Identification of Milling Stability by using Signal Analysis and Machine Learning Techniques

Tung-Thanh Vo, Meng-Kun Liu, and Minh-Quang Tran

***Abstract*—Nowadays, milling stability is one of the most concerns in the manufacturing industry in order to reduce the cost of tool replacement, increase the productivity as well as increase precision and surface quality of the metal cutting process. One of the most critical components of the machining process is to identify chatter during the cutting process. This paper proposed a cutting signal processing methodology to create, analyze, and select relevant features for the chatter identification. An effective technique based on feature learning was proposed to monitor the cutting stability using vibration signals. The technique of signal transformation such as Fourier Transform (FT) is an effective tool to determine the frequencies related to machining operation and cutting stability. Machine learning models such as Random Forest, Decision Tree, and eXtreme Gradient Boosting were applied for selected features as the step of classification. The success of this proposed method was proved by solid statistical support for the features selection method and the performance of Random Forest achieved 98% of accuracy at two states of milling process including stable, and unstable conditions.**

***Keyword*: Milling process, cutting stability, cutting signal and analysis, machine learning.**

I. Introduction

CNC machines are prevalent in the manufacturing industry. Along the cutting process, the combination of cutting parameters and a large amount of material removal cause a self-excited vibration called chatter [1]. The prevention of chatter is a major concern in the modern industry not only to reduce tool damage but also to avoid poor quality of product such as poor surface, scraps, inaccuracy, and noise [2]. Furthermore, modern manufacturing enterprises are transforming to the automation system and a reliable monitoring process should be proposed [3]. Without a doubt, chatter investigation has become the most crucial part of improving the performance of CNC machines. There are several reasons to make this become an uneasy task. First of all, the nonlinearity of unstable cutting vibration complicates the investigation [4,5]. Besides, the sensitivity and dependability of sensors used to acquire data under various cutting parameters such as spindle speed, depth of cut, and feed rate have to be controlled and optimized in order to perform a good result.

Tung-Thanh Vo is a student of International Technology Program (IATP), National Taiwan University of Science and Technology, Taipei City 106335, Taiwan (ROC) (e-mail: votung1997@gmail.com).

Meng-Kun Liu is an Associate Professor of Mechanical Engineering Department, National Taiwan University of Science and Technology, Taipei City 106335, Taiwan (ROC) (e-mail: mkliu@mail.ntust.edu.tw).

Minh-Quang Tran is an Assistant Professor of Industry 4.0 Implementation Center, National Taiwan University of Science and Technology, Taipei City 106335, Taiwan (ROC) and also with the Department of Mechanical Engineering, Thai Nguyen University of Technology, Tich Luong ward, 250000 Thai Nguyen, Vietnam (e-mail: minhquang.tran@mail.ntust.edu.tw).

Many analytical, numerical, and experimental methods have been proposed in several previous researches to predict the milling stability. Sridhar et al. [6] created a mathematical model to explain the dynamic milling process and used a numerical approach to solve it. Smith and Tlusty [7] demonstrated a method for generating stability lobes using time domain simulations of chatter vibrations in the milling process. Altintas and Budak [8] proposed an analytical technique called zeroth order approximation (ZOA) for estimating milling stability lobes using the mean of the Fourier series of dynamic milling coefficients. Minis and Yanushevsky [9] introduced the idea of periodic differential equations to provide a complete analytic technique for solving the two-dimensional milling issue. Insperger and Stépán's [10,11] introduced a semi-discretization (SD) approach which is an effective numerical method for analyzing the stability of linear delayed systems. It can be used to forecast milling stability. All of the techniques mentioned above have their advantages and disadvantages. The ZOA method so far is the quickest method for resolving the chatter-free cutting situation. It is, nevertheless, unsuitable for the low radial immersion problem. Numerical simulation approaches in the time domain are extremely powerful. They consider real milling kinematics, cutting mechanics, the impact of inner and outer modulation, cutter geometry, runout, and other nonlinearities, but their computing costs are too high [12]. Some others proposed dynamic cutting force techniques as a method to diagnose the degradation of the machine [13]. However, using the dynamometer and acoustic emission is a drawback because they require a huge computational time. In addition, these sensors themselves are way too expensive and make it hard to scale to industry size.

This paper develops a method of using an accelerometer (ACC) and a microphone (MIC) to collect vibration and sound signals for predicting the milling stability. Accelerometer and microphone are used in this case due to their high sensitivity to chatter vibration and ease to set up in different cutting conditions. The detection of milling stability in this study is achieved by conducting the following procedures: data collection, data processing, features extraction, features selection, model training, optimization, and milling stability prediction. At the stage of data processing, some advanced transformations are the requirement [14]. Time domain method sometimes gives the advantage to diagnose the fault of machine part. However, it is not enough in this case [15]. This is where the application of Discrete Fourier Transform (DFT) starts to show its effectiveness in transforming the time domain signal to the frequency domain [16]. One of the benefit of Fourier analysis is very little information lost from the signal during the transformation. It maintains the information on the amplitude, harmonics, and phase. The Fourier spectrum decomposes signal into discrete frequency components. This is a very good method to observe the change in cutting conditions. Feature extraction is then applied to both the time domain and the frequency domain. Features are extracted based on some common statistical indexes. Due to a huge amount of data during the experiment and monitor the cutting vibration in real-time, it makes traditional approaches almost impossible to succeed [17]. A machine learning technique is evaluated based on the amount of data it can process, the training speed, and its precision and accuracy. There are several classification models developed in recent years, and this study exploited some different machine learning models. The decision tree is a supervised learning algorithm that is commonly used to solve classification problems. This is achieved by creating as many cases as possible based on the most important attributes or independent variables [18]. However, the weakness of the decision tree is that its model relies on high importance to a particular set of features and it sometimes deals with the overfitting as well as errors during the training process [19]. In this case, The Random Forest – a model built from a collection of decision trees – will be added to deal with those problems [20]. An eXtreme Gradient Boosting (XGBoost) and Support Vector Machine (SVM) model were also used to achieve chatter detection in the milling process [21].

This paper investigates the influence of feature selection and hyparameters optimization to the determination of cutting stability in different cutting conditions. The result indicates that the accuracy of the classification model can be greatly improved. The proposed method can reduce the unqualified product outcomes and protect the machine tool. The rest of the paper is organized as follows. Section 2 explains research methods in detail. Following that, the experimental data acquisition is described in section 3. Various aspects of signal analysis and features selection are elaborated in section 4. Classification results are exhibited in section 5. Optimization and conclusion are put forward in section 6 and 7, respectively.

II. Research Methodology

A. Fast Fourier Transform.

The Discrete Fourier Transform (DFT) is the most common method by mapping the time or space domain signal to the frequency domain. By observing the result from the DFT, the difference in frequency can be pointed out clearly. This paper used the Fast Fourier Transform which is a fast and efficient computation of DFT. Computer programing algorithm for FFT is commonly known as "split-radix" decomposition [22]. The algorithm computes the $Nlog_2N$ operation instead of N^2 floating point multiplication of DFT. Good frequency resolution, fast computing speed, and removal of redundant features are some of the benefits of using FFT. The function of DFT is defined in Eq. (1):

$$X_k = \sum_{n=0}^{N-1} x_n \omega_N^{nk} \tag{1}$$

Where k is an integer ranking from 0 to N-1 and ω_N denotes the primitive root of unity:

$$\omega_N = e^{-\frac{2\pi i}{N}} \tag{2}$$

B. Machine Learning Approach

In order to predict milling stability, Karandikar, Jaydeep, et al [23] introduced a method of chatter identification using Bayesian model. However, the Bayesian model assumes that all features are independent which is rarely happened in the real world. It makes the computing time of the model faster than other models but also reduces the accuracy of prediction. In this study, several classification models such as decision tree, random forest, and XGBoost were used and their performances were compared. In this case, the most important reason to use decision tree is that we have a lot of features in the dataset. This is really crucial to make a decision based on the build of the decision tree algorithm. Especially, that the dataset only has two class labels that are stable and unstable makes the decision tree become very suitable in this case. Furthermore, a decision tree model is also an effective way when there is limited computational power. However, it also has some problems, such as the high probability of overfitting and the lower accuracy when the model itself has high variance during the training process [24]. In order to improve the classification accuracy, this paper exploited the random forest model. The random forest is an algorithm that builds multiple decision trees and merges them together to achieve a more accurate and stable prediction [25]. By using random forest algorithm, we can avoid almost all of the problems that the decision tree has. In addition, the XGBoost model is also a well perform model which can handle normalizing data and missing values very well. One more reason for choosing these three models above is they all have the ability to find out important features through recursive features elimination at the step of features selection. These models are suitable for large datasets, especially in this case. To produce the massive training and testing datasets, a window size of 1028 samples was employed to glide along with each signal [26]. Moreover, there is very little pre-processing to be done when applying the proposed model. On the other hand, support vector machine was also applied to see the difference in performance when using an inappropriate classification model. All of these models use the same dataset extracted from the time domain and frequency domain through the feature extraction step based on 14 statistical indexes. The calculation of indexes in the time domain are presented from Eq. (3) to Eq. (10) and indexes in the frequency domain are from Eq. (11) to Eq. (16).

$$\text{Root mean square (RMS)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{3}$$

$$\text{Mean (ME)} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{4}$$

$$\text{Standard deviation (SD)} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x}_i)^2} \tag{5}$$

$$\text{Max Value (MAX)} = (x_{max}) \tag{6}$$

$$\text{Kurtosis (KU)} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - \bar{x}_i}{S}\right)^4 \tag{7}$$

$$\text{Skewness (SKE)} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - \bar{x}_i}{S}\right)^3 \tag{8}$$

$$\text{Crest factor (CRE)} = \frac{x_{max}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}} \tag{9}$$

$$\text{Variance (VAR)} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}}{\frac{1}{n}\sum_{i=1}^{n} x_i} \tag{10}$$

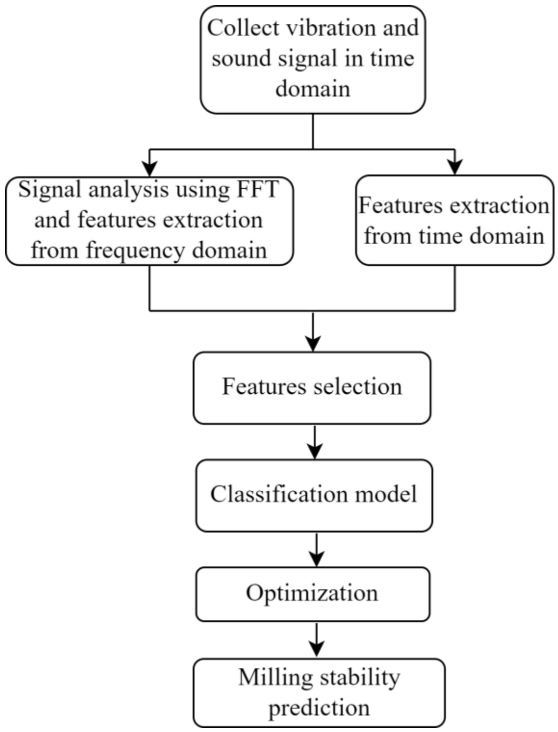

Figure 1. Flow chart of proposed milling stability prediction methodology.

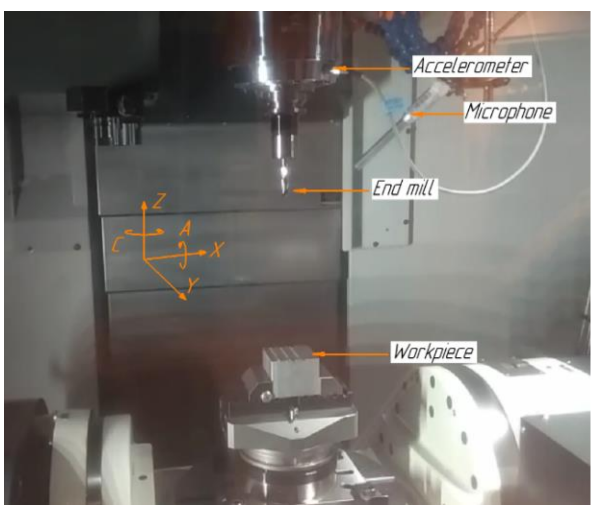

Figure 2. Experiment setup.

$$\text{Energy} = \sum_{k=0}^{N-1} \frac{1}{N} |X[k]|^2 \quad (11)$$

$$\text{Spectral Skewness (SS)} = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{x_i - \bar{x}_i}{s}\right)^3 \quad (12)$$

$$\text{Spectral Kurtosis (SK)} = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{x_i - \bar{x}_i}{s}\right)^4 \quad (13)$$

$$\text{Root variance frequency (RVF)} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (f_i - X_{fc})^2} \quad (14)$$

$$\text{Root mean square frequency (RMSF)} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} f_i^2} \quad (15)$$

TABLE I
CUTTING CONDITION

Spindle speed (rpm)	Cutting depth (mm)	Cutting condition
3000	0.6	stable
3000	0.8	stable
3000	1.4	unstable
3500	0.6	stable
3500	0.8	stable
3500	1.4	unstable
4000	0.6	stable
4000	0.8	stable
4000	1.2	unstable
4000	1.4	unstable

$$\text{Frequency center (FC)} = \frac{1}{N} \sum_{i=1}^{N} f_i \quad (16)$$

After feature extraction, the feature selection step was applied to eliminate the redundant features. This study applied the feature recursive elimination (RFE) method to rank the feature importance for the prediction model [27]. This is an old but fine approach to eliminate a small number of features per loop. RFE tries to eliminate dependencies and collinearity that may exist in the model. The final dataset was then randomly split into 2 subsets, test data (30% of the dataset) and training data (70% of the dataset). All of the working processes of this study are briefly represented in Figure 1.

III. EXPERIMENT SETUP

A high accuracy 5-Axis trunnion table machining center (Tongtai CT-350) with maximum spindle speed of 15000-20000 rpm was used for the experiment. The workpiece was a block of Al6061-T6 which is commonly used in the automobile and aerospace industries owing to its high strength to weight. An end mill cutter with a diameter of 12 mm, helix angle of 26 °, and two flutes was utilized. An accelerometer was installed on the support of the spindle assembly to record the vibration signal, and also a microphone was fixed near the spindle to receive the sound signal. During the experiment, 10 measurements were carried out in which the CNC machine worked in two different modes: stable and unstable cutting modes. Figure 2 shows the configuration of the experimental setup, and Table I shows the values of the cutting parameters for different cutting conditions. The stability lobe diagram (SLD) diagram illustrates the relationship between spindle speed and cutting depth [28]. It is divided into two regions: stable zones and unstable zones, which are separated by a barrier formed by a succession of overlapping stability lobes. By observing the SLD, we know that the higher depth of cut and material removal rate, the more likely the chatter occurs. This provides the first realization about cutting conditions and it is completely helpful for the signal analysis step.

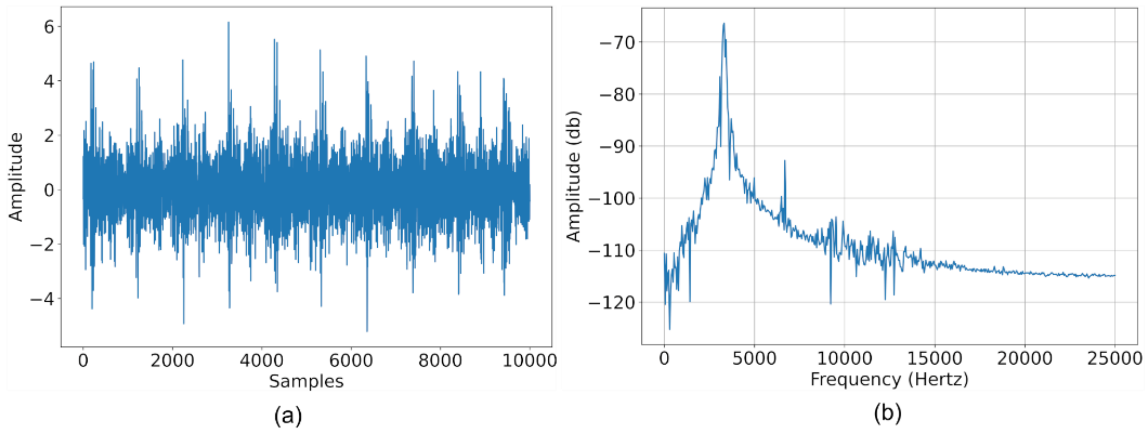

Figure 3. (a) Time domain response and (b) Fourier spectrum of the vibration signal under the stable cutting condition.

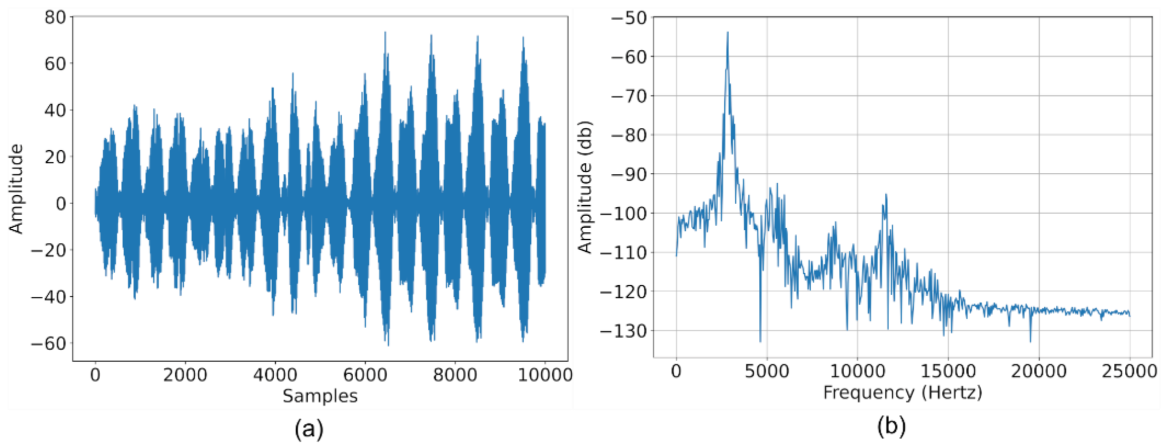

Figure 4. (a) Time domain response and (b) Fourier spectrum of the vibration signal under the unstable cutting condition.

IV. Signal Analysis and Features Selection

Figures 3 to 6 show the sound and vibration signals measured under the stable and unstable cutting conditions, respectively. Figure 3 (a) to Figure 6 (a) contain the cutting signals collected in the time domain, whereas Figure 3 (b) to Figure 6 (b) show their Fourier spectra. By observing the signals in the time domain, we can realize the difference in amplitude change between the stable and unstable conditions. The phenomenon of frequency modulation can be clearly observed, but it is hard to know the exact frequency that occurs during the cutting process. It causes trouble to the feature extraction process where we are only able to extract features from the time domain and it leads to a low prediction accuracy. Fortunately, the FFT illustrates the burst on both sound and vibration spectra which show clear signs of change in the cutting condition as well as the increase of energy between 5000Hz and 6000Hz. This is really effective because from that we know exactly where we need to extract features on the frequency domain. The improvement of final prediction accuracy by extracting features from both the time and frequency domains in section 6 is a proof which shows using FFT is absolutely necessary.

A set of feature list selected from 28 features of vibration and sound signals shows the output of feature extraction. RFE approach was used to rank the feature importance for the classification model. Figure 7 shows the change in accuracy based on the number of input features for each model. As observed, random forest has the best performance. Its accuracy increases to 96,3% at the point of 25 features and it remains stable. In the meantime, the XGBoost requires 15 features to reach an accuracy around 95,1%, and the decision tree needs 9 features to reach an accuracy around 94,5%. The SVM has the worst performance, which needs 21 features to reach an accuracy of 87,4%. There is a thing we can consider that the change in accuracy from 10 input features to 28 input features is relative small which around 0.01 % to 0.02%. In this case, in order to significantly increase the computation time, we can trade a little model accuracy. From Figure 7, it is clearly see that we can cut off around a half of the input features of Random Forest to get the accuracy around 96,0% at 13 features. We also can apply the same thing to SVM with 87,1% accuracy at 16 features. Figure 7 is a proof to show the necessity of feature selection. This is completely effective to reduce redundant features that have less contribution to the model. Table II shows the feature ranking of each classification model by using RFE. Although each model has a different sequence of feature ranking, there are a few things in common that can be pointed out. Firstly, we can see that features extracted from vibration signals always exist on the top of the ranking list. This means that the vibration signal (ACC) are more significant than the sound signals (MIC) in terms of stability prediction. Time domain features such as kurtosis (KU), skewness (SKE), and max value (MAX) are always on the top ranking of all classification models. However, frequency domain features are also necessary to further improve the classification accuracy.

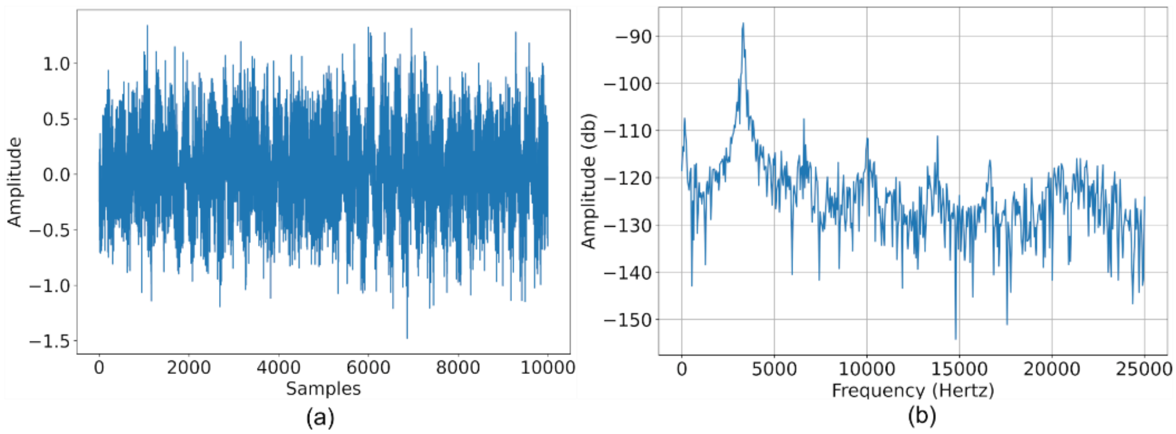

Figure 5. (a) Time domain response and (b) Fourier spectrum of the sound signal under the stable cutting condition.

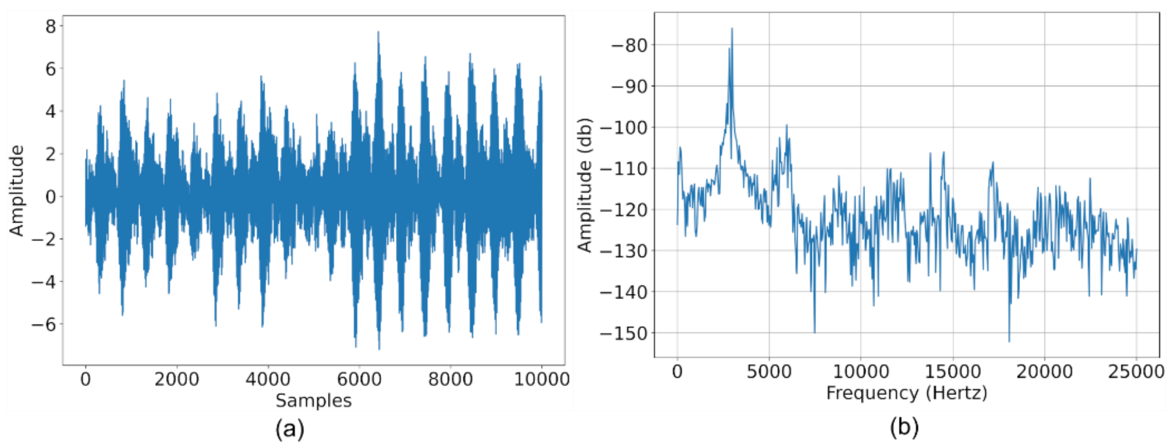

Figure 6. (a) Time domain response and (b) Fourier spectrum of the sound signal under the unstable cutting condition.

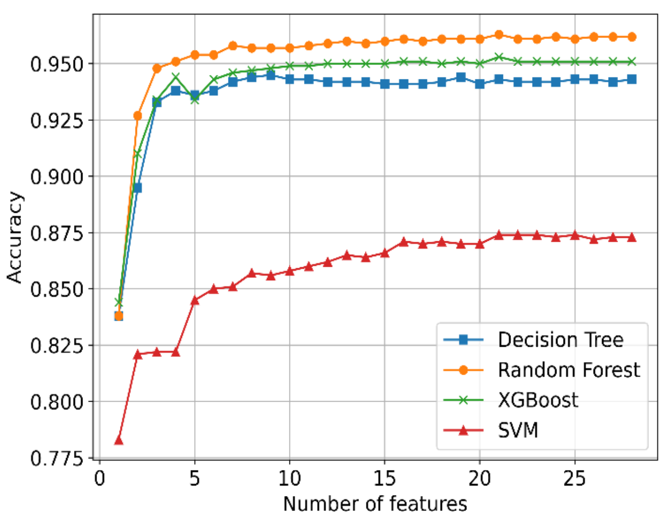

Figure 7. Accuracy change based on number of features selection.

V. Classification Result

Table III shows the difference in classification results of the models when extracting features from the time domain and combination features from both the time and frequency domain. It is observable that the list features extracted from the time and frequency domain performed better prediction. The SVM had a change in accuracy with an increase from 85% to 87%. The average accuracy difference between two set features in Decision Tree, Random Forest, and XGBoost are around 1% to 2%. Table IV illustrate various aspect of classification perform measurement. By examining Table IV, we can see that most of the measure index of Decision Tree, Random Forest and XGBoost achieved above 95%. Random Forest shows the best result in most of the prediction result include precision, recall, f1-score, and accuracy. Eventhough the accuracy of Random Forest and XGBoost shows the same number, we can say that Random Forest has better result in milling stability prediction. In milling stability, in order to improve the surface quality and reduce the tool breakage, we need to reduce the False Negative Rate (Miss Detection Rate). Based on that reason, we know that recall is the measure index that we need to focus on to evaluate which model perform better than others. Eq. (17) shows the calculation of recall.

$$Recall = \frac{TP}{TP + FN} \tag{17}$$

TABLE II

FEATURE RANKING BY RFE

Ranking	Decision Tree	Random Forest	XGBoost	SVM
1	KU_ACC	KU_ACC	KU_ACC	KU_ACC
2	SKE_ACC	RMS_ACC	SKE_ACC	SKE_ACC
3	MAX_ACC	VAR_ACC	MAX_ACC	FC_ACC
4	MEAN_ACC	SK_ACC	CRE_ACC	MAX_ACC
5	SD_ACC	MAX_ACC	FC_ACC	SS_ACC
6	CRE_ACC	SD_ACC	RVF_ACC	MEAN_ACC
7	FC_ACC	CRE_ACC	SS_ACC	SD_ACC
8	RVF_ACC	Energy_ACC	SK_ACC	Energy_ACC
9	SS_ACC	RMSF_ACC	KU_MIC	RVF_ACC
10		RVF_ACC	VAR_MIC	SK_ACC
11		SS_ACC	SKE_MIC	RMSF_ACC
12		SK_ACC	FC_MIC	SKE_MIC
13		RMS_MIC	RVF_MIC	FC_MIC
14			SS_MIC	KU_MIC
15			SK_MIC	VAR_MIC
16				SS_MIC

where TP means true positive and FN means false negative,

It is clearly visible from the Figure 9 that the Random Forest model has the lowest false negative rate with 0.05% that is higher than XGBoost with 0.09%. From Figure 9 The ROC curve of Random Forest almost reaches to the perpendicular line – the ideal ROC. Corresponding to that is the area under curve (AUC) of 0.99 with a low false positive rate and high true positive rate. Decision Tree and XGBoost ROC curve illustrate the same thing. The SVM (Linear kernel) performed the poorest result with 87% of accuracy. The reason for this problem is that the dataset has a lot of noise due to the cutting process. Furthermore, the data processing method using the sliding window method with overlaps 50% makes the dataset become larger and target class overlapping. These reasons make the computing time of the model is time consuming and affect the accuracy of the SVM model.

TABLE III

ACCURACY COMPARISON BETWEEN TIME DOMAIN FEATURES AND ALL FEATURES

Classification report	Time Domain Features	All Features
	Accuracy	Accuracy
Decision Tree	92%	94%
Random Forest	95%	96%
XGBoost	94%	96%
SVM	85%	87%

VI. OPTIMIZATION

It is rare that the machine learning model can perform at the maximum level just for the first attempt. In order to solve this problem, the model has to go through an iterative cycle. The

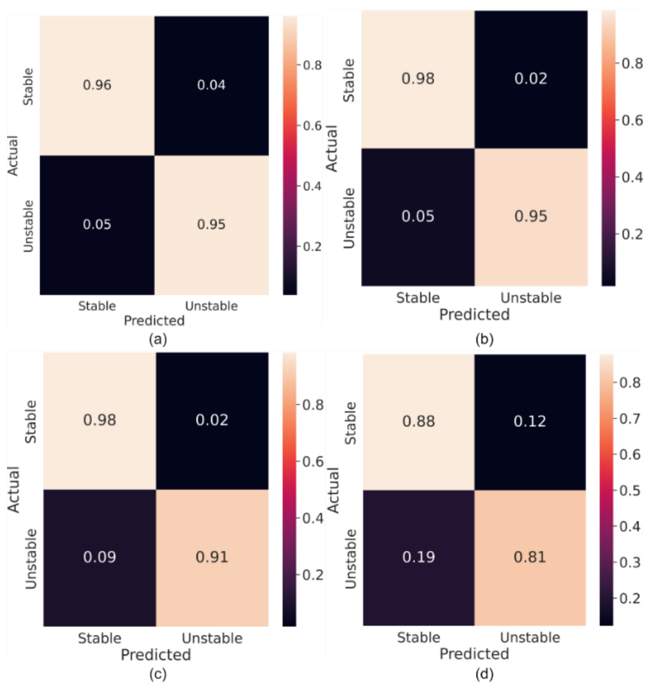

Figure 8. Confusion matrix; (a) Decision Tree, (b) Random Forest, (c) XGBoost, (d) SVM.

process may need to train and assess many models with various data setups and techniques, undertake feature engineering several times, or even supplement more data. To regulate the behavior of an ML algorithm, hyperparameters are knobs or settings that may be tweaked before performing a training operation. In other words, hyperparameter tuning is searching for the right set of features to achieve high accuracy and precision. The basic goal of hyperparameter tuning is to discover the sweet spot for the model's parameters in order to perform better. The world of hyperparameter tuning typically has two common approaches, grid search and random search. Each of them has its own advantages and drawbacks. The

TABLE IV

CLASSIFICATION MEASUREMENT INDEX WITH ALL FEATURES INPUT

Classification report	**Decision Tree**	**Random Forest**	**XGBoost**	**SVM**
	Unstable	Unstable	Unstable	Unstable
Precision	0.94	0.98	0.97	0.81
Recall	0.95	0.95	0.91	0.81
F1-score	0.95	0.96	0.94	0.81
Accuracy	0.94	0.96	0.96	0.87

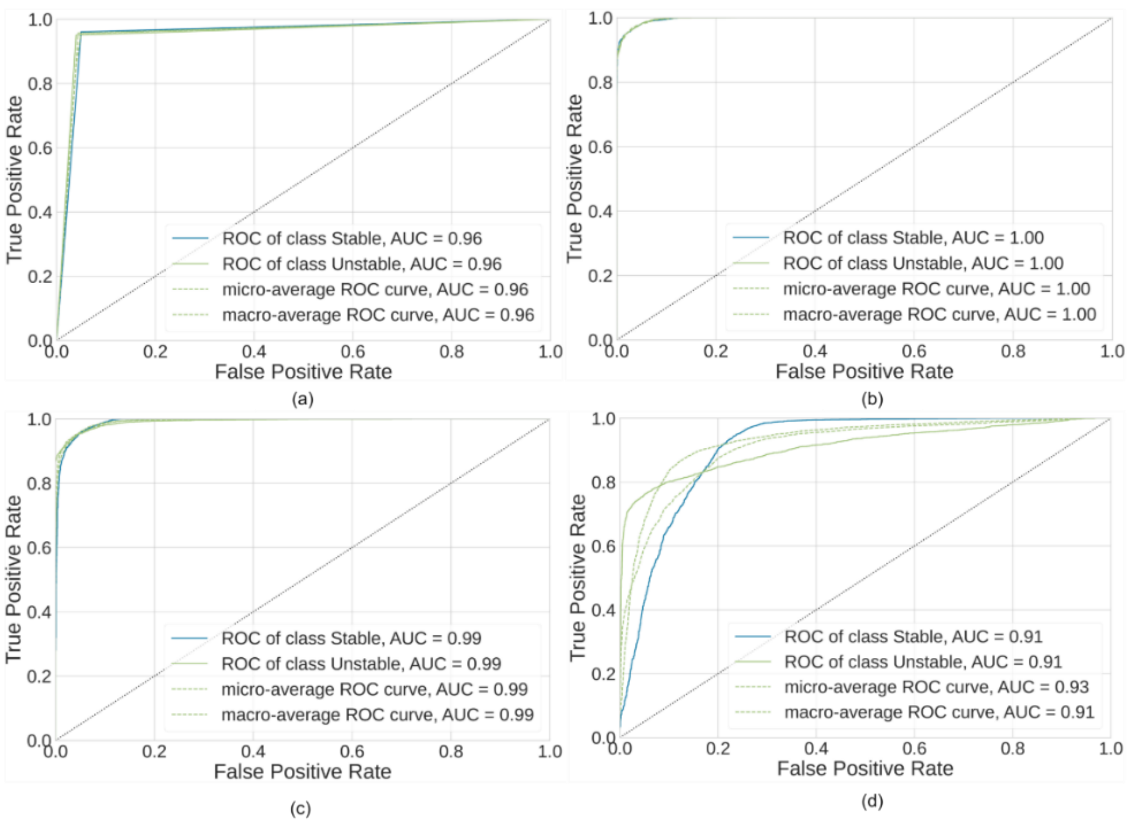

Figure 9. ROC; (a) Decision Tree, (b) Random Forest, (c) XGBoost, (d) SVM.

random search in most cases outperforms the grid search and its computing time is faster, but it does not guarantee the best results. This paper used grid search as a tool for the optimization process based on the reason that the performance of model almost reaches the highest level as it can be, and the search space is relatively small. It is possible to make a complete search for a given subset of the hyperparameter space. Once all of the combinations are evaluated, the models will set parameters that give the highest accuracy. From Figure 10, it is clearly seen that all of the classification models reach better classification accuracy when applying the grid search algorithm. The average enhancement of accuracy is around 1%. This is a solid proof that the input features we used for the classification model does not lead to the best prediction accuracy and the addition of grid search is necessary for the model to reach a better result. Table V lists the set of features that perform the best accuracy for each model. The machine learning process reflects human interference as well. There are no predefined guidelines for selecting the hyperparameters. Parameters defined in Table.5 are based on experience and the optimal performance cannot be guaranteed. The final accuracy might change due to the selection of hyperparameters as well as their search space. The more hyperparameter and search space considered for the model, the more computing time and power required and this will be dealt with in the future work.

VII. CONCLUSION

The application of milling process monitoring throughout the cutting process can increase the productivity and the tool life. The milling process monitoring system not only prevents the transition from a stable to an unstable cutting condition in advance, but also forecasts the cutting process. This can reduce

TABLE V

THE BEST PARAMETER AFTER USING GRID SEARCH FOR ALL FEATURES INPUT

Decision Tree	Random Forest	XGBoost	SVM
criterion: gini	criterion:entropy	learning_rate:0.25	C:10
max_depth: 16	max_features:auto	max_depth:5	Gamma:0.001
min_samples_leaf: 2	n_estimator:600	min_child_weight:5	
min_samples_split:2	warm_start: true	n_estimator:600	

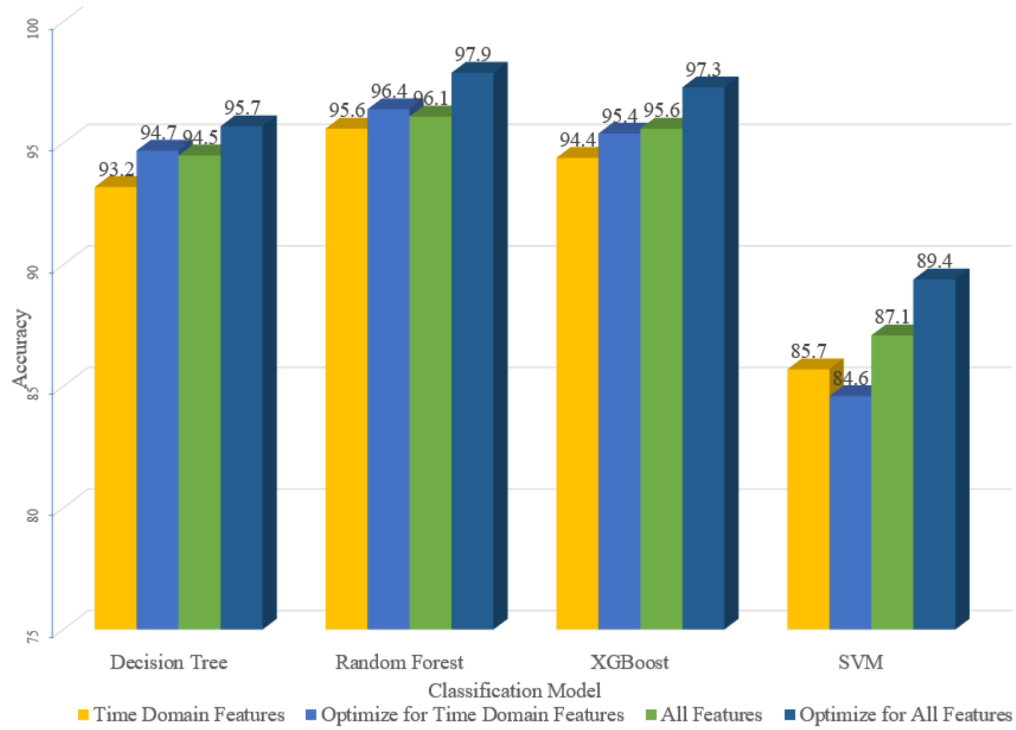

Figure 10. Classification result.

the excessive scrap production during the manufacturing process. Previously established milling process monitoring systems used complicated signal-processing techniques to create and select relevant features for classification. They generally created features around the system's resonant frequencies to indicate the incidence of chatter. Because the resonance frequencies of various CNC machines vary, this is not a generic method. In this work, a novel technique for milling chatter detection based on the conventional feature engineering was suggested. According to the research, we can draw certain important conclusions:

- The traditional feature engineering method was designed to classify two states of the milling process: stable and unstable states. The features used in this research consists of amplitudes in several frequency ranges. These sets were determined using the Fourier transform. The proposed approach provides good accuracy (up to 98% by random forest).
- Recursive feature elimination is an effective method to remove redundant features. This process truly helps to know the combination of features for the model to obtain the highest prediction accuracy as well as reduce the computation time. Based on the result of features selection, we also know that the vibration signal is more reliable than the sound signals in terms of predicting milling stability.
- Future development of real-time milling process monitoring might incorporate a chatter suppression technique to create a smart system for chatter suppression. In such a case, the monitoring system may read the CNC controller information, collect and evaluate sensor data, and transmit the control command to the automated control interface. Furthermore, the milling process monitoring approach described in this work is applied to signals recorded by sensors such as accelerometers and microphones. These shop floor sensors are inexpensive and simple to install.
- Future work of milling stability should consider the interaction between machine tool subsystem to increase the machine cutting performances and maximize the

removal rate. Moreover, the application of deep learning models [29] such as ANN, CNN has full potential in this case because it can handle noisy data without much pre-processing and save more time and computational power. An IOT architecture could also be applied [30].

APPENDIX

Nomenclature

Acronyms

DFT	Discrete Fourier Transform
FFT	Fast Fourier Transform
ML	Machine Learning
DT	Decision Tree
RF	Random Forest
XGBoost	Extreme Gradient Boost
SVM	Support Vector Machine
RMS	Root Mean Square
ME	Mean Value
SD	Standard Deviation
MAX	Maximum Value
KU	Kurtosis Value
SKE	Skewness Value
CRE	Crest Factor
VAR	Variance
SS	Spectral Skewness
SK	Spectral Skewness
RVF	Root Variance Frequency
RMSF	Root Mean Square Frequency
FC	Frequency Center
RFE	Recursive Feature Elimination
ACC	Accelerometer
MIC	Microphone
SLD	Stability Lobe Diagram
ROC	Receiver Operating Characteristic
AUC	Area Under Curve
ANN	Artificial Neural Network
CNN	Convolutional Neural Network
TP	True Positive
FN	False Negative

Symbols

ω_N	The Primitive Root of Unity
n	The sample size in time responses
$\bar{x}$	The mean value of observation
x_i	Element value
f_i	Frequency
X_{fc}	Value of Frequency Center
X_k	Function of the wave number k by carrying a Fourier Transform

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