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Prediction of Tool Wear by Machine Learning Method in Turning Process

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Abstract

An intelligent monitoring system has the benefit of being able to predicting tool condition, preventing a turning machine from catastrophic failure as well as to guarantee the accuracy of the worn-out cutting tool that can be replaced in a timely manner. The objective of this research is to predict the tool condition during turning based on the time series of vibration sensor signal by using the K Nearest Neighbor approach. Experiments have been carried out on turning of AISI 1045 carbon steel using carbide inserts. Time domain, frequency domain and time and frequency domain is extracted which is subsequently employed as an input for the output-corresponding classification model. Four different distance matrix types which are the "Euclidean," "Minkowski," "Chebychev," and "Cityblock" methods is used to classify the cutting tool condition. The result found that "Euclidean" technique yielded the lowest mean square error of 24.167% and the highest accuracy of 88.333% among the three models, according to the data.

1. Introduction

CNC turning is one of the manufacturing process that are widely used in industries nowadays. This manufacturing process involves holding bars of material in a chuck and rotating them while feeding a tool to the piece. This machining process will remove the material until the desired shape achieved. To succeeding this material removal process, CNC turning machine is equipped with a cutting tool called cutting inserts. This turning process required a rotating part while a single-point cutting tool is moved parallel to the axis of rotation. However, the highly usage of this cutting inserts lead to cutting tool wear that can cause low accuracy of the desired part. Since it reduces tool life, tool wear is the most undesired machining characteristic and is therefore unavoidable.

A useful tool wear monitoring system allows worn tools to be replaced on schedule, preventing unplanned downtime and discarded parts. Various techniques have been suggested to track the wear of cutting instruments. The two categories into which these techniques are separated are direct method and indirect method [1]. Direct method is a technique that uses direct measurement to assess the tool wear state is the direct method tool wear monitoring system. This approach consists of the radiometric, contact resistance, and optical image methods. While this direct approach can monitor the tool wear status instantly, it is no longer suited to the present development trend and is not viable for application in industry [2]. This is due to the fact that the direct method required a stoppage in order to detect tool wear, which can disrupt the continuity of the machining operation. Additionally, this technology lacks real-time monitoring capabilities, and the chips, lighting, and cutting fluid all have an impact on the measurement results.

For the indirect method in tool wear monitoring, it uses the effect of tool wear state when it is worn or about to break on different working parameters [2]. The indirect methods are based on the measurement of flank wear using the calibration procedures. Vibration signal helps to detect the cutting tool wear and describe the tool wear quality at the cutting tool [3]. Vibrations in turning occur when the rubbing between the workpiece and chips are against the tool. The increase in vibration lead to increase in tool wear. The vibration monitoring technique is a practical way and cost effective [4] as it can predict the flank wear and the normalization of process parameters at the digital preprocessing level (An improvement of the visual data that reduces unintentional distortions or increases certain aspects of the image that are crucial for subsequent processing) can enhance the accuracy of tool wear results [5]. This results in more reliable and efficient assets.

One common application in industry is the use of machine learning to detect tool wear. One of the popular machine learning models used in business is Naïve Bayes. Nevertheless, there are a few drawbacks to this model. For example, the algorithm encounters the "zero-frequency problem," which leads to zero probability for a categorical variable whose category is absent from the training dataset [6]. Additionally, Naïve Bayes makes the assumption that each predator also referred to as a feature is independent, which restricts the algorithm's application in actual situations.

In machine learning, linear discriminant analysis (LDA) is a dimensionality reduction technique used to address issues involving more than two classes of categorization [7]. LDA's use is not appropriate for small variable categories and necessitates the normal distribution assumption on features or predictors, which could result in erroneous data for tool wear monitoring. The linear relationship between a dependent variable and one independent feature is calculated using linear regression analysis [8]. This algorithm is used to determine which linear equation, given an independent variable, best predicts the value of the dependent variable. It does, however, have some limitations because linear regression is sensitive to outliers and frequently extremely susceptible to noise and over fitting [9].

Support Vector Machine (SVM) is a set of supervised learning methods that used the classification algorithm for two group classifications problem. For tool wear detecting using the SVM, it requires higher time consuming as this technique does not suitable for large sets of data [10]. The SVM also not suitable for the data set that have noises for example target classes that are overlapping during the cutting process. This lead to impractical data output during detecting the tool flank wear [10].

Artificial Neural Network (ANN) is a series of algorithm that act as a human brain to recognize data patterns during the tool wear detection process [11]. As ANN have the similar function to the human brain, the proper network structure of ANN for tool flank wear detection may not be determine. This could lead to inaccurate data and error during the flank wear classifications. ANN can only be trained by using the numeric data as this aids to difficulty to control the ANN to understand the problem statement [11]. This may lead to difficulty during handling the ANN algorithm to classify the tool wear classes.

K-Nearest Neighbor (KNN) is a non-parametric supervised learning classifier as it use the proximity to make the classifications or predictions about the grouping of an individual data point [12]. This technique works with the similarity of available categories as it put the new data or available cases into the nearest available category listed. For instance, K Nearest Neighbor algorithm stores all the available data and classifies the new data based on the similarity of the available data in the system. The used of K- Nearest Neighbor algorithm gives many advantages as it is easy to be used, required low calculation time that make it a preferred algorithms among scientist and it is more effective with large training data. KNN technique is a technique that easy to implement as it give the simplicity and accuracy algorithms for the first time users to learn. It also can be adapt easily as the new training sample is being added and the algorithms will be adjusted automatically to account for new data since all the training data is being stored into the memory. Therefore, the objective of this research is to develop an effective tool wear monitoring system that predicts and classifies cutting tool conditions in CNC turning operations using vibration sensor signals and K Nearest Neighbor (KNN) machine learning.

2. Methodology

2.1 Experiment Set Up

To experimentally validate the effectiveness of the proposed tool wear monitoring method in turning operations, the experimental datasets according to the cutting speed, depth of cut and feed rate is taken into consideration. The CNC machine that being used during the experiment is the Harrison Alpha 400 CNC lathe as shown in Figure 3.2. This machine use spindle bore of 2 1/8”, spindle speed of 2500RPM and variable motor of 10HP. This machine required voltage of 480V or 415V and the distance between the centers is 24” with maximum swing of 16”.

The workpiece material that undergo turning process is carbon steel of AISI 1045 using the carbide insert. Table 2.1 shows the machine condition for the experiment and Table 2.2 shows the machine cutting condition for this experiment according to the cutting speed (m/min), feed rate (mm/rev) and depth of cut (mm). Table 2.2, shows the cutting parameter combinations that being examined in this experiment with three class of tool wear data which is less than 0.1, larger than 0.1 and chipping.

Table 1: *Machine Condition for Experiment*

Lathe Machine	Harrison Alpha 400 CNC lathe Machine
Cutting Tool Insert	Carbide Insert TNMG160408-MA (Depai)
Workpiece	AISI 1045 Carbon Steel
Cutting Condition	Dry Condition

Table 2: *Machine Cutting Condition*

Depth of Cut (mm)	0.2
Feed Rate (mm/rev)	0.2
Cutting Speed (m/min)	300

2.2 Sensor Signal Acquisition

Sensor signal acquisition is a process that involves in data collecting information in order to understand the electrical or physical phenomenon using the sensors, measurement device and a computer. To detect the tool flank wear using vibration sensor, accelerometer is often a good choice [13]. This accelerometer helps in detecting the instantaneous acceleration in one direction and this can lead to value of velocity by integrating the acceleration equations and displacement by integrating the velocity equations.

The placement of vibration sensor during detecting of tool flank wear, this sensor signal being placed at the tool holder. Sensors need to be mounted as near as feasible to the vibration source and to a smooth, unpainted, flat area that is free of oil and grease and is larger than the sensor's base [14]. This vibration sensor being placed 2 cm from the tip at the right side of the handle as this position gave the best value of signal strength in independent direction [15].

The collection of vibration signals during the turning process were collected using the Movipack vibration analyzer and this signal will be process by the signal processing in order to extract the data to useful features. From the accelerometer signal, this data undergo the signal processing of texture analyzing and feature extraction of time domain, frequency domain and time and frequency domain to extract the data to a useful information. Next, decision making process from the data extraction were done by using the K Nearest Neighbor and the tool flank wear are classified.

2.3 Measurement Tool Wear

The tool flank wear is being observed using the Nikon MM-60 Toolmaker's Microscope. According to the ISO 3685:1993 as shown in Figure 2.1, the flank wear will be measure from the top of the tool edge until the bottom of the worn surface.

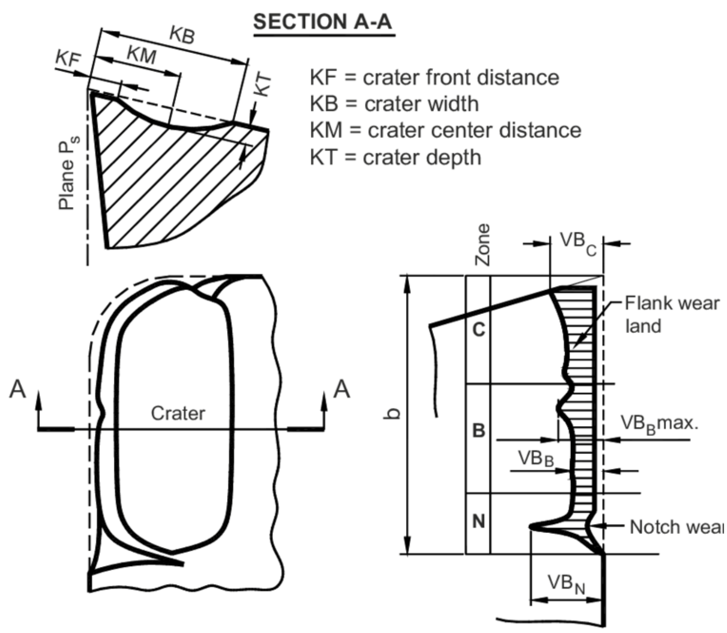

Fig. 1: *Types of Tool Wear according to Standard ISO 3685:1993[16]*

2.4 Data Analysis

Data analysis for this experiment include the development process of the tool wear monitoring system. The development of tool wear monitoring system include the feature extraction, feature selection and construction of diagnostic model. Figure 2.2 shows the development stages of the K Nearest Neighbor tool wear monitoring system.

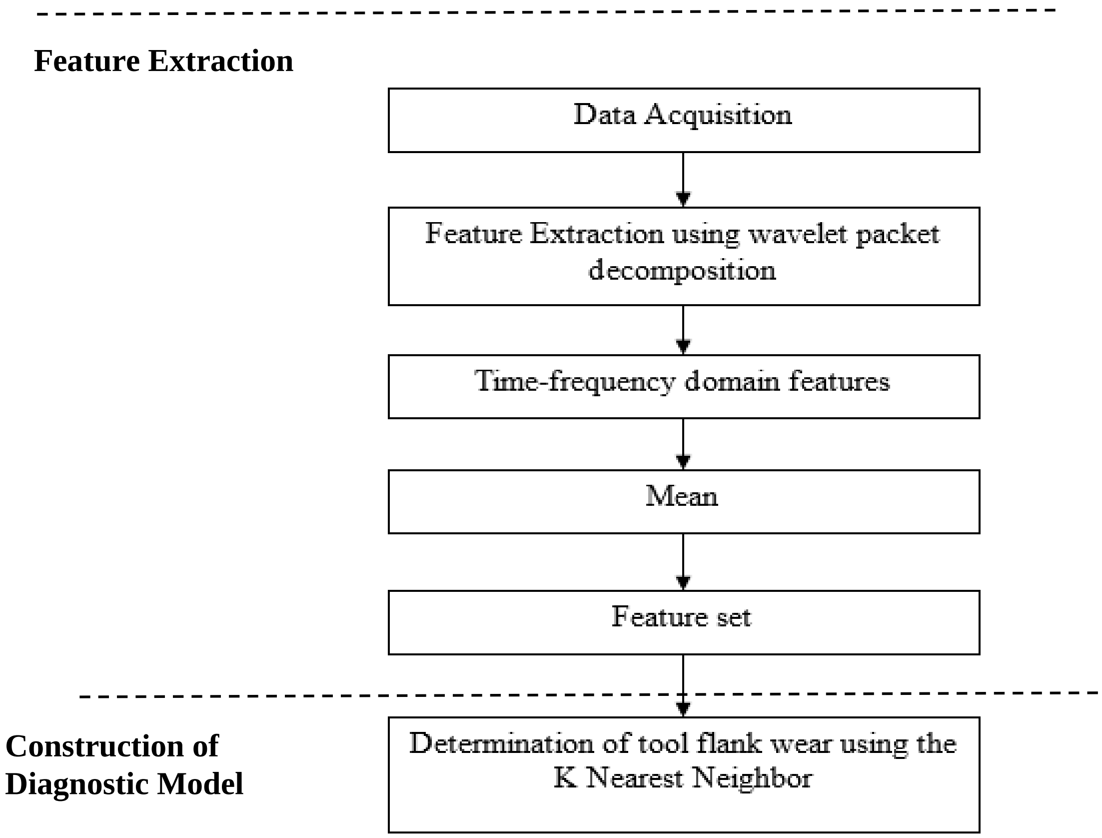

Fig. 2: *Development Stages of Tool Wear Monitoring System*

2.4.1 Feature Extraction

Feature extraction is a technique of turning raw data into numerical features that can be handled while keeping the information in the original data set. The use of specialized algorithms for this experiment helps to extract data automatically from signals without the need of human intervention. The signals from vibration sensor is the input data to predict the tool flank wear and the signal processing which have a precise time resolution helps to predict the time which the tool breakage starts. For example, wavelet scattering which transform process data in stages and the output of one stage will become the input for next stage.

To extract the features for signal processing, statistical features being used in this experiment. Statistical features of mean and standard deviation is being used for vibration signals in time-frequency domain. The mean and standard deviation values can be determine by using the equation below:

$$mean, \bar{x} = \frac{\sum_i^n = 1\, x_i}{n} \qquad (1)$$

Where:

x_i is the measured vibration data

$\bar{x}$ is the mean of measured vibration data

n is the number of samples in the range

σ is the standard deviation

For this research, the statistical features of mean is being used to extract the input data that being received from the vibration tester.

2.4.2 Flank Wear Prediction by K Nearest Neighbor

Figure 2.3 shows the operation flow chart of the KNN model. There are several important phases in the operation flowchart of a k-nearest neighbor (KNN) model. The algorithm starts with a dataset that has samples which have been categorized. Selecting the value of k, or the number of closest neighbors to take into account, is the next stage. The model then evaluates the distance, using distance metrics which is Euclidean, Minkowski, Chebychev and Cityblock between the target instance and every other instance in the dataset. After that, using the computed distances, the method determines who the k-nearest neighbors are. The target instance is classified by the model by giving it the majority class label among its k-nearest neighbors in the feature space after the neighbors have been identified. KNN is very useful for straightforward classification jobs because it has an easy-to-understand decision-making mechanism.

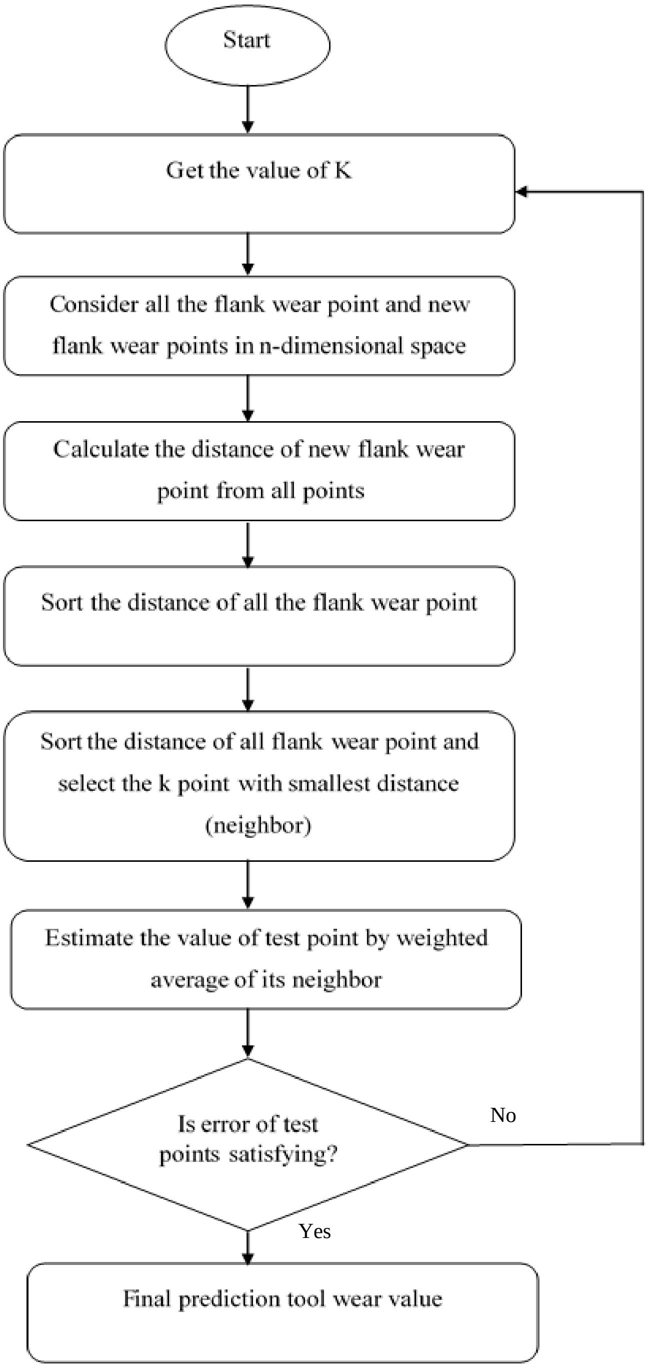

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Fig. 3: *Operation Flow of KNN Model*

2.5 Accuracy Evaluation

The accuracy evaluation of extracted data is being done to evaluate whether the K Nearest Neighbor machine learning method is accurate in detecting the tool flank wear. This accuracy evaluation are done by using the confusion chart with the formula below.

Table 3: *Confusion Chart Metric*

	Predicted Positive	Predicted Negative
Actual Positive	True positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (2)$$

$$Recall\ or\ Sensitivity = \frac{TP}{TP+FN} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

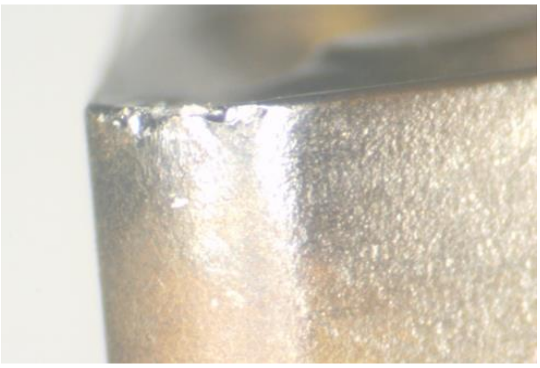
$$Specificity = \frac{TN}{FP+TN} \quad (5)$$

$$F1\ Score = 2\left(\frac{Precision \times Recall}{Precision + Recall}\right) \quad (6)$$

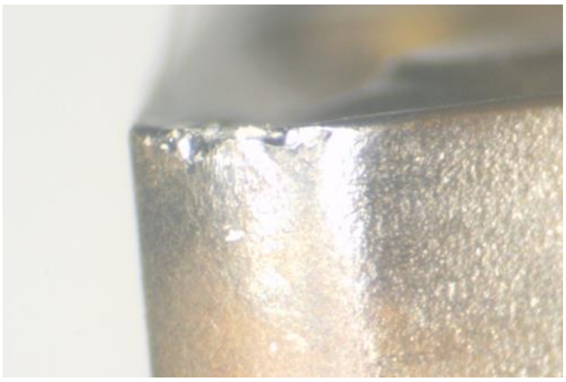
3. Result and Discussion

3.1 Result Analysis

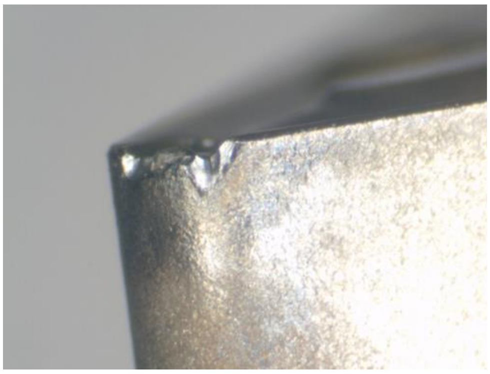
Figure 4 (a), (b) and (c) shows the result of tool flank wear for three class which are less than 0.1mm, larger than 0.1mm and chipping after the turning process.



(a)



(b)



(c)

Fig. 4: *Tool Flank Wear at Cutting Tool (a) less than 0.1mm; (b) larger than 0.1mm; (c) chipping*

A data of 600 sample features from vibration signals is taken during the turning process and being divided to three class of tool wear (200 sample features for each class) which are less than 0.1, larger than 0.1 and chipping are acquired. This data is divided to ration of 80:20 with two groups which were 160 training sample data and 40 test sample data that were used for performance testing for the trained model. This step was repeated until a total of three tool wear class prediction value being obtained. The accuracy of the KNN classification model were determined by the measure of mean square error, accuracy and sensitivity, precision, specificity and F1 score for each KNN distance matrix method.

Figure 5 to Figure 8 shows the confusion chart for each KNN distance matrix method which is 'Minkowski', 'Euclidean', 'Chebychev and 'Cityblock' respectively to classify the flank wear less than 0.1mm and greater than 0.1mm as well as chipping. This confusion chart shows total number of observations in each cell and being divided into two part which is rows confusion matrix correspond to true class and columns corresponds to predicted class of tool flank wear. For this chart, a row-normalized displays the percentages of correct and incorrect classified observations for each true class and a column-normalized shows the percentages of correct and incorrect classified observations for each predicted class.

Figure 5 shows that 32 datasets of flank wear greater than 0.1 mm are classified correctly with accuracy of 91.4% while the class of chipping achieve accuracy of 91.1% which 41 datasets out of 45 datasets were classified correctly. To improve the model's performance, one should focus on the predictive results in class of flank wear less than 0.1 mm as a total of 7 datasets were misclassifies by the Minkowski classifier. It has the highest misclassification rate among all the classes. Accuracy in prediction for class is thus, 82.5% only. A total of 106 datasets were correctly predicted out of the total of 120 datasets. Thus, the overall accuracy is 88.33%.

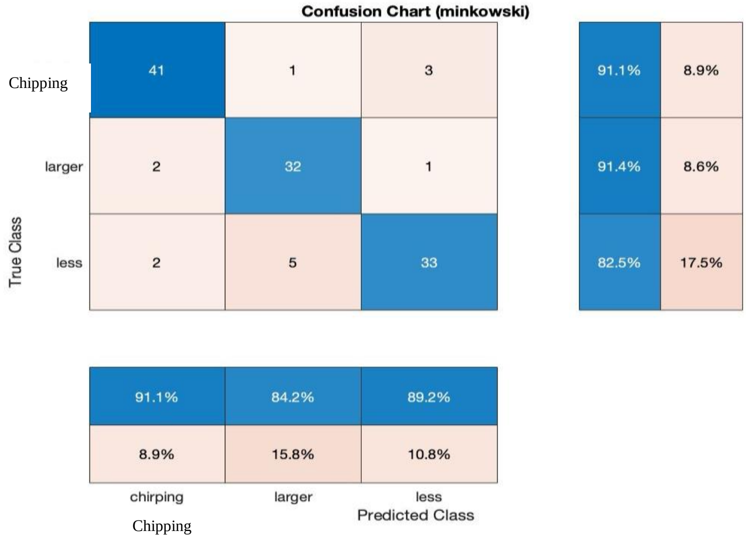


Fig. 5: *Confusion Chart of Minkowski Distance Matrix*

Figure 6 shows the confusion chart of Euclidean Distance Matrix illustrates that 3 datasets of flank wear greater than 0.1 mm are misclassified with accuracy of 8.6% while the class of less than 0.1 mm achieve the accuracy of 17.5% which 7 datasets out of 40 datasets were misclassified. From this Euclidean confusion chart, it can be seen that the overall accuracy for this datasets is 88.33% with only 106 datasets were correctly predicted out of the total of 120 datasets.

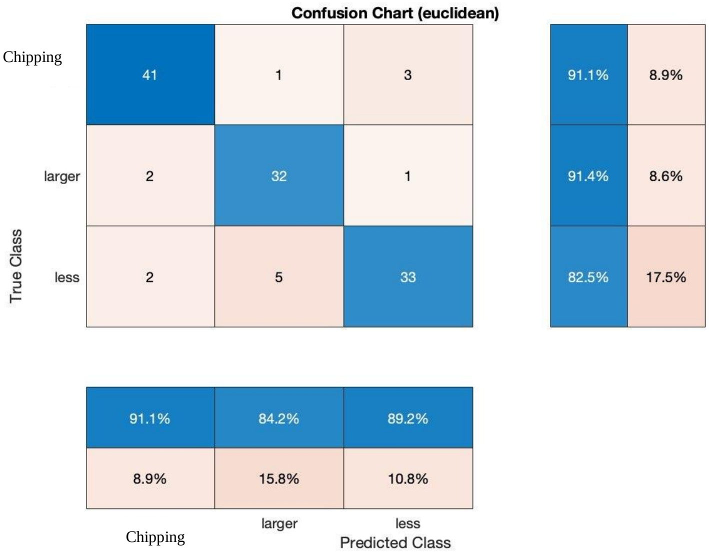


Fig. 6: *Confusion Chart of Euclidean Distance Matrix*

Figure 7 shows the confusion chart for chebychev method with 41 datasets of flank wear under chipping class are classified correctly with accuracy of 91.1% while less than 0.1 mm achieve the accuracy of 80.0% which only 32 datasets out of 40 datasets were classified correctly. A total of 7 datasets were misclassified by the Chebychev classifier under less than 0.1mm tool wear class. For a total of 120 datasets, 104 datasets were correctly predicted a give the overall accuracy of 86.67%.

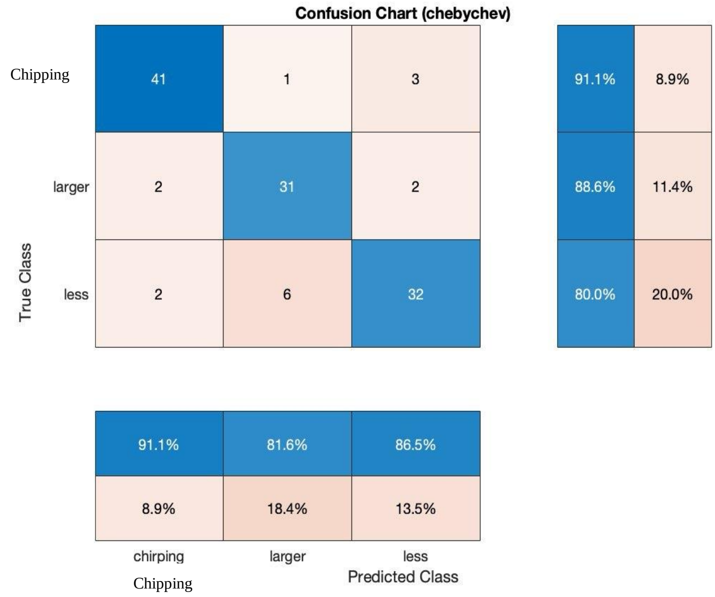


Fig. 7: *Confusion Chart of Chebychew Distance Matrix*

Cityblock method confusion chart shows that 10 datasets of flank wear less than 0.1 mm are misclassified with accuracy of 25.0% while the class of larger than 0.1 mm achieve the accuracy of 8.6% which 3 datasets out of 35 datasets were misclassified. A total of 32 datasets were correctly classified by Cityblock classifier at the larger than 0.1 mm class which it has the highest data classification rate among all the classes with accuracy of 91.4%. For a total of 120 datasets, only 103 datasets were classified correctly which give the overall accuracy of 85.83% for all the classes.

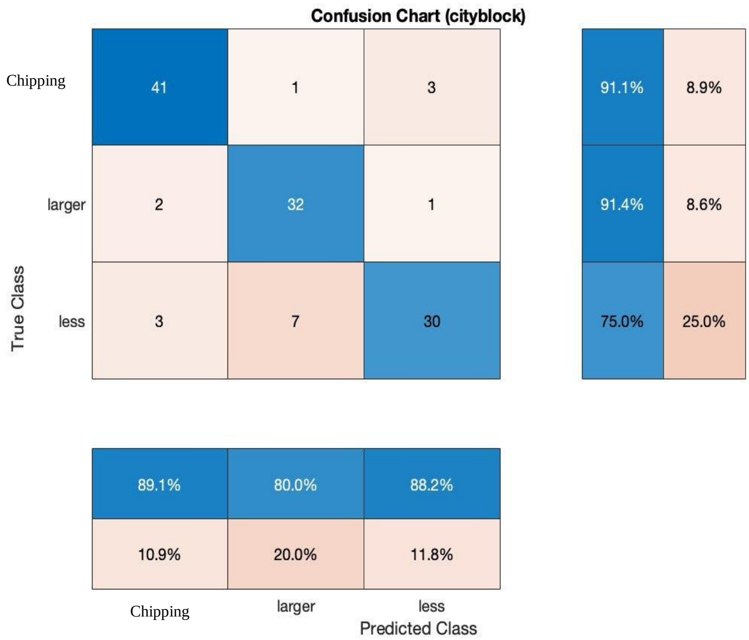


Fig. 8: *Confusion Chart of Cityblock Distance Matrix*

To improve the model's performance from Figure 5 to Figure 8, one should focus more on the predictive results in class of flank wear less than 0.1 mm. The increasing number of datasets that are misclassified along the distance matrix method influence the datasets accuracy. With 7 datasets that are misclassified at this class, it give the accuracy of 88.33% for the Minkowski classifier while the 10 datasets that are misclassified at the Cityblock classifier gave the accuracy of 85.83%. This shows that the accuracy value is decreasing with the increasing of misclassified due to the number of correct predictions is divided by the total number of predictions made by the model.

Table 4 tabulates the tool flank wear data classification, it can be seen that 'minkowski' and 'euclidean' are the best method to classify the tool wear data with mean square error of 24.167%. From the overall KNN distance matrix method, the performance of 'minkowski' and 'euclidean' method result in the best tool flank wear classification as the value of accuracy is 88.333%, followed by 'chebychev' method which is 86.667% and 'cityblock' method which is 85.833%. For the mean square error (MSE), 'cityblock' method gave the highest error value which is 29.167% compare to 'euclidean' and 'minkowski' method which is 24.167%. This value have slightly 5% different between this two methods. However, the specificity which are used to detect the false alarm in all negative instances for each four method results in same percentage value which is 96.97%.

Table 4: *Tool Flank Wear Data Classification*

DistanceMetric	MSE	Accuracy	Precision	Recall	Specificity	F1Score
{'minkowski'}	24.167	88.333	88.347	88.17	96.97	88.258
{'chebychev'}	25.833	86.667	86.561	86.392	96.875	86.476
{'euclidean'}	24.167	88.333	88.347	88.17	96.97	88.258
{'cityblock'}	29.167	85.833	85.847	85.789	96.97	85.818

By comparing this four method, cityblock method have the highest mean square error with lowest accuracy compare to Minkowski method and Euclidean method. For the column-normalized of less than 0.1, cityblock method have the highest incorrect percentage value which is 25% compare to another three method. The row-normalized for chipping true class for cityblock method have the lowest percentage value compare to Euclidean method, minkowski method and chebychew method which is 89.1%. This shows that the cityblock method is not suitable for tool flank wear classification compare to Euclidean method and minkowski method as the cityblock method is suitable for sparse and high dimensional data compare to Euclidean which is good for continuous data with meaningful scale.

Similar result is found by Chris Aldrich [17], Euclidean distance matrix gives the best result as features extracted from this distance matrix can consistently yielded the best performance compared to other method. Therefore, the used of Euclidean distance matrix is better in order to classify the cutting insert flank wear as it results in lower mean square error, higher in accuracy and precision and higher specificity compared to other distance matrix.

4. Conclusion and Recommendation

In a nutshell the objectives of this study on machine learning-based tool wear prediction in turning operations has been accomplished. The KNN classification method was effectively used in this study to forecast flank wear based on cutting circumstances and statistical characteristics gleaned from a time-domain vibration signal.

Euclidean method, Minkowski method, ChebyChev method and Cityblock method are being used to predict the tool wear classification and its accuracy according to KNN classification method. As the result obtained, the Cityblock method have the highest mean square error (29.167%), followed by the Chebychev method (25.833%) and Minkowski and Euclidean method (24.167%). The Minkowski method and Euclidean method share the same value of mean square error (24.167%) which is the lowest among four method with the highest accuracy value (88.333%). The lowest percentage value of mean square error indicate the highest accuracy of tool flank wear classification according to its method.

K-Nearest Neighbor Classification helped in classified the cutting tool wear condition according to its class which is less than 0.1, larger than 0.1 and chipping with aids of distance matrix which is Euclidean, Minkowski, ChebyChev and Cityblock.

This distance matrix helped in determine the accuracy of each class according to predicted class and true class percentage value. The result of this study indicated that the Euclidean and Minkowski method in KNN classification could be used to evaluate the tool flank wear in turning process accurately as it have the lowest mean square error with highest accuracy..

4.1 Recommendation for Future Work

Several suggestions for the purpose of studies for future projects can be made considering the findings of this research study. The following is a list of suggestions for further research on this topic:

i.Investigate how real-time data can be obtained during the turning process by integrating IoT (Internet of Things) devices and sophisticated sensors. This could provide a more complete dataset for forecasting tool wear, such as temperature, vibration, and sonic emission sensors.

ii.Analyze the use of deep learning methods to represent intricate relationships in the turning process data, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs). Large datasets with complex patterns have been successfully captured by deep learning architectures.

iii.Extend the dataset by using methods like simulation or data creation. This can contribute to the creation of a more broadened dataset, particularly in situations when gathering an adequate amount of real-world data is difficult.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Nor Aziera Azman, Lee Woon Kiow****; data collection****: Nor Aziera Azman****; analysis and interpretation of results:*** *Nor Aziera Azman, Lee Woon Kiow****; draft manuscript preparation:*** *Nor Aziera Azman, Lee Woon Kiow. All authors reviewed the results and approved the final version of the manuscript.*

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