS_{Total} sum of the squared difference from the mean of the target variable.

5. DISCUSSION

While machining the EN8 steels with TiN coated silicon carbide tool insert under dry conditions, the surface roughness of the workpiece, flank wear of tool insert cutting forces in X, Y, and Z Cartesian coordinates are recorded. Turning tests exhibit the flank wear increases with increasing feed rate. Flank wear is measured using a profile projector. Grain structures are analyzed using the scanning electron microscope. The depth of cut is increased in 0.5 steps from 1 mm, cutting speed is increased from 250 rpm to 1250 rpm in 5 steps. Using regression model and curve fitting technique the correlation between the turning parameters and tool wear is related. The goodness of fit is validated using R^2 values which yields 96.2 %. The following regression equation shows the correlation between the cutting speed, depth of cut, and feed rate. The feed rate strongly influenced the tool wear, followed by the depth of cut and cutting speed.

Wear = - 0.748 + 1.42 Feed rate + 0.295 Depth of cut + 0.000013 Speed

The experimental tool wear and predicted tool wear using the Random forest algorithm are depicted in Fig. 3. The Random forest technique shows more R squared values than the support vector machines and KNN models. The R squared values of 91.82 are achieved for the tool wear prediction using a random forest algorithm for 90 % of the training data set. The machine learning model results show that the prediction accuracy increases with the training dataset. The training dataset rose from 75 % to 90 %. It was observed that hyperparameter tuning in machine learning algorithms leads to predict more similar results after 90 % of training data. The saturation region followed after the ten trials of hyperparameter tuning. The estimated tool wear using KNN and SVM algorithm with experimental tool wear is depicted in Figs.4 and 5. The surface roughness predictions similar to the tool wear prediction are exhibited in Figs. 6, 7, and 8 for SVM, Random forest, and the KNN algorithm. The plot reveals the closeness of the predictions with the experimental turning tests with an R squared value of 91.82 %. The variation of R-Squared values for the Train dataset is exhibited in Table 1.

Table 1. Variation of R-Squared values for train dataset

Trials	R-Squared Values for Train dataset								
	75%			80%			90%		
	RF	SVM	KNN	RF	SVM	KNN	RF	SVM	KNN
1	80.26	75.65	71.32	85.95	76.64	71.89	85.82	81.56	73.65
2	81.65	76.48	75.65	86.54	78.92	72.32	86.54	82.15	74.65
3	82.36	77.89	76.45	87.21	80.44	75.32	86.95	82.65	75.45
4	83.45	78.64	77.56	88.97	81.64	76.65	87.54	83.12	76.21
5	84.65	79.46	78.45	89.91	82.46	77.65	87.23	84.56	77.54
6	86.64	80.45	79.21	90.15	83.45	80.65	88.12	85.78	78.65
7	87.56	81.64	80.64	90.56	84.65	81.65	88.45	86.45	79.45
8	88.94	82.46	81.94	91.56	89.54	82.64	89.65	87.56	80.65
9	89.64	83.64	81.65	91.75	90.52	85.64	90.54	88.45	84.65
10	89.65	85.64	81.76	91.98	90.95	85.64	91.82	89.94	85.64

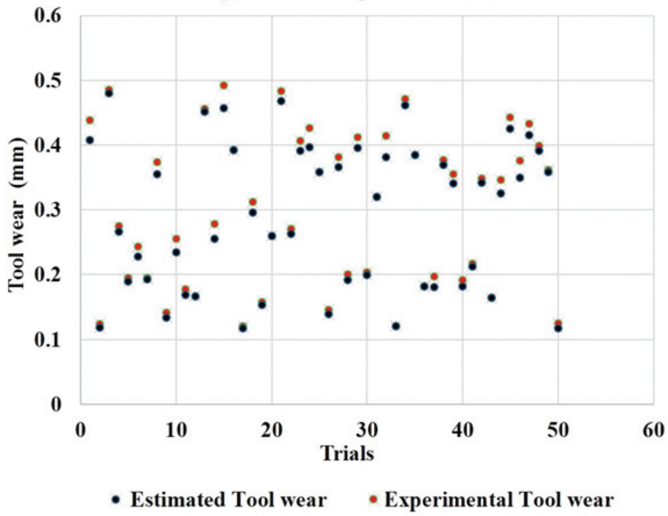

Figure 3. Estimated tool wear by random forest machine learning algorithm Vs experimental tool wear .

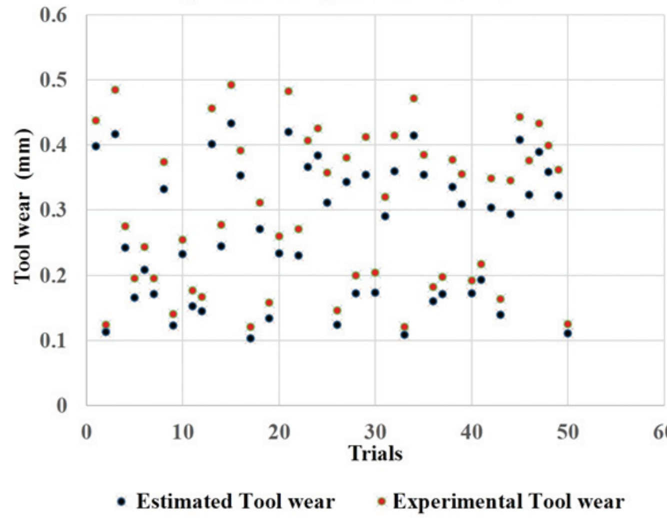

Figure 4. Estimated tool wear by KNN machine learning algorithm Vs experimental tool wear.

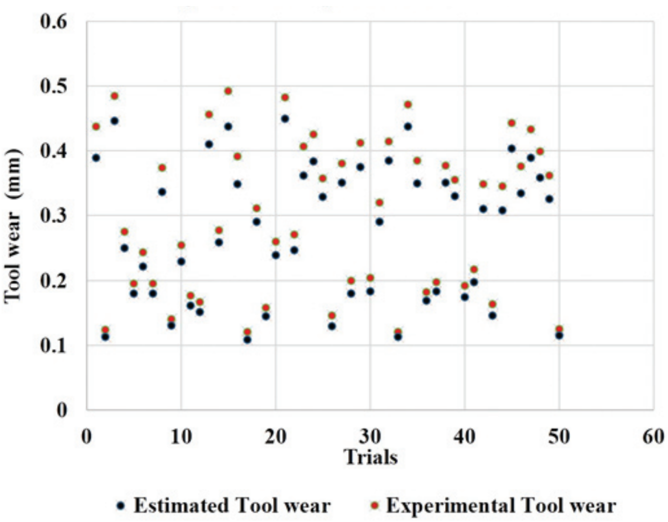

Figure 5. Estimated tool wear by SVM machine learning Vs experimental tool wear.

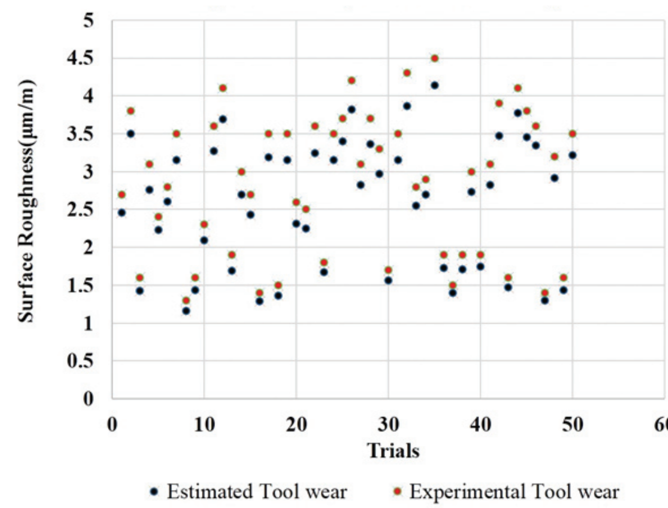

Figure 6. Estimated surface roughness by SVM machine learning algorithm Vs experimental surface roughness.

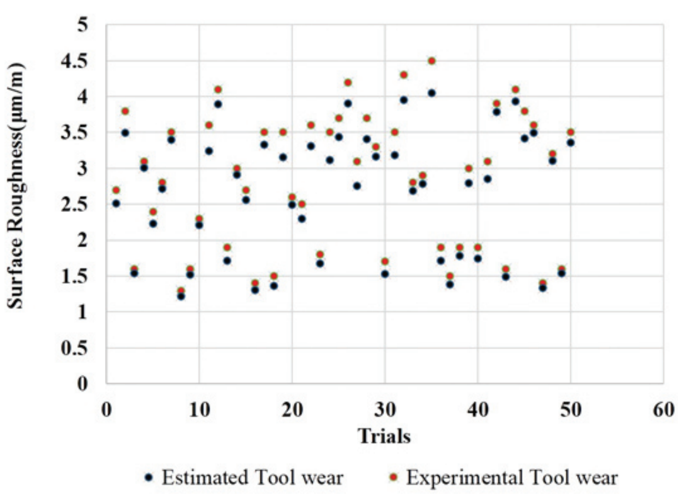

Figure 7. Estimated surface roughness by random forest machine learning algorithm Vs experimental surface roughness.

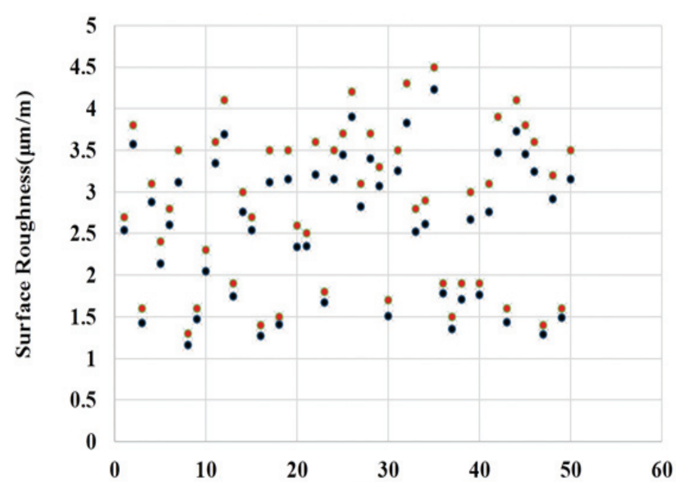

Figure 8. Estimated surface roughness by KNN machine learning algorithm Vs experimental surface roughness.

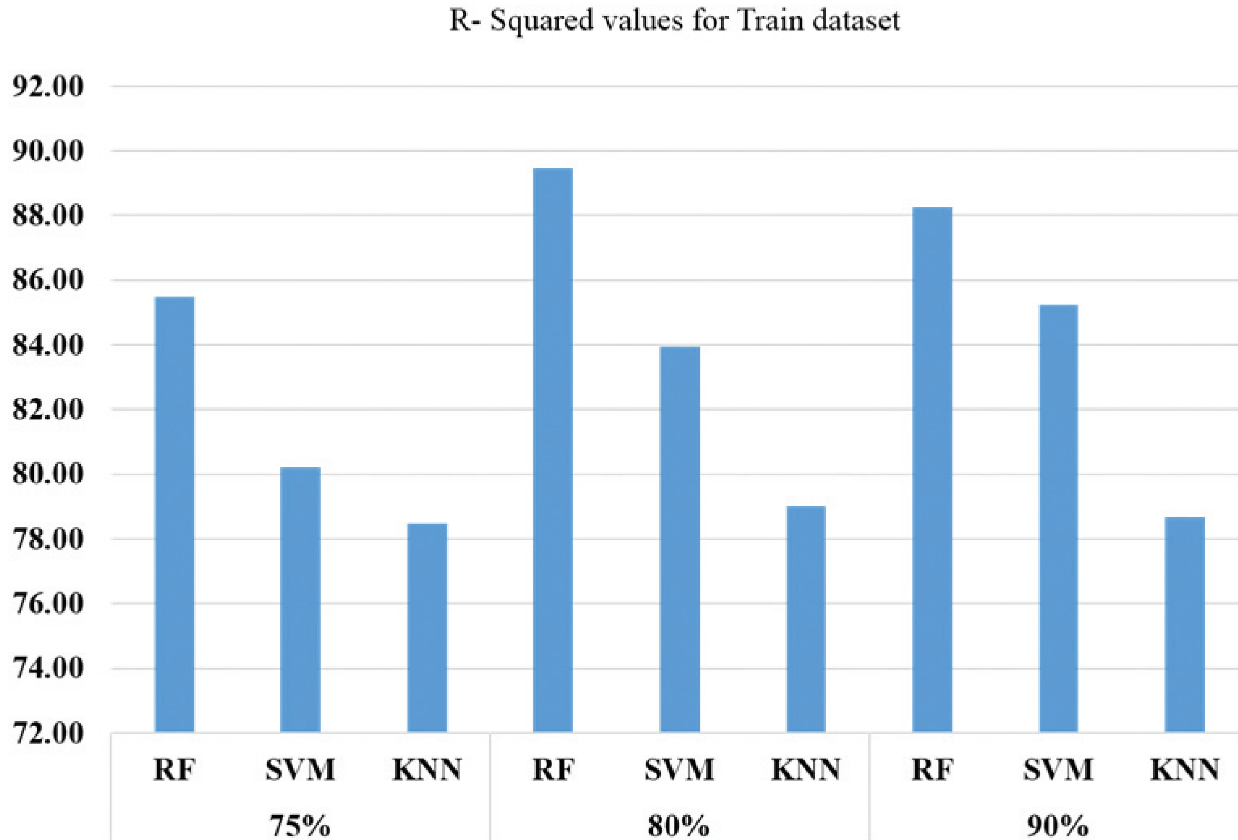

Figure 9. Variation of R-squared values for train dataset for tool wear.

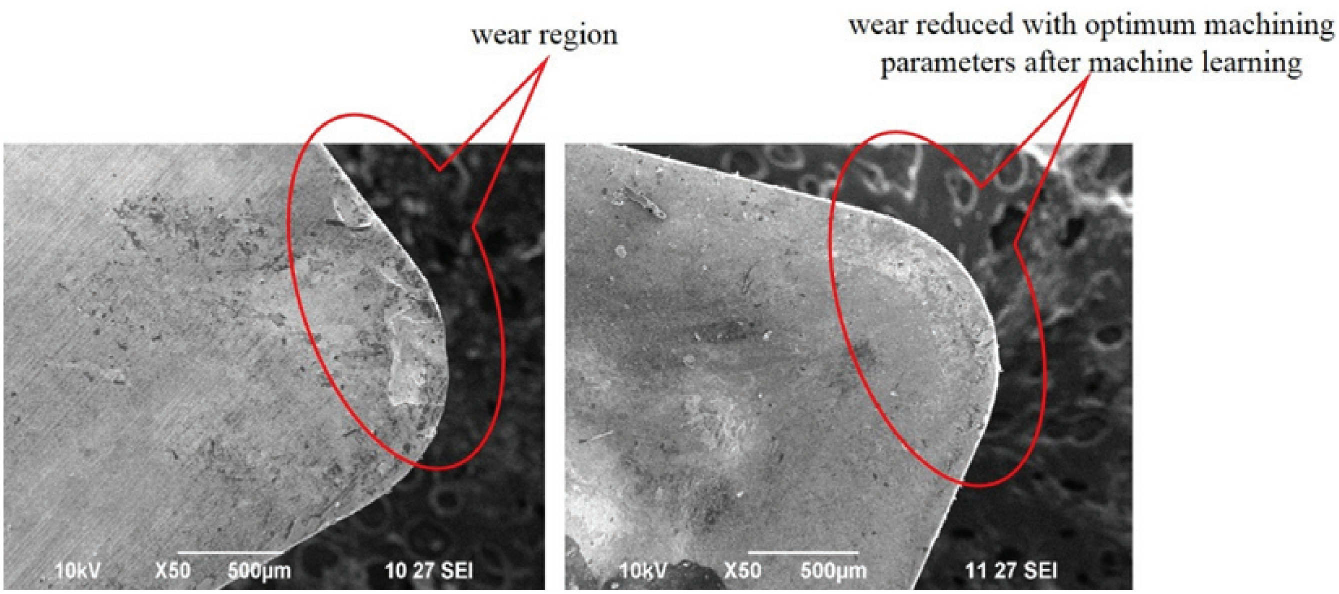

Figure 10. Micrographs of tool inserts after turning tests before and after optimisation of machining parameters.

The R squared values for 75 %, 80 %, and 90 % of the training dataset are exhibited in Fig. 9. which shows random forest algorithm is higher than the KNN and SVM. The feed rate of 0.14 mm/rev, cutting speed of 30 mm/min, depth of cut 1 mm are the turning parameters before optimisation yields the wear of 0.58mm. The feed rate of 0.7 mm/min, depth of cut of 0.5 mm, and spindle speed of 250 rpm are turning parameters after optimisation which leads to the tool wear of 0.18 mm as shown in Fig. 10.

6. CONCLUSION

In the present study, various machining parameters such as cutting speed, depth of cut, and feed rate is considered. The surface roughness of the workpiece, flank wear of the tool insert in dry cutting of EN8 steel with TiN coated silicon carbide tool insert were analyzed. In a supervised machine learning model, the wear prediction ability is investigated. Based on the results obtained, the following conclusions were drawn.

- Tool wear is strongly influenced by the depth of cut and slightly influenced by the depth of cut
- The surface roughness of the workpiece is influenced by cutting speed. The Surface finish is high at higher cutting speeds and vice versa.
- In the machine learning model, Random forest regression with 90 % of training data achieves (91.82 %) of the accuracy of flank wear with the experimental results.
- Random forest machine learning model exhibits more accurate results compared to KNN and Support vector regression models
- In Training of machine learning model, more number training data increases the accuracy of results compared to experimental data.
- The advantage of the proposed machine learning model is easily used in industrial use case applications for tool wear prediction.
- The prediction model is industry 4.0 ready and can be easily applied in digital manufacturing to increase the productivity of the manufacturing industries.

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