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IMPROVING QUALITY OF PREDICTIVE MAINTENANCE THROUGH MACHINE LEARNING ALGORITHMS IN INDUSTRY 4.0 ENVIRONMENT

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A B S T R A C T

Smart manufacturing is the modern form of manufacturing that utilizes Industry 4.0 enablers for decision making and resources planning by taking advantage of the available data. With the advancement of digitalization and industrial machine connectivity, it is now feasible to gather data in real-time from a variety of sensors (e.g. current, acoustic, vibration etc.) while the process is being carried out. The aim of the paper is to propose a framework for predictive maintenance PdM 4.0 and validate the framework by implementing it for a manufacturing process, milling in which a public data set from NASA repository is used to build and test the proposed PdM 4.0 system. The various machine learning classifiers such as: support vector regression SVR, RF, DT, XGBoost and MLP regressor have been used for remaining useful life and tool wear rate prediction. The model evaluation and comparison is based on metrics like (R- square), root mean square error and mean absolute error.

1. INTRODUCTION

Today's manufacturing organisations are under pressure to be more flexible, reduce downtime and costs and increase efficiencies. In addition to making new investments in production and technology, data-driven manufacturing companies are responding to these pressures by leveraging the capabilities of artificial intelligence (AI), the industrial internet of things, (IIoT), cloud computing technologies and innovations in smart measurement and quality data management systems—resulting in greater visibility into their operations. Today, poor maintenance strategies can reduce a plant's overall productive capacity by 5 to 20 %. Recent studies also show that unplanned downtime is costing industrial manufacturers an estimated $50 billion each year.This begs the question, "How often should a machine be taken offline to be serviced?" Traditionally, this dilemma forced most organizations into a trade-off situation where they had to choose between maximizing the useful life of a part at the risk of machine downtime (run-to-failure) or attempt to maximize uptime through early replacement of potentially good parts (time-based preventive maintenance), which has been demonstrated to be ineffective for most equipment components. Artificial Intelligence (AI) is already transforming manufacturing by outperforming humans in its ability to provide insights that inform timely, data-driven decisions and productivity improvements. In some operations, it looks for conditions like idle equipment or scheduled maintenance in order to make decisions about reassigning parts measurement.

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Industry 4.0 which is focused on the interconnectivity of the system through the digitalization of industry, the amount of data generated by the sensors is enormous and there is a lot of information which can be gathered after applying proper techniques. Industry 4.0 comprises of two sections, the front-end technologies address four dimensions: smart manufacturing, smart products, smart supply chain, and smart working, whereas base technologies consider four elements: Internet of Things, cloud services, big data, and analytics are all buzzwords these days (Frank, Dalenogare, & Ayala, 2019). It contains a wide scope of processes, systems and technologies that are primarily relevant to industry's digitalization. The four technologies that are related to the data and it's processing comprises of Industrial Internet of Things (IIoT), Cyber Physical Systems (CPS), Cloud Solutions & Decentralized Services, and the Big Data & Stream Processing which is responsible for processing the enormous amount of data generated from the production lines (Nabati & Thoben, 2017; Tao, Qi, Liu, & Kusiak, 2018). Techniques like machine learning is a feasible way for overcoming many of nowadays major problems in complex production systems. These data-driven approaches can detect patterns which are highly complex and non-linear from the data, comprises of variety in nature and sources, and then transform this raw data collected into feature spaces, or models, which can subsequently be used for prediction, identification, classification, regression, or forecasting (Siddhpura & Paurobally, 2013; Wuest, Weimer, Irgens, & Thoben, 2016).

Data-driven concept of PdM has been applied vastly in the sector of industrial manufacturing with the help of machine learning algorithms, such as linear regression (LR), support vector machine (SVM), decision tree (DT) or random forest (RM), and neural networks (NN) (Wuest et al., 2016; W. Zhang, Yang, & Wang, 2019). Previous research, on the other hand, has mostly concentrated on a single type of sensor measurement, on a single learning method, and on dataset generated by performing computer simulations or from performing private experiments. Besides this, not many addressed cutting machine maintenance, while the majority of work is focused on bearing or motor failure detection. In the work of (Lee et al., 2019) health monitoring of two machine tools, cutting tool and spindle motor bearing is done using SVM and artificial neural network (ANN) respectively. ANN was trained and established to acquire the characteristics of backlash error under normal wear and tear for a certain machine centre, and the backlash error was predicted (Li, Wang, & Wang, 2017). Authors (Madhusudana, Kumar, & Narendranath, 2017) have used sound signal for the monitoring and for the classification of the condition of face milling tool, SVM is performed on the extracted discrete wavelet transform features. SVM is used in a variety of applications, including condition monitoring of tool/machine, fault detection and tool wear (Widodo & Yang, 2007; Wuest et al., 2016). PdM system has been developed and implemented in real production line (Ayvaz & Alpay, 2021), RF and Extreme Gradient Boosting (XGBoost) were the two top performers among six selected algorithms.

Following are the main contributions of the work presented in the paper.

- Development of a framework for implementing data driven PdM 4.0 using machine learning methods
- Implementation of the framework on a manufacturing process and finally comparing the prediction performance of machine learning classifiers

2. PROPOSED FRAMEWORK FOR PREDICTIVE MAINTENANCE

Figure 1. presents the details of the proposed framework. The paragraphs discuss the various phases in the framework. The framework covers data collection, data pre-processing, feature engineering and finally building ML model and its improvement for estimating the tool heath so that correct maintenance decision could be taken.

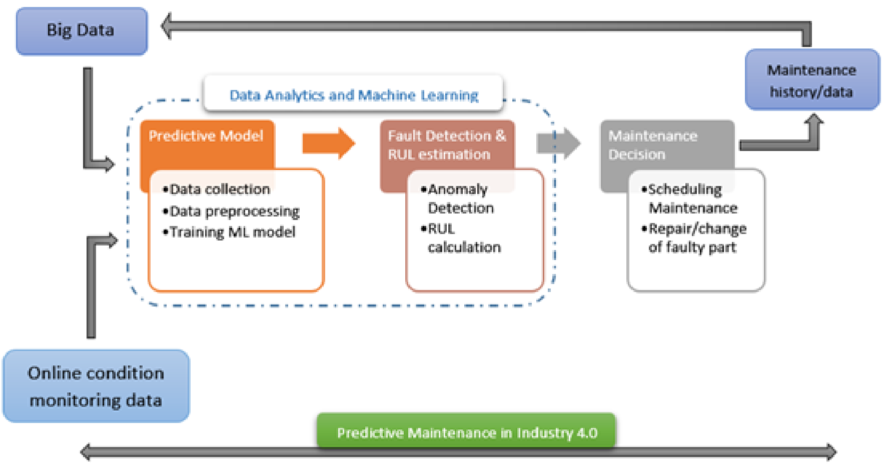

Figure 1. Framework for implementing PdM 4.0

2.1 Data collection

Data is gathered in numerous ways from various sources. Above all, it is collected through the Internet of Things, which allows data generated from various equipment and product acquired quickly via various technologies like radio frequency identification, sensors and other monitoring devices, allowing for real-time monitoring of equipment and product health (Caesarendra & Tjahjowidodo, 2017; Y. Zhang et al., 2015).

The huge amount of data gathered throughout manufacturing operations must be properly kept and integrated. In general, industrial data can be divided further into three categories: first include the segment where data is saved in the format of tables, symbol, digit etc. known as structured. Second type uses graphs, tress, documents in XML format etc. called as semi-structured and the third comprised data store in the format of image, audio and video etc. known as unstructured data.

During CBM data stored is of two different cases which can be classified into two categories namely the event data and condition monitoring data. The event data tells about the events like breakdown, repair, installation and overhaul and its causes, what corrective actions have been taken and on the other side the condition monitoring data are measurements related to the state of a physical asset or the health condition. Data for condition monitoring can be collected in a variety of ways including pressure, vibration, acoustic, oil analysis, temperature, moisture, content using sensors.

2.2 Data Pre-Processing

To make intelligent and sensible decisions, data should be turned into a form of useful information and knowledge. The major steps which are generally involved in data pre-processing stage includes data cleaning (removing the unnecessary or correcting faulty readings), data integration (merging data from various sources). Data cleaning aims to address the problem of missing values and duplicate data.

The raw data normally comprises of outliers and is to be treated before building a model as it could negatively affect the model accuracy. According to (Zonta et al., 2020) the outlier is checked using the inter quartile rule. Interquartile range, for a distribution is the difference between or the data present in the third quartile and the first quartile of that distribution. It tells about the distribution of data and how wide is the distribution. As depicted in Figure 2, the points which are falling outside or are not in range of the box plot are termed as outliers and should be removed.

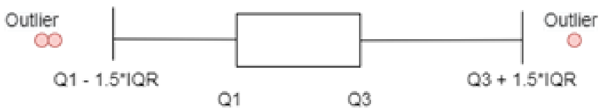

Figure 2. Outlier detection using interquartile range

2.3 Feature Engineering

The machine leaning algorithms need input data on the basis of that output is generated. So this input data is composed of structured columns also called as features. For the case of supervised machine learning algorithms with the help of these features the prediction is done thus feature engineering is required to made the data compatible with the ML algorithms and it also improves the performances of the ML model as well.

Feature generation is basically a process of transformation of the data to generate meaningful features which are more suitable input for ML algorithms. In the analysis of time domain, the response parameter is presented as function of time (Ambhore, Kamble, Chinchanikar, & Wayal, 2015). The time waveform is directly used in time-domain analysis. Traditional time-domain analysis derives descriptive statistics like maximum, mean, standard deviation, peak-to-peak interval, crest factor, skewness, root mean square and kurtosis from time waveform data. These characteristics are known as time-domain characteristics (Jardine, Lin, & Banjevic, 2006).

2.4 Training ML model

The data after being pre-processed is now ready for the purpose of training the ML model. For the case of supervised ML algorithms, the data comprises of dependent variables, which is generally the output and more than two independent variables which are the features. This section describes a prediction model for the monitoring of tool's condition along with the remaining useful life is presented using the historical data. For the purpose of training and testing the model, the processed data is randomly divided into training data, which comprises of 70% of the complete data and rest 30% is taken for the testing the ML model. Our study focusses on the regression task so for this some supervised ML algorithms like support vector regression (SVR), random forest (RF), decision tree (DT), Extreme Gradient Boosting (XGBoost) and MLP regressor (MLP) are chosen for the training and testing purpose. Same ML algorithms are utilized for RUL and tool wear prediction. ML model needs improvement before using getting into action in order to improve and boost the performance of the model this is achieved by the Hyperparameter Tuning. Most commonly used methods for hyperparameter tuning are manual search and grid search. As per the study (Wall, Rechtsteiner, & Rocha, 2005) manually selecting the parameters for tuning is more efficient than grid search. So to get the best performance for the ML model, iteratively check the suitable parameter.

2.5 Prediction and Maintenance Decision

After the various ML algorithms have been trained and are tested on the basis of the evaluation metrics the best performing ML model has to be chosen for predicting the condition of tool and RUL. Since the model have been trained using the historical data, when new unseen data from online monitoring will come, tool wear and RUL of tool can be predicted so that the right decision could be taken within the time, regarding the tool change or replacement so that minimum maintenance cost, fewer production stop and better surface quality can be achieved. For the case when tool is changed too soon before it reaches the end of its usable life, making it impracticable to completely exploit the tool's useful life. In another scenario, tool fails before it is replaced, resulting in unanticipated downtime and degraded surface finish.

3. PREDICTIVE MAINTENANCE (PDM 4.0) FRAMEWORK APPLICATION

The case selected is the data set related to the milling operation prepared by (Bergstra & Bengio, 2012) in the “Prognostic Center of Excellence (NASA – PCoE)”. The data set is generated by different experiment situation and runs on a milling machine under different operating conditions which are combinations of different feeds, depth of cut and material of work-piece. For all types of cuts i.e. entry cut, regular cut and exit cut, tool wear (flank wear) was investigated for all types of cuts and as a result the flank wear of milling insert was measured and noted down. Three different types of sensors are used for data sampling and are placed at several positions. Vibration sensors, acoustic emission sensors, and current sensors are used for data sampling, resulting in recording of 167 data samples. The data is formatted in a matlab structure of 1x167 array with different fields and their notation used is shown in Table 1 and each field of the 6 sensors reading consists of 9000 data points. The notation of the sensor signal are also shown in Table 1. Total 16 cases are present with varying number of runs. CI stand for Cast Iron and SS stands for Stainless Steel. The flank wear is measured at irregular interval of time sometimes up to a wear limit and sometimes even beyond the wear limit. When no measurement of flank wear is taken, no entry of flank wear has been made.

The experiment were conducted on Matsuura machining center (MC) at 510 V which is a vertical CNC milling machine. A cutter with six number of inserts and KC710 was selected as the insert for milling cutter as per the recommendations for roughing. The insert KC710 is coated with three different layers of titanium carbide (TiC), titanium carbonitride (TiC-N) and titanium nitride (TiN) all these three materials are used in sequence. Acoustic emission sensor and vibration sensor each are mounted on table as well as on machining center’ table. The selection of the parameters for the experiment was guided by industrial applicability and as per the settings recommended by manufacturer. Cutting speed chosen 200 m/min or 826 rev/min. Depth of cut selected was 1.5 mm or 0.75 mm. The selected feed was 0.5 mm/s and 0.25 mm/s. Cast iron and stainless steel were the two choices selected for work-piece material. The dimension of the work-piece was 483×178×51 mm.

Table 1. Description of the fields in the data set

Notation	Description
R	Counts the number of runs for which the tool has been used for machining
C	Different number of cases ranging from (1,16)
T	Time duration of each run of experiment
W	The measurement of flank wear (mm)
F	Feed, two different values were chosen
M	Work piece material
D	Depth of cut, two different values were chosen
a	Alternating current reading from the spindle
b	Direct current reading from the spindle
c	Vibration signal generated from the table
d	Vibration signal generated from the spindle
e	Acoustic emission generated from the table
f	Acoustic emission generated from the spindle

3.1. Data preprocessing

To eliminate incorrect, duplicate, redundant and inconsistent data, it must be preprocessed. The following activities are included in data cleaning: format, duplication, missing value, and junk data cleaning. After observing the data file which has the readings from sensors, there are many cases in which the tool wear VB is not measured thus the data set have some missing values in the VB measurement, so the entire row has been deleted.

The readings which are recognized as outlier have already been removed during the data cleaning method because the flank wear associated with those reading was not present in the data, hence the complete row was deleted and outlier signals were also removed. Each field entry in the signal was treated with a fill outlier in which a clipping fill method in MATLAB was used where the outliers were detected and the data points lying inside the percentiles specified in the threshold of the fill outlier are kept. For the example first case of 2nd run spindle AC current signal in Figure 3 shows how the signal looks before and after the outlier treatment.

In the data set the variable material is a categorical variable, work-piece material cast iron is assigned numerical value 1 and steel as 2, that needs to transformed because it can degrade the ML algorithm performance, so for this one hot encoding is used to transform it into numerical variable.

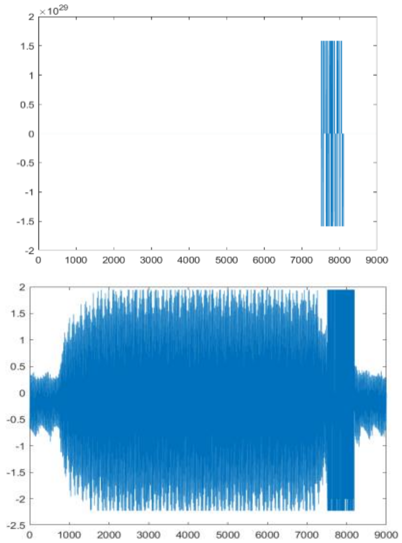

Figure 3. Signal before (left hand side) and signal (right hand side) after the outlier treatment

3.2. Feature Engineering

During the feature extraction stage, the most appropriate features are extracted from the sensor signals that correlate well with tool wear and are unaffected by process circumstances. The characteristics in the literature are primarily generated from the frequency, time, time–frequency, or statistical domains, but we are focusing on time domain features in this work. As per the work of (Siddhpura & Paurobally, 2013) it is mentioned that most of the publications has used the time domain features and offer a great level of ease for the extraction purpose. Time domain features are extracted for 6 sensors leading to a total of 54 numbers of time domain features. Notation is also added has been used in the work so that it is easy to understand features have been selected.

The Figure 4 shows the features selected based on f_score for building the ML model based on XGBoost as it was outperforming as compare to other. Out of all the 59 features the top 20 features were selected for predicting the flank wear. From sklearn which is a open source library for machine leaning, Select Kbest class has been used in which the method of f_regression has been applied reduce the number of features. The table A.1 and table A.2 describes about the selected features for tool wear and RUL prediction. The Figure 5 shows the features selected on the basis of f_score for building the ML model base on XGBoost as it was outperforming as compared to other algorithms as mentioned in the Chapter 5. Out of all the 59 features the top 20 features were selected for predicting the RUL. Again SelectKbest class has been used in which the method of f_regression has been applied reduce the number of features

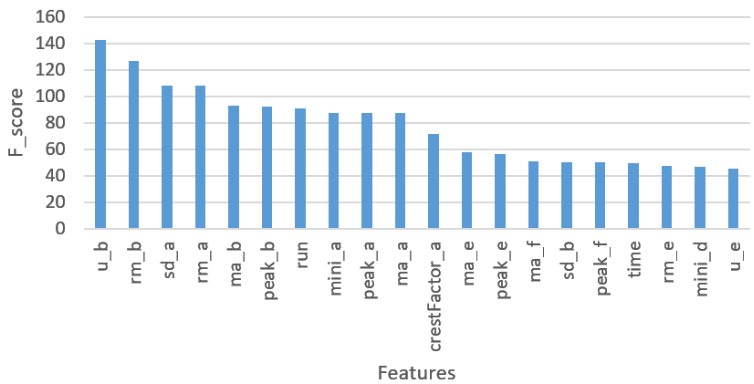

Figure 4. Selected features for building the ML model for tool wear prediction

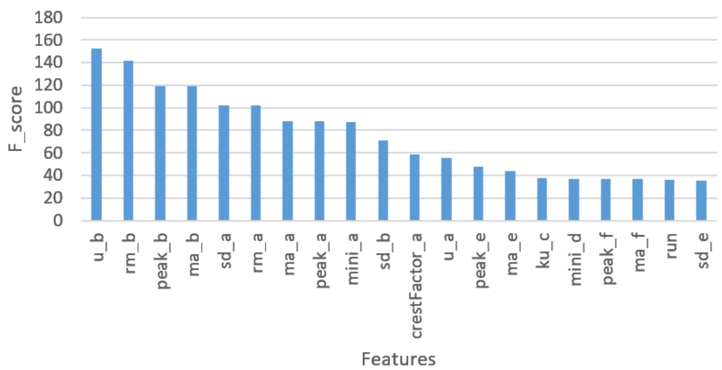

Figure 5. Selected features for building the ML model for RUL prediction

3.3. Training ML model

The cleaned and simplified data is then used in data analysis and mining to generate new information when data reduction is completed. Machine learning, large-scale computation, and the usage of forecasting models are just a few of the techniques that can greatly improve the effectiveness of data analysis (Tao et al., 2018). In the examined literature, the most commonly utilized ML algorithms are SVM, RF, and ANN. They've been used successfully in a variety of PdM applications (Çinar et al., 2020). In our study we have used Linear Regression (LR), Random Forest (RF), Decision Tree (DT), Extreme Gradient Boosting (XGBoost) and Multi-Layer Perceptron (MLP) method. The performances of all the ML algorithms has been compared. Each algorithm performance has been improved using Hyperparamter tuning and finally the best performing algorithm has been selected for the model building.

The RUL is estimated for each observation by subtracting the maximum number of feasible runs and the current run for the tool. Similar to the tool wear, RUL is also a regression problem, all the ML algorithms applied are same but only difference lies in the target variable.

In order to train the machine learning model, the data set is needed to be split into two parts one is the training data set and the other one is the test data set. In our case to get the best results from the ML algorithm, for tool wear prediction data set is split into 70% training and 30% test data and for RUL training is done with 80% of the data set and rest 20% for testing. Various configurations, also known as hyperparameters in ML, must be studied and compared against a benchmark in order to understand a specific predictive modelling problem. The effectiveness of the model is determined by the algorithms chosen and the hyperparameters associated with them (Ayvaz & Alpay, 2021). Multiple machine learning techniques and hyperparameters were investigated in order to discover the best prediction models. The parameters that have been used to train the ML model for predicting the tool wear and RUL has been depicted in the Table 2. The comparisons of these algorithms is presented in the next section using three different evaluation metrics.

Table 2. Parameter settings for training different ML algorithms

Algorithms	Tool wear	RUL
LR	Default	Default
SVR	kernel='rbf', C =2	kernel='rbf'
DT	Default	Default
RF	n_estimators = 30	n_estimators = 30
XGBoost	n_estimators=200, max_depth=7, eta=0.05, subsample=0.4, colsample_bytree=0.8	n_estimators=400, max_depth= 4, eta=0.1, subsample=0.8, colsample_bytree=0.9
MLP	Default	max_iter=8000

4. RESULTS AND DISCUSSION

After training the ML model, their performance need to be tested. This is done using the $R2$ (R- squared), called as the coefficient of determination, root mean square error (RMSE) and mean absolute error (MAE), have been selected as shown in Table 3 (for tool wear) and Table 4 (for RUL).

The coefficient of determination ($R2$) indicates that the percentage of the variation in response variable that is explained by a regression model. If R2 value is greater, it shows that the regression model explains more variability. An R of 100% or R2 score of one, for example, means that the regression model build for fully explains all variation in the response data around its mean. Better the regression model fits the data, the greater the R2. (Draper & Smith, 2014). MAE measures the average of the difference between the predicted value from the actual value (Chai & Draxler, 2014) smaller the MAE better the model predictions. The RMSE (Hyndman & Koehler, 2006) measures the standard deviation of the predicted errors. For prediction to be more accurate, RMSE should be close to zero.

The ML algorithms use 70% of the input data for training or model development and uses the remaining data set, 30% for testing or model validation. Tables below list the RMSE, R-squared and MAE for the predictive models trained by the LR, SRV, DT, RF XGBoost and MLP regressor.

4.1 Tool wear prediction VB

In addition to R2, MAE, RMSE we have also consider the time taken (in second) to train and to make prediction for the unseen data, to compare all the six ML algorithms. For flank wear prediction the comparison is shown in Table 3.

Table 3. Comparison of various ML algorithms for predicting tool wear

Algorithm	R^2	MAE	RMSE
LR	0.8347	0.0795	0.1193
SVR	0.7377	0.0978	0.1338
DT	0.7330	0.1107	0.1471
RF	0.7297	0.0990	0.0184
XGB	0.8624	0.0663	0.0789
MLP	0.7593	0.0962	0.1282

As a result of comparison, the best performing algorithm comes out XGBoost with maximum R2 of 0.8624 and the minimum 0.7297 R2 obtained for RF and is close to DT and SVR. The time taken for training and prediction for the case of RF is 0.045 second. Thus after building ML model using various regression algorithms XGBoost outperforms all the algorithms. XGBoost is able to fit with the data well as compared with the other algorithms. The time taken for training and making the prediction using XGBoost comes out 0.2525 second.

4.2 Remaining useful life (RUL)

Similar to the metrics for comparing the performances of ML algorithm for predicting flank wear the same evaluation metrics are used for comparing algorithms performances for predicting remaining useful life as shown in the Table 4. From the table it is observed that XGBoost outperforms among all the other algorithms with the highest R2 score.

Table 4. Comparison of various ML algorithms for predicting RUL

Algorithm	R^2	MAE	RMSE
LR	0.7581	2.0270	2.6540
SVR	0.7108	1.7388	2.2666
DT	0.5167	3.1034	4.0684
RF	0.6494	2.3345	3.0248
XGB	0.7860	1.8793	2.3632
MLP	0.5822	2.4543	3.1676

After evaluations from the Table 4, the best results for RUL calculation comes out 0.786 R2 for XGBoost with a training and prediction time of 0.3995 second. The minimum R2 0.516 is obtained for DT with a time of 0.0040 second. Again XGBoost outperform as compared to remaining five ML algorithms.

From the plots it can be seen that the level of flank wear increases gradually for each cases. The unit of flank wear has been taken in mm. For the Figure 6 has six sub figures from (a) to (f) which represents the plot of comparison for actual flank wear and predicted flank wear (a) using XGBoost, (b) using DT, (c) using LR, (d) using MLP, (e) using RF and (f) using SVR respectively. In order to compare in between the figures, the plot in which the predicted values are close to the actual value can be taken as a better fit as compared to the others because in that case the actual values and the predicted values are comparable.

In general, the algorithm which is having a better R2 score have better fit in the plot as which is evident in this study. When all the figures are compared with each other it is clear that XGBoost is outperforming among all the other algorithms because it is fitting better and have the highest R2 score when compared with others.

In Figure 6 the graph has been plotted with all the data points on the x-axis. The total number of data points are 145. The number of runs in the y- axis. From the plots it can be seen that the RUL decreases gradually for each cases. Again on comparing all the plots with each other it is clear that XGBoost is outperforming again among all the other algorithms for predicting the RUL because it is fitting better and have the highest R2 score when compared with others.

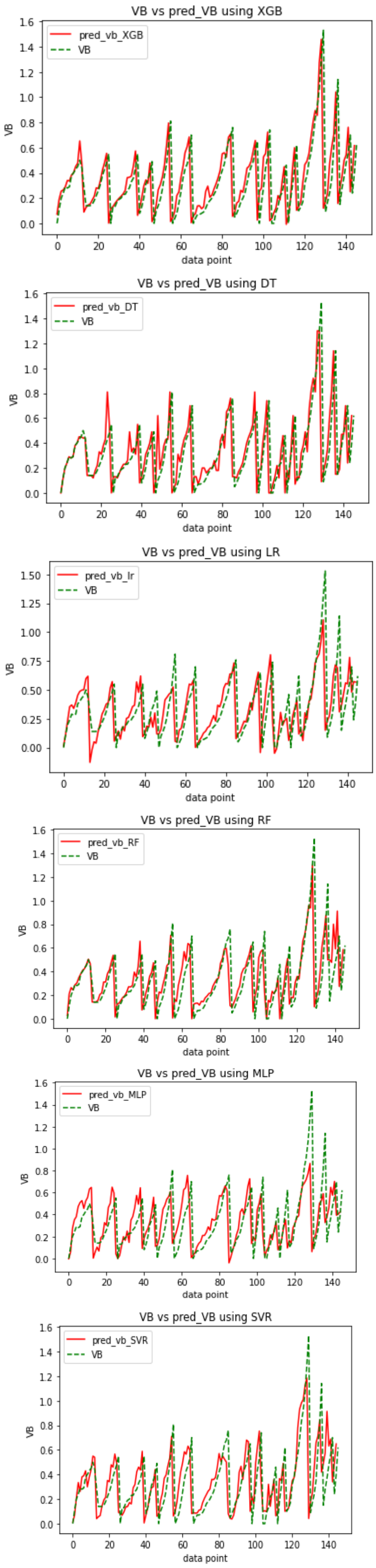

Figure 6. Comparison of predicted flank wear vs actual flank wear

5. CONCLUSIONS

In this paper a framework has been proposed for predictive maintenance using machine learning algorithm. The proposed framework can be used and applied in the similar manufacturing domain or the processes which utilizes the sensors for collecting data. The output of the framework results in predicting RUL and tool wear during the milling operations using the ML algorithms which are widely used in the literature, which includes LR, DT, RF, SVR, XGboost and MLP. In order to evaluate the performance of these selected six ML algorithms, each algorithm is separately trained and tested on the dataset gathered from a milling experiment.

The metrics used for benchmarking the performances of ML algorithms include r-squared, mean absolute error and root mean squared error. From all three sensors i.e. current, vibration, and acoustic emissions sensors, the features based on time domain were extracted. The experimental results, for the case of tool wear prediction have shown that on the particular dataset using XGboost, generates more accurate predictions than the other algorithms. The main contribution of this paper can be understood in two ways, firstly we demonstrated that the predictive model trained by XGBoost can predict tool wear in milling operations with better results (R2 = 0.8624, MAE =0.0663, RMSE = 0.0789 and time = 0.2525 sec) while using time domain features only and secondly the RUL calculation we compared the performance of the all the taken ML algorithms, and observed that XGBoost again outperform in our case (R2 = 0.786, MAE =1.8793, RMSE = 2.3632 and time = 0.3995 sec), but this time the training and prediction time is greater than that was in the case of flank wear.

In the future, a comparison of the performances of the six ML algorithms considered in our study with that of other types of neural network, such as recurrent neural networks, could be conducted. In addition to future work will focus on deploying the ML model into action so that it can be applied to large-scale and real-time prognosis. In our study we limit our work to estimate the tool conditions i.e. flank wear and RUL both covers the regression problem.

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Appendix

Table A1. Table for selected features for tool wear

Features	Description
u_b	Mean of Direct current reading from the spindle
rm_b	RMS of Direct current reading from the spindle
sd_a	Standard deviation of Alternating current reading from the spindle
rm_a	RMS of Alternating current reading from the spindle
ma_b	Maximum of Direct current reading from the spindle
peak_b	Peak-to-Peak of Direct current reading from the spindle
run	Counts the number of runs for which the tool has been used for machining
mini_a	Minimum of Alternating current reading from the spindle
peak_a	Peak-to-Peak of Alternating current reading from the spindle
ma_a	Maximum of Alternating current reading from the spindle
crestFactor_a	Crest factor of Alternating current reading from the spindle
ma_e	Maximum of Acoustic emission generated from the table
peak_e	Acoustic emission generated from the table
ma_f	Maximum of Acoustic emission generated from the spindle
sd_b	Standard deviation of Direct current reading from the spindle
peak_f	Peak-to-Peak of Acoustic emission generated from the spindle
time	Time duration of each run of experiment and it restart from zero for each new case
rm_e	RMS of Acoustic emission generated from the table
mini_d	Minimum of Vibration signal generated from the spindle
u_e	Mean of Acoustic emission generated from the table

Table A 2. Table for selected features for RUL

Features	Description
u_b	Mean of Direct current reading from the spindle
rm_b	RMS of Direct current reading from the spindle
peak_b	Peak-to-Peak of Direct current reading from the spindle
ma_b	Maximum of Direct current reading from the spindle
sd_a	Alternating current reading from the spindle
rm_a	RMS of Alternating current reading from the spindle
ma_a	Maximum of Alternating current reading from the spindle
peak_a	Peak-to-Peak of Alternating current reading from the spindle
mini_a	Minimum of Alternating current reading from the spindle
sd_b	Standard deviation of Direct current reading from the spindle
crestFactor_a	Crest factor of Alternating current reading from the spindle
u_a	Mean of Alternating current reading from the spindle
peak_e	Peak-to-Peak of Acoustic emission generated from the table
ma_e	Maximum of Acoustic emission generated from the table
ku_c	Kurtosis of Vibration signal generated from the table
mini_d	Minimum of Vibration signal generated from the spindle
peak_f	Peak-to-Peak of Acoustic emission generated from the spindle
ma_f	Maximum of Acoustic emission generated from the spindle
run	Counts the number of runs for which the tool has been used for machining
sd_e	Standard deviation of Acoustic emission generated from the table