SSRG International Journal of Mechanical Engineering
ISSN: 2348-8360/ https://doi.org/10.14445/23488360/IJME-V13I7P112

Volume 13 Issue 7, 145-155, July 2026

Original Article

Time-Domain Vibration-Based Fault Diagnosis of Round Insert Face Milling Tools Using SVM and XGBoost: A Machine Learning Approach

Prashant Ashok Patil[1*], Nitish Kumar Gautam[1], Bhuvaneshwar Patil[1]

[1]*Department of Mechanical Engineering, SJJT University, Rajasthan, India.*

**Corresponding Author : pappvpit@gmail.com*

Received: 09 March 2026 Revised: 30 April 2026 Accepted: 13 July 2026 Published: 30 July 2026

Abstract - *Tool Condition Monitoring (TCM) plays a significant role in maintaining machining quality, reducing equipment idle time, and improving TCM often affords near-real-time detection of wear-out phenomena. A new method for vibration-based fault diagnosis of round insert face milling tools based on analysis in the time-domain and machine learning, the vibration signals were obtained using a spindle-integrated piezoelectric accelerometer during milling with controlled conditions. Healthy, flank wear, edge chipping, built-up edge and mixed fault conditions were studied from the statistical features extracted. Feature selection was implemented using Recursive Feature Elimination and Mutual Information ranking. Distributed computing was used to pilot SVM and XGBoost classifiers. The output indicated that the test accuracy of XGBoost was better (92.4% accuracy) than SVM (89.2%), while both had lower errors and shorter estimates as well. The presented approach is a cost-effective and real-time applicable method for intelligent monitoring of the condition of the monitoring tool in CNC machining. This study contributes to the development of data-driven predictive maintenance systems for smart manufacturing.*

Keywords - *Extreme Gradient Boosting (XGBoost), Fault Diagnosis, Machine Learning, Round Insert Tool, Support Vector Machine (SVM).*

1. Introduction

Intelligent manufacturing relies heavily on Tool Condition Monitoring (TCM), which directly impacts machining accuracy, production efficiency and surface quality, as well as maintenance costs. As Industry 4.0 technologies have gained traction, much effort has been invested in building smart monitoring systems to detect tool failure just before catastrophic breaking happens. By virtue of recent achievements in sensors, machine learning, and data-driven analytics, TCM has evolved from traditional model-based offline inspection towards new real-time predictive monitoring systems for autonomous manufacturing environments [1, 2].

Due to the rich Information embedded in vibration signals associated with tool-workpiece interaction, cutting dynamics and progressive tool degradation during machining processes, among them, vibration signal analysis becomes one of the most useful ones for observing the milling process. While optical imaging, force measurement, and acoustic emission techniques have relatively high implementation cost and difficulty of installation, vibration sensors are more cost-effective with lower installation effort, which fits better with the industrial application environment. It has been shown by many investigations that in-situ tool wear can be tracked closely with vibration characteristics, including flank wear, edge chipping, built-up edge formation and unstable cutting conditions [3-5].

Conventional analysis, early studies mainly focused on the correlation between vibration amplitude and tool wear. Dimla [6] developed one of the early correlations between tool wear and vibration signatures, showing that increasing amplitude vibration is correlated with the progression on the tool wear. In later studies, together with machine learning algorithms and based on the wavelet transform, it was demonstrated that time-frequency analysis enhances wear evolution predictions in different cutting conditions [7]. Other investigations reported that multiple signal domain extraction of vibration features contains more discriminative Information than a single-domain analysis, as different types of fault mechanisms affect the vibration characteristics in different ways [8-10].

Machine learning and deep learning have significantly enhanced the fault classification performance of TCM. Traditional supervised learning algorithms like Decision Trees, k-Nearest Neighbour (kNN), Artificial Neural

Networks (ANN) and Random Forest have been used successfully for classifying different tool wear conditions [11-13]. These techniques typically perform well once the features extracted are distributed clearly across classes. However, their classification ability is mostly weakened since they have limited functioning for the nonlinear and overlapped data distributions typically met in the machining tasks due to the simultaneous influence of cutting speed, feed rate, depth of cut, workpiece material and machine dynamics on tool wear progression.

For this reason, Support Vector Machine (SVM) is one of the focus areas you are trained in due to its robust theoretical background for nonlinear classification problems. SVM applies kernel methods to build maximum-margin hyperplanes in these high-dimensional feature spaces while ensuring good generalization performance with comparably small sample sizes.

The use of Radial Basis Function (RBF)-based Support Vector Machine (SVM) models offers higher classification accuracy in both the vibration-based fault diagnosis of rotating machinery and milling operations, have been demonstrated by a wide variety of studies [14-16]. While these advantages all exist, the performance of an SVM model is highly dependent on the kernel parameters and also becomes computationally intensive as industrial datasets grow larger at present.

Ensemble learning algorithms have been of more and more interest for intelligent manufacturing applications to escape these limitations. They contain a function that is more powerful for prediction, based on the sequential arrangement of weak learners, particularly Extreme Gradient Boosting (XGBoost), i.e., if other weak learners are added but regularization mechanisms are included to reduce overfitting. Several works have proven that XGBoost yields better generalization performance than many traditional machine learning algorithms for predictive maintenance, fault diagnosis and industrial monitoring applications since it can capture the complex nonlinear relationships of multi-process variables [17-19]. Its robustness to noisy measurements and ranking of feature importance also make it appealing for the practical applications of TCM, where sensor signals are subject to noise due to machine vibration and process variability.

Feature Engineering: Feature engineering is another important factor affecting the performance of machine learning-based fault diagnosis systems. Various features extracted from time, frequency, and time-frequency domains have been examined to describe machining conditions. For instance, frequency-domain based methods effectively extract periodic vibration components related to dynamic processes enveloped by spindle dynamics and chatter [18, 19] whilst time-domain methods such as wavelet transform, Empirical Mode Decomposition (EMD), are regularly used to capture transient signal behaviour induced during tool wear or damage [20-22]. While these signal processing techniques generally increase classification accuracy, they also entail an increased computational complexity and parameter selection for optimal results, which hinder applications of real-time deployment in plant production systems.

As a result, multiple recent studies have taken a new look at time-domain statistical features due to their relatively low computational cost with respect to other approaches and the fact they retain meaningful diagnostic Information. Statistical descriptors such as Root Mean Square (RMS), variance, kurtosis, skewness, crest factor, peak value, shape factor and impulse factor can accurately separate various tool wear states in the milling process [23, 24]. The classical statistical parameters, designed for binary classification problems, yield competitive performance while keeping the computation speed appropriate for online monitoring systems when coupled with well-suited feature selection algorithms.

Thus, feature selection has increasingly become an important research direction to ameliorate the robustness of classifiers and redundancy. Common dimensionality reduction methods such as Recursive Feature Elimination (RFE), Mutual Information (MI), ReliefF and Principal Component Analysis (PCA) have been extensively used to search for useful variables before model fitting [25, 26]. In addition to lowering the computational cost, these approaches may also boost model interpretability, especially after removing irrelevant or highly correlated features. This would result in improvements in generalization directly across different machining conditions.

While significant strides have been made in vibration-based TCM, many key research gaps still exist. This is because mostly the literature published consists of conventional inserts like square, triangular or single point cutting tools and not much work has been done in round insert face milling cutters as compared to other subjects. With continuously varying engagement angles, larger tool-workpiece contact regions and more complex chip formation mechanisms, the unique geometry of round inserts gives rise to vibration characteristics which di↵er significantly from those seen aq conventional inserts. Due to the difference in uncertainty, models developed for traditional cutting tools cannot be simply applicable to round insert machining.

Second, most of the existing studies focus on binary tool wear classification or considering only one single degradation mechanism, while real machining environments contain multi-type fault scenarios with multiple fault conditions, including flank wear, edge chipping, crater wear and combined failure modes. The determination of multiple fault types remains a difficult problem as the vibration signatures associated with those faults overlap.

Third, a Need for balance between accuracy and interpretability. Trade-offs: conventional predictive methods, such as sophisticated deep learning and hybrid signal processing models, show excellent predictive performance but generally have high computational costs, large amounts of training data required to avoid overfitting and poor biological interpretability, which limits the implementation in industrial online monitoring systems in regions without sufficient technical support resources (especially small to medium manufacturing enterprises). Far less work has been conducted to determine whether a few carefully selected time-domain statistical features based on computationally low-cost machine learning algorithms provide similar diagnostic performance in realistic machining scenarios. Inspired by these gaps in research, this study proposes a multi-fault diagnosis framework for round insert face milling tools based on vibration dynamics. Statistical features are then extracted in the time domain from spindle vibration signals measured during actual machining experiments and then selected using Recursive Feature Elimination and Mutual Information ranking. We use two complementary machine learning classifiers, Support Vector Machine and XGBoost, to assess the classification performance and choose the best approach for industrial applications. Model evaluation is performed using k-fold cross-validation along with accuracy, precision, recall, F1-score, receiver operating characteristic analysis and confusion matrices. The framework offers a computationally efficient, reliable and practically deployable solution in the area of intelligent tool condition monitoring of round insert face milling operations on smart manufacturing environments.

2. Methodology & Contributions

The proposed method is a vibration-based fault diagnosis framework for round insert face milling tools, which utilizes only time-domain statistical features and supervised machine learning methods. Vibration data was also collected and analyzed during face milling via a spindle-mounted piezoelectric accelerometer, integrated to a data acquisition system; signals were acquired at high speed to study the dynamic tool–workpiece interaction.

Stable cutting segments were chosen and normalized to avoid noise and amplitude bias. It was proposed to extract the time-domain statistical features (mean, RMS, standard deviation, variance, skewness, kurtosis, peak-to-peak value and crest factor) from each vibration signal representing tool health conditions. To measure relevancy of the features, we applied correlation and ranking techniques to remove redundancy. As shown in the Figure 1. The extracted feature dataset was split into training and testing datasets and fed into SVM with RBF kernel and XGBoost classifiers. Cross-validation, confusion matrix, accuracy, precision, recall and F1-score were used to analyze the performance of the model to guarantee its capability of identifying faults accurately and original fault Sensors 2020, 20, x 31 for real-time implementation.

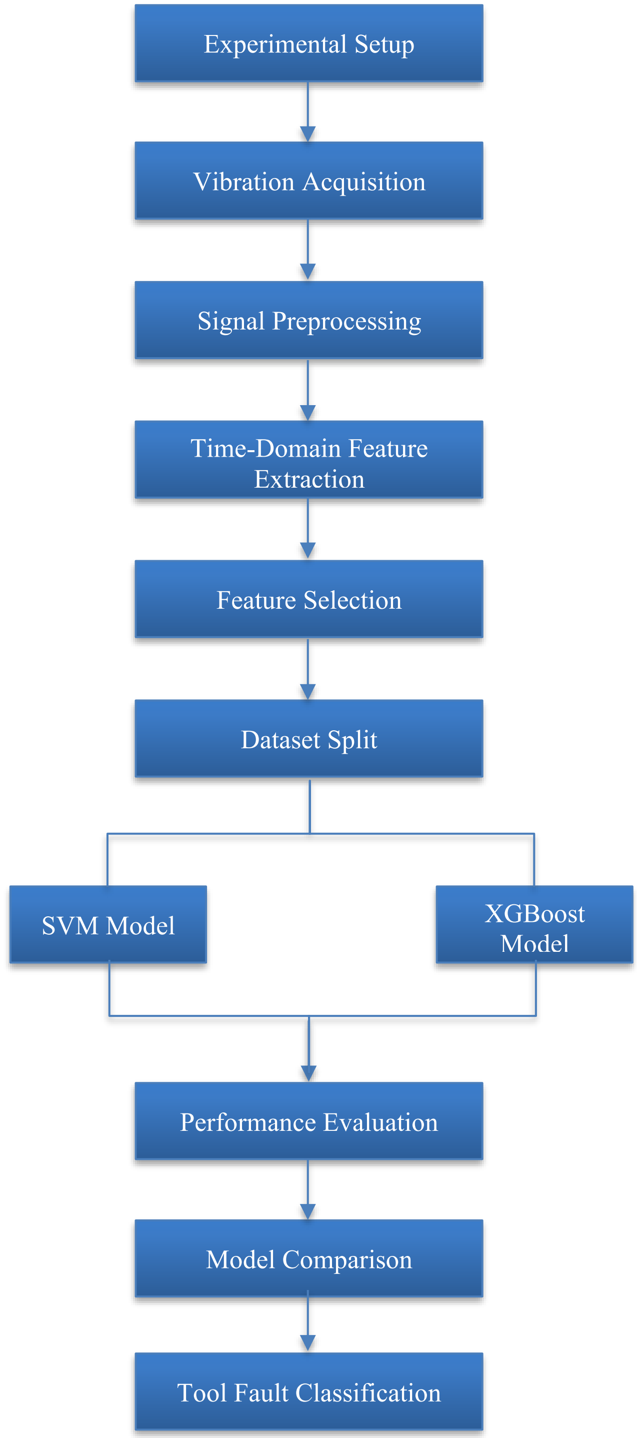


Fig. 1 Vibration-based fault diagnosis framework using SVM and XGBoost classifiers

The novelty of this work lies in the integration of computationally efficient time-domain statistical features with a hybrid two-stage feature selection framework combining Recursive Feature Elimination (RFE) and Mutual Information (MI) ranking, followed by a comparative evaluation of SVM and XGBoost classifiers for multi-class fault diagnosis of round insert face milling tools. Unlike conventional studies that employ either feature selection or complex signal processing independently, the proposed framework simultaneously reduces feature redundancy, enhances feature relevance, and improves classification performance while maintaining low computational complexity, making it suitable for real-time industrial tool condition monitoring.

The organization of this paper is introduced as: Section 2 on Methodology and Section 3 on the experimental setup, including input conditions and vibration signal acquisition protocol. Sections 4-5 explain the ML process used for classification. The findings are discussed, and conclusions are drawn in Section 6. Limitations of the study and suggestions for future research is addressed in Section 7, while final remarks are made in Section 8.

3. Experimental Setup

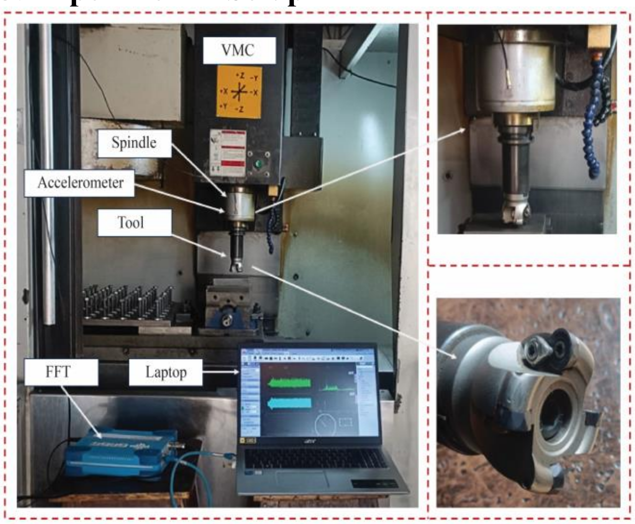


Fig. 2 Experimental setup

Figure 2 presents the experimental setup, which mainly consists of an accelerometer, a Data Acquisition (DAQ) system, and a CNC-VMC.

Specifications:

- Make: VMC -800
- X-Y-Z Axis Travel:800 x 550 x 550 mm
- Spindle speed: 1200 rpm
- Feed Rate: - 2500 mm/min
- Depth of Cut: - 0.35 mm
- Workpiece: The MS material 250 x 150 x 100 mm
- The milling cutter, with a diameter of 80 mm, was equipped with six triangular inserts.
- Executed Operation: Face Milling
- FFT: OROS 34-VS-4 four-channel
- Accelerometer: Piezotronics-Model 333B32, ICP type

The main machining parameters, such as spindle speed, feed rate and depth of cut, have significant effects on tool wear advancement and machining performance in operation. The selection of these parameters was made in line with the practice in industry; it guaranteed stable cutting conditions and ensured a reliable collection of vibration signals. All the experiments of face milling were performed with the selected machining inputs and five different tool-setting arrangements: Table 1. For common round insert faults in this investigation, flank wear, edge chipping, built-up edge formation and combined fault conditions were studied as well as the defect-free (healthy) one. The non-polished inserts corresponding to separate health conditions, Healthy (H), Flank Wear (FW), Edge Chipping (EC), Built-Up-Edge (BUE) and combined fault wear (CFW) were tested in isolation milling experiments. For those configurations in Figure 3(a)-(d), the vibration signals were collected continuously by a spindle-mounting accelerometer from which time-domain features were extracted for machine-learning-based fault diagnosis.

Table 1. Various Tool Configuration

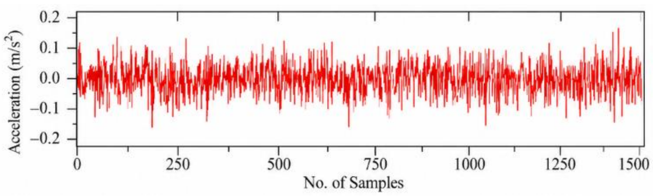
Configuration	Insert 1	Insert 2	Insert 3	Insert 4	Class Label
A	Healthy	Healthy	Healthy	Healthy	H
B	Flank Wear	Healthy	Healthy	Healthy	FW
C	Edge Chipping	Healthy	Healthy	Healthy	EC
D	Built-Up Edge	Healthy	Healthy	Healthy	BUE
E	Healthy	Edge Chipping	Flank Wear	Built-Up Edge	CFW

(a) Healthy **(b) Flank Wear** **(c) Edge Chipping** **(d) Built-Up Edge**

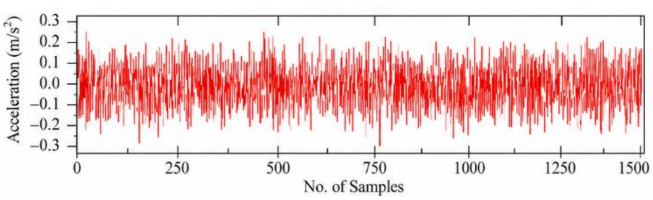
Fig. 3 Both different healthy and faulty insert.

The attachment and inclination of the accelerometer influence the acquisition of vibration signals during the measurement of dynamic response. During the cutting process of CNC-VMC machining, oscillations caused by tool–workpiece engagements are transferred directly to the spindle assembly; thus, the sensor had to be attached in proximity to the spindle housing for proper measurement of cutting-induced vibrations.

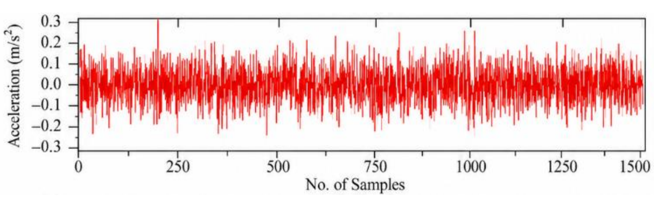
Because the spindle revolves around a vertical axis, the accelerometer was mounted in vertical orientation to capture dominant vibration contributions along the primary direction of motion. The vibration responses of the five tool considerations (healthy and with different faults) in the time domain were measured at identical machining conditions.



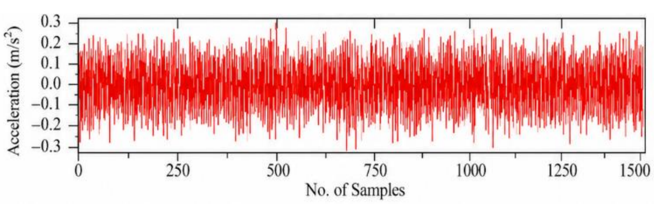
(a) For tool configuration 'A'



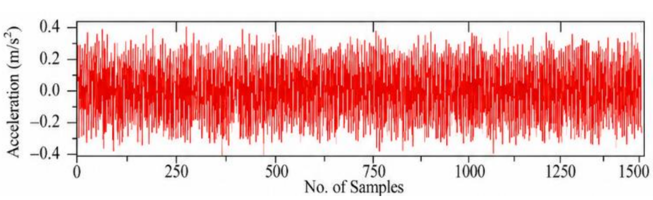
(b) For tool configuration 'B'



(c) For tool configuration 'C'



(d) For tool configuration 'D'



(e) For tool configuration 'E'

Fig. 4 Time-series plots of the configuration of different tool Operations shown in Table 1

A sampling frequency of 20 kHz was chosen so that the vibration signals could be accurately captured based on the Nyquist rule. Each acquisition record contained 4096 data points in the time domain. Before cutting, data were acquired by performing initial milling passes to stabilize the cut and remove surface aberrations. The three peaks of acceleration amplitudes were also distinctly different for these four conditions, as shown in 4(a–e). The vibration signals captured by transducers were also found that the inserts with healthy state produced relatively constant low amplitude vibrations, while this pattern got irregular design for a faulty insert due to the unstable cutting condition, which occurred from intermittent tool-workpiece contacts.

Edge chipping and combined fault wear were more pronounced in some of the simulations between these fault conditions, as they reproduce periodic impact forces applied to parts during machining. In built-up edge conditions, reflected signal variations were also observed from time to time due to chip adhesion on the cutting edge. The variations show that vibration signals can accurately reflect the dynamic evolution of tool wear status during milling processes.

4. Signal Processing Methodology - Feature Extraction

Since the focus was on computational complexity and a real-time implementation, only time domain processing of the acquired vibration data was performed. Each segment presented a vibration signal, and the improvement in these signals was represented as a statistical parameter that reflected the health condition of the tool. In fact, Time-domain features are suitable to characterize some aspects of signal amplitude distribution, energy content and impulsive behavior (due to impact forces) in addition to variability related to mechanical wear dynamics [19, 20].

The parameters that were extracted consisted of the mean, RMS, standard deviation, variance, kurtosis, skewness, max amplitude, min amplitude, peak amplitude and peak-to-peak, as well the crest factor. RMS and variance are indicative of signal energy, while kurtosis and skewness capture impulsive properties associated with edge chipping and built-up edge formation. The dataset was compiled into a structured form for classification by representing each vibration sample as a feature vector.

5. Feature Selection

5.1. Recursive Feature Elimination (RFE) Type of Support

Recursive Feature Elimination (RFE) is a wrapper-based approach that trains the model multiple times while removing sequentially lower-ranking features until an optimal feature subset is reached from one or more features based on feature importance rankings [21]. RFE may not overfit and reduce the model generalization error while conserving some computational resources.

Recursive Feature Elimination (RFE) is a wrapper-based feature selection technique that recursively removes the least important features according to the prediction model. Let the extracted feature vector be represented as

$$X = [x_1, x_2, x_3, \dots, x_n] \quad (1)$$

where
- n= total extracted statistical features.

The objective of RFE is to determine the optimal subset.

$$X^* \subseteq X \quad (2)$$

that maximizes the classifier performance.

For a trained classifier, each feature receives an importance score.

$$I_i = f(x_i)\ X^* \subseteq X \quad (3)$$

where
- I_i= importance of feature x_i.

For linear models,

$$I_i = \mid w_i \mid X^* \subseteq X \quad (4)$$

where
- w_i is the coefficient of feature i.

At every iteration,

$$X^{k+1} = X^k - \arg min(I_i) \quad (5)$$

meaning the feature having the minimum importance is eliminated.

The procedure continues until the desired number of features remains.

Algorithmically,
1. Train classifier.
2. Compute feature importance.
3. Remove least important feature.
4. Retrain classifier.
5. Repeat until an optimal feature subset is obtained.

RFE minimizes redundant variables while preserving highly discriminative statistical features, thereby improving classifier accuracy and reducing computational complexity.

5.2. Mutual Information based Ranking

In terms of the statistical dependency between input features and class labels, MI estimates how much Information a feature carries toward classification [22]. We focused on features with higher MI scores, having a high discrimination level between the tool conditions,

The combination of RFE and MI ensured that only the most relevant time-domain features were retained for model training.

Mutual Information measures the statistical dependency between an input feature and the target class.

For two random variables $X$and Y,

$$I(X;Y) = \sum_x \sum_y p(x,y) \log(\frac{p(x,y)}{p(x)p(y)}) \quad (6)$$

where
- $p(x,y)$= joint probability
- $p(x)$= marginal probability of feature
- $p(y)$= marginal probability of class.

If

$$I(X;Y) = 0$$

then
- The feature and class are independent.

Larger MI values indicate greater discriminative capability. The features are ranked according to

$$MI_i = I(x_i;Y) \quad (7)$$

The selected subset is

$$S = \{x_i \mid MI_i > \tau\} \quad (8)$$

where
$\tau$is the ranking threshold.

In this study, Mutual Information was employed after RFE to verify that the retained features possess maximum Information regarding the five tool health conditions (Healthy, Flank Wear, Edge Chipping, Built-Up Edge and Combined Fault Wear). The combined RFE–MI framework removes redundant variables while preserving highly informative statistical descriptors for machine learning.

6. Machine Learning Framework

The optimal features were used to develop the supervision safety classifier for tooling damage identification. Additionally, the database was stratified 80%–20% into training and testing sets at random, and robustness of adaptability of models were also evaluated with a 10-fold cross-validation. We used two advanced classifiers — Support Vector Machine (SVM from Scikit-learn and XGBoost.

6.1. Support Vector Machine (SVM)

Support Vector Machine is a kind of supervised learning algorithm that finds an optimal hyperplane such that the margin between two classes is maximized. Cell features were nonlinearly classified using a Radial Basis Function (RBF) kernel, which projected input features into a space in which they could be separated.

The optimization problem is expressed in equation 1.

$$\min_{\omega,b,\xi} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}\xi_i \quad (9)$$

where C specifies the trade-off between maximizing margin and minimizing training error. The hyperparameters C and the kernel parameter of γ were tuned through grid search to reach good performance. SVM is especially suitable for vibration-based fault diagnosis because of its anti-overfitting property and good generalization ability.

A/P	H	FW	EC	BUE	CFW
H	90	5	0	5	0
FW	5	88	7	0	0
EC	0	6	89	5	0
BUE	4	0	6	90	0
CFW	0	5	6	0	89

Fig. 5 Confusion Matrix: SVM

Confusion matrix of the SVM classifier as shown in Figure 5 The overall classification accuracy of 5 was 89.2%. Out of these 500, there were 446 correctly classified samples. The diagonal of the confusion matrix depicts high recognition performance across all five tool conditions. All three edge classes that were healthy or built up yielded the highest correct classifications, with 90 identified samples each.

Due to similarities in vibration characteristics caused by edge chipping and flank wear conditions during machining, minor misclassifications were seen between these two classes. The fault wear class was very well separated from the other classes with minimal classification errors, as opposed to the non-fault series. This illustrates the ability of the extracted time-domain statistical features to distinguish between severe tool faults well.

The performance metrics of the SVM model are described in Table 2. The recall basing from 0.88 to 0.90, indicating a good fault detection capability. Precision and recall were 0.896 and 0.892, respectively, with an error rate of 0.027 רק false positives CFW class has a precision value of 1.0, hinting that combined faults are not classified as false positives.

Table 2. Descriptive Accuracy SVM

Class	TP Rate	Recall	Precision	FP Rate
H	0.9	0.9	0.909	0.022
FW	0.88	0.88	0.846	0.04
EC	0.89	0.89	0.824	0.048
BUE	0.9	0.9	0.9	0.025
CFW	0.89	0.89	1	0
Weighted Avg	**0.892**	**0.892**	**0.896**	**0.027**

Descriptive Metrics in SVM Model. Descriptive metrics are shown in Table 2. All classification units have a recall of between 0.88 to 0.90, making our detection very precise.

In this scenario again, we obtain good scores for the sensitive class with a micro-precision and recall of 0.892 and 0.896 respectively, as well as perfect precision (1.0) for class CFW due to not having any false positives on it The overall FP rate is rather small 0.027; These results confirm the classification capability of time-domain vibration features, and although the SVM model was acceptable for at least 3 types of fault classes, some confusion between similar fault types was also observed.

6.2. XGBoost Model

XGBoost Extreme Gradient Boosting (XGBoost) is a state-of-the-art ensemble learning method, like that of gradient boosting. It is constructed by multiplexing a sequence of weak decision trees, each of which remedies the errors produced by its predecessor.

Loss minimization combined with a regularization for the order of relationship to prevent overfitting are used in the objective function as shown in equation 2.

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \quad (10)$$

where l represents the loss function, and Ω is the regularization term.

XGBoost is widely used for its high prediction accuracy, computational efficiency , as well as capability to represent nonlinear feature interaction. In this research, hyperparameters including learning rate, number of estimators and maximum tree depth were tuned for better classification.

A/P	H	FW	EC	BUE	CFW
H	93	4	0	3	0
FW	3	92	5	0	0
EC	0	4	93	3	0
BUE	3	0	4	93	0
CFW	0	3	5	0	91

Fig. 6 Confusion Matrix: XGBoost Model

Table 3. Descriptive Accuracy XGBoost Model

Class	TP Rate	Recall	Precision	FP Rate
H	0.93	0.93	0.939	0.017
FW	0.92	0.92	0.893	0.027
EC	0.93	0.93	0.869	0.035
BUE	0.93	0.93	0.939	0.017
CFW	0.91	0.91	1	0
Weighted Avg	**0.924**	**0.924**	**0.928**	**0.019**

For improved classification, the XGBoost classifier outperformed SVM. The confusion matrix based on the results presented in Figure 6 had an accuracy of 92.4%, with 462 samples correctly classified from a total of 500. These results demonstrated that the model correctly classified all tool conditions with higher classification consistency.

This produced 93 correctly classified samples for the healthy, chip edge, and built-up edge conditions, while flank wear and combination fault wear produced 92 and 91 correct classifications, respectively. The number of misclassification cases was greatly minimized compared to the SVM model. Most of the errors were between flank wear and edge chipping conditions, caused by overlapping vibration signatures in stages of progressive wear.

The descriptive metrics provided in Table 3 are further proof of the classifier robustness for XGBoost. The weighted average recall and precision averaged 0.924 and 0.928, respectively, and the false positive rates were reduced to about 0.019. The precision was again perfect for the combined fault wear class (i.e., no false positives).

7. Comparative Discussion and Performance Evaluation

The comparative performance analysis of the SVM and XGBoost classifiers is depicted in Table 4. XGBoost provided a slightly better overall classification accuracy of 92.4% than the one achieved with the SVMB (89.2%). The Kappa statistic with 0.905 and 0.865 for XGBoost and SVM, respectively, shows strong concordance between predicted and real labels; the reliability was better in XGBoost. In addition, the error measures of the XGBoost classifier are lower (MAE xg = 0.076 and RMSE xg = 0.152) than that of SVM (MAE svm = 0.108 and RMSE svm = 0.187). Similarly, RAE and RRSE go down to 7.6% and 15.2% of the XGBoost, while SVM shows as 10.8% and 18.7%. From these results, it can be concluded that XGBoost exhibits better predictive capability and lower classification error than the SVM-based model for time-domain vibration-based tool fault diagnosis.

Table 4. Classifier Performance Comparison Metrics

Sr. No.	Attributes / Tree based classifiers	SVM	XGBoost
1	Properly Classified Samples (%)	89.2	92.4
2	Kappa	0.865	0.905
3	MAE	0.108	0.076
4	RMSE	0.187	0.152
5	RAE (%)	10.8	7.6
6	RRSE (%)	18.7	15.2

The obtained feeding models were then tested on unseen test data to measure their generalization capacity. The whole data set was randomly partitioned into the training and testing sets, with 80% samples used for training, while 20% samples were kept for testing. At the first stage, models were trained based on the chosen time-domain features and tested with an independent test set. The comparative results are shown in Figure. 7, and the accuracy of previously published work is shown in Table 5.

The SVM model obtained a training accuracy of 91.6%, test accuracy of 89.2% and a 10-fold cross-validation accuracy is also calculated for it (88.85%), with the SVM build being equal to 0.19 sec. On the other hand, the XGBoost classifier (tuned model) showed better training accuracy of 94.1%, test accuracy of 92.4%, and cross-validated accuracy of 91.75 % with a lesser model build time of just 0.14 seconds.

These results suggest that the generalization performance and the model-building speed of XGBoost are superior to SVM. Thus, the introduced time-domain vibration-based framework (especially with XGBoost) works well for accurate and online tool fault classification while face milling is in process.

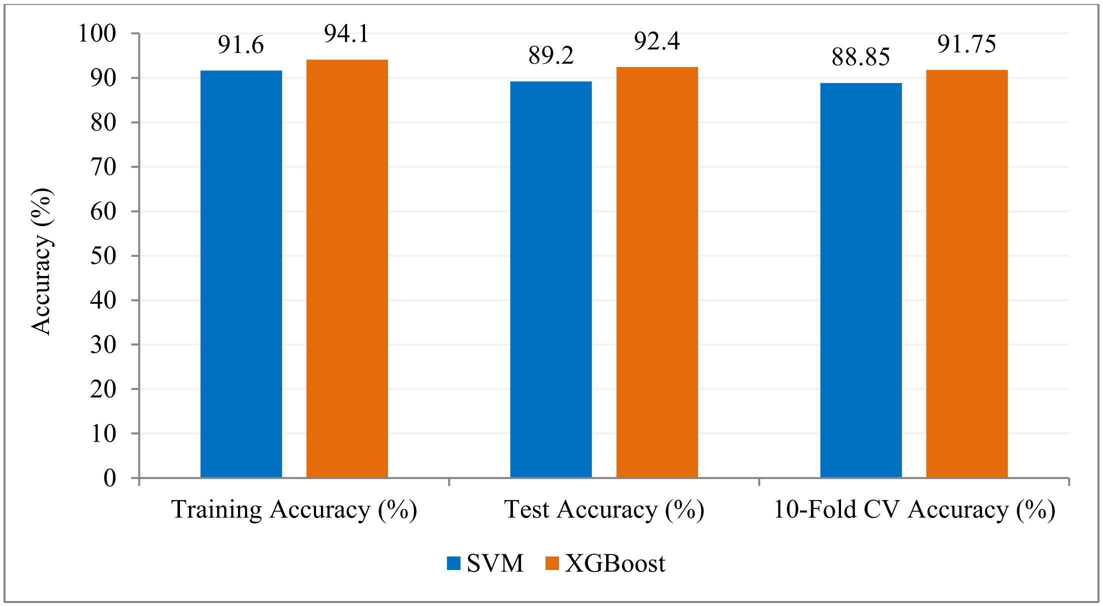


Fig. 7 Classifier classification accuracy using an untrained test dataset

Table 5. Accuracy of TCM from previously published research

Sr. No.	Authors (Year), [Ref.]	Signal presentation	Feature extraction	Feature classification	Result accuracy
1	S. Sun et al., (2020) [23]	Time-frequency	mean, wavelet	Support vector	91.18%
2	Khalil AF (2024) [24]	Frequency domain	FFT	SVM	90.0%
3	S. Khomfoi (2007) [25]	Frequency domain	FFT	Neural	85%
4	C. Zhou (2020) [26]	Time-frequency	Wavelet	Support Vector	90.8%
5	**Proposed Work**				**92.40%**

8. Limitations and Future Scope

The developed vibration-based fault diagnosis approach of round insert face milling tools is mostly confined to the classification with time-domain features acquired under constant cutting parameters. After training, the obtained models can successfully recognize pre-defined machining states (i.e., turn wear, flank wear, edge chipping, built-up edge and a combination of all the defects), but they have limitations when shifted to other cutting conditions or workpieces for which no training data are available. Moreover, due to using only time-domain Information the capability to model complicated frequency-dependent properties of tool wear development may be constrained.

Real-time CNC machining applications can use the vibration-based fault diagnosis framework proposed in this paper since computationally efficient time-domain statistical features are used with machine learning classifiers. The proposed system could facilitate predictive maintenance, prevent tool unexpected failure, reduce machining procedure downtime and enhance process reliability in smart manufacturing environments under Industry 4.0 directionality. Moreover, the lower computational complexity and higher execution time of the XGBoost classifier demonstrate good scalability and are appropriate to industrial online monitoring applications.

This study improves on these limitations, however. The first is that the tests were conducted at constant machining conditions in a small range of fault classes, which may restrict the generalization ability of the framework under variable machine operating conditions typically found in industry. The method proposed in this work has used only time-domain vibration features, but frequency domain, time-frequency and deep learning-based methods would synthesize more powerful diagnostic abilities. We aim to broaden the dataset under different machining conditions, discuss new ways of feature extraction, and establish adaptive learning approaches for industrial applications in future work.

Moreover, deep learning-based methods incorporated with real-time adaptive learning schemes could facilitate the automatic diagnosis of fault unknown states as well as extend the capability of prognosis maintenance. These would enable us to realize a more universal and intelligent tool condition monitoring system for Industry 4.0.

9. Conclusion

An efficient vibration-based fault diagnosis methodology for round insert face milling tools is proposed in this paper through domain signal processing and machine learning algorithms. Vibration signals were obtained using a spindle-mounted accelerometer and important statistical f-values which represent various tool conditions such as healthy, flank wear, edge chipping, built-up edge (BUE) and mixed fail state BUE. The feature selection with Recursive Feature Elimination and Mutual Information ranking preserved the most informative descriptors, resulting in better classification performances.Two supervised learning algorithms, SVM and XGBoost, were applied and compared. The outcomes show that both models achieved reasonable classification performance, but the XGBoost classifier supersedes SVM with an accuracy of 92.4% and 89.2%, as well as lesser error metrics when it comes to the building time of the model. The confusion matrix analysis also indicated strong class discrimination, and misclassification was only made between structurally similar fault conditions.

The results show that the time-domain vibration features combined with a highly intelligent pattern recognition approach provide a computationally efficient technique which is capable of real-time tool condition monitoring. The developed concept is applicable to industrial machining where CNC technologies are used, for an increased reliability of the machining process during operation with less downtime and support a predictive maintenance strategy. In general, this study helps toward the implementation of intelligent and data-driven fault diagnosis systems in smart manufacturing applications.

Conflicts of Interest

We, Authors declares that there is no conflict of interest regarding the publication of this paper.

Acknowledgments

The authors are thankful to Stalwart Technology, Pvt. Ltd., Pune, India, for extending the laboratory facilities at its disposal to carry out the reported experimental work.

References

[1] Melvin Alexis Lara de Leon et al., "Tool Condition Monitoring Methods Applicable in the Metalworking Process," *Archives of Computational Methods in Engineering*, vol. 31, no. 1, pp. 221-242, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] T. Benkedjouh et al., "Health Assessment and Life Prediction of Cutting Tools based on Support Vector Regression," *Journal of Intelligent Manufacturing*, vol. 26, no. 2, pp. 213-223, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[3] Yuqing Zhou et al., "Time-Frequency Representation-Enhanced Transfer Learning for Tool Condition Monitoring During Milling of Inconel 718," *Maintenance and Reliability*, vol. 25, no. 2, pp. 1-13, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Thanassis Souflas et al., "Tool Condition Monitoring in Milling Using Cutting Force and Temperature Data from an Instrumented Milling Head," *The International Journal of Advanced Manufacturing Technology*, vol. 139, no. 11, pp. 6049-6072, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[5] Muralidhar Ingale, Rupesh Bhortake, and Kishor Waghulde, "Vibration-Based Fault Diagnosis of Multi-Point Tool Inserts in Vertical Machining Centers Using Decision Tree, Random Forest Classifiers and Hybrid Stacking Model: A Machine Learning Approach," *Journal of Mines Metals and Fuels*, vol. 73, no. 4, pp. 881-900, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[6] Mahardhika Pratama et al., "Online Tool Condition Monitoring Based on Parsimonious Ensemble+," *IEEE Transactions on Cybernetics*, vol. 50, no. 2, pp. 664-677, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[7] Achmad Zaki Rahman et al., "Innovative Tool Condition Classification: Utilizing Time–Frequency Moments as Inputs for BiLSTM Networks in Milling Processes," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, vol. 46, no. 9, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[8] Suhas S. Aralikatti, K. N. Ravikumar, and Hemantha Kumar, "Fault Diagnosis of Single-Point Cutting Tool Using Vibration Signal by Rotation Forest Algorithm," *SN Applied Sciences*, vol. 1, no. 9, pp. 1-8, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[9] Swathi Kotha Amarnath et al., "Combining Sensor Fusion and a Machine Learning Framework for Accurate Tool Wear Prediction During Machining," *Machines*, vol. 13, no. 2, pp. 1-15, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[10] T. Mohanraj et al., "Review of Advances in Tool Condition Monitoring Techniques in the Milling Process," *Measurement Science and Technology*, vol. 35, no. 9, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[11] Agata Przybyś-Małaczek et al., "Application of Machine Learning Algorithms for Tool Condition Monitoring in Milling Chipboard Process," *Sensors*, vol. 23, no. 13, pp. 1-31, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] D. Pradeep Kumar, V. Muralidharan, and Shaul Hameed Syed, "Multi-Point Tool Condition Monitoring System: A Comparative Study," *FME Transaction*, vol. 50, no. 2, pp. 193-201, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[13] V Raja Sekhar Reddy et al., "Experimental Study of a Sensor Based Toolwear Detection Using Machine Learning Models," *International Journal of Scientific Research in Engineering and Management*, vol. 10, no. 2, pp. 1-9, 2026. [CrossRef] [Publisher Link]

[14] Muralidhar Ingale, Rupesh Bhortake, and Kishor Waghulde, "Vibration-Based Fault Diagnosis of Multi-Point Tool Inserts on a Vertical Machining Centre Using Histogram Features and Ensemble Voting Clasifiers," *2025 5th Asian Conference on Innovation in Technology (ASIANCON)*, PIMPRI, India, pp. 1-9, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[15] Sameer Sayyad et al., "Milling Tool Wear State Classification and Prediction Using Machine Learning, Homogeneous and Heterogeneous Ensemble Learning Approach," *Journal of Remanufacturing*, vol. 16, no. 1, pp. 1-26, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[16] Yang Hui et al., "Milling Tool Wear State Recognition by Vibration Signal Using a Stacked Generalization Ensemble Model," *Shock and Vibration*, vol. 2019, no. 1, pp. 1-16, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[17] D. Vetrithangam et al., "Machine Fault Diagnosis Using Random Forest with Recursive Feature Elimination and Cross Validation," *Journal of Machine and Computing*, vol. 5, no. 3, pp. 1700-1711, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[18] Agata Przybyś-Małaczek et al., "Comparative Study of Conventional Machine Learning versus Deep Learning-Based Approaches for Tool Condition Assessments in Milling Processes," *Applied Sciences*, vol. 14, no. 13, pp. 5913-5913, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Xintian Zi, Shangshang Gao, and Yang Xie, "An Online Monitoring Method of Milling Cutter Wear Condition Driven by Digital Twin," *Scientific Reports*, vol. 14, no. 1, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] John Henry Navarro-Devia et al., "Chatter Detection in Milling Processes—A Review on Signal Processing and Condition Classification," *The International Journal of Advanced Manufacturing Technology*, vol. 125, pp. 3943-3980, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[21] Matthew Alberts et al., "Chatter Detection in Simulated Machining Data: A Simple Refined Approach to Vibration Data," *The International Journal of Advanced Manufacturing Technology*, vol. 132, pp. 4541-4557, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] Muhammet Ali Aykanat, and Rifat Kurban, "Comparative Study of Machine Learning and Ensemble Learning Approach on Tool Wear Classification," *Journal of Advances in Manufacturing Engineering*, vol. 2, no. 6, pp. 86-93, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[23] Shixu Sun, Xiaofeng Hu, and Wenjuan Zhang, "Detection of Tool Breakage During Milling Process Through Acoustic Emission," *The International Journal of Advanced Manufacturing Technology*, vol. 109, pp. 1409-1418, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[24] Ardalan F. Khalil, and Sarkawt Rostam, "Machine Learning-Based Predictive Maintenance for Fault Detection in Rotating Machinery: A Case Study," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13181-13189, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[25] Surin Khomfoi, and Leon M. Tolbert, "Fault Diagnostic System for Multilevel Inverter using Neural Network," *IEEE Transactions on Power Electronics*, vol. 22, no. 3, pp. 1062-1069, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[26] Zhou Chang'an et al., "Vibration Singularity Analysis for Milling Tool Condition Monitoring," *International Journal of Mechanical Sciences*, vol. 166, 2020. [CrossRef] [Google Scholar] [Publisher Link]