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Prediction of the remaining useful life of a milling machine using machine learning☆,☆☆

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ABSTRACT

The cutting tool is a key component of the milling machine that decides productivity. Hence, an adequate predictive maintenance (PdM) strategy for the cutting tools becomes necessary. This research seeks to develop a smart maintenance web application that utilizes Machine Learning (ML) supervised models to predict the Remaining Useful Life (RUL) for milling operations. The ML models were developed using a four-stage process including data pre-processing, training, evaluation, and deployment. Several ML algorithms were applied and the results were evaluated using five measures involving Accuracy, Mean Absolute Error (MAE), Mean Squared Error (MSE), R-squared, and R-squared adjusted. It was found that the Multi-Layer Perceptron Regressor provided the largest accuracies, adjusted R-squared, MAE, and MSE of 99 %, 0.99, 3.7, and 23.13, respectively. A web application for maintenance was finally developed with several ML algorithms at the evaluation stage. Maintenance engineers can utilize the developed smart web application to monitor the machine's health state and predict failure occurrence. In conclusion, the developed web application assists engineers in developing reliable predictions of maintenance activities, which may save costly production and maintenance losses.

- A Web application based on machine learning techniques was developed for RUL predictions for the milling cutting tool.
- A comparison between the prediction results from various machine learning techniques was conducted.
- The web application is found to be valuable for maintenance prediction and planning.

Specifications table

Subject area:	Engineering
More specific subject area:	Maintenance, Machine Learning
Name of your method:	Machine Learning
Name and reference of original method:	Machine Learning
Resource availability:	Python

☆ **Related research article:** None
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Background

Nowadays, industries face the challenge of predicting accurately the failures of milling operations. Estimating the Remaining Useful Life (RUL) for tools has become a critical activity in prognostics management [1]. RUL is the length of time that a machine can operate before a tool loses its capacity based on condition monitoring information. Maintenance engineers can utilize RUL prediction to improve machine reliability, avoid breakdowns, and reduce maintenance costs. For milling operations, the cutting tool is a crucial component where its failure causes losses in productivity and maintenance resources. Therefore, an effective PdM strategy must be developed to accurately predict the tool RUL [2]. Generally, high failure costs can prevent manufacturers from reaching their production goals [3]. PdM is beneficial in enhancing production efficiency through the reduction of machine downtime. PdM tasks include failure prediction, failure detection, failure type classification, and prediction of the machine's RUL. Further, PdM relies on the real-time monitoring of the machine condition to make tool RUL predictions [4].

RUL prediction approaches can be classified based on either the type of available data and knowledge about the machine or the type of used methodology or algorithms. Machine learning (ML) has a key role in PdM and has proven to be beneficial for predicting machine failures in industrial applications [5]. Leukel et al. [6] stated that ML technology is increasingly being used for solving maintenance issues, especially to predict machine degradation and breakdowns, and save resources incurred from unnecessary maintenance. Typically, ML algorithms use historical data to learn the machine's behavior and make decisions [7–9]. The supervised learning type predicts the future outcome based on past data and labeled data which requires an input and an output to be given to the model to be trained and predict the output [10]. Supervised learning provides more accurate results and is divided based on the type of label used into (1) Classification: when the output being monitored consists of a finite and discrete set of values, the problem can be formulated as a classification approach. In classification problems, the label is used to determine whether or not a machine failure has occurred and (2) Regression when the output being monitored refers to the remaining time until a system fails. When the output values are continuous, a regression problem is obtained. Regression is generally used when predicting the RUL of a machine while classification is employed to predict machine conditions at a specific instant like a healthy or unhealthy machine. Although a classification problem seems easier to apply, a regression approach provides more valuable information regarding the timing of the next maintenance.

In some cases, PdM can be achieved by calculating the RUL of the machine [11]. RUL is the length of time a machine can operate before tool replacement or repair. RUL estimates can support maintenance engineers in the effective planning of maintenance activities and prevent unplanned shutdowns. RUL prediction can improve the reliability of machines, avoid breakdowns, and reduce maintenance costs [8]. Accurate predictions of RUL have an important role in avoiding serious failures and achieving the ultimate goal of zero-downtime performance in manufacturing applications. If the RUL model can accurately predict when the machine will fail, the maintenance activities are done at the right time at a low cost [12]. RUL prediction approaches can be calculated according to the available data are lifetime data collected over the entire lifetime of a machine (Survival Model), run-to-failure, used histories of similar machines (Similarity Model), and threshold value, a threshold value is a predefined limit or boundary that is used to distinguish between normal and abnormal behavior of the machine (Degradation Model).

The milling cutting tool is a critical component that significantly impacts machine productivity. Effective monitoring of tool condition in the high-speed milling machine is important to guarantee its safe and high utilization. RUL is defined as the remaining time for tool usage for cutting operations before it becomes worn, damaged, and replaced. In these regards, this research develops a smart web application for predicting the RUL of milling machines using ML algorithms. The results provide valuable support to engineers in developing an effective planning of maintenance activities, saving costly production and maintenance losses, and enhancing machine productivity.

Method details

The ML algorithms applied to predict the RUL are presented briefly as follows:

1. Stochastic Gradient Descent (SGD) Regressor is an LR model that uses Stochastic Gradient Descent (SGD) to optimize model parameters. SGD minimizes the loss function measured as the difference between the predicted and actual values.
2. Random Forest Regressor (RF Regressor) is an ensemble method for regression based on decision trees. It is an extension of decision trees that builds multiple trees and averages the results. Typically, the prediction made by an RF Regressor is an average of the predictions made by each tree in the forest.
3. Decision Tree Regressor (DT Regressor) is a type of supervised learning algorithm (SLA) that is used for regression problems. It is based on the DT algorithm and is easy to understand and interpret, as it clearly represents the decision-making process. Additionally, it can handle both categorical and numerical features, and it can handle missing data.
4. Support Vector Regression (SVR) is an SLA applied to handle both linear and non-linear data and is used for regression problems with high-dimensional data, as the Kernel can be used to map the data into a higher-dimensional space where a linear hyperplane can be found. Additionally,
5. Multi-Layer Perceptron (MLP) is used for regression tasks and involves one or more layers of artificial neurons, where each neuron receives input from the previous layer and produces an output that is sent to the next layer. The final output layer produces a single continuous value, which is the predicted target value. The _sizes parameter is a tuple that specifies the number in each hidden layer of the MLP neural network. The hidden layer size and tuple length determine the number of neurons and hidden layers, respectively.

The challenge of RUL prediction has been studied extensively. For example, Lei et al. [12] proposed a model-based method for predicting the RUL of machinery using a particle filtering-based algorithm. Vibration signals from accelerated degradation tests of rolling element bearings were utilized for illustration. Mathew et al. [13] conducted a comparative study of RUL prediction of NASA aircraft's turbofan engine. Data was collected from 21 sensors for different engine state measurements at operating time. A comparison of RUL prediction accuracy was conducted between ML algorithms. Results revealed that the RF algorithm generated the lowest RMSE value. Lee et al. [14] adopted Support Vector Machine (SVM) and Artificial Neural Network (ANN) algorithms with various feature extraction methods to predict the RUL of cutting tools and spindle motors in milling machines. They utilized two datasets (Milling and Bearing) to create and assess the predictive models. The SVM with a confusion matrix and RNN were used to evaluate the milling model and bearing dataset, respectively. The study's findings indicated that utilizing PdM techniques can decrease machine downtime and increase the RUL of any machine. Yang et al. [15] conducted an intelligent RUL prediction using a Double-Convolutional Neural Network (CNN) model architecture. The prediction involved two stages: incipient fault point and CNN model. Data from four tests of bearing degradation were employed for RUL prediction. The used method resulted in high prediction accuracy and robustness. Yurek et al. [16] conducted a study to examine how different feature engineering selections could impact the accuracy of RUL using different feature selection methods. They used different ML algorithms like linear Regression (LR), Neural Networks, and Decision Tree (DT). The results were compared to evaluate their performances and choose the best model for RUL prediction. The result shows that the ML algorithm's performances vary according to the different feature selection methods. Deng et al. [17] predicted the RUL of NASA aircraft engines using data-driven approaches. They discussed three main challenges they may face in predicting RUL for engines; such as how to find actual degradation, how to address the correlation between raw data, and how to handle the nonlinear data. A new concept for RUL prediction was introduced which involved three steps. The initial phase involves suggesting a differential technique for extracting features over the long term, followed by introducing the Fibonacci window to extend short-term features and culminates in utilizing the CatBoost algorithm to handle non-linear data. The result shows that the following three steps can perform better RUL prediction. Ge et al. [18] studied the RUL of Lithium batteries used in industrial applications to ensure safety and reduce the operation cost. Four battery datasets were analyzed using State of Health estimation and RUL techniques regarding user requirements and data availability. Wu et al. [19] created a prediction model using Multi-Stage RUL estimation, which integrates classification and regression algorithms. The approach involved three steps: feature extraction, modeling, and evaluation. The combination of ML classification and regression methods was used to improve accuracy. The experimental results showed a 6.5 % improvement in accuracy compared to the algorithms used in RUL prediction. Wang et al. [20] utilized Multi-task Feature Selection (MTFS), SVM, and Support Vector Regression (SVR) to jointly predict the RUL of train wheel sets and failure types. An optimization method was used to integrate the least square loss and negative maximum likelihood of logistic regression. The results showed that the method outperformed the single-task method by 3 % in prediction accuracy. Zhao et al. [21] predicted the RUL using a Neural Architecture Search (NAS) method based on gradient descent. NAS is a form of reinforcement learning that can be time-consuming. Results showed that the NAS method was superior in terms of cost, capability, and resources. Kang et al. [22] used Multi-Layer Perceptron Neural Network (MLP), SVR, RF, and LR algorithms to predict machines' RUL. Four datasets of NASA turbo engines were analyzed and tested. The first model involved learning from labeled data and using the LR algorithm for interpolation, while the second model learned from the entire dataset and predicted the Health Index using MLP, RF, and SVR algorithms. The predicted RUL can help the management plan PdM activities to avoid unexpected production line failures. Yan et al. [23] adopted ML algorithms for RUL predicting bearings using dimensionless measurements to identify the degradation level of bearings. The SVM algorithm was adopted to classify the level of bearing degradation and RUL prediction. The results showed that the SVM provided good generalization ability and high accuracy in classification. Bagri et al. [24] used Artificial neural networks (ANNs) to predict the tool RUL in micro-milling under different feed, depth of cut, spindle rotation speed, and tool path radius. The results revealed that ANNs provided 93–99 % accuracy for the RUL prediction. An et al. [25] introduced a hybrid model using a convolutional neural network (CNN) with a stacked bi-directional and unidirectional LSTM network to predict the tool RUL prediction for a milling process. The accuracy of the predicted RUL was 90 %. Kumar et al. [26] used ML classification models to perform feature selection and predictive analysis to predict aircraft systems failures by setting a threshold RUL value (maximum number of the completed cycle for the engine) to indicate failure and then transfer it to Binary classification model which flags a warning before the breakdown occurred using KNN, RF, DT, and SVM ML algorithms. They used NASA Engine Degradation Simulation Datasets which is a collection of four datasets. Liu et al. [27] proposed a three-stage Wiener-process-based degradation model for the cutting tool wear estimation and effective prediction of the tool RUL. Sayyad et al. [28] adopted deep learning models to predict the RUL of the milling cutting tool. The results showed that the TFD feature extraction provides satisfactory RUL estimation.

However, this research aims to predict RUL using machine learning algorithms and then develop a web application for RUL prediction utilizing several controllable factors of the milling machine. The framework adopted in this research for cutting tool RUL prediction using ML algorithms is depicted in Fig. 1.

The milling process displayed in Fig. 2 allows the manufacturing of complex parts and trimming materials. During the milling process, various types of failures can occur, and the geometry of the cutting tool changes because of the interaction between the cutting tool and work piece, which leads to failure. Implementing PdM techniques in milling operations can provide valuable information to the maintenance team, such as the estimated RUL of the cutting tool, and the potential machine failure modes that may occur. This information allows the maintenance team to proactively address and prevent machine failures, ensuring optimal performance and reducing downtime.

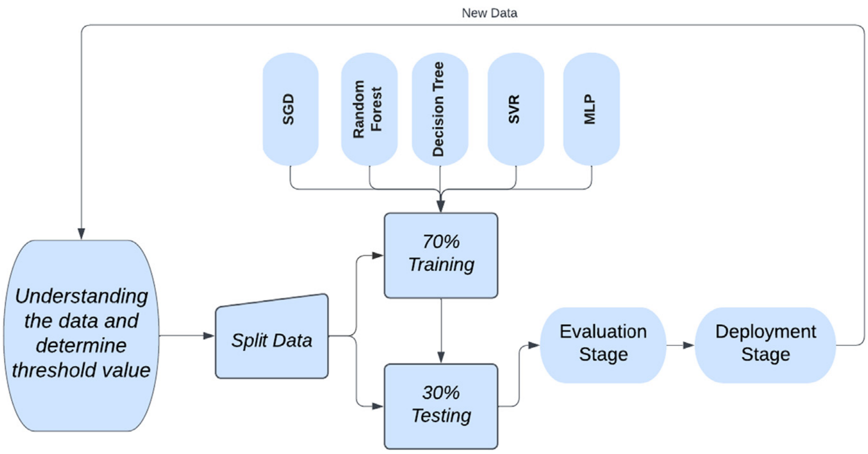


Fig. 1. Framework for RUL prediction.

Fig. 2. The milling machine under study.

Setup of the computation environment

To set up the computational environment for our RUL prediction model, the following requirements are necessary:

• Software Requirements: Programming Languages: Python, which offers various libraries for machine learning and data analysis, such as Scikit-learn, NumPy, Pandas, and Matplotlib, can be easily integrated with data sources and other tools. Hence, Python is utilized in this research for RUL prediction.

(i) Hardware Requirements: Historical Dataset (data over one year, stored in CSV or database format), sensors, and devices to monitor critical features during operation, along with data acquisition systems to collect and feed new data for continuous model enhancement.

Data pre-processing

Data pre-processing involves various tasks including data acquisition, visualization, and RUL estimation. These tasks are presented as follows:

(a) Data Acquisition

The collected dataset contained 10,000 records, and 348 points labeled as failures. Six different features values were collected during operation including (1) Three categories of work-piece quality: Low, medium, and high quality representing 60 %, 29.97 %, and 10.03 % of work-piece data, (2) air temperature (AT) in Kelvin (K); where 1 K= −272.15 °Celsius (°C), (3) process temperature (PT,

	Type	Air temperature [°C]	Process temperature [°C]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Target	Failure Type	Temperature difference [°C]
7295	M	27.95	38.35	1329	57.4	99	0	No Failure	10.4
4709	M	31.25	39.45	1446	50.0	163	0	No Failure	8.2
9637	L	27.05	38.15	1463	38.9	160	0	No Failure	11.1

Fig. 3. A Common data format.

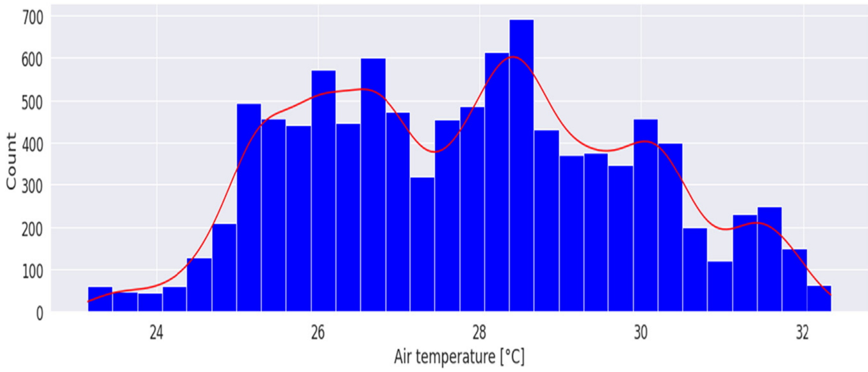


Fig. 4. AT distribution.

Table 1
Statistics of features.

Statistics	Feature AT[°C]	PT[°C]	RS [rpm]	T[Nm]	TW [min]	TD [°C]
Count	10,000	10,000	10,000	10,000	10,000	10,000
Mean	27.85	37.86	1538.78	39.99	107.95	10.00
Standard deviation	2.00	1.48	179.28	9.97	63.65	1.001
Minimum	23.15	33.55	1168	3.80	0	7.60
25th percentile	26.15	36.65	1423	33.20	53	9.30
50th percentile	27.95	37.95	1503	40.10	108	9.80
75th percentile	29.35	38.95	1612	46.80	162	11
Maximum	32.35	41.65	2886	76.60	253	12.10

K); where 1 K= −272.15 ˚Celsius (˚C), (4) rotational speed (RS, rpm), (5) torque (T, Nm), and (6) tool wear (TW, min). Temperature Difference (TD) feature is added to the model to improve model performance which is calculated as given in Eq. (1).

$$Temperature\ difference\ (\circ C) = Process\ Temperature\ -\ Air\ Temperature \tag{1}$$

Fig. 3 shows random rows of data sets containing the new feature (temperature difference). Table 1 highlights some statistics summary of features.

(b) Data visualization

Histograms are useful for understanding the shape of a dataset and identifying patterns or outliers. For example, Fig. 4 shows that air temperature lies within a specific range of 23–33 ˚C and is arranged in consecutive and fixed intervals with bin size equal to 2. Overall, this feature appears to have a relatively narrow distribution, with temperatures mostly ranging between 26.15 ˚C and 29.35 ˚C.

Fig. 5 shows that process temperature lies within a specific range of 33–42 ˚C and is arranged in consecutive and fixed intervals with a bin size equal to 1. The mean and median of process temperature are aligned. Overall, this feature appears to have a relatively narrow distribution, with temperatures mostly ranging between 36.65 ˚C and 38.95 ˚C. Fig. 6 shows the temperature difference distribution, where it is noted that differences lie within a specific range of 7–13 ˚C. Overall, this feature appears to have a narrow and relatively consistent distribution, with temperatures mostly ranging between 8.30 ˚C and 10.30 ˚C.

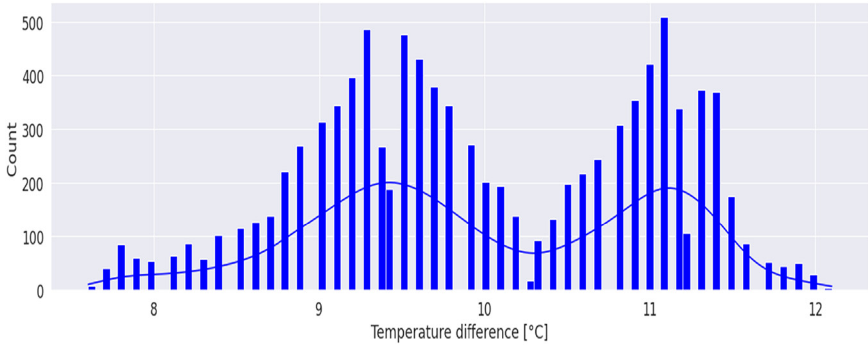


Fig. 5. TD distribution.

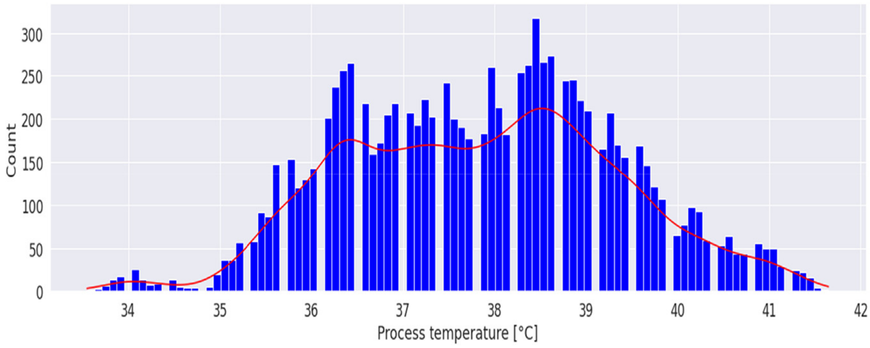


Fig. 6. PT distribution.

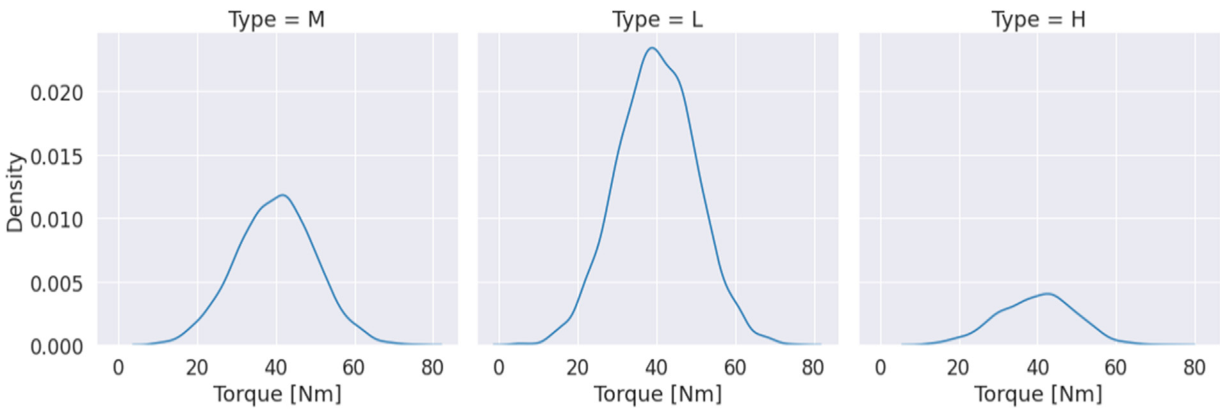


Fig. 7. Density versus Torque.

Fig. 7 presents a continuous distribution view of the work piece type about torque values. The density plot indicates that the "L" type has a higher density of torque values than the "H" type, which has a lower density. The peaks of the density plot reveal that the "L" type is concentrated around the interval of 40. This aligns with the observation from the histogram plot where the torque values are mostly concentrated around 40.

Fig. 8 illustrates the distribution of workpiece type concerning rotational speed values. The density plot shows that the "L" type has a higher density of rotational speed values than the "H" type and type “M”, which have a lower density. Additionally, the plot indicates that the rotational speed has its highest occurrence at 1500rpm.

A heatmap is a graphical representation of a matrix often used to visualize the correlations between different features in a dataset. Correlated features over 0.9 must be removed to avoid overfitting models. Based on Fig. 9, it is evident that there is a strong correlation between Air temperature and Process temperatures. Additionally, a negative correlation is observed between Torque and Rotational speed and hence both factors can be utilized for predicting the target variables.

(c) RUL estimation

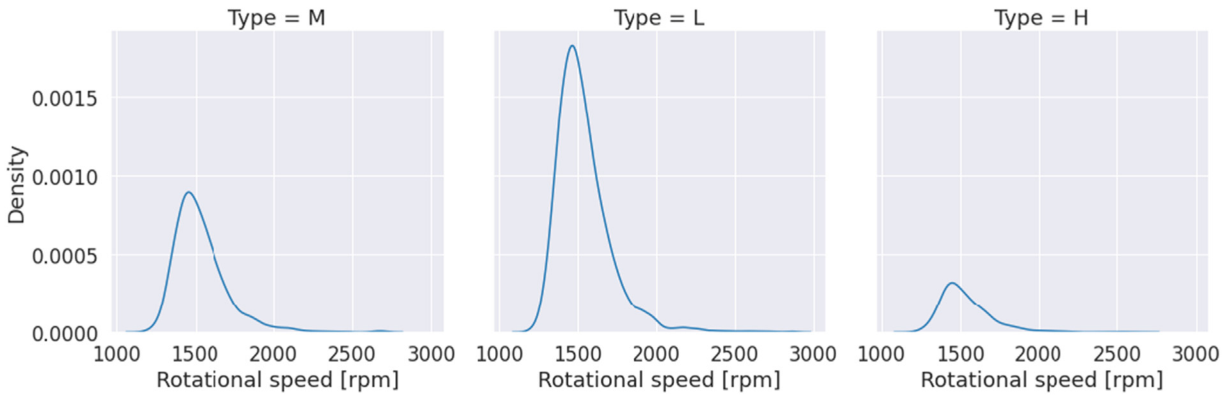


Fig. 8. Density plot for RS.

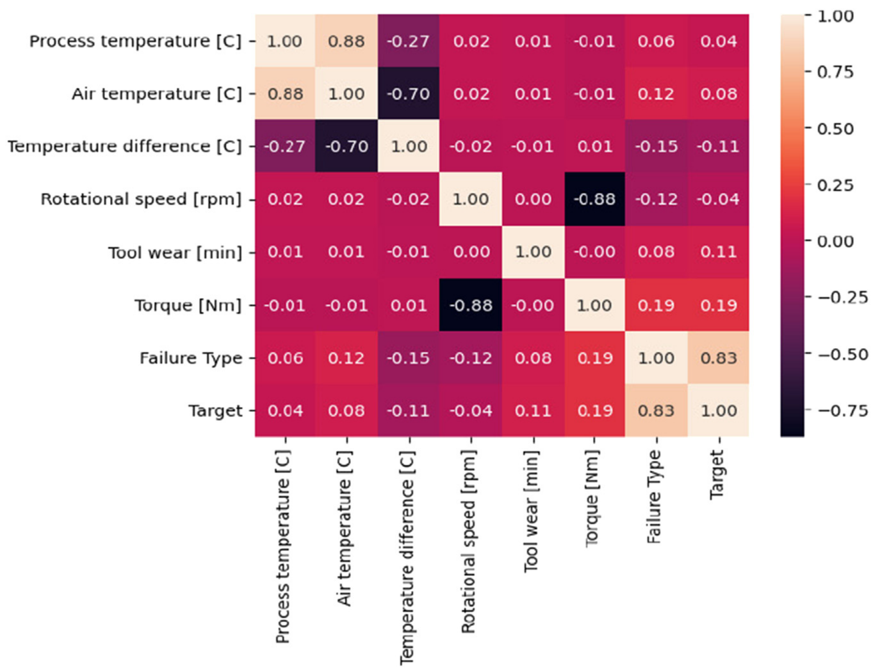


Fig. 9. Heat map.

The available dataset revealed that the average life of the cutting tool is between 198 and 253 min s, as shown in Fig. 10. The cutting tool was replaced 46 times throughout data collection. Each instance of tool failure can be considered as a cycle and each cycle consists of 200 to 240 records to reach failure.

From Fig. 10 the threshold of the cutting tool life is around 200 mins after which the cutting tool shall be replaced. With this kind of information, a RUL model can be fit to predict when the records will cross the 200-minute threshold. It is seen in Fig. 10 that the minimum and maximum cutting time for tool failure are 198 and 253 mins, respectively, over a total of 46 cycles. To provide a safe margin and give an alert to the maintenance team before the tool is worn, the RUL threshold is set at 190 mins. To implement this, a new column can be added to the data using Eq. (2).

$$RUL = TTF - TTI \tag{2}$$

where TTF and TTI are the time to failure and the time of the last test or inspection of the cutting tool, respectively. The RUL value of zero indicates that the tool is near its end of life and needs to be replaced or repaired. As shown in Fig. 11, if the current status of the tool is at 50 mins, then the RUL would be calculated as 140 mins (190 mins minus 50 mins).

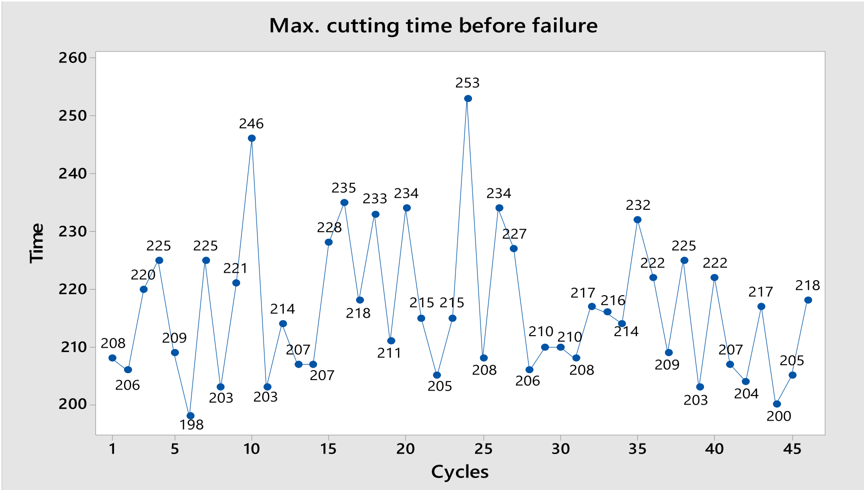


Fig. 10. Cutting tool failure cycles.

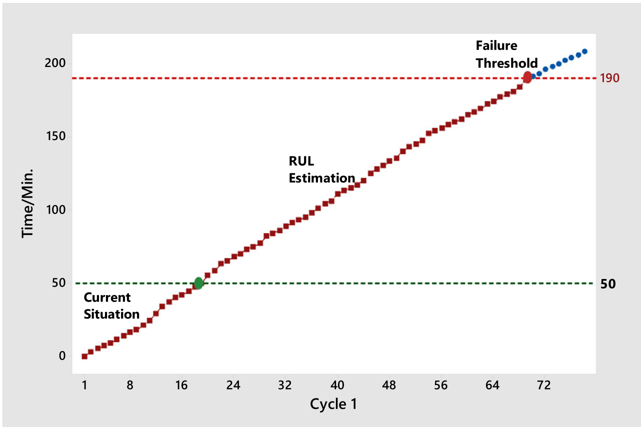


Fig. 11. RUL Example.

Method validation

The training stage covers 70 % of the dataset while the remaining 30 % are held for testing. Then, the ML algorithms were used to classify the machine condition. After training each model, the model accuracy was estimated. Once the model is trained, it is evaluated on the testing set to determine its accuracy and performance using several metrics including [29]:

(i) *Mean Squared Error (MSE)* is calculated as the difference between predicted and actual values. MSE can be calculated as (Chicco, 2021):

$$MSE = \frac{\Sigma(\text{predicted value} - \text{actual value})^2}{\text{n}} \tag{3}$$

where *n* is the number of observations.

(ii) *R-squared* indicates the proportion of variance in a dependent variable that can be explained by an independent variable. It is commonly used to evaluate the performance of a regression model and its value ranges between 0 and 1. An *R-squared* value of 1 indicates that all of the variations in the dependent variable can be explained by the independent variable, while an *R-squared* value of 0 indicates that none of the variations in the dependent variable can be explained by the independent variable. *R-squared* measures how well the regression model fits the data.

R-squared can be calculated using the following formula Eq. (4).

$$R - squared = 1 - \left(SS_{res} / SS_{tot}\right) \tag{4}$$

where SS_{res} and SS_{tot} denote the sum of squares of residuals and the total sum of squares, respectively.

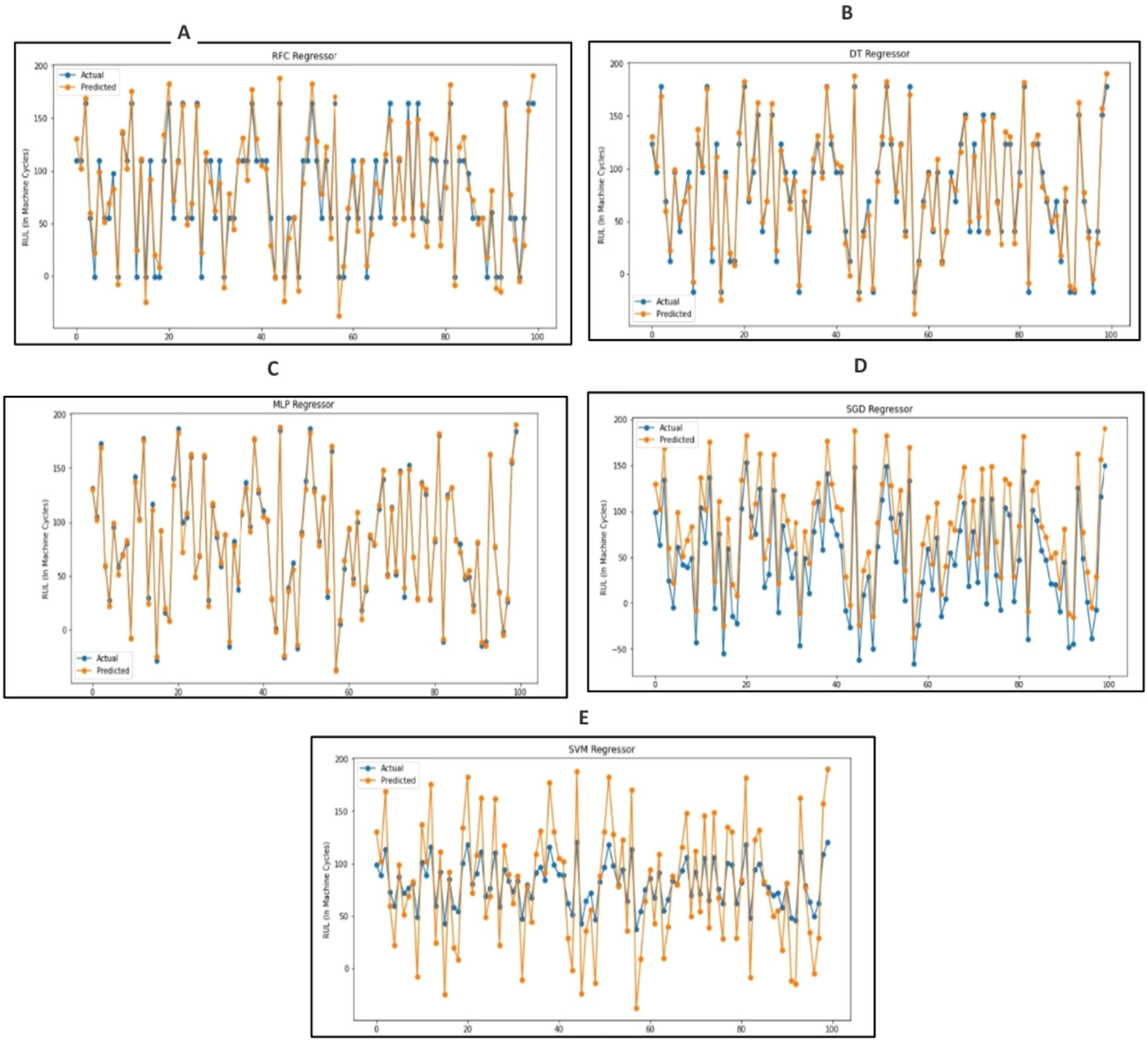


Fig. 12. Prediction versus actual Charts (Actual: Blue/Prediction: Orange) for RUL.

(iii) Mean Absolute Error Value (MAE) assesses the accuracy of regression models by measuring the average magnitude of the errors in the predictions made by a model as given IN Eq. (5).

$$MAE\ =\ (1/n).\ \sum |y-\hat{y}| \tag{5}$$

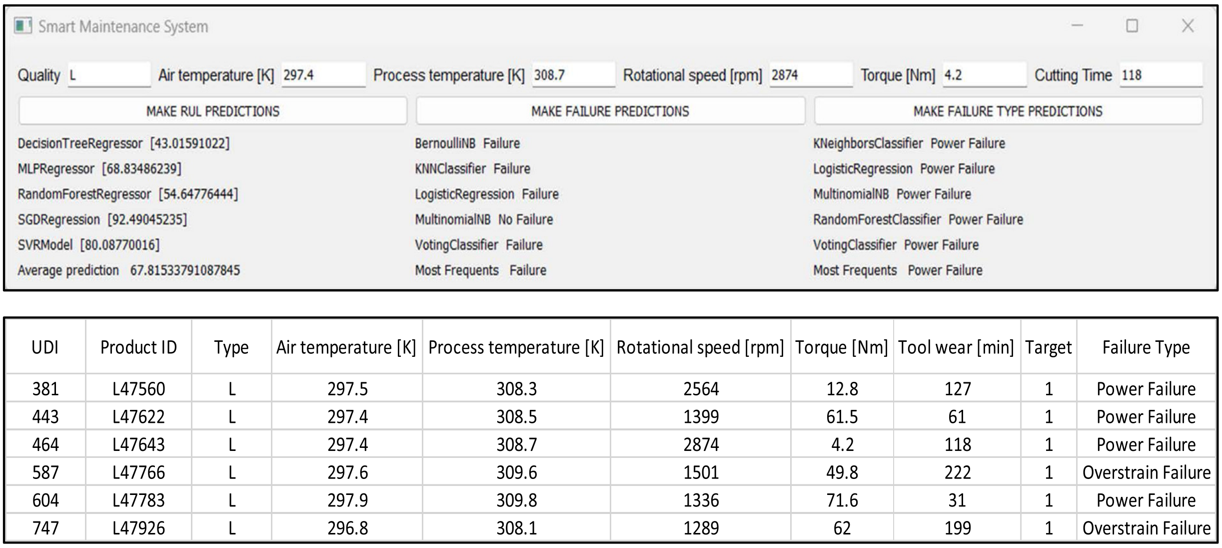
where n is the number of observations, y and $\hat{y}$ are the actual and predicted values of the dependent variable, respectively. The $\Sigma|y - \hat{y}|$ means the sum of the absolute differences between the actual and predicted values. A lower value of MAE indicates a better fit of the model. This metric is not influenced by the direction of the error (positive or negative), and all errors have the same impact on the overall value of the metric.

(iv) *R-squared adjusted* adjusts for the number of independent variables in a regression model as given in Eq. (6).

$$Adjusted\ R-squared = 1-\left[\left(1-R^2\right)(n-1)/(n-k-1)\right] \tag{6}$$

where k is the number of independent variables.

The results of the ML Algorithms are shown in Table 2. Based on the performance metrics, the MLP Regressor model provides the best fit for the given dataset among all models. Predictions versus actual charts are established to visually assess model performance. The predicted versus the actual RUL values for 100 random test observations are shown in Fig. 12, where it is confirmed that the MLP Regressor algorithm provides the best predictions for RUL.



UDI	Product ID	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Target	Failure Type
381	L47560	L	297.5	308.3	2564	12.8	127	1	Power Failure
443	L47622	L	297.4	308.5	1399	61.5	61	1	Power Failure
464	L47643	L	297.4	308.7	2874	4.2	118	1	Power Failure
587	L47766	L	297.6	309.6	1501	49.8	222	1	Overstrain Failure
604	L47783	L	297.9	309.8	1336	71.6	31	1	Power Failure
747	L47926	L	296.8	308.1	1289	62	199	1	Overstrain Failure

Fig. 13. Developed intelligent program for RUL prediction.

Table 2
Results of ML algorithms.

Algorithm	Train Score	Test Score	MSE	MAE	R^2	R^2 Adjusted
SGDRegressor (alpha=0.1,random_state=33,penalty='l2',loss = 'Huber')	0.9729	0.9688	124.86	7.8503	0.7263	0.7257
Random Forest Regressor (n_estimators=100,max_depth=2, random_state=33)	0.9408	0.9390	244.29	13.44	0.93896	0.93883
Decision Tree Regressor (max_depth=3,random_state=33)	0.9829	0.9827	69.27	7.070	0.98269	0.98265
SVR(C = 1.0,epsilon=0.1,kernel = 'rbf')	0.5939	0.5911	1636.88	34.86	0.59105	0.59018
MLP Regressor (activation='identity', solver='adam', learning_rate='adaptive', early_stopping= False,alpha=0.0001,hidden_layer_sizes=(20, 2),random_state=33)	0.9945	0.9942	23.13	3.70	0.99422	0.99420

Then, an intelligent maintenance program was developed for the dataset features to predict the likelihood of failure, failure type, and RUL of the cutting tool utilizing AI algorithms implemented through several Python libraries were employed to provide tools for designing and handling the Graphical User Interfaces (GUIs) elements, such as buttons, text boxes, and images for the program. The benefits of using a GUI in Python include improved usability and interactivity, enhanced user experience, and the ability to create applications with a professional, useful look and feel. The program utilizes the dataset features; Quality, Air Temperature, Process Temperature, Rotational Speed, Torque, and Cutting Time. To predict the likelihood of failure, failure type, and RUL of the cutting tool, the program developed offers multiple options for prediction, utilizing the same algorithms employed during the evaluation stage. In addition, the program incorporates an Average prediction feature to enhance the accuracy of the results. The input data includes the dataset features, while the output data shows the results of the ML algorithms. It is seen in Fig. 13 that when Quality Type=L, Air Temperature=297.4 K, Process Temperature=308.7 K, Rotational Speed=2874 rpm, Torque=4.2 Nm, and Tool Wear =118 min, the RUL of the cutting tool using MLP Regressor and the average prediction are 69 and 68 mins, respectively. These values are very close to the actual value (72 mins) as shown in Fig. 14.

The developed smart maintenance web application is found effective in predicting the machine's RUL. Implementing this web application supports maintenance engineers in planning maintenance activities and predicting failure occurrence with high accuracy. This may save costly losses in productivity due to machine unavailability.

The research utilized supervised ML algorithms for PdM to assist maintenance engineers in reducing machine downtime and maintenance costs, as well as extending the machine's lifespan through reliable prediction of RUL for a milling machine. The data was initially subjected to visualization and then split into two parts, with 70 % of it assigned for training purposes, while the remaining 30 % was reserved for testing. A set of ML algorithms were employed to train the data, and resulted in accuracy values were compared. The results showed that the MLP Regressor algorithm was the most accurate prediction, with an accuracy of 99 %. A smart maintenance web application was finally developed for future RUL predictions. In conclusion, the developed prediction framework using AI algorithms can provide valuable assistance to maintenance engineers in predicting the RUL for the parts of a milling machine as well as other key production machines.

UDI	Product ID	Type of WP	Air temperature [C]	Process temperature [C]	Rotational speed [rpm]	Torque [Nm]	cutting time	RUL
419	L47598	L	24.25	35.25	2151	17.7	0	190
420	M15279	M	24.15	35.15	1501	38.2	2	188
421	M15280	M	24.15	35.15	1301	39.6	5	185
422	M15281	M	24.15	35.15	1657	31.1	8	182
423	L47602	L	24.15	35.15	1333	55.2	11	179
424	L47603	L	24.15	35.15	1484	43.9	13	177
425	L47604	L	24.15	35.25	1430	45.7	15	175
426	M15285	M	24.15	35.25	1665	28.9	17	173
427	L47606	L	24.25	35.35	1501	44.9	20	170
428	M15287	M	24.35	35.35	1496	42.2	22	168
429	M15288	M	24.45	35.45	1595	36.9	25	165
430	L47609	L	24.35	35.45	1208	62.3	28	162
431	L47610	L	24.35	35.45	1596	37.1	30	160
432	L47611	L	24.35	35.35	1446	41.9	32	158
433	M15292	M	24.45	35.35	1466	39.7	34	156
434	M15293	M	24.45	35.35	1848	23.7	37	153
435	M15294	M	24.35	35.35	1484	44.7	40	150
436	L47615	L	24.25	35.15	1493	41.2	43	147
437	L47616	L	24.15	35.15	1504	36.3	45	145
438	L47617	L	24.15	35.15	1538	38.5	47	143
439	L47618	L	24.25	35.25	1341	52.2	49	141
440	M15299	M	24.25	35.15	1535	34.6	51	139
441	L47620	L	24.25	35.35	1389	39.2	54	136
442	H29855	H	24.35	35.35	1393	46.6	56	134
443	L47622	L	24.25	35.35	1399	61.5	61	129
444	H29857	H	24.25	35.35	1469	45.1	63	127
445	L47624	L	24.25	35.25	1582	37.2	68	122
446	L47625	L	24.35	35.45	1793	26.7	70	120
447	L47626	L	24.35	35.45	1452	39	72	118
448	M15307	M	24.45	35.55	1376	59.9	74	116
449	L47628	L	24.35	35.45	1552	44.9	77	113
450	L47629	L	24.45	35.55	1622	37.9	79	111
451	M15310	M	24.45	35.55	1419	41.7	81	109
452	H29865	H	24.35	35.45	1440	46.1	84	106
453	M15312	M	24.25	35.45	1643	31	89	101
454	L47633	L	24.25	35.55	1510	36.2	92	98
455	L47634	L	24.25	35.55	1468	46.6	94	96
456	L47635	L	24.25	35.55	1429	57.4	96	94
457	H29870	H	24.15	35.55	1478	47.6	98	92
458	L47637	L	24.25	35.45	1276	53.6	103	87
459	L47638	L	24.15	35.45	1486	42.6	105	85
460	L47639	L	24.25	35.45	1476	42.3	107	83
461	H29874	H	24.15	35.45	1431	42	109	81
462	L47641	L	24.25	35.55	1402	40.2	114	76
463	L47642	L	24.25	35.55	1433	43.4	116	74
464	L47643	L	24.25	35.55	2874	4.2	118	72
465	L47644	L	24.15	35.45	1511	35.7	120	70
466	M15325	M	24.15	35.45	1456	42.9	122	68
467	L47646	L	24.05	35.35	1550	41.5	125	65
468	L47647	L	24.05	35.35	2182	16.5	127	63
469	L47648	L	24.15	35.55	1619	31.6	129	61
470	M15329	M	24.15	35.65	1586	32.7	131	59
471	H29884	H	24.15	35.65	1499	44.2	134	56
472	H29885	H	24.15	35.65	1419	42.4	139	51
473	M15332	M	24.25	35.85	1497	41.8	144	46
474	M15333	M	24.25	35.85	1520	37	147	43
475	L47654	L	24.25	35.95	1478	49.8	150	40
476	L47655	L	24.25	35.95	1380	41.1	152	38
477	L47656	L	24.25	35.85	1570	37.9	154	36
478	H29891	H	24.25	35.85	1468	41.4	156	34
479	L47658	L	24.25	35.85	1833	22.6	161	29
480	M15339	M	24.25	35.75	1323	57.3	163	27
481	L47660	L	24.25	35.85	1583	32	166	24
482	M15341	M	24.15	35.85	1556	39.5	168	22
483	L47662	L	24.15	35.85	1548	37.4	171	19
484	L47663	L	24.25	35.85	1324	56.9	173	17
485	L47664	L	24.25	35.85	1568	33.7	175	15
486	M15345	M	24.25	35.85	1685	30.7	177	13
487	M15346	M	24.25	35.95	1582	35.9	180	10
488	M15347	M	24.25	35.95	1463	35	183	7
489	L47668	L	24.25	36.05	1584	42.8	186	4
490	M15349	M	24.35	36.05	1347	55.8	188	2

Fig. 14. Actual RUL values.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Abbas Al-Refaie: Supervision, Conceptualization, Writing – review & editing. **Majd Al-atrash:** Conceptualization, Methodology, Validation, Writing – original draft. **Natalija Lepkova:** Validation, Writing – review & editing.

Data availability

No data was used for the research described in the article.

Limitations

Sufficient data set should be used to improve the prediction accuracy of RUL.

Ethics statements

This work complies with ethical issues.

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References

[1] M. Ma, Z. Mao, Deep-convolution-based LSTM network for remaining useful life prediction, IEEe Trans. Industr. Inform. 17 (3) (2020) 1658–1667.
[2] S. Sayyad, S. Kumar, A. Bongale, P. Kamat, S. Patil, K. Kotecha, Data-driven remaining useful life estimation for milling process: sensors, algorithms, datasets, and future directions, IEEe Access. 9 (2021) 110255–110286.
[3] M. Calabrese, M. Cimmino, F. Fiume, M. Manfrin, L. Romeo, S. Ceccacci, D. Kapetis, SOPHIA: an event-based IoT and machine learning architecture for predictive maintenance in industry 4.0, Inform. J. 11 (4) (2020) 202.
[4] F. Mauthe, S. Hagmeyer, P. Zeiler, Creation of publicly available data sets for prognostics and diagnostics addressing data scenarios relevant to industrial applications, Int. J. Progn. Health Manage 12 (2) (2021).
[5] S. Manikandan, K. Duraivelu, Fault diagnosis of various rotating equipment using machine learning approaches–A review, Proc. Instit. Mech. Eng., Part E 235 (2) (2021) 629–642.
[6] J. Leukel, J. González, M. Riekert, Adoption of machine learning technology for failure prediction in industrial maintenance: a systematic review, J. Manuf. Syst. 61 (2021) 87–96.
[7] C. Ferreira, G. Gonçalves, Remaining useful life prediction and challenges: a literature review on the use of machine learning methods, J. Manuf. Syst. 63 (2022) 550–562.
[8] Y. Wang, Y. Zhao, S. Addepalli, Remaining useful life prediction using deep learning approaches: a review, Procedia Manuf. 49 (2020) 81–88.
[9] K.T. Nguyen, K. Medjaher, A new dynamic predictive maintenance framework using deep learning for failure prognostics, Reliab. Eng. Syst. Saf. 188 (2019) 251–262.
[10] R. Saravanan, P. Sujatha, A state of art techniques on machine learning algorithms: a perspective of supervised learning approaches in data classification, *Intell. Comput. Control Syst.* (ICICCS) (2018) 945–949.
[11] H. Löfsten, Measuring maintenance performance–in search for a maintenance productivity index, Int. J. Prod. Econ. 63 (1) (2000) 47–58.
[12] Y. Lei, N. Li, S. Gontarz, J. Lin, S. Radkowski, J. Dybala, A model-based method for remaining useful life prediction of machinery, IEEe Trans. Reliab. 65 (3) (2016) 1314–1326.
[13] V. Mathew, T. Toby, V. Singh, B.M. Rao, M.G. Kumar, Prediction of remaining useful lifetime (RUL) of turbofan engine using machine learning, in: IEEE International Conference on Circuits and Systems (ICCS), 2017, 2017, pp. 306–311, doi:10.1109/ICCS1.2017.8326010.
[14] W.J. Lee, H. Wu, H. Yun, H. Kim, M.B. Jun, J.W Sutherland, Predictive maintenance of machine tool systems using artificial intelligence techniques applied to machine condition data, Procedia CIRP. 80 (2019) 506–511.
[15] B. Yang, R. Liu, E. Zio, Remaining useful life prediction based on a double-convolutional neural network architecture, IEEE Transactions on Industrial Electronics 66 (12) (2019) 9521–9530.
[16] O.E. Yurek, D. Birant, Remaining useful life estimation for predictive maintenance using feature engineering, in: *Innovations in Intelligent Systems and Applications Conference* (ASYU), IEEE, 2019, pp. 1–5.
[17] K. Deng, X. Zhang, Y. Cheng, Z. Zheng, F. Jiang, W. Liu, J. Peng, A remaining useful life prediction method with long-short term feature processing for aircraft engines, Appl. Soft. Comput. 93 (2020) 106344.
[18] M.F. Ge, Y. Liu, X. Jiang, J. Liu, A review on state of health estimations and remaining useful life prognostics of lithium-ion batteries, Measurement 174 (2021) 109057.
[19] J.Y. Wu, M. Wu, Z. Chen, X. Li, R. Yan, A joint classification-regression method for multi-stage remaining useful life prediction, J. Manuf. Syst. 58 (2021) 109–119.
[20] Wang W. (2021). Joint prediction of remaining useful life and failure type of train wheelsets: a multi-task learning approach. ArXiv preprint arXiv:2101.03497.
[21] S. Zhao, Y. Zhang, S. Wang, B. Zhou, C. Cheng, A recurrent neural network approach for remaining useful life prediction utilizing a novel trend features construction method, Measurement 146 (2019) 279–288.
[22] Z. Kang, C. Catal, B. Tekinerdogan, Remaining useful life (RUL) prediction of equipment in production lines using artificial neural networks, Sensors 21 (3) (2021) 932.
[23] M. Yan, X. Wang, B. Wang, M. Chang, I. Muhammad, Bearing remaining useful life prediction using support vector machine and hybrid degradation tracking model, ISA Trans. 98 (2020) 471–482.
[24] S. Bagri, A. Manwar, A. Varghese, S. Mujumdar, S.S. Joshi, Tool wear and remaining useful life prediction in micro-milling along complex tool paths using neural networks, J. Manuf. Process. 71 (2021) 679–698.

[25] Q. An, Z. Tao, X. Xu, M. El Mansori, M Chen, A data-driven model for milling tool remaining useful life prediction with convolutional and stacked LSTM network, Measurement 154 (2020) 107461.
[26] V. Kumar, M Mokashi, Predicting aircraft equipment failure using machine learning classification algorithms, *Int. Res. J. Eng. Technol.* (IRJET) 8 (11) (2021) 974–981.
[27] W. Liu, W.A. Yang, Y. You, Three-stage wiener-process-based model for remaining useful life prediction of a cutting tool in high-speed milling, Sensors 22 (13) (2022) 4763.
[28] S. Sayyad, S. Kumar, A. Bongale, K. Kotecha, A. Abraham, Remaining useful-life prediction of the milling cutting tool using time–Frequency-based features and deep learning models, Sensors 23 (12) (2023) 5659.
[29] D. Chicco, M.J. Warrens, G. Jurman, The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation, PeerJ Comp. Sci. 7 (2021) e623.