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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

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Abstract

The condition of multi-point tool inserts is crucial for optimal machining performance, impacting surface finish, power consumption, and process stability. Early detection of tool faults can signifi-cantly enhance machining efficiency and prevent potential failures. This study presents a vibration-based real time fault diagnosis approach for triangular multi-point tool inserts using Machine Learning (ML) techniques. Time-domain vibration data is collected from various both defective and fault-free configurations of six tool inserts while performing surface milling operations on a Vertical CNC Milling Machine (VMC). An event-driven method that is developed in a Visual Basic Environment (VBE) is used to extract statistical information. The most significant features are selected using the Decision Tree (DT), Random Forest (RF) classifiers and Hybrid Model (DT + RF Stacking) for effective classification. The study evaluates the performance of these two su-pervised tree-based ML algorithms with Ensemble Learning Approach to determine the most accu-rate classifier for predicting tool insert faults.

Major Findings: *Results indicate that the DT classifier achieved a classification accuracy of 98.75 % using 10-fold cross-validation, while the RF classifier achieved 97.53 % and hybrid stacking achieved accuracy of 99.25 %. This approach facilitates early detection of tool defects, improving machining process-es and reducing downtime.*

Keywords: Decision Tree, DT + RF Hybrid Stacking, Machine Learning, Multi Point Tool Insert, Random forest Classifiers, Statistical Features, Vibration Based Fault Diagnosis

1.0 Introduction

A cutting tool is a crucial component of the metal removal procedure. Cutting tool performance deteriorates during continuous machining because of tool wear and breakage. Tool failure modifies the product's dimensions and lowers its quality. One important factor in the manufacturing industry is the health of the tool. Therefore, an online Tool Condition Monitoring (TCM) system is required. By employing continuous parameter monitoring, TCM improves the state of the process, especially with regard to the cutting tool. This TCM system claims to save idle time and save maintenance costs while increasing productivity. Researchers have presented analytical and numerical models, but they do not appear to be suitable for real-time tool condition monitoring due to the influence of in-process created flaws. The most realistic models are those created using real-time information

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to show the behavior of a process[1]. There are two methods for measuring tool wear: direct and indirect. Direct measurement of the cutting edge provides the most accurate information about tool wear. Vibration signals have been widely used in research to assess tool health, with signal processing playing a crucial role in extracting meaningful features from raw, complex data. Effective vibration monitoring helps link tool condition to dimensional changes and surface quality, considering factors like noise, temperature, and spindle load. Milling generates two types of vibrations: independence, caused by machine component issues, and dependence, resulting from cyclical variations in machining conditions. Yiquan Dai *et al.* used a direct sensor system with LED illumination and vision inspection to capture images[2]. Park *et al.*[3] used computer vision systems to apply the direct measurement method utilising optical sensor techniques. A laser displacement sensor was utilised by Ryabov *et al.*[4] to measure the tool geometry in real time throughout the milling operation. According to N. Ghosh *et al.*[5], TCM can be ascertained using optical, laser, electromechanical, and ultrasonic methods. Although these direct measures offer the benefit of high precision under specific circumstances, they have not yet shown to be very appealing from a technical or financial standpoint. Now, online process applications are better suited for indirect measurements. Data on the machining process of measurement Systems for acquiring signals such as Triaxial dynamometer and accelerometer used for surface roughness[6,7], sensory tool holder for surface integrity[8,9], Accelerometer vibration signals, Temp. & pressure sensors for rolling mill, gearbox bearing defects[10,11], audio and vibration signals for machine state monitoring[12], AE – signals for edge tool[13,14], 3D optical profiler for surface roughness[15], Signal - triaxial vibrations for tool flank wear and machine state monitoring[9,16,17]. These retrieved features are then used, together with artificial intelligence approaches, to diagnose the tool conditions. Nevertheless, due to the nonstationary and stochastic character of the measured signals, relatively few indirect approaches are appropriate for industrial applications.

Chang'an Zhou *et al.*[18] Employed the Holder Exponent (HE) to quantitatively characterize the variation of vibration waveforms using the singularity analysis method based on wavelet transform. To extract effective, HE characteristics from the HE indices that correlate with the varied tool circumstances, the probability density distribution and statistical analysis were used. Kai Guo *et al.*[19] used wavelet analysis that provides a range of optional characteristics, such as wavelet coefficients, scaling coefficients, and wavelet domain statistics. Among these, wavelet-based singularity analysis has excellent potential for estimating various tool conditions. Changan Zhoua *et al.*[20] demonstrated TCM milling cutting condition via vibration singularity analysis. The results of an experimental investigation show that the number of singular points of feed direction vibration components and the means of the HE values are the parameters most closely related to tool conditions. Yuekai Liu *et al.*[21] Indirect monitoring techniques, which assess tool condition through sensor signal analysis, are widely used in production settings. Signals such as cutting force, vibration, motor current, and AE can indicate tool condition. Signal analysis methods, including time domain, frequency domain, WT, EMD, and multi-domain analysis, help extract relevant features. These features are then used with pattern recognition methods like Artificial Neural Networks (ANN), Hidden Markov Models (HMM), or Support Vector Machines (SVM) to evaluate tool condition. Indirect methods are more cost-effective and practical than direct approaches. PoTsang B *et al.*[22] The quick learning feature of a PNN is used to create a breakage detection system that is highly accurate and real-time self-learning tool. Four unique classifiers are empirically compared under increasingly challenging generalization tasks: KNN, SVM, Random Forest, Bayes classifier, and One-Dimensional Convolutional Neural Network, K- star algorithm is some of the algorithms used[23-26]. The online approach uses a variety of sensors and transducers to acquire data about characteristics such as cutting forces, vibration, tool temperature, surface roughness, noise, feed rate, and cutting speed. Therefore, it is helpful to investigate the slow deterioration of tools, or to monitor soft flaws, by looking at how these characteristics vary over time[27,28]. The main objective of signal processing is to analyses raw, often complex and noisy, vibration signals to extract reliable features. Monitoring vibrations effectively can help correlate tool condition with dimensional variations and assess the influence of factors like surface roughness, noise, temperature, and spindle load[29]. The time-dependent vibration response is sufficiently capable of inspecting

the degree of deterioration of a cutting tool, according to a study that used time-domain signals[30]. Dimla's research[31] investigated the relationship between cutting tool vibrations and tool wear. It was observed that catastrophic failure occurred when the nose wear exceeded 0.2 mm, while the notch wear exhibited a linear increase at the start of machining and remained stable for the remainder of the tool's life span. A study by Prasad *et al.*[32] explored the connection between flank and surface damage, incorporating vibrations of cutting tool into their experimental analysis. It was shown that increasing tool wear corresponds to increasing displacement. The TCM system consists of two main steps: first, features are extracted from unclear or noisy data, and then, these features are used to diagnose or categories the state of the process or cutting tool. The signal's characteristics, including its statistical, histogram, Empirical Mode Decomposition (EMD), Discrete Wavelet Transform (DWT), and other properties, as well as artificial intelligence methods such Artificial Neural Networks (ANN)[33,34], support vector machine -SVM[35,36], Bayesian network - BN[37,38], Fuzzy Neural Network - FNN[39], Decision Tree-DT[40], Hidden Markov Model-HMM[41], etc. are evident in the manufacturing research sector and contemporary industries. Therefore, research into the signal's characteristics and how they relate to the state of the tool is necessary, particularly for intermittent cutting processes like face milling.

The following is a summary of the current study's literature review findings:

- It is customary to choose conservative parameters, such as feed rate, cutting depth, and spindle speed, to account for most unfavorable cutting conditions for safe and high-quality machining. Additionally, it is common to draw arbitrary conclusions about the condition of the tool. Beyond that, though, there are recognized moments that contribute to the formation of flaws and must be investigated.
- An accelerometer, a data gathering system, and some less sophisticated additional instrumentations are needed for the vibration signal acquisition. Since vibration signals are thought to be more self-explanatory, informative, responsive, careful, and dependable, they are advised for use in onboard health monitoring. The scope of this study is therefore confined to analyzing the correlation between cutting tool condition and machining vibrations within the time domain.
- The time needed for extracting statistical features and selecting them using decision tree methods is relatively short. Additionally, 'supervised-tree-based' algorithms have not yet been applied for live training of tool insert damage concerning feature categorization. Therefore, employing classifiers such as Random Forest, Decision Tree.
- Studies on lathes[24] and traditional milling machines[22,27–32] have been published. Therefore, research is required to diagnose tool faults in triangular multi-point tool inserts and anticipate their effects on CNC-VMC. Based on the literature review, a machine learning framework for vibration-based health diagnosis of multi-point tool inserts on VMCs has been proposed

The objectives of this study are to review various vibration-based condition monitoring techniques and their applications in Vertical Machining Centre (VMC) systems to understand different failure modes. Additionally, the study aims to investigate the vibration signals of defective tools in VMC systems using advanced signal processing techniques, facilitating early fault detection and real time fault diagnosis through machine learning methods. Another key objective is to design and train different tree-based ML algorithms for the classification of tool faults and real time fault diagnosis. Finally, the study seeks to evaluate the accuracy of these machine learning algorithms by analyzing their performance using confusion matrices.

2.0 Methodology and Contributions

The current research's graphic methodology is shown in Figure 1. This study focuses on demonstrating a monitoring system designed to predict the condition of a triangular multipoint tool insert using a combination of vibration analysis and machine learning techniques. Six insert tool configurations, both defect-free and flawed, had their time-domain vibration response recorded while they were being face milled on a Vertical Machining Center (VMC).

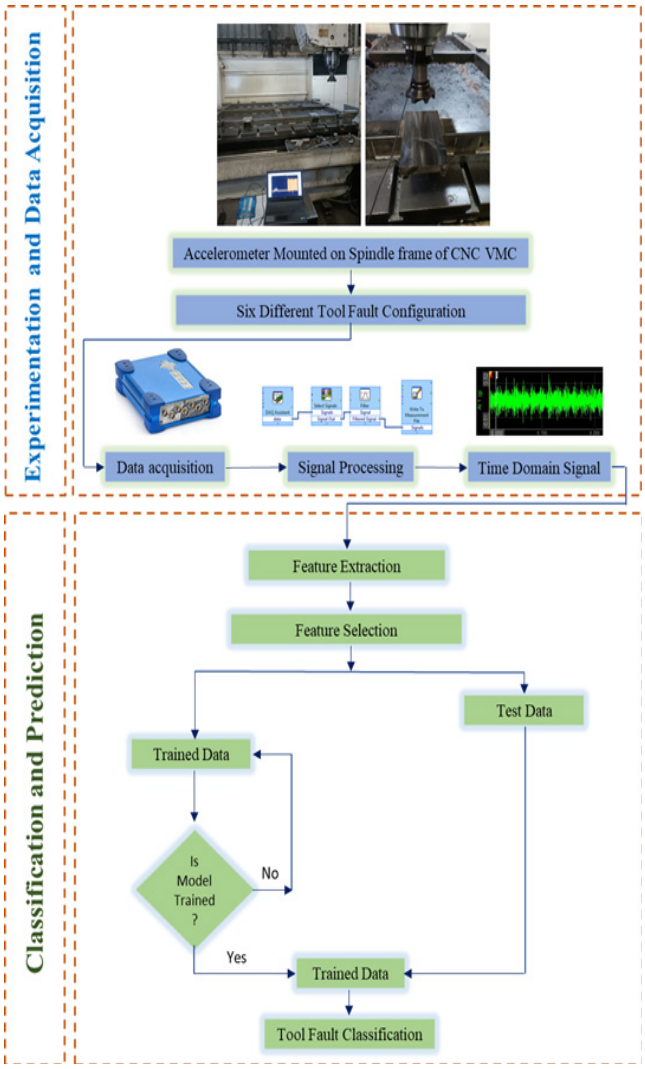


Figure 1. Multipoint tool inserts health prediction methodology.

The current study considers tool flaws including built-up edges, notch wear, crater wear, tip breaking, and wear at the nose and flanks. Using Visual Basic Environment (VBE), an event-driven algorithm was created to extract more statistical information. Ultimately, diverse tool circumstances were classified by distinct algorithms, and an analysis of comparisons is shown to identify the optimal classifier.

The following is a list of the primary contributions:

- Proposes an approach that integrates vibration signal acquisition with machine learning techniques for monitoring triangular multi-point tool insert damages on Vertical Machining Centers (VMCs).
- Vibration signature characterization developed from unidentified moments resulting in in-process tool faults
- For fault classification design and training of different algorithm
- Class predictions are made using test datasets and trained classifier models, and these predictions are validated by a validation set.

The structure of this study is outlined as: Section 2 describes the experimental setup, including input conditions and process of acquiring vibration signals. Sections 3 to 5 outline the ML methodology applied for classification. Section 6 presents the results and evaluates the findings, Section 7 addresses the study's limitations and suggests directions for future research, while Section 8 concludes the paper.

3.0 Experimental Setup

Figure 2 presents the experimental setup, which mainly consisted of an accelerometer, a Data Acquisition (DAQ) system, and a CNC Vertical Machining Center (VMC).

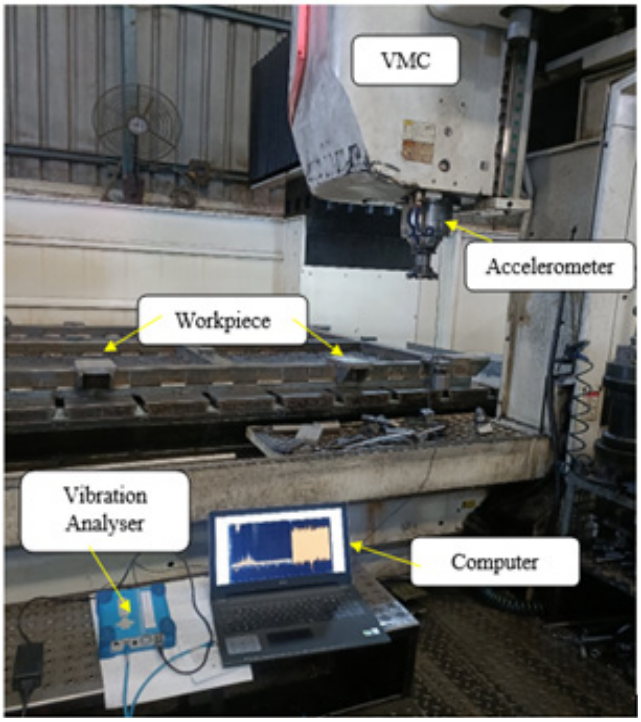


Figure 2. Experimental setup.

Outlined below are the specifications:

Make: VTEC Model CCS00605: specifications as 4200 mm in the X-axis, 2600 mm in the Y-axis, and 920 mm in the Z-axis.

Piezoelectric accelerometer:(Make: PCB, Model: 333B32 ICP of sensitivity factor = 100 mV/g, acceleration with +/- 490g range & Frequency Range: (±5 %)0.5 to 3000 Hz),

Data acquisition card (Vibration analyzer): Model: OROS 34-VS-4 with four channels).

Spindle speed: 1000 rpm

Feed Rate: - 2000 mm/ min

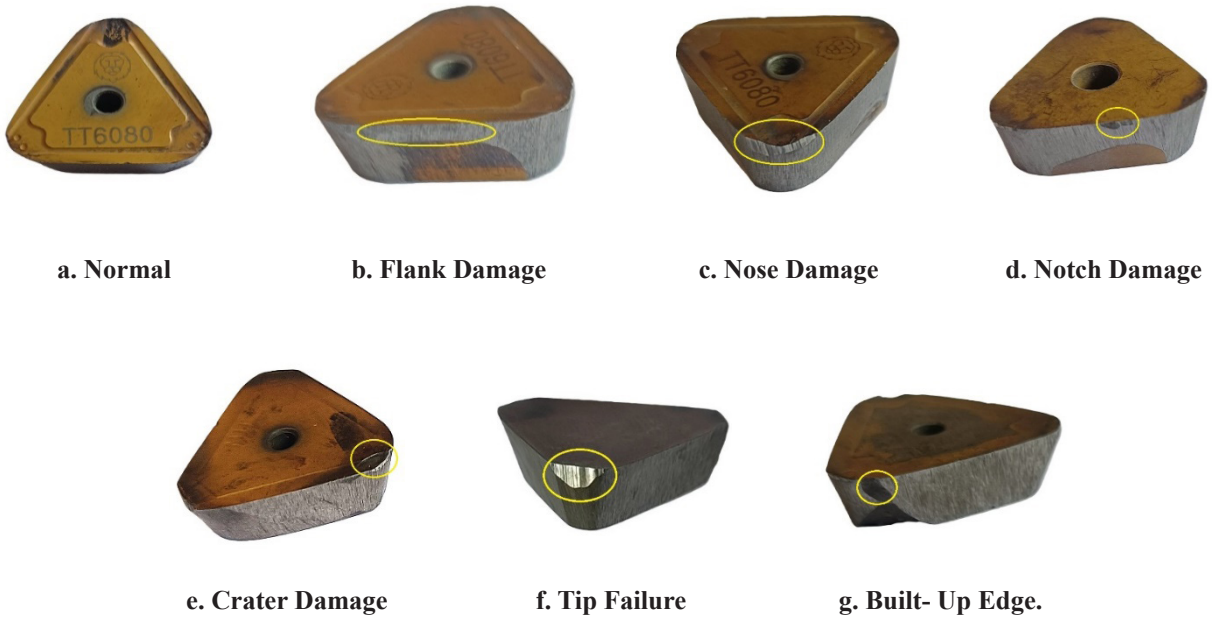


Figure 3. Both Different Defective and Flawless Insert Combinations

Table 1. Various tool setups were considered for eight operations

Insert no. / Configuration	Insert No. 1	Insert No. 2	Insert No. 3	Insert No. 4	Class Label
A	Healthy	Healthy	Healthy	Healthy	NW
B	Healthy	Healthy	Healthy	*Flank Damage*	FD
C	Healthy	Healthy	Healthy	*Nose Damage*	ND
D	Healthy	Healthy	Healthy	*Notch Damage*	NTD
E	Healthy	Healthy	Healthy	*Crater Damage*	CD
F	Healthy	Healthy	Healthy	*Tip Failure*	TF
G	Healthy	Healthy	Healthy	*Built-Up Edge*	BUE
H	*Flank Damage*	*Nose Damage*	*Notch Damage*	*Crater Damage*	FNC

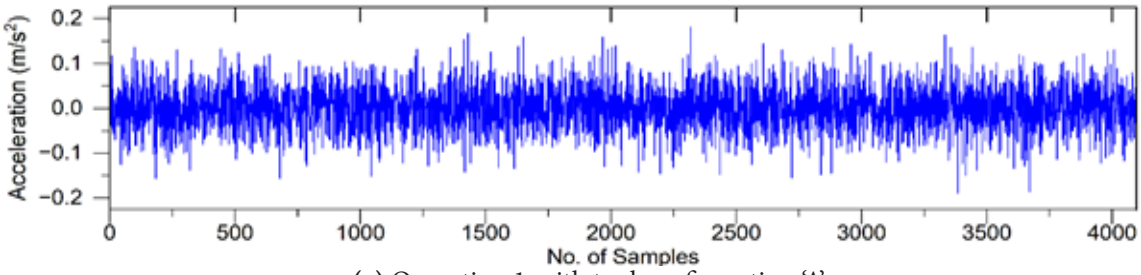
Depth of Cut: - 0.25 mm

Workpiece: The C45 material (10 Rectangular plate with dimensions 350mm*150mm*50mm mounted of the work bench)

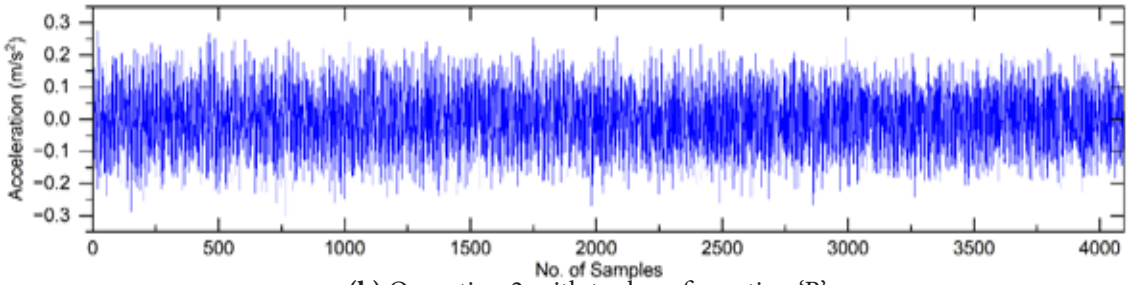
The milling cutter, with a diameter of 80 mm, was equipped with six triangular inserts.

Executed Operation: Face Milling.

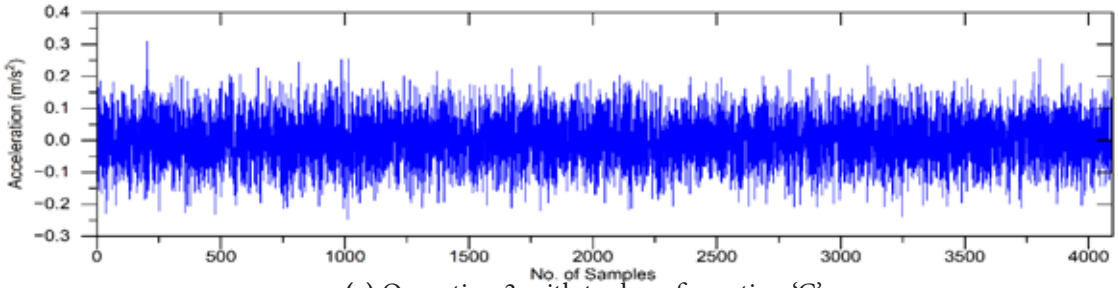
The fundamental machining specification, including driving speed, feed of table, and depth of cut, influence both the tool condition and the efficiency of the machining process. The industry standard was followed by estimating the parameters. The machining operations



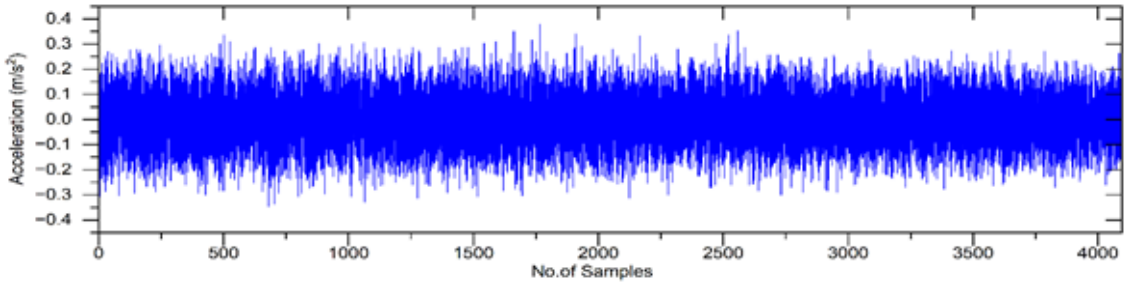
(a) Operation 1-with tool configuration 'A'.



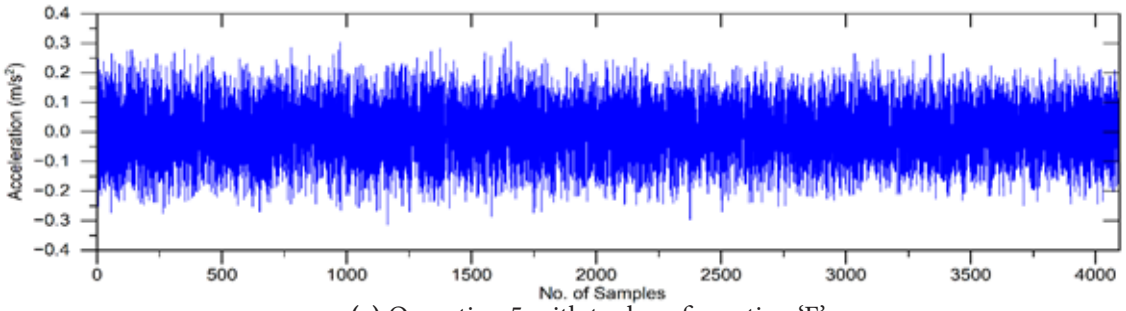
(b) Operation 2-with tool configuration 'B'.



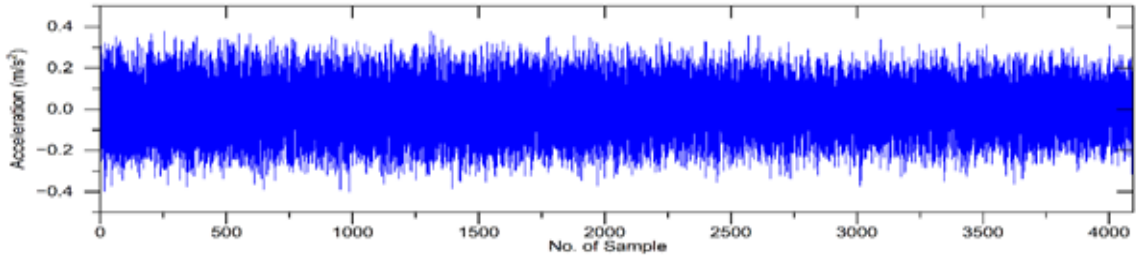
(c) Operation 3-with tool configuration 'C'.



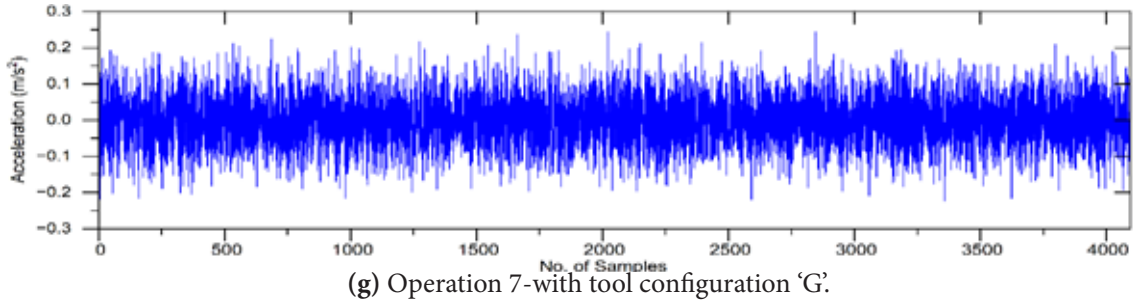
(d) Operation 4-with tool configuration 'D'.



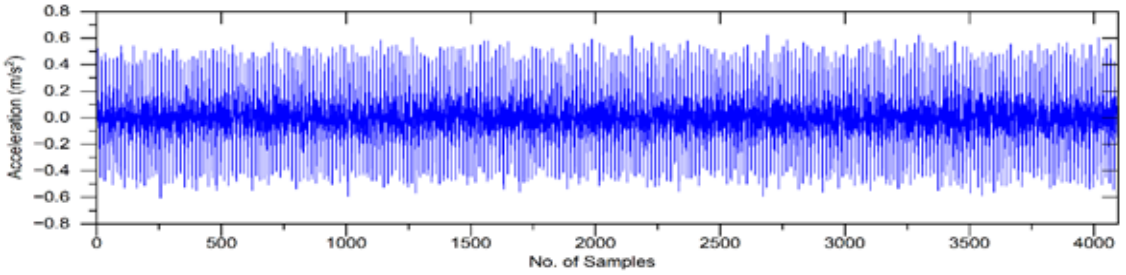
(e) Operation 5-with tool configuration 'E'.



(f) Operation 6-with tool configuration 'F'.



(g) Operation 7-with tool configuration 'G'.



(h) Operation 8-with tool configuration 'H'.

Figure 4. Time-series plots of configuration of different tool as shown in Table 1.

were carried out considering the machining inputs mentioned previously, and the various tool combinations listed in Table 1. The study took into consideration the six most frequent fault types: built-up edges, notch wear, crater wear, tip breaking, wear at the nose, and flank wear. The tool inserts in various stages, including defect-free (good), normal, flank, nose, notch, crater, tip fracture, and built-up edge, are displayed in Figures 3(a) through 3(g). For every machining operation, the vibration signal was recorded.

When collecting the vibration signals, the accelerometer's orientation and placement are crucial. Vibration response is typically measured at points nearest to a machine's dynamic components. In CNC-VMC machining, vibrations generated during the process can interfere with the cutting tool, subsequently impacting the spindle. To facilitate measurement, the accelerometer mounted near the spindle. Additionally, due to the vertical rotation of the drive shaft, the accelerometer was positioned vertically. Six insert tool configurations, both defect-free and with varied faults, had their time-domain vibration response recorded.

Using the Nyquist theorem, a sampling frequency of 20 kilo-Hertz was selected. The sampling length of 4096 was selected at random, and it correlates to 212, which means that there are around 4096 acceleration amplitude data points (readings). Before achieving stability in the machining process, a few rough milling passes were made to get rid of undesired deposits and work sample irregularities. The time-dependent vibration signatures corresponding to different multi-insert tool configurations are shown in Figures 4(a) through 4(h), and Lab VIEW software is used to process this data. The time-domain charts show how the acceleration amplitude changed significantly for operations 1 through 8. This is because the condition of the insert changed. Since the combination of defects was taken into consideration, the amplitude has increased dramatically for the fifth and sixth operations. Nevertheless, it is not possible to accurately distinguish between different defective states using this visual examination of the amplitude change of analogue plots. As such, machine learning approaches for statistical feature extraction and categorization are recommended. Figure 1 displays the flow chart of the machine learning system used to diagnose the face milling tool's faults.

4.0 Features Extraction

To assess the variation between fault-free and faulty classes of the tool, descriptive statistics characterizing the signal were extracted. Thirteen statistical properties were computed from the data, including Count, Kurtosis, Maximum value, Minimum value, Mean, Mode, Median, Range, Standard Error, Summation, Skewness, Standard Deviation and Variance. Additionally, an event-driven algorithm was developed in the Visual Basic Environment (VBE) to summarize these properties.

5.0 Feature Selection

Selection of features plays a crucial role in enhancing the classifiers performance by identifying the most notable features from a comprehensive set of descriptive data. This process is essential in machine learning, as it involves reducing data dimensionality, accelerating classification, boosting accuracy, and generating more coherent results[42,43].

5.1 Decision Tree Algorithm

The Decision Tree (DT) method organizes data into a structure where instances are similar in nature, allowing for classification into distinct categories. It employs a top-down strategy for categorization, progressing from the root node to the leaves through several branches. Each internal node represents a test on a specific feature, each branch indicates a possible outcome, and each leaf node signifies a class or condition. The root node identifies the most significant attribute. The characteristics of the tree are considered key attributes. There is a saying that states, 'The broader the tree, the more complex the decision rules, leading to improved selection and classification accuracy. "Information gain" and "entropy reduction" are two important variables that influence the selection of meaningful qualities. Entropy is used by the DT algorithm to quantify disorder, which is also helpful in defining similarity within a sample. Findings showing that the entropy is unity in the case of an evenly dispersed sample and zero in the case of a fully homogeneous sample are simple to understand. Reducing entropy by partitioning datasets based on attributes reflects a 'gain of information.' A decision tree identifies the most significant attribute that provides maximum information. Initially, entropy is calculated from the dataset, followed by the total entropy across branches using a weighted summation. The future entropy after splits is subtracted from the initial entropy to determine 'information gain.' The most informative attribute is designated as the root, the dataset is divided among branches, and the process is repeated for each branch[44,45].

5.2 Study to Validate Feature Selection

By looking at and comparing attribute plots for each tool condition and analyzing how the quantity of attributes affects efficiency, the features selection can be verified. Here, visualizing variance within and between classes makes it easy to identify the important trait. For the variation across classes to be considered a major trait, it must be "maximum." One may take into consideration the list of qualities that the DT algorithm displays. Here are the stages required in determining how features affect categorization accuracy. Only the characteristic at the main node of the decision tree can be used for classification initially. The subsequent nodes with significant features are then utilized in a similar manner. Finally, the effects of any absent features on classification accuracy can also be explored.

6.0 Feature Classification

Recent advances in a number of classifier families, including Tree, Bayes, SVM, Regressions, ANN, etc., have improved classification jobs' accuracy, precision, and other metrics. When compared to all other machine learning algorithms, the "supervised-tree-based" techniques show the best classification accuracy and need the least amount of time to create the model; for these reasons, they were chosen for the current study. Therefore, tree such as Random Forest (RFT), Decision Tree (DT) classifiers and Hybrid Model (DT + RF Stacking) is covered.

6.1 Decision Tree Classifier

When it comes to judgmental inquiry, a decision tree is a useful instrument. This unique algorithm helps with both the selection of attributes and the construction of the categorization model. It displays a decision-making hierarchy akin to a tree structure based on the related influences determined by "condition governed rubrics." A decision tree consists of three key elements: the leaf nodes at the bottom represent the final outcomes for various classes, at the top root node denotes the attributes being tested, and the branches illustrate the classifications for anticipated results. This hierarchical structure, which connects the root to the leaves, allows for easy tracing of the rule sets generated during the decision-making process[46].

Various techniques for optimized classification have been developed, including the Iterative Dichotomies (ID3, ID4, ID5), Concept Learning Systems (CLS), and Classification and Regression Tree (CART). The ID3 algorithm, created by Ross Quinlan, is well-known for generating decision trees from real-world datasets. It assesses disorder, or entropy, relative to information gain, starting from the root node with the initial set A. The algorithm evaluates unused sub-attributes, selecting those with the lowest entropy and highest information gain to divide set A into subsets. This process is repeated for remaining attributes according to established guidelines[47–49].

- Discrete and continuous features can both be handled in C4.5. After extracting a threshold from the data, characteristics are categorised with the criteria "more or less than or equal to" in accordance with the threshold.
- The features that have vanished are indicated with a "?" and are not considered for calculating knowledge gain.
- It removes unnecessary branches and replaces them with leaves, a process known as "Pruning post-generation"[50].

6.2 Random Forest Classifier

A binary decision tree consists of a series of binary questions that can be depicted as a directed acyclic graph stemming from a root node and can be structured programmatically as a series of if-then-else statements. Its characteristics include:

- Each node may have either zero descendants (if it's a leaf) or two descendants (if it's a test node).
- Every node, except for the root, has one parent.

A top-down divide-and-conquer approach is used to construct the tree, aiming for a model that effectively represents the training data while maintaining manageable complexity. The tree grows by partitioning the attribute space into minimal regions, ideally containing samples from a single class. Starting with a simple tree consisting of the root node and training data, the process involves selecting a test based on an input feature to distinguish samples from different classes. Once the test is determined, the training data is split into two subsets for each outcome, and subtrees are built recursively. The

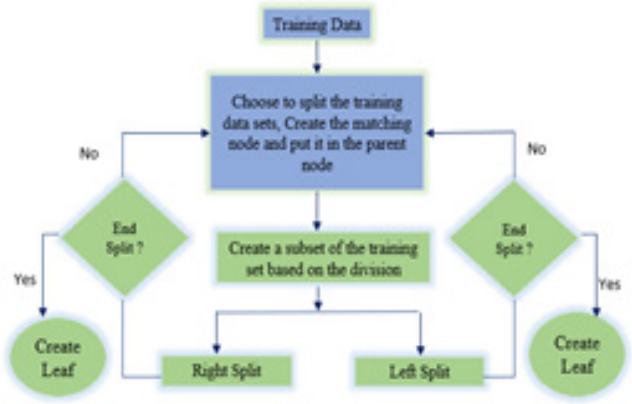


Figure 5. Creation of a Binary Tree.

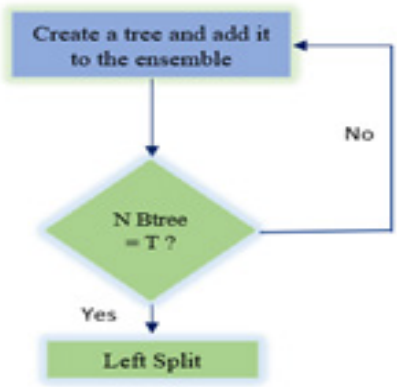


Figure 6. Generation of Binary Tree.

algorithm evaluates whether to expand nodes or make them leaves in the final tree, as illustrated in Figure. 5[51].

Consequently, the following are the three essential components for developing a decision tree:

- Identifying Splits: Determine a 'question' that divides the dataset into two groups by selecting a feature and a corresponding value, creating distinct segments.
- Evaluating Splits: Use a scoring metric to assess the effectiveness of each potential split, focusing on the increase in class purity to form homogeneous subsets.
- Defining Leaf Conditions: Establish criteria for when a node becomes a leaf, ensuring the tree remains finite, based on user-defined rules and data characteristics[52].

The random forest classifier is built on the concept of generating multiple decision trees during the training phase. These trees collectively enhance the reliability and consistency of classification and prediction outcomes. By using oblique hyperplanes, this approach minimizes the risk of overfitting, leading to improved accuracy. Each tree in the forest is constructed using a random selection of features, allowing it to focus on specific characteristics of the data. This method mitigates the issue of overfitting in training datasets. Instead of evaluating all features when splitting nodes, the model prioritizes the most significant ones, resulting in a more robust model due to its diverse set of trees. The final output from the random forest classifier is calculated as the weighted average predictions from all leaf nodes. The correlation among trees affects the overall error rate, with higher correlations indicating increased error; thus, lower correlation is desirable. A visual representation of the random forest tree creation can be found in Figure 6[53].

Two techniques that help de-correlate individual trees in the forest and improve generalization are:

1. Train each tree using a subsample of the training data (with replacement), where the subsample size equals the square root of the total training samples.
2. Use a subset of variables for each node during training, introducing two key meta-parameters:

'T' represents the number of trees in the ensemble, chosen based on computational constraints; larger T usually enhances performance, but results stabilize after a certain point.

'K' indicates the number of variables evaluated at each node, with optimal K varying by problem: higher K is preferable when fewer descriptors are useful, and lower K when many variables are significant[54,55].

7.0 Result and Discussion

To acquire vibration signals, a face milling operation was performed while taking into account different insert tool configurations. This was followed by the extraction, selection, and classification of statistical features. Here we discuss the stepwise result.

- It was decided to extract descriptive statistics that showed how the tool's signal varied between its defective and fault-free configurations.
- Thirteen statistical features were derived, including Count, Kurtosis, Maximum value,

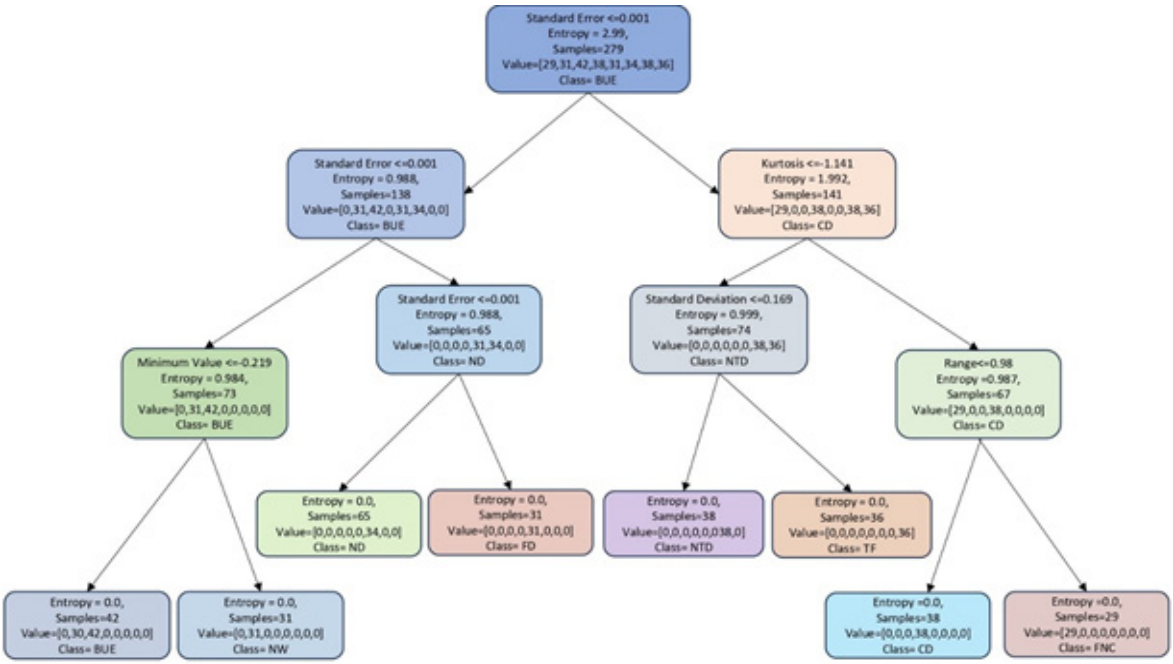


Figure 7. Structure of the decision tree.

Minimum value, Mean, Mode, Median, Range, Standard Error, Summation, Skewness, Standard Deviation and Variance.

- A total of 400 samples that described every possible combination of the tools were examined in this study. This indicates that each tool setup has 50 samples. Each sample consists of 4096 data points that show how acceleration changes over time. A training data sheet with 400 samples for all 13 was made.
- For finding the attributes which distinguish the various tool settings, the extracted features were utilized in the decision tree model. The tree was formed based on principle of entropy reduction, as illustrated in Figure 7. It is recommended that the attributes displayed in this model such as kurtosis, mean, median, maximum, minimum, range, skewness, sum, standard deviation, standard error, and variance are further classified due to their prominence as the 'most distinctive' features.

The decision tree shows how data is classified by splitting based on features like "Standard Error," "Kurtosis," etc. Each node represents a decision, with "entropy" indicating the level of uncertainty (lower entropy = more certainty). At each split, the model chooses the feature that best separates the data. The leaf nodes at the bottom represent the final classifications with high certainty (low entropy), predicting different classes like "BE," "ADF," etc. The tree refines decisions as it moves down, leading to more confident classifications.

• Additionally, DT and Random Forest (RFT) were used to classify tool setups based on 10-fold cross-validation. The Waikato Environment's "WEKA"-57 machine learning software was utilised to create and hone the "tree-based" algorithms.

• The classification results were evaluated using a confusion matrix, which illustrates how samples are categorized according to both the actual and predicted tool classes. Key metrics such as Precision, Receiver Operating Characteristic area (ROC), False Positive rate (FP) rate, True Positive rate (TP), and Recall provide insight into the classifiers' accuracy.

The True Positive rate reflects the proportion of correctly samples which are identified, while the False Positive rate indicates the samples percentage of that were misclassified. The True Positive rate should reach 100%, and the False Positive rate should be 0%. Precision is defined as the ratio of true positives to the total number of samples within a specific class. Recall,

on the other hand, is simply the TP rate. The F-Measure combines both precision and recall into a single metric. The ROC curve offers an overall view of classifier performance. Additionally, the Kappa statistic assesses the agreement between the observed and expected classifications by analysing the proportion of samples along the diagonal of the confusion matrix and adjusting values for better agreement. This value is regarded as optimal for classification if it falls between 80 and 100 %. Since the average squared error of the predictors is essentially estimated by the MAE (Mean Absolute Error), a model's training is less effective the higher the MAE. The mutually scalable errors and targets are determined by taking the second root of the mean square error, or RMSE.

7.1 Classification Using Decision Tree

Taking the Decision Tree (DT) into account, the classification accuracy achieved is 98.75%. Figure 8. Illustrates the Misperception matrix for the DT. This matrix is a crucial instrument for evaluating the performance of a classifier, where the diagonal entries indicate correct classifications, and the off-diagonal entries represent incorrect ones. For tool configuration 'A' in Figure 8, there are '14' samples accurately identified as belonging to 'A,' of which 6 are defect-free. In the case of tool configuration 'E,' 5 samples are defect-free while 1 shows crater wear; here, '1' sample was mistakenly

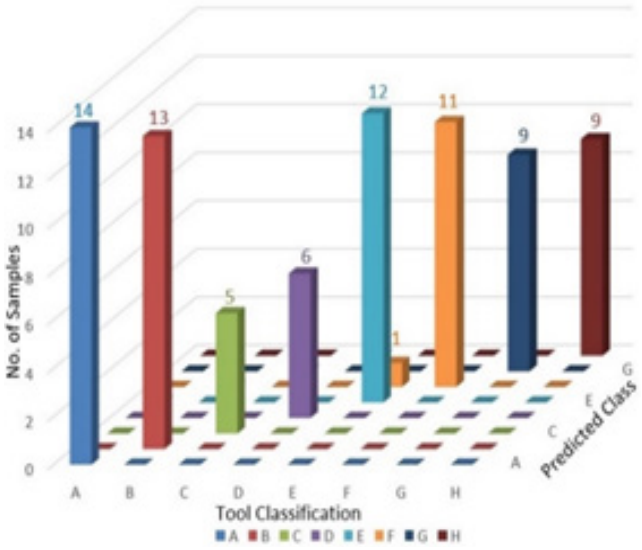


Figure 8. Misperception matrix: DT classifier.

classified under 'E' configuration. Similarly, for configuration 'B' (with 5 healthy samples and 1 showing flank damage), '13' samples were correctly classified. The matrix allows for further classification on its own. Configuration-wise accuracy overview is presented in Table 2. Notably, configuration 'A' boasts a true positive rate of 1, indicating that all 50 samples were accurately identified as defect-free, with a false positive rate of 0 very minimally. In this study, both the false positive and true positive rates are remarkably ideal values are

Table 2. Descriptive accuracy decision tree

Tool Class	True Positive Rate	Recall	Precision	False Positive Rate	F-Measure
A	1	1	1	0	1
B	1	1	1	0	1
C	1	1	1	0	1
D	1	1	1	0	1
E	1	1	0.923077	0.014706	0.96
F	0.916667	0.916667	1	0	0.956522
G	1	1	1	0	1
H	1	1	1	0	1
Weighted Avg	0.987500	0.987500	0.988462	0.002206	0.987478

close. Likewise, other metrics such as precision, recall, F-measure, and ROC area approach unity.

7.2 Classification Using Random Forest

As noted in Table 3, six features were considered for data classification. The Random Forest (RF) classifier achieved an accuracy of 97.53 %. Figure 9 presents the clear misclassification matrix, while Table 3 shows the accuracy for each specific tool condition.

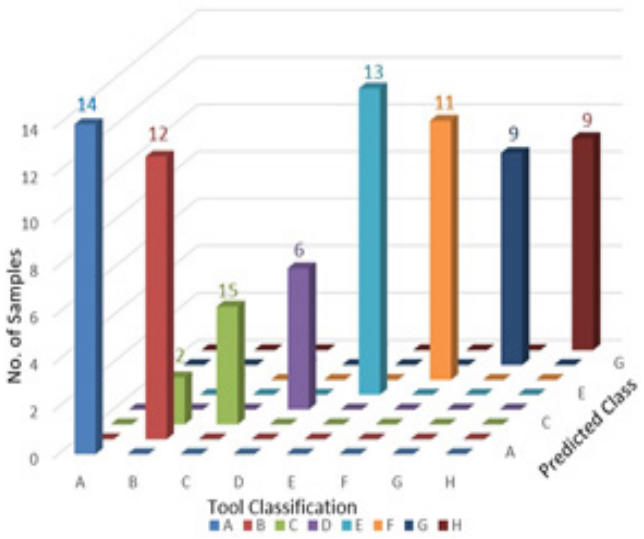


Figure 9. Misperception matrix: Random Forest classifier.

7.3 Classification using Hybrid Model (DT + RF Stacking)

The hybrid stacking model (Ensemble Learning) is implemented by combining Decision Tree (DT) and Random Forest (RF) with a meta-learner to enhance the accuracy of fault diagnosis for multi-point tool inserts. By using weighted contributions from DT and RF in an ensemble formula, classification accuracy is improved to 99.25 %, which surpasses the performances of individual models. The meta-learner efficiently refines the weaker classifications and maintains strong predictions, reducing false positives and improving the reliability of the model. This approach displays the robustness of ensemble learning in real-time fault detection, which is for machining applications. Configuration-wise accuracy overview is presented in Table 4.

Table 5 provides an explanation of the comparison research for tree family classifiers. Every classifier has a Kappa value greater than 0.95, indicating that it is the best. For every classifier, the RMS error and mean absolute error are both limited to values of 0.015 and 0.025, respectively. The highest relative absolute error for the Random Forest

Table 3. Random forest for evaluating descriptive accuracy

Tool Class	True Positive Rate	Recall	Precision	False Positive Rate	F-Measure
A	1	1	1	0	1
B	1	1	0.857143	0.028986	0.923077
C	0.714286	0.714286	1	0	0.833333
D	1	1	1	0	1
E	1	1	1	0	1
F	1	1	1	0	1
G	1	1	1	0	1
H	1	1	1	0	1
Weighted Avg	0.975309	0.975309	0.978836	0.004294	0.974201

Table 4. Descriptive accuracy hybrid model

Tool Class	True Positive Rate	Recall	Precision	False Positive Rate	F-Measure
A	1	1	1	0	1
B	1	1	0.90	0.02	0.947368
C	0.85	0.85	1	0	0.918919
D	1	1	1	0	1
E	1	1	1	0	1
F	1	1	1	0	1
G	1	1	1	0	1
H	1	1	1	0	1
Weighted Avg	0.9925	0.9925	0.993	0.002	0.992

Table 5. Comparison Parameters for Classifiers DT and RF

Sr. No.	Attributes / Tree based classifiers	Decision Tree	Random Forest	DT + RF with Meta-Learner
1	Properly Classified Samples (%)	98.75	97.530864	99.25
2	Kappa	0.985518	0.971449	0.9901
3	MAE	0.0125	0.024691	0.0103
4	RMSE	0.111803	0.107135	0.0954
5	RAE (%)	0.585823	1.175958	0.512
6	RRSE (%)	4.664806	6.627868	4.120

classifier is recorded at 1.17%. In contrast, the highest relative squared error for the decision tree algorithm is 4.66%.

7.4 Discussion on Results

A comparison of the time required to build models for various ML classifiers and the classification accuracy is displayed in Figures 10(a) and 10(b), respectively. It has been shown that the Decision Tree method produces the best results with an accuracy of 98.75% and the shortest build time - 0.1 seconds for the model. The Random Forest model takes 0.15 seconds to construct and produces an accuracy of 97.53% and DT + RF with Meta-Learner improved accuracy is 99.25%.

Subsequently, the trained model was evaluated using untrained data. The collected dataset was split into training and testing sections, with 80% (40 samples from each condition) allocated for training and 20% (10 samples from each condition) for testing. The model was initially trained and then assessed using the test dataset, which contained untrained samples. The results of this evaluation are presented in Table 6. This study found that both the Decision Tree and Random Forest algorithms along with DT + RT Meta Learner provided superior classification accuracy. Consequently, these algorithms performed effectively across all tests, making them suitable for implementation in real-time class predictions. As demonstrated in Table 7, the highest classification

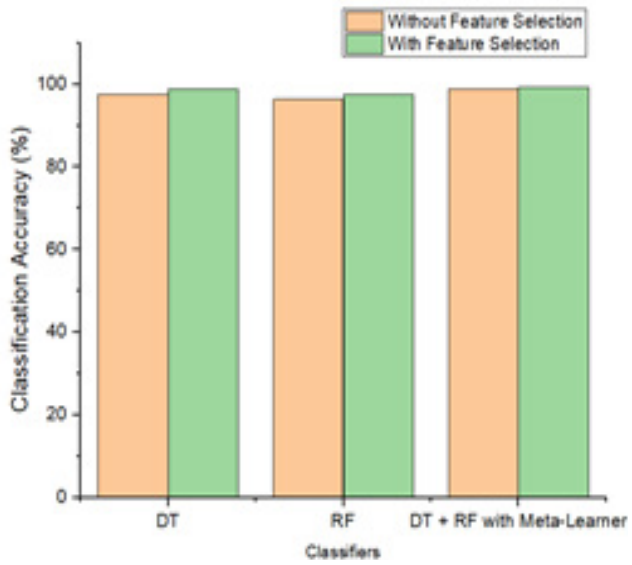


Figure 10(a). Accuracy comparison of classifiers.

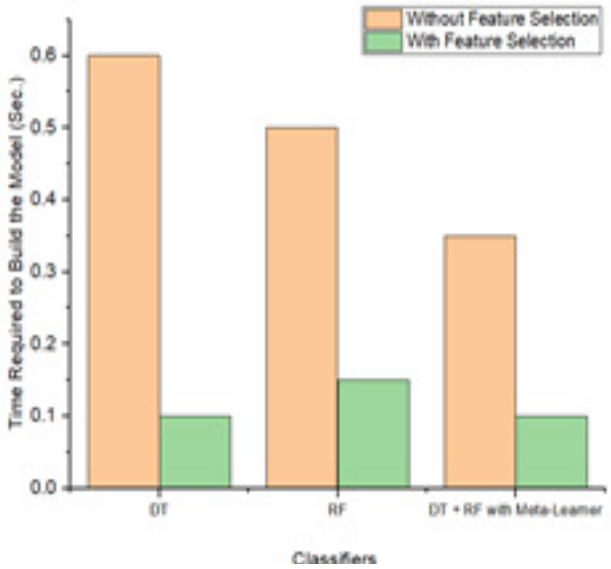


Figure 10(b). Comparison of the time needed to construct the classifier model.

Table 6. Classifier classification accuracy using an untrained test dataset

Sr. No.	Classifiers	Accuracy of classification (%) 50 samples of training data	Testing Data (10 Sample Points)	Cross-validation using 10 folds with a sample size of 50
1	DT	100	99.1	98.75
2	RF	99.5	96.5	97.53
3	DT + RF with Meta-Learner	100	98.8	99.25

Table 7. Accuracy of classification of published research on tool fault monitoring in milling

Authers	Tool	Defect area	Measurement System for Acquiring Signals	Technique of AIML sub technique	Feature Extraction Classification Techniques	Accuracy Result
Mariane Prado Motta[6]	Inserts-Tungsten Carbide	Surface Roughness	Triaxial Dynamometer and Accelerometer	NN And SVM	Random Forest Gaussian Process Regression and Tech	67 to 90 %
V. Kryzhanivskyy[8]	Ceramic Tool	Surface Integrity	Sensory Tool Holder	KNN	Using Pareto Chart	64.7% to 84.9%
Sotirios Panagou[10]	Rolling Tool	Rolling Mill,	Accelerometer, Temp. and Pressure Sensors	Digital Twin Model With ML	Xgboost Model	99%

Paweł Twardowski[13]	Milling Cutter Made of Carbide And Diamond	The Edge Tool	AE - Signals	SVM, NN And KNN Algorithm	NN Distance Classifiers Statistical, Approximation, Fuzzy	94%
Chang'an Zhou[9]	A Tool Holder Embedded Wireless Vibration Sensor	Tool Wear Condition	Signal - Triaxial Vibrations	SVM	HE Features,	86.10%
H. C. Mohring[7]	End Milling Tool	Surface Roughness	Acceleration Signals	CNN, KNN, SVM, ANN	Trained Using Labview and Python Algorithm	80%.
T. Mohanraj[17]	Tungsten Carbide Insert	Flank Wear	Vibration Signals	SVM, and DT	HE, Wavelet Coeff. and Statistical Feature	99.86% to 100%
Thomas Walter Rauber[11]	Bearing	Bearing Fault Diagnosis	Vibration Signals	KNN, SVM, FR, CNN	Four Distinct Classifiers are Experimentally Compared,	90.65%
CHANG'AN ZHOU[19]	Single Point Cutting Tool	Tool Tipping, Tool Wear	Vibration Signals	SVM	Statistical Analysis, Wavelet Transform with the Holder Exponent (He)	99.4% , 98.7%
Changan Zhou[20]	Multi Point Cutting Tool	Tool Life on a CNC Milling M/C	Vibration Signals	SVM	Fdr is Used, And the he Were Chosen as the Index of Singularities.	94.9%.
Pauline Ong[23]	End Milling	Tool Wear	Vibration signals, sound signals	ANNs, WNN	MLP, RBFNN	90%
Abhishek Dhananjay Patange[56]	Multipoint Tool Insert	Tool Wear, Face Milling	Time-Domain Vibration	ANN, SVM	In order to extract statistical features, an event-driven algorithm was created	97%

accuracy achieved for proposed framework compared to recent studies.

8.0 Limitations and Future Scope

In terms of health prediction, the vibration-based triangular multipoint tool limits its application to class predictions derived from specific data related to face milling with defined input parameters. The developed model is capable of categorizing faults into predefined classes, even for unanticipated events beyond those explored in this research; however, this is not guaranteed. To effectively predict faults from unknown future incidents, further investigation is needed, particularly regarding varying tool faults levels within each class.

Moreover, for target domains it is essential to enhance the training of relevant testing datasets to facilitate future onboard fault diagnosis and address the variability

between data distributions. This aspect falls outside the current study's scope, as it would necessitate additional trials for data enhancement. A deep learning-based generic framework is proposed to meet this requirement. Furthermore, if unexpected issues arise that are not covered by the generic model, human intervention will be necessary to provide the "feedback" essential for Reinforcement Learning (RL), Isolation Forest, CNN-LSTM Hybrid model.

Machines operate under different loads, speeds, and environmental conditions, which can affect vibration patterns and make it challenging to establish consistent fault baselines during deployment.

9.0 Conclusion

This study introduces an effective technique for health prediction of vibration-based triangular multipoint tool inserts, applied to Vertical Machining Centers (VMC) through a machine learning approach. The results demonstrate that this framework is suitable for health prediction and classification purposes.

This method is adaptable to older machine tools found in medium to small workshops, requiring minimal hardware and software.

The tree-based classification approach not only enhances process integrity and maximizes the efficiency of cutting tools but also helps to minimize downtime.

Implementing this framework will expedite the development of a smart health monitoring system for tool inserts, emphasizing repeatability and generalizability.

The analysis indicates that the time-domain vibration responses, arising from inherent insert faults and various configurations, exhibit cyclic and periodic characteristics, which are effectively utilized for fault prediction.

The performance of the Random Forest and Decision Tree classifiers was impressive, achieving classification accuracies of 97.53 % and 98.75 %, respectively, with calculation times of 0.1 and 0.15 seconds, reflecting robust model training and hybrid model using Ensemble Learning Approach (DT + RF with Meta-Learner) improved accuracy as 99.25 %.

Ultimately, the trained classification model is positioned to serve as a real time predictor for future class predictions on unseen datasets, paving the way for its application to data with fixed time intervals.

10.0 Authorship Contribution Statement

Muralidhar Chandrakant Ingale: Developed the methodology and design, built the model, implemented the computer code and auxiliary algorithms, tested existing code, and contributed to writing the first draft, evaluating and editing the text, as well as creating illustrations. Dr. Rupesh Bhortake: Verification, ideas, development or creation of broad research goals and objectives, and methodology. Dr. Kishor Waghulde: Methodology, review and editing.

11.0 Declaration of Competing Interest

The authors affirm that the research presented in this study was not affected by any recognized financial interests or personal relationships that could be considered competing.

12.0 Acknowledgement

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