Post-processing for Three Class of Tool Wear Prognosis using Two Class ANN Classifier based on Vibration of CNC Milling

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Abstract: This research propose a novel method of utilizing bi-levels tool wear classifiers to prognose three levels of tool wear through additional post-processing stages. The classifier uses a multi-layer perceptron (MLP), single hidden layer, trained using the resilient backpropagation method. The original classifier output range -1 to 1 and threshold 0.0 for the separator of two classes, has been able to achieve 100% classification accuracy of two CNC tool conditions, severe wear and normal one, based on vibration features in the time domain and order domain. This classifier was tried to classify three levels of tool wear: normal, moderate wear, severe wear, according to ISO 8688 standard. Output of existing MLP classifier is passed through a moving average filter with period 4 and using threshold of -0.8 and +0.8 for three level separation, normal tool, moderate wear, severe wear. The proposed method is proven to achieve 89.98% accuracy from 459 tests. Fail safe missclassification occurred from 153 test cases which were supposed to be moderate wear, 46 of them were incorrectly indicated as severe wear. For the severe wear test case and normal tool test case, no prediction errors were found. The 100% accuracy for both test case prediction.

1 INTRODUCTION

The CNC machining role has wide spread and increasingly important in the manufacturing industry (Cheng et al., 2019) and (Teti et al., 2010), as well as tool condition monitoring technology (Huang et al., 2019) and (Zhou et al., 2019). Tool Condition Monitoring (TCM) technology is constantly being developed to ensure the quality and efficiency of machining(Ahmad and Kamaruddin, 2012). The TCM method is generally divided into: qualitative-based method, model-based method, data-based method(Cheng et al., 2019). Model-based methods analytically build the mathematical models to explain the phenomenon of machining tool wear, like the method used by Mishra, (2015), Rmili et al., (2016), Liu et al., (2010), and Mei et al., (2018). But this is not an easy build, given the complexity of the mechanical machining system(Yau et al., 2014) and (Huang et al., 2019). While the data-based method does not require analytical knowledge, it only requires empirical knowledge about the relationship of tool wear with physical phenomenon of the machining (Jemielniak et al., 2012), so this method is more practical to use (Wei and Wang, 2019).

2 PREVIOUS WORK

Sensors commonly used in tool wear detection are acoustic emission sensors and accelerometer(Murat et al., 2017). Lembke, (2019) and Casoli, (2019)sated, data-based methods of TCM require classifiers that are supervisically trained as used in research by Zhou et al., (2019), Casoli et al., (2019) and Pappachan et al., (2017), or unsupervisically-trained based on databases as used in research by Barraza, (2017), Sakthivel et al., (2014) and Benkedjouh et al., (2017). Commonly used classifiers are Support Vector Machine (SVM) as used by Zhou et al., (2019), Artificial Neural Network (ANN) used by Arendra and Herianto, (2020), Arendra et al., (2020), and Prasetyo et al., (2018), K-Nearest Neighborhood (KNN) used by Junior et al., (2018), Genetic Algorithm used by Goti et al., (2019), and Bayesian Network used by Tobon-Mejia et al., (2012). The supervised training method

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for classifier requires a database for training, validation and testing(Leturiondo et al., 2016). The number of database subsets for this classifier is the same as the number of classes to be grouped(Wiharto et al., 2016).

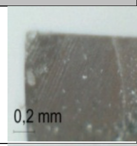
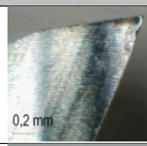
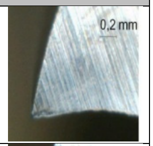
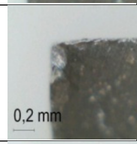
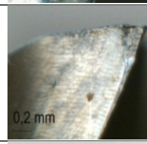
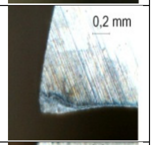
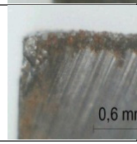
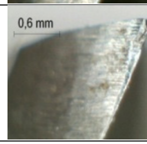
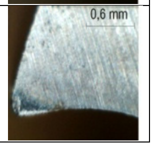
Multiclass SVM classifier has been used by Wiharto et al., (2015) and Cheng et al., (2019)for the classification of five levels of heart disease cases and the classification of three levels of of CNC tool wear, respectively. Wiharto et al., (2015)used five subsets of data at healthy, sick-low, sick-medium, sick-high, sick-serious levels. Cheng et al., (2019)use three subset data at healthy state level, degradation state level, and failure state level. As expected, for *n* class classifiers a number of *n* training data sub-sets are required. Yiqian He et al., (2019)uses a different approach, exploring the correlation between the mahalanobis distance of vector features to the wear level, then setting two thresholds to separate the three wear levels of tool. The approach taken by Tobon-Mejia et al., (2012)is constructing the model behavior of tool degradation phenomena with a set of mathematical models for predicting the evolution of tool degradation. This paper proposes a new approach to classifying three levels of tool wear using a classifier that is trained with twower classes, then followed by post-processing.

3 EXPERIMENT SETUP AND METHODS

The sensors used to collect data are MEMS Accelerometer MMA7361 and DT-SENSE Tracking SFH-300. MMA7361 sensor sensitivity is 800mV / g in the range of 0g - 1.5g. The sensor output is analog voltage 0 - 3.3V for X, Y, and Z channels. This sensor is installed in the workpiece fixture. The DT-SENSE Line Tracking Sensor SFH-300 is used as an optical proximity sensor to detect the spindle rotation phase that has been marked with a white reflector strip. This sensor works on a 5VDC voltage power supply, has four channel voltage outputs from 0 to 4.9V, the rise and fall response time is 10µs.

Data acquisition equipment uses DAQ NI USB-6008 with NI-DAQmx 9.9 device driver. The DAQ works on USB interface, input voltage range of ± 10V, the maximum aggregate sampling rate for multichannel is 10kS/s. In this study, DAQ NI USB-6008 is set in differential analog input mode with a resolution of 12bits and a maximum of 4 input channels. Channels 1,2,3, respectively measure the vibration of the milling machine table in the X, Y, Z axis. Channel 4 for detection of spindle rotation phase.

Table 1:Micro photo of end mill tool wear gradation.

	Tool Face	**Major Flank**	**Minor Flank**
Normal Wear			
Moderate Wear			
Severe Wear			

The experimental treatment used a 4SE-LIST6210 10X25X75X10 HSS-Co RA26 nachi end-mill, a four flute end mill tool with a diameter of 10mm. This tool is used for up-milling machining of mild steel with depth of cut 0.2 mm and 5 mm cutting width, without coolant. Parameters of machining spindle speed vary from 550rpm, 650rpm, 750rpm, and feed per tooth varies from 0.02mm, 0.05mm, 0.08mm. The first row and third row of table 1 show the appearance of normal toll and severe wear that were used for classifier training in this study. While the second row of table 1 shows the appearance of moderate tool wear, for testing three level classifier alongside with normal tool and severe wear tool.

4 RESULT AND DISCUSSION

Data acquisition of four channels with a sampling size of 1024 datapoints was carried out at a sampling frequency of 2.5 kHz for 409.6 ms. The four channels consist of X Y Z axis vibrations and spindle rpm. Feature extraction is performed to get features represent 3 × 1024 time-domain datasets and 3 × 513 order-domain datasets. The time-domain vibration feature is represented by statistical measure of data distribution, std, skewness, kurtosis, range for each XYZ axis. Whereas the order-domain feature is represented by the magnitudes of acceleration in 1st order to 90th order. Feature selection is based on correlation analysis, ten features are selected: stdz, rangey, stdy, rangex, stdy, rangez, X2nd, Y13th, Z13th, Y2nd.

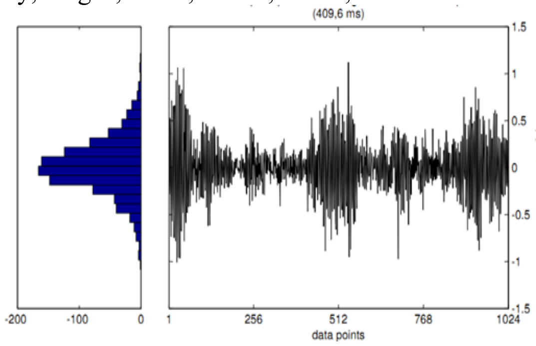


Figure 1: Discrete waveforms of 1024 time-domain datapoints, 409.6ms, represented by a statistical measure of data distribution for the extraction of time-domain features.

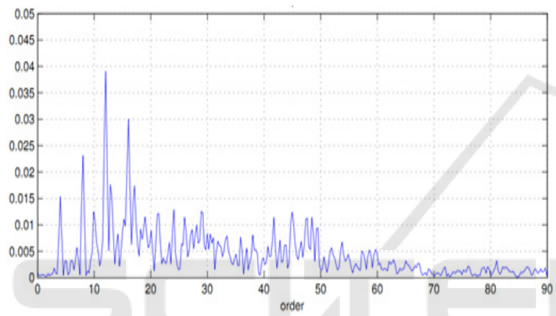


Figure 2: The vibration order spectrum as a result of Fast Fourier Transform and normalization to the spindle rpm, for the use of order-domain features extraction.

4.1 MLP Training using Two Level of Tool Wear

The artificial neural network used for the classifier is MultiLayerPreceptron (MLP) with a single hidden layer. In the context of MLP learning and discovering the general pattern of training data, the MLP training process is stopped when the training process begins to show symptoms of overfitting. In this study, the symptoms of overfitting were monitored from the MSE of validation sub-set data. The database of vibration features is divided into three parts; training data subset to train the classifier, test data subset to assess the training progress and validation data subset for early stopping use. During in the training progress, if the MSE training data subset decreases but the MSE validation data subset does not goes down and occurs in 4 epochs consecutively, then this shows the MLP begins to learn the specific characteristics of the training data subset and ignores the generality of the whole data pattern so that the training process must be stopped.

This MLP training is carried out by setting the max_fail training parameter by 4 and separate the dataset in three groups randomly at8: 1: 1 proportion for the training data subset, the test data subset and the validation data subset.

A summary of training, testing and validation of ten MLP is tabulated in Table 2. A performance comparison of the ten MLP iteration is shown in Figure 9, in the MSE order of the largest to the smallest. MLP training with resilient backpropagation can achieve MSE in the range of 0.0524 to 0.0376. None of the test accuracy in the group reached 100% accuracy, the highest accuracy that can be achieved is 97.2%. But the validation results show the opposite, 3 out of 10 iterations are able to achieve 100% accuracy. The lowest MSE training data in the 2nd iteration provides the worst accuracy in this test group validation. Validation of 100% accuracy is achieved by MLP with MSE ranging from 0.0524 to 0.0411. The best MLP case chosen for the classifier is the result of 4th iteration neuron weighting. The TCM system used in this study is able to perform the tool wear detection based on vibration measurements of the CNC machine.

The detailed output of TCM prediction for severe tool wear detection with an output target at value of positive one, is shown in Figure 3. While Figure 5 displays the detailed output of TCM prediction for normal tool with the target output at value of negative one. Both images displays 20 predicted conditions of tool wear for 9 treatment machining parameter. The first row, second row, third row of the plot data consecutively are the spindle speed of 750 rpm, 650 rpm, 550 rpm treatment. The first column, the second column, the third column of the data plot consecutively are cutting depth parameter of 0.08; 0.05; 0.02 mm/tooth.

Generally speaking, the MLP predictions have reached the target, especially on parameters machining of spindle speeds at 750 rpm and 650 rpm. In the parameters machining of spindle speed at 550 rpm, there are some MLP predictions that are less close to the target even though they are included in the right classification. This incidents occurred in the machining parameter of 0.08 mm/tooth cutting thickness of severe tool wear condition. MLP prediction uses a threshold value of 0, then the positive numbers output of MLP will be concluded that the tool condition is severe wear, and vice versa. The negative numbers output of MLP will be concluded as a normal tool condition. MLP accuracy for the validation of these 2 classes attain 100% accuracy for the 360 test cases.

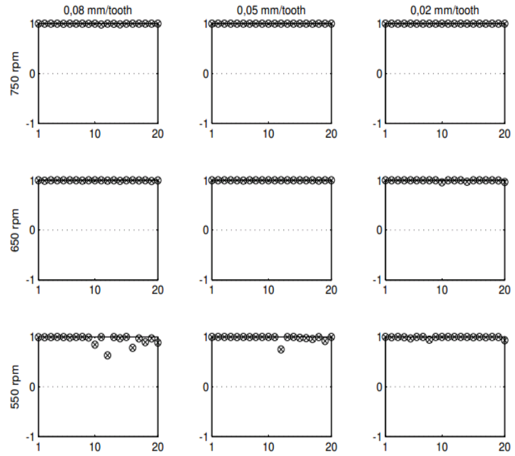


Figure 3: TCM prediction output before post-processing on the use of severe tool wear for nine machining parameter.

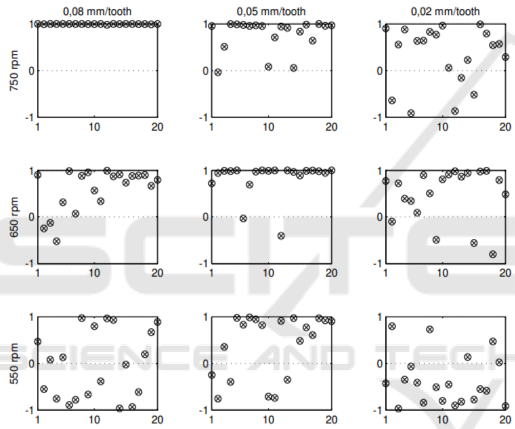


Figure 4: TCM prediction output before post-processing on the use of moderate tool wear for nine machining parameter.

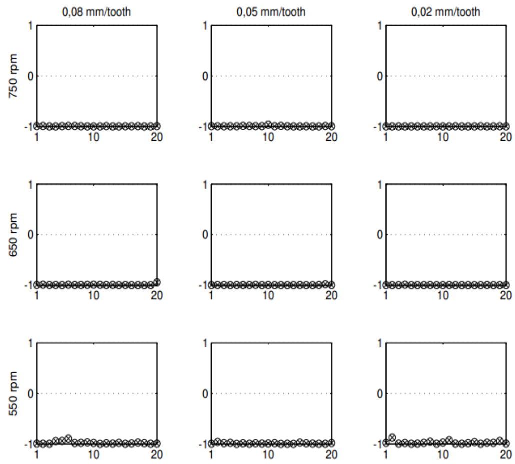


Figure 5: TCM prediction output before post-processing on the use of normal tool for nine machining parameter.

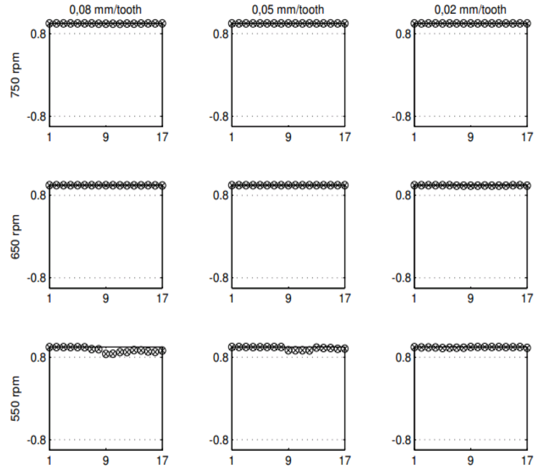


Figure 6: TCM prediction output with post-processing on the use of severe tool wear for nine machining parameter.

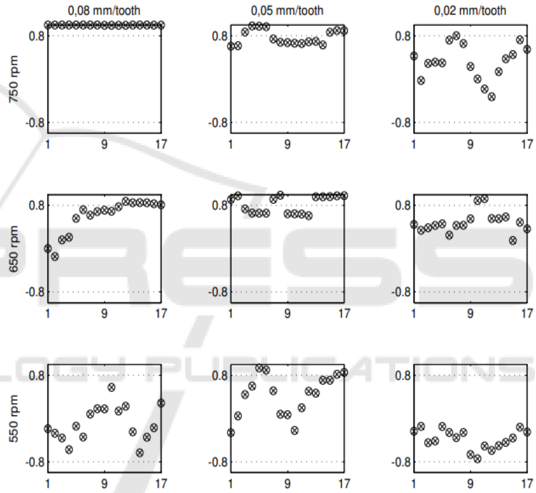


Figure 7: TCM prediction output with post-processing on the use of moderate tool wear for nine machining parameter.

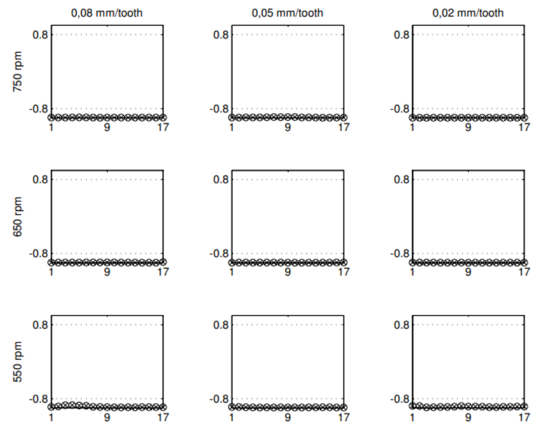


Figure 8: TCM prediction output with post-processing on the use of normal tool for nine machining parameter.

4.2 Post-processing for Three Level Classification

The range for deducing tool conditions in the existing classifier is very wide, above the threshold value of 0 to 1, it is concluded that the condition is severe wear, and below the threshold value of 0 to -1, it is concluded that the tool condition is normal. If the inference output range is narrowed, the inference range for severe wear condition is set at the limit of 0.8 to 1, and the normal tool condition inference range is set at the range -1 to -0.8. Then there is a range that cannot be defined as a severe wear condition or normal tool conditions, i.e. range above -0.8 to below 0.8. The range between -0.8 to 0.8 is what will be used as thresholds to the prognosis of a moderate tool wear.

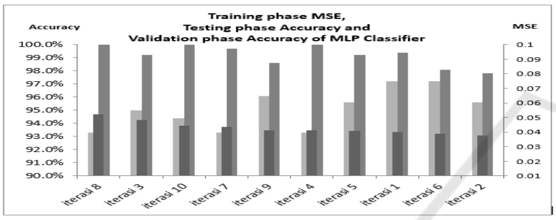


Figure 9: Training phase MSE, testing phase accuracy and validation phase accuracy of MLP classifier.

For the validation of three levels classification, three levels of tool wear were used; normal tool, moderate wear tool and severe wear tool. The first tool was a severe wear tool shown in third row of table 1. The flank wear of this tool has reached the tool wear criterion based on ISO 8688 recommendations. The second tool is a moderate worn tool shown in second row of Table 1. The third tool is a normal tool, there is no significant flank wear on the cutting edge shown in first row of Table 1.

Detailed output of MLP predictions on the use of moderate wear tools is shown in Figure 4. MLP predictions on the use of moderate wear tool show floating values between -1 to 1, especially in the machining parameters 0.02 mm/tooth feed and 550 rpm spindle speed. For machining parameters of 0.05 mm/tooth feed, 750 rpm and 0.08 mm/tooth feed, 650 rpm, MLP output tends to scatter in the range of 0 to 1. For machining parameters of 0.08 mm/tooth feed, 750 rpm , MLP output tends to close to 1.

To reduce the fluctuation of MLP output values and improve the quality of MLP inferencing, post-processing is applied by smoothing filter using a simple moving average with a period of 4. Detailed MLP conclusion output by smoothing on the use of severe wear tool, moderate wear tool and normal tool, consecutively is shown in Figure 6, Figure 7, and Figure 8. With the application of smoothing post-processing, MLP output fluctuations are considerably damped. The MLP prediction output for the use of severe wear tool is always in the range of 0.8 to 1 for 153 test cases on 9 parameters of machining. With these results, the accuracy of MLP for the classification of severe wear tool conditions attain 100% accuracy. TCM prediction output on normal tool use is always in the range -1 to -0.8 for 153 test case on 9 parameters of machining. With these results, the accuracy of TCM for the classification of normal tool conditions attain 100% accuracy.

Unlike the results of validation on the use of severe wear tools and normal tools, the validation of TCM prediction for the use of moderate wear tools have not reached 100% accuracy. In general, most TCM conclusions are in the range -0.8 to 0.8. But in cutting parameters with 0.08 mm/tooth feed, 750 rpm, all test case samples were indicated severe wear because they were in the range 0.8 to 1. In cutting parameters 0.05 mm/tooth feed, 650 rpm, 9 of 17 test case samples were indicated severe wear, even though it was moderate wear.

Table 2: MSE of classifier during training phase and accuracy of classifier in testing phase and validation phase.

Training Phase				**Testing Phase**			**Validation Phase**		
Train Iteration	**Epoch**	**MSE**	**Gradient**	**Missed**	**False Alarm**	**Acuracy**	**Missed**	**False Alarm**	**Acuracy**
1^{st}	44	0,0402	0,0498	**3,0%**	2,5%	**97,2%**	0,6%	0,6%	**99,4%**
2^{nd}	62	**0,0376**	**0,00631**	6,4%	**2,3%**	95,6%	2,8%	1,7%	97,8%
3^{rd}	18	0,0485	0,0193	5,4%	4,5%	95,0%	**0,0%**	1,7%	99,2%
4^{th}	25	0,0411	0,036	8,5%	4,7%	93,3%	**0,0%**	**0,0%**	**100,0%**
5^{th}	50	0,0408	0,0112	4,7%	4,2%	95,6%	1,1%	0,6%	99,2%
6^{th}	53	0,0389	0,00834	3,2%	**2,3%**	**97,2%**	3,9%	**0,0%**	**98,1%**
7^{th}	43	0,0436	0,00771	8,9%	5,0%	93,3%	0,6%	**0,0%**	99,7%
8^{th}	18	0,0524	0,0138	7,2%	6,0%	93,3%	**0,0%**	**0,0%**	**100,0%**
9^{th}	41	0,0413	0,0093	5,4%	**2,3%**	96,1%	1,1%	1,7%	98,6%
10^{th}	45	0,0443	0,0221	6,5%	4,6%	94,4%	**0,0%**	**0,0%**	**100,0%**
Best	18	**0,0376**	**0,00631**	**3,0%**	**2,3%**	**97,2%**	**0,0%**	**0,0%**	**100,0%**
Average	40	0,04287	0,01838	5,9%	3,8%	95,1%	1,0%	0,6%	99,2%
Worse	62	0,0524	0,0498	8,9%	6,0%	93,3%	3,9%	1,7%	97,8%

Table 3: Detail of TCM prediction.

Spindle (rpm)		**750**			**650**			**550**			**Total**
Feed (mm/tooth)		**0,08**	**0,05**	**0,02**	**0,08**	**0,05**	**0,02**	**0,08**	**0,05**	**0,02**	
	treatment	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	
Predicted	severe	17	7	1	6	9	2	0	4	0	46
	moderate	0	10	16	11	8	15	17	13	17	107
	normal	0	0	0	0	0	0	0	0	0	0
Sub-total		17	17	17	17	17	17	17	17	17	153
Accuracy(%)		0,0	58,8	94,1	64,7	47,1	88,2	100	76,5	100	69,9

Table 4: Confussion matrix of TCM classifier.

		True Class			
		severe	moderate	normal	
Predicted Class	severe	153	46	0	
	moderate	0	107	0	
	normal	0	0	153	
Accuracy		100%	69,9%	100%	**89,98%**

The detailed results of the TCM inference for the 9 cutting parameter treatments are shown in Table III. The best accuracy of 100% on moderate wear tool use is achieved for 0.02 mm/tooth feed. The thicker the feed per tooth, the lower the inference accuracy, and there tends to be misclassification as the tool is severe wear. Likewise for spindle speed cutting parameter. The faster the spindle turns, the more accurate the inference is, and the prediction error tends to misclassification as severe tool wear.

Detailed confusion matrix 3 × 3 TCM validation using 3 levels of tool wear is shown in Table IV. The TCM summary was obtained from TCM predictions by Figure 6, Figure 7, and Figure 8. It appears in TCM validation on use of severe wear tool, that 153 out of 153 test cases indicated precisely as a severe wear condition. Likewise in TCM validation using normal tools, 153 out of 153 test cases are correctly indicated as normal tools. In both classes there is no misclassification.

5 CONCLUSIONS

Validation of TCM predictions using moderate wear tools, 107 out of 153 inferences are precisely indicated as moderate wear tools, 46 missclassifications as broken tools, and no missclassification as normal tools. Missclassification that occurs in the validation of moderate wear test cases is more conservative, because the actual tool that are moderate wear are incorrectly indicated as severe wear, and none are incorrectly indicated as normal tool. This characteristic is safer (fail safe design) for monitoring tool conditions, because no case detection is missed. Overall TCM accuracy for 3 level of tool wear is 89.98% from 459 test cases.

Multi-layer perceptron that has been trained using 2 classes; normal tools and severe wear tools, with appropriate threshold and post-processing settings can be used to classify 3 level of tool wear. Using moving average smoothing with period 4, threshold -0.8 for normal tool and 0.8 threshold for severe wear tool, the multi-layer perceptron can classify severe wear, moderate wear, and normal tool condition with an accuracy of 89.98% of 459 test case of validation dataset.

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