RESEARCH PROGRESS IN MECHANICAL AND MANUFACTURING ENGINEERING VOL. 4 NO. 2
(2023) 353-359

RPMME

Homepage: http://penerbit.uthm.edu.my/periodicals/index.php/rpmme
e-ISSN : 2773 - 4765

Monitoring And Prediction of Tool Condition Using Machine Learning

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DOI: https://doi.org/10.30880/rpmme.2023.04.02.043
Received 01 July 2023; Accepted 01 Nov 2023; Available online 15 Dec 2023

Abstract: The condition of cutting tools plays a crucial role in machining operations, impacting productivity, quality, and cost-effectiveness. This study aimed to develop an intelligent tool condition monitoring system using a Support Vector Machine to estimate the tool wear of cutting tools. This research aimed to address the challenges faced by industries in effectively monitoring and predicting tool conditions, enabling proactive maintenance strategies and optimising machining processes. Vibration signals were acquired using accelerometers connected to an OneproD MVP-200 analyser during machining. Feature extraction involved identifying the relevant feature from the vibration signals, specifically the Root Mean Square (RMS) and Standard Deviation (Stdev), to capture patterns and characteristics indicative of tool wear. The SVM function in MATLAB was utilised to train a model using the extracted feature as input and surface finish as the label. The trained model was then used to estimate the tool wear of the cutting tool. The findings show that the RMS feature exhibited better accuracy compared to the stdev feature. Notably, the Gaussian SVM kernel achieved the highest accuracy of 83.07% for the RMS, surpassing the Linear (77.78%) and Polynomial (81.82%) SVM kernels.

Keywords: Tool Condition Monitoring, Machine Learning Techniques, Tool Wear Estimation, Vibration Signals, Support Vector Machine (SVM), Kernel Functions

1. Introduction

Machine learning, a rapidly growing field of computing algorithms that aims to mimic human intelligence by learning from data, has found widespread applications across various industries [1]. One area where machine learning techniques hold great potential is in tool condition monitoring for machining processes. By leveraging these techniques, it becomes possible to estimate tool wear and provide early warnings of tool failure. The monitoring and maintenance of cutting tool condition are crucial in manufacturing industries, as it directly impacts production efficiency, product quality, and the overall economics of machining operations. Traditional methods, such as manual inspection using tool maker's microscopes, are time-consuming, offline, and prone to errors. Online methods, such as

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acoustic emission and temperature measurement, have their limitations, including signal attenuation and inaccuracies caused by thermal conductivity and heat dissipation. To address these challenges, this study aims to develop an intelligent tool condition monitoring system using a Support Vector Machine (SVM). This system aims to accurately estimate the tool wear of cutting tools by analysing vibration signals.

2. Method

This project focuses on using vibration sensor signals and a Support Vector Machine (SVM) for tool condition monitoring in the turning process. Vibration signals can provide valuable information about the condition of the cutting tool, including signs of wear and impending tool failure. SVM, a machine learning algorithm, is employed to analyse the vibration signals and predict the tool condition. The vibration signals are obtained by placing vibration sensors on the machine or cutting tool. These sensors detect the vibrations generated during the machining process, which can be influenced by factors such as tool wear, cutting parameters, and the material being machined. By analysing the patterns and characteristics of these vibration signals, it is possible to determine the condition of the cutting tool and make predictions about its remaining life.

The materials and equipment used in this study included a carbon steel workpiece, a CNC turning machine (Harrison A400 Alpha), an accelerometer, a vibration analyser (OneproD MVP-200), a carbide insert (Kyocera Indexable Turning Insert), and a tool maker's microscope. These items were selected to facilitate the collection and analysis of data related to tool wear in machining processes. The carbon steel workpiece served as the substrate for the cutting operations, while the CNC turning machine provided the means to perform the machining tasks. The accelerometer was utilized to capture vibration signals during the machining process, and the vibration analyzer facilitated the analysis and interpretation of these signals. The carbide insert was the cutting tool used in the experiments, and the tool maker's microscope allowed for detailed inspection and measurement of the tool condition. Together, these materials and equipment formed the foundation for conducting the research and obtaining valuable insights into tool wear estimation.

The experiment began by setting up the CNC turning machine, loading a carbon steel workpiece, and selecting the Kyocera Indexable Turning Insert TNMG332PSCA025P as the cutting tool. The workpiece was machined in three stages, while vibration signals were captured and measured using accelerometers connected to the OneproD MVP-200 analyser. The acquired signals underwent filtering, amplification, and feature extraction using MATLAB functions such as filter, fft, and pwelch. Machine learning techniques were then applied to develop an intelligent tool condition monitoring system. The extracted features were used in the decision-making process to estimate tool wear and make decisions about the cutting process.

The experiment commenced by configuring the linear SVM model for tool condition monitoring. The chosen kernel functions included Linear, Gaussian, and Polynomial. The linear kernel was suitable for linearly separable classes and high-dimensional data, which aligns with the goal of classifying tool wear based on vibration signals. The Gaussian kernel was effective for capturing complex relationships in non-linearly separable data, while the polynomial kernel excelled in capturing polynomial relationships between features. The training process involved data preprocessing, model training, model tuning, and model evaluation using independent testing data. The dataset was split into a training set (80%) and a testing set (20%). The model's performance was assessed by evaluation metrics such as accuracy, precision, recall, and F1 score. These metrics provided valuable insights into the model's ability to classify different tool wear conditions accurately.

3. Results and Discussion

This section presents the performance metrics achieved by the linear SVM model on the testing data, including accuracy. These metrics provide a quantitative assessment of the model's predictive capability for tool wear. The results are further analysed to gain insights into the significance of specific features, such as RMS and Stdev, in predicting tool wear. The performance of the linear SVM model is also compared across different kernel functions (Linear, Gaussian, and Polynomial) to evaluate its effectiveness in tool condition monitoring and prediction. This comprehensive evaluation aims to assess the efficacy of the linear SVM model in accurately monitoring and predicting tool conditions.

The linear SVM model was trained and tested using a dataset specifically collected for tool condition monitoring and prediction. The dataset consisted of 500 instances, with 20% (100 instances) used as the testing set and the remaining 80% (400 instances) as the training set.

Scatter plots were used to visualise the separation of Class 1 and Class 2 for both the RMS and Stdev features. As shown in Figure 1, the RMS scatter plot showed scattered points with partial separation between the two classes. Some class 2 points were mixed within the region primarily occupied by class 1, indicating potential misclassifications. This suggests that the RMS feature alone may not be sufficient for accurate classification despite capturing relevant signal power variations.

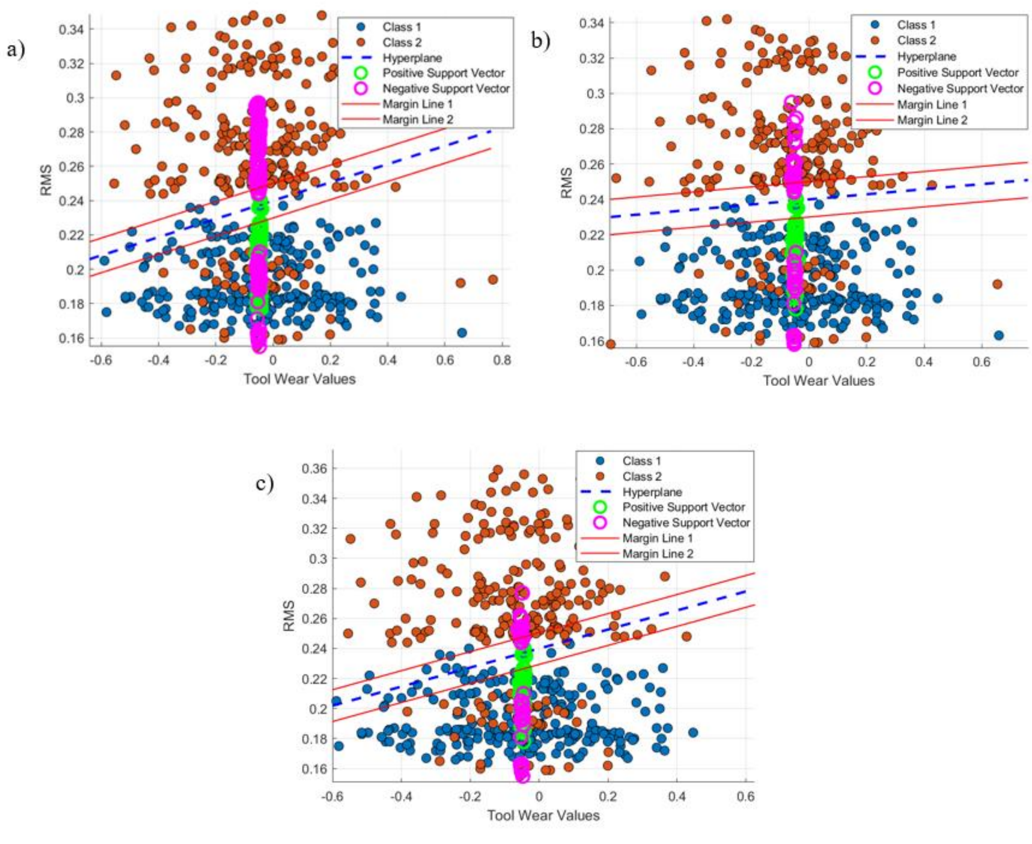

Figure 1: Scatter Plot of RMS vs Tool Wear Values by a) Linear, b) Gaussian and c) Polynomial

Confusion matrices were analysed for each kernel function (Linear, Gaussian, and Polynomial) to assess the classification accuracy. For the RMS feature, all three kernel functions demonstrated relatively accurate classification.

As shown in Figure 2, the confusion matrix presented the rows representing the true classes, while the columns represented the predicted classes. For the linear kernel function, there were 192 observations of Class 1 correctly predicted as Class 1, and 8 observations misclassified as Class 2.

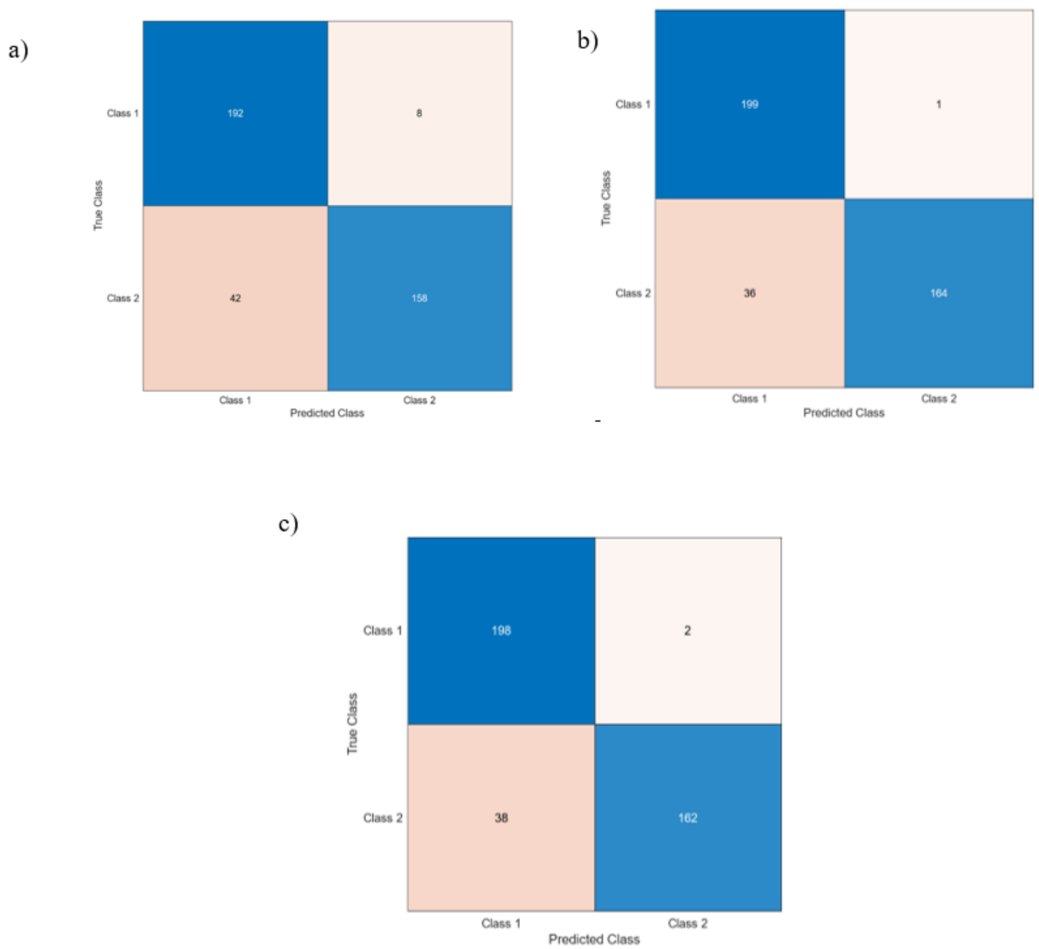

Figure 2: Number of Observations for RMS Feature by a) Linear, b) Gaussian and c) Polynomial

Similarly, for the Gaussian kernel function, there were 199 correct predictions of Class 1, with 1 misclassification. In the case of the polynomial kernel function, there were 198 accurate predictions of Class 1 and 2 misclassifications. For Class 2, the linear kernel function had 42 misclassifications, while the Gaussian and polynomial kernel functions had 36 and 38 misclassifications, respectively. Additionally, all three kernel functions correctly predicted Class 2 in 158, 164, and 162 observations, respectively.

As shown in Figure 3, the Stdev scatter plot showed a distinct distribution pattern, with a straight horizontal line separating points above and below it, representing class 2 and class 1, respectively. This indicated the potential of the stdev feature to contribute to the separation and classification of tool wear levels. However, the scatter plot of the Stdev feature displayed a scattered distribution of points without clear separation or distinct patterns between the two classes. This implies that the Stdev feature alone is not enough to classify the tool wear levels accurately. Additional features or more advanced classification techniques would be necessary to enhance the classification accuracy.

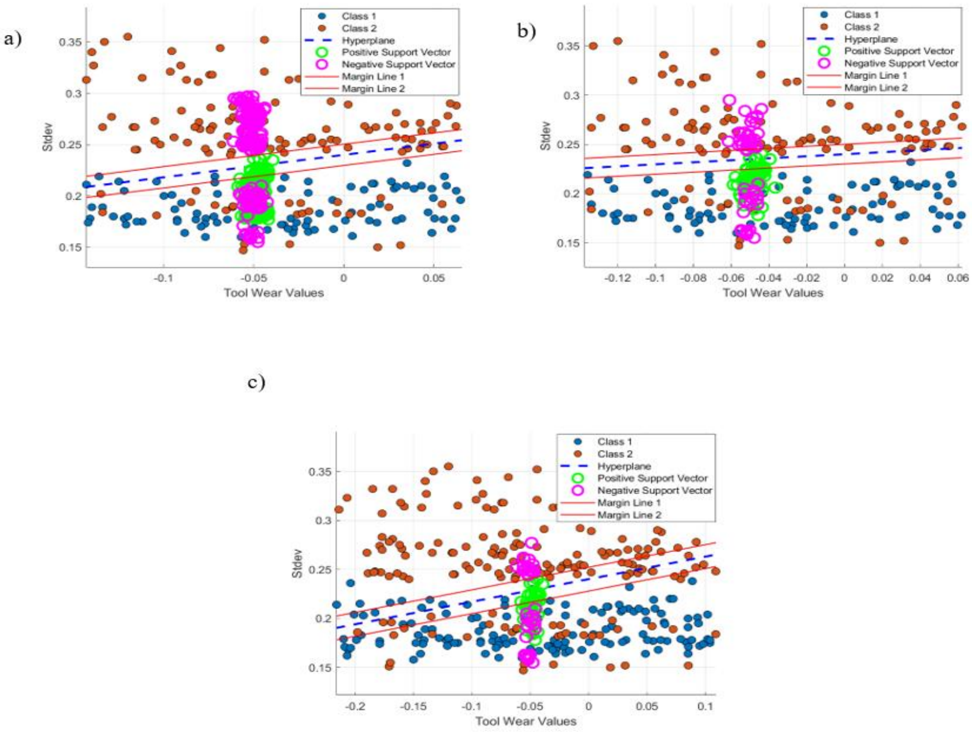

Figure 3 Scatter Plot of Stdev vs Tool Wear Values by a) Linear, b) Gaussian and c) Polynomial

However, for the Stdev feature, there were misclassifications and less distinct patterns between the classes. This suggests that additional features or advanced techniques may be needed to improve the accuracy of classification. The analysis of support vectors provided insights into the model's accuracy and identified areas for potential improvement.

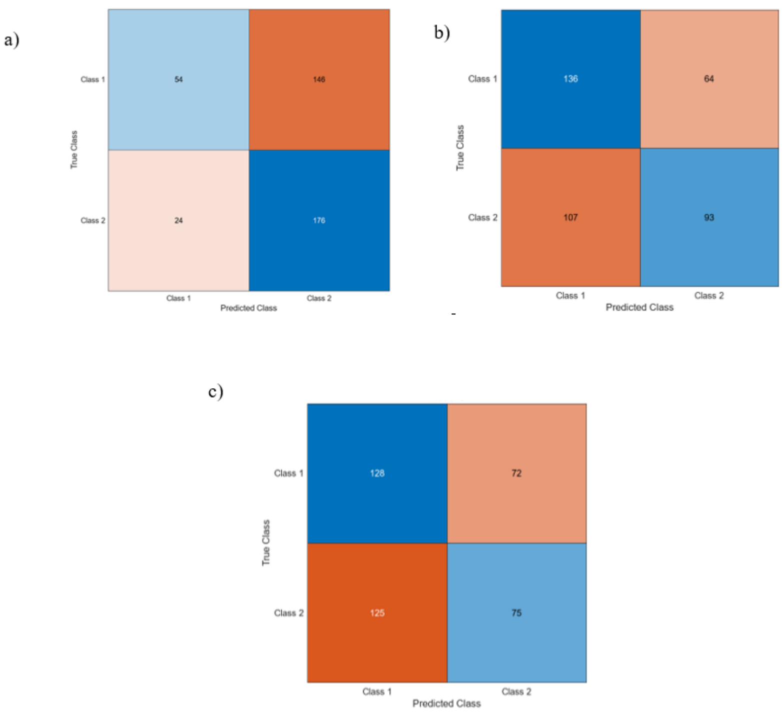

Figure 4 Number of Observations for Stdev Feature by a) Linear, b) Gaussian and c) Polynomial

The confusion matrix in Figure 4 compared true class labels with predicted class labels. For the linear kernel function, 54 observations were correctly predicted as Class 1, while 146 observations of Class 1 were mispredicted as Class 2. Similarly, 24 observations of Class 2 were mispredicted as Class 1, and 176 observations were correctly predicted as Class 2. For the Gaussian kernel function, 136 observations were correctly predicted as Class 1, with 64 observations of Class 1 mispredicted as Class 2. Likewise, 107 observations of Class 2 were mispredicted as Class 1, and 93 observations were correctly predicted as Class 2. For the polynomial kernel function, 128 observations were correctly predicted as Class 1, with 72 observations of Class 1 mispredicted as Class 2. Similarly, 125 observations of Class 2 were mispredicted as Class 1, and 75 observations were correctly predicted as Class 2.

Table 1 presents evaluation metrics for each kernel function in the context of tool condition monitoring. The linear kernel achieved an accuracy of 77.78% for the RMS feature, while the Gaussian kernel achieved the highest accuracy of 83.07%. The polynomial kernel achieved an accuracy of 81.82%. Precision values for the RMS feature were 87.50% (linear), 90.75% (Gaussian), and 90.00% (polynomial).

Table 1 Evaluation Metric for each Kernel Function

Evaluation Metric	Linear		Gaussian		Polynomial	
	RMS	Stdev	RMS	Stdev	RMS	Stdev
Accuracy	77.78%	40.35%	83.07%	40.11%	81.82%	34.00%
Precision	87.50%	57.50%	90.75%	57.25%	90.00%	50.75%
Recall	87.50%	57.50%	90.75%	57.25%	90.00%	50.75%
F1 Score	87.50%	57.50%	90.75%	57.25%	90.00%	50.75%

Precision values for the Stdev feature were 57.50% (linear), 57.25% (Gaussian), and 50.75% (polynomial). Recall values were consistent, with 87.50% (linear, Gaussian, and polynomial) for the RMS feature and 57.50% (linear, Gaussian, and polynomial) for the Stdev feature. The F1 score was 87.50% (linear, Gaussian, and polynomial) for the RMS feature and 57.50% (linear, Gaussian, and polynomial) for the Stdev feature. Overall, the Gaussian kernel outperformed other kernels in accuracy, precision, recall, and F1 score for both the RMS and Stdev features, aligning with findings from previous studies [2]. The Gaussian kernel is effective in capturing complex patterns and relationships in vibration signals.

4. Conclusion

The study successfully achieved its objectives by developing an intelligent tool condition monitoring system using Support Vector Machine (SVM) classification. SVM effectively classified the tool wear levels based on extracted features from vibration signals. The RMS feature performed better than the Stdev feature across all three kernel functions, with the Gaussian kernel achieving the highest accuracy, precision, recall, and F1 score (83.07%, 90.75%, 90.75%, and 90.75% respectively). Recommendations for future research include exploring additional feature extraction techniques, evaluating alternative machine learning models, implementing real-time monitoring, collaborating with industry partners, conducting long-term evaluation studies, and integrating with predictive maintenance strategies. Implementing these recommendations will advance the field of tool condition monitoring and improve productivity and decision-making in manufacturing processes.

Acknowledgement

The authors would like to thank the Faculty of Mechanical and Manufacturing Engineering, Universiti Tun Hussein Onn Malaysia, for giving the opportunity to conduct this study.

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