ON THE APPLICABILITY OF MACHINE LEARNING METHODS FOR VIBRATION-BASED PREDICTIVE TOOL MAINTENANCE: A CASE STUDY

A GÉPI TANULÁS ALAPÚ REZGÉSDIAGNOSZTIKA ALKALMAZHATÓSÁGÁRÓL A SZERSZÁMKOPÁS ELŐREJELZÉSE ÉRDEKÉBEN: EGY ESETTANULMÁNY

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Abstract

This study presents a machine learning–based approach for predicting tool wear and preventing tool breakage using vibration diagnostics in machining processes. By analysing vibration signals (and, where applicable, acoustic emission), the proposed method enables early fault detection and supports predictive maintenance strategies. The approach contributes to sustainable manufacturing by reducing material waste, improving resource efficiency, and extending tool lifetime. Experimental results demonstrate that vibration features effectively distinguish between normal and abnormal tool conditions, highlighting the potential of AI-assisted diagnostics in green innovation and Industry 4.0 applications.
Keywords: *vibration diagnostics, predictive maintenance, machine learning, sustainable manufacturing*
JEL code: *C45, C49*

Összefoglalás

A tanulmány egy gépi tanuláson alapuló megközelítést mutat be a szerszámkopás és a szerszámtörés előrejelzésére, a megmunkálási folyamatok során keletkező rezgésjelek elemzésével. A javasolt módszer a rezgés- és – ahol releváns – akusztikus emissziós (AE) jelek feldolgozásával lehetővé teszi a hibák korai felismerését és a prediktív karbantartás támogatását. A megközelítés hozzájárul a fenntartható gyártáshoz az anyagveszteség csökkentésével, az erőforrás-hatékonyság növelésével és a szerszám élettartamának meghosszabbításával. A kísérleti eredmények igazolják, hogy a rezgésalapú jellemzők alkalmasak a normál és rendellenes szerszámállapotok megkülönböztetésére, ami alátámasztja a mesterséges intelligencia által támogatott diagnosztikai rendszerek alkalmazhatóságát a zöld innováció és az Ipar 4.0 keretrendszerében.
Kulcsszavak: *rezgésdiagnosztika, prediktív karbantartás, gépi tanulás, fenntartható gyártás*

Introduction

In modern machining, unexpected tool breakage threatens not only the tooling but also the integrity of high-value workpieces. Preventing such events through early detection reduces scrap, rework, and unplanned downtime—key aspects for resource efficiency and sustainable manufacturing. Within this context, *tool condition monitoring* (TCM) has become a central enabler of predictive maintenance, with recent surveys consolidating advances across sensing, signal processing, and data-driven decision-making (MOHAMED et al., 2022; ABELLÁN-NEBOT - SUBIRÓN, 2010; KISHAWY et al., 2018).

Among indirect sensing modalities for TCM, vibration and acoustic emission (AE) are prominent due to their sensitivity to mechanical anomalies and suitability for real-time monitoring (KRISHNAKUMAR et al., 2018; KISHAWY et al., 2018). AE, with its high-frequency content, is particularly effective for anticipating crack initiation, chipping, and imminent fracture during tool–workpiece engagement, enabling timely intervention before catastrophic failure (DORNFELD - DIEI, 1987; KRISHNAKUMAR et al., 2018). Effective use of these signals requires appropriate preprocessing—amplification, sampling consistent with Nyquist–Shannon considerations, filtering, and segmentation—before feature extraction and classification (MOHAMED et al., 2022).

While Fourier-domain features (e.g., spectra, cepstra) have long been standard in vibration-based diagnostics (RANDALL - TECH, 1973; RANDALL, 2013), and modern classifiers are well established in the applied machine learning (ML) literature (BOEHMKE - GREENWELL, 2019; KUHN, 2008), the present work deliberately focuses on the application aspects—measurement design, practical feature engineering, model comparison, and validation on experimental data—rather than re-deriving known mathematical foundations.

The goal of this study is to demonstrate a robust and practically applicable workflow for predicting tool wear and imminent breakage from vibration and AE data. Beyond its diagnostic accuracy, the approach aims to highlight operational benefits such as reduced material waste, extended tool lifetime, and measurable improvements in energy efficiency and production costs.

Specifically, we (i) design a vibration/AE acquisition setup tailored to milling operations, (ii) extract frequency-distribution–based features and train multiple supervised machine learning models (e.g., Support Vector Machines (SVM), random forest, logistic regression), (iii) evaluate performance with standard metrics and cross-validation, and (iv) discuss sustainability impacts arising from fewer defective parts and longer useful tool life. The remainder is organized as follows: Section 2 reviews related work in vibration/AE-based TCM and ML approaches; Section 3 details the measurement setup, preprocessing, feature extraction, and models; Section 4 reports comparative results; finally, Section 5 discusses implications, limitations, sustainability aspects and outlines future directions.

Background

Vibration and Acoustic Emission in Tool Condition Monitoring

Tool Condition Monitoring systems have evolved from heuristic thresholding of physical signals to advanced, data-driven decision-support frameworks. Among indirect sensing modalities, vibration and acoustic emission (AE) have proven to be highly informative indicators of tool wear and fracture phenomena (ABELLÁN-NEBOT - SUBIRÓN, 2010; KISHAWY et al., 2018; MOHAMED et al., 2022). Vibration analysis captures characteristic mechanical resonances and transient responses associated with tool–workpiece interactions, while AE extends the observable frequency range to several hundred kilohertz, revealing micro-crack formation and sudden failure events (DORNFELD - DIEI, 1987; KRISHNAKUMAR et al., 2018).

Both techniques are non-intrusive and suitable for continuous monitoring in harsh industrial environments. Early studies such as RANDALL - TECH (1973) and RANDALL (2013) established the importance of frequency-domain representations—particularly Fourier and cepstral methods—for isolating harmonic components linked to mechanical wear. However, these classical approaches assume stationarity, which limits their applicability under variable spindle speed or load conditions typical of modern high-speed machining.

Recent developments have shifted attention toward feature-based signal representations, where time- and frequency-domain descriptors (e.g., root mean square (RMS), kurtosis, spectral entropy, band energy ratios) are extracted prior to classification (MOHAMED et al., 2022). Feature engineering is often complemented by dimensionality reduction such as Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA), facilitating efficient model training.

In this work we therefore employ standard Fourier-domain and statistical feature extraction techniques as established in the literature (RANDALL, 2013), focusing on their practical integration with machine learning models.

The transition from descriptive to predictive diagnostics has been largely driven by machine learning. Supervised classifiers such as Support Vector Machines (SVM), Decision Trees, Random Forests, and Artificial Neural Networks have demonstrated robust performance in tool wear and breakage detection (KRISHNAKUMAR et al., 2018; ABELLÁN-NEBOT - SUBIRÓN, 2010; MOHAMED et al., 2022). Data-driven predictive maintenance enables adaptive scheduling, reduced downtime, and improved productivity, aligning with the broader objectives of Industry 4.0 (KUHN, 2008; BOEHMKE - GREENWELL, 2019).

Although deep learning approaches (e.g., convolutional networks) attract growing interest, traditional algorithms remain highly relevant in industrial contexts due to their transparency, interpretability, and lower computational requirements (MOHAMED et al., 2022). Integrating ML-based diagnostics into machining enhances operational reliability and directly supports sustainability: fewer scrapped parts, optimized tool usage, and lower energy consumption per produced component.

Condition monitoring and predictive maintenance are integral to sustainable manufacturing systems. By enabling early fault detection, such systems minimize waste material, reduce the carbon footprint associated with rework, and extend equipment lifetime. Consequently, ML-assisted vibration and AE diagnostics can be viewed as technological enablers of green innovation, supporting resource efficiency and circular manufacturing paradigms. As summarized by (MOHAMED et al., 2022). Integrating artificial intelligence into production lines creates measurable environmental and economic benefits, reinforcing the motivation for continued research in this direction.

Materials and Methods

Experimental Setup

The experimental measurements were conducted on a CNC vertical milling machine equipped for multi-axis operation and designed for precision finishing processes. The test setup included a tri-axial accelerometer mounted near the tool holder to capture vibrations originating from the cutting zone, as well as an acoustic emission (AE) sensor attached to the machine frame to record high-frequency stress waves associated with crack formation. Both sensors were connected to a National Instruments data acquisition (DAQ) unit through charge amplifiers, providing synchronized analogue inputs with adjustable gain and filtering options.

The experiments were performed using tungsten–carbide end mills of diameter 10~mm, cutting a standardized steel workpiece under controlled feed and speed parameters. The machine's spindle speed and feed rate were varied systematically to induce measurable changes in vibration characteristics during tool wear progression.

The machining experiments conducted within the project framework involved face-milling cycles that alternated between up-milling and down-milling along the Y-axis, using a 50 % tool diameter overlap. The variable machining parameters were the spindle speed (1000, 1200, and 3000 rpm), feed rate (250, 500, and 1000 mm/min), and depth of cut (1–2 mm). The tested workpiece materials included engineering plastics (POM), two different aluminium alloys, and steel (C45). The applied tools were 20 mm and 8 mm diameter end mills, as well as a milling head equipped with five inserts. For aluminium and steel, the experiments were performed with emulsion-based cooling. Both new and pre-worn tools were included in the tests. These quantitative and qualitative parameters jointly influence the onset of tool failure and the corresponding vibration and acoustic emission patterns observed during fracture. A detailed description of the measurement procedures can be found in ZSIDAI et al. (2025).

Each machining trial was continued until visible wear marks or fracture appeared on the cutting edge. The AE signal amplitude and root mean square values were monitored continuously to detect the onset of micro-cracks. Sensor placement and signal routing were selected to minimize electromagnetic interference and cross-talk from spindle drive components. All signals were sampled at 50 kHz to ensure compliance with the Nyquist–Shannon sampling theorem and to preserve sufficient spectral resolution for subsequent analysis (RANDALL - TECH, 1973; RANDALL, 2013). Ambient temperature and humidity were recorded for reference but had negligible influence on the results.

Figure 1 illustrates the schematic representation of the bidirectional face-milling process applied during the vibration and acoustic emission measurements. This configuration ensured consistent tool–workpiece engagement and repeatable load conditions under controlled spindle speed and feed parameters.

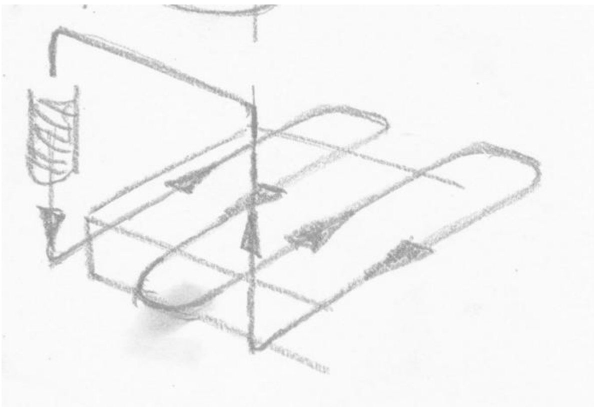


Figure 1. Schematic illustration of the bidirectional face-milling pattern used in the experiments.

Among the several experimental configurations, the following setup was selected to illustrate the applicability of ML methods for predicting tool breakage: a spindle speed of 1200 rpm, feed rate of 1000 mm/min, and depth of cut of 2 mm. Two representative measurements were performed under these conditions—one using a new tool and another with a pre-worn tool—hereafter referred to as measurement #296 and measurement #300, respectively. In both cases the workpieces were C45 steel.

Data Processing and Feature Extraction

As mentioned earlier, the analysis relies primarily on the acoustic emission (AE) and vibration signals measured during the cutting process.

In addition to the usual data preprocessing procedures—such as handling outliers, measurement errors, and missing values—it is essential to emphasize the importance of signal segmentation (DORNFELD - DIEI, 1987; KRISHNAKUMAR et al., 2018).

Since tool damage or breakage can occur only when the tool is in contact with the workpiece, the idle (non-cutting) sections of the AE signal must first be identified and excluded.

These idle periods are characterized by significantly lower amplitude and frequency content, and they can be readily detected by visual inspection of the recorded waveform.

Figures 2 and 3 present the AE signals from measurements #296 and #300, respectively. The normalized signal amplitude is markedly lower during idle operation compared with the active cutting phase. The figure was generated from the corresponding .wav file using the open-source program Audacity (AUDACITY TEAM, 2024), which proved useful for visual inspection and preliminary segmentation of the acoustic data.

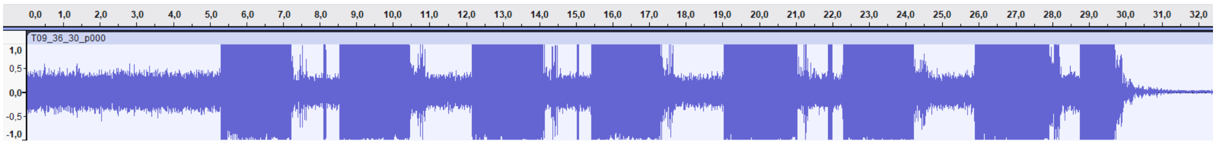


Figure 2. Acoustic emission amplitude as a function of time for measurement #296. The normalized amplitude is considerably lower during idle operation than during tool–workpiece contact. The figure was generated from the original .wav file using Audacity.

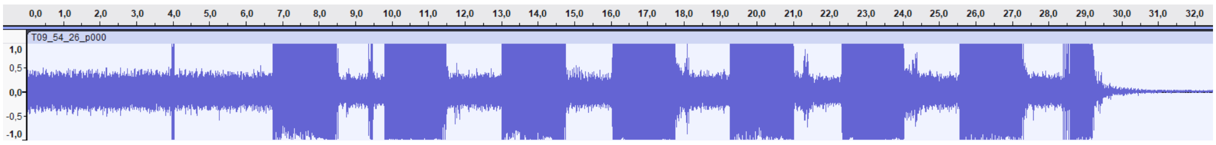


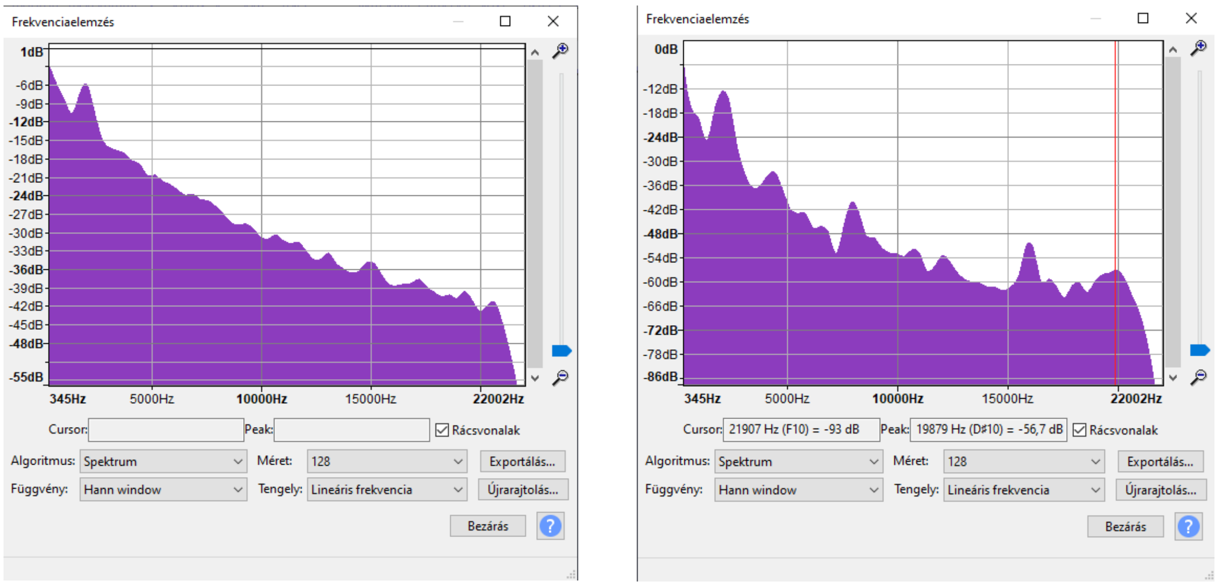
Figure 3. Acoustic emission amplitude as a function of time for measurement #300. The normalized amplitude is considerably lower during idle operation than during tool–workpiece contact. The figure was generated from the original .wav file using Audacity.

After segmentation, the raw vibration and AE signals were pre-processed to remove low-frequency noise and unwanted environmental disturbances. A fourth-order Butterworth high-pass filter with a 500 Hz cutoff frequency was applied to eliminate structural resonance effects from the machine frame while maintaining the frequency content relevant to tool–workpiece interaction. The AE signal was additionally subjected to envelope detection to capture impact-like transient phenomena associated with crack initiation and tool chipping (KISHAWY et al., 2018; KRISHNAKUMAR et al., 2018).

For spectral analysis, the Fast Fourier Transform (FFT) was applied to the filtered vibration signals to obtain amplitude spectra. Although advanced time–frequency representations (e.g., short-time Fourier transform or wavelet analysis) could have been employed, the classical FFT-based approach proved sufficient for detecting dominant frequency bands correlated with tool wear (RANDALL - TECH, 1973; RANDALL, 2013).

Following the recommendations of CAUSOL et al. (2021), a window length of approximately 2500 samples was found to provide the most reliable estimation of frequency-dependent variations in tool condition. Since the FFT algorithm requires window sizes that are powers of two, a length of $2^{11} = 2048$ samples was selected as the closest suitable value. Given the 0.000005 s sampling interval of the AE signal, this window covers a time span of 0.01024 s. According to best practices reported in the literature, a 50 % overlap between consecutive windows offers an optimal trade-off between computational efficiency and information retention. Therefore, this configuration was adopted in our study. Among various possible windowing functions, the Hann (Hanning) window was chosen due to its smooth spectral leakage characteristics (BOASHASH, 2003). All FFT computations were performed in the MATLAB environment (MATHWORKS, 2025).

Figure 4 depicts a representative frequency-domain signal obtained during stable and worn tool conditions, showing clear amplitude growth near the tool's natural vibration frequency.



(a) (b)

Figure 4. Frequency spectra of the vibration signal under (a) normal and (b) broken tool conditions, corresponding to measurement #296.

To facilitate machine learning–based classification, statistical and spectral features were extracted from the processed signals in both time and frequency domains. These included RMS, variance, skewness, kurtosis, spectral centroid, spectral entropy, and band power ratios computed over characteristic frequency intervals. The AE features additionally incorporated event counts and cumulative energy within defined time windows. All subsequent statistical analyses and visualizations were performed using the RStudio environment (POSIT, 2025).

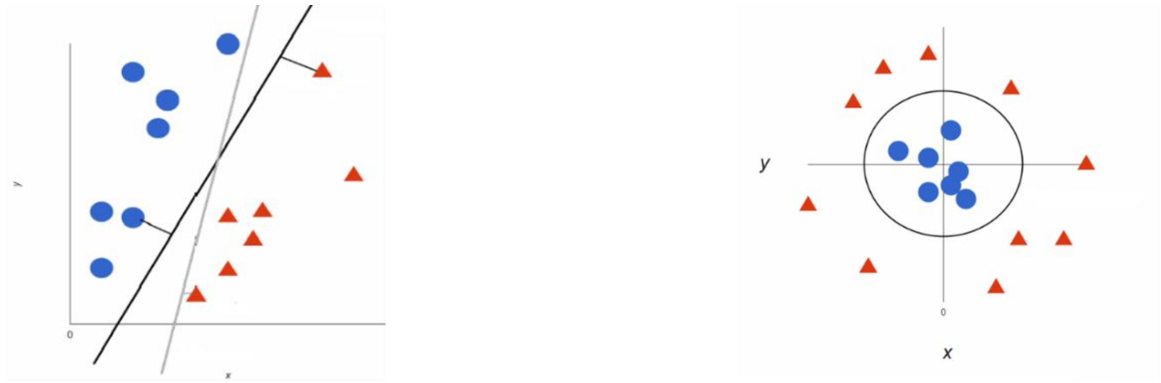
Prior to training, all feature vectors were standardized to zero mean and unit variance to ensure balanced scaling across dimensions. Principal Component Analysis (PCA) was used to reduce redundancy and highlight the most discriminative features before model fitting.

To validate data integrity, segments with missing samples or excessive noise were automatically removed based on signal energy thresholds. Approximately 5 % of the raw data was discarded due to mechanical disturbances such as tool changes or spindle ramp-up phases. The resulting dataset served as the input for model training and validation described in the following subsection.

Machine Learning Models

Based on the extracted statistical and spectral features, several supervised machine learning algorithms were applied to classify tool conditions into *normal* and *failure* states. A comprehensive set of ten supervised learning algorithms was tested to evaluate classification performance and model robustness. The investigated models included Random Forest (RF), Support Vector Machine (SVM) (including the case with linear and polynomial kernels as well as kernel-based regression (SVML, SVMP , SVMR), and Artificial Neural Network (ANN) classifiers. In addition, additional algorithms such as k-Nearest Neighbours (KNN), Generalized Linear Models (GLM), Linear and Quadratic Discriminant Analysis (LDA, QDA) and Logistic Regression (LogReg) were also examined for completeness. Each model was trained using 80 % of the available samples, with the remaining 20 % reserved for validation. To minimize overfitting, ten-fold cross-validation was applied during model selection, and hyperparameters were tuned using a grid search approach. All model training, tuning, and evaluation were conducted in R 4.1.2 using the caret framework, and performance was assessed using both overall accuracy and Cohen's Kappa coefficient.

The SVM algorithm was implemented with both linear and nonlinear kernels. In the linear case, the algorithm determines a hyperplane that maximizes the margin between two data classes, as illustrated in Figure 5. Nonlinear kernels, particularly the Radial Basis Function (RBF), were also evaluated to capture higher-order feature dependencies. In some configurations, polynomial kernels (SVMP) were additionally tested to explore more complex boundary shapes within the feature space.



(a) (b)

Figure 5. Illustration of (a) linear and (b) nonlinear Support Vector Machine (SVM) classification boundaries separating the two classes.

Decision Tree classifiers were trained with varying maximum depths and minimum leaf sizes to balance model complexity and accuracy. The Random Forest approach, as an ensemble of decision trees, provided improved generalization by averaging across multiple randomized trees. The RF offered interpretable results, allowing identification of the most influential vibration and acoustic features. Additionally, the k-Nearest Neighbours (KNN) method was included as a non-parametric benchmark model, which provided insight into local decision behaviour within the feature space.

A feed-forward Artificial Neural Network (ANN) was also trained, consisting of an input layer matching the feature vector dimension, one hidden layer with ReLU activation, and an output layer using the softmax function for binary classification. Although the schematic representation of the applied ANN is omitted here, it followed the standard fully connected architecture commonly used in two-class problems.

Results

The classification results are presented for two representative measurements, #296 and #300, which correspond to distinct cutting trials conducted under comparable spindle speed and feed conditions. Both measurements exhibit clear spectral differences between normal and failure states, demonstrating the discriminative potential of vibration-based features.

Figures 6 and 7 show the spectral amplitude distributions across the 1st–10th decile quantiles. In both cases, the frequency bands associated with tool failure display a broader and more asymmetric distribution, indicating higher vibrational energy dispersion as the cutting edge degrades. This spectral spreading is a typical precursor of chipping and progressive wear, confirming that vibration-based spectral indicators can serve as early warning features for tool health monitoring.

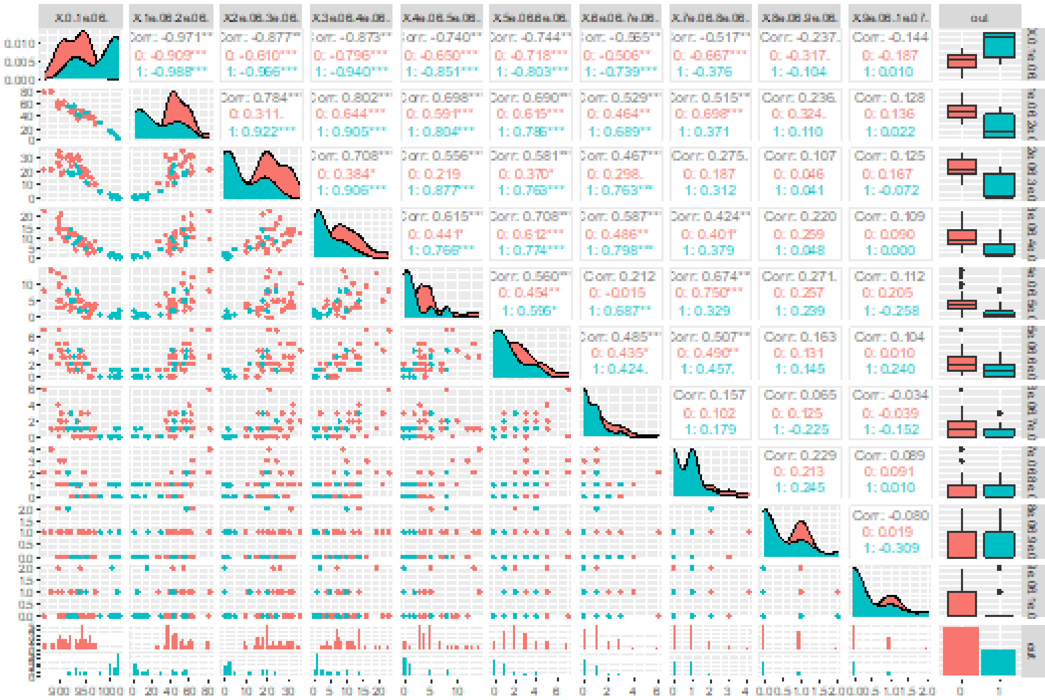


Figure 6. Spectral distributions for the 1st–10th decile quantiles based on Measurement #296 (0: normal operation; 1: tool failure).

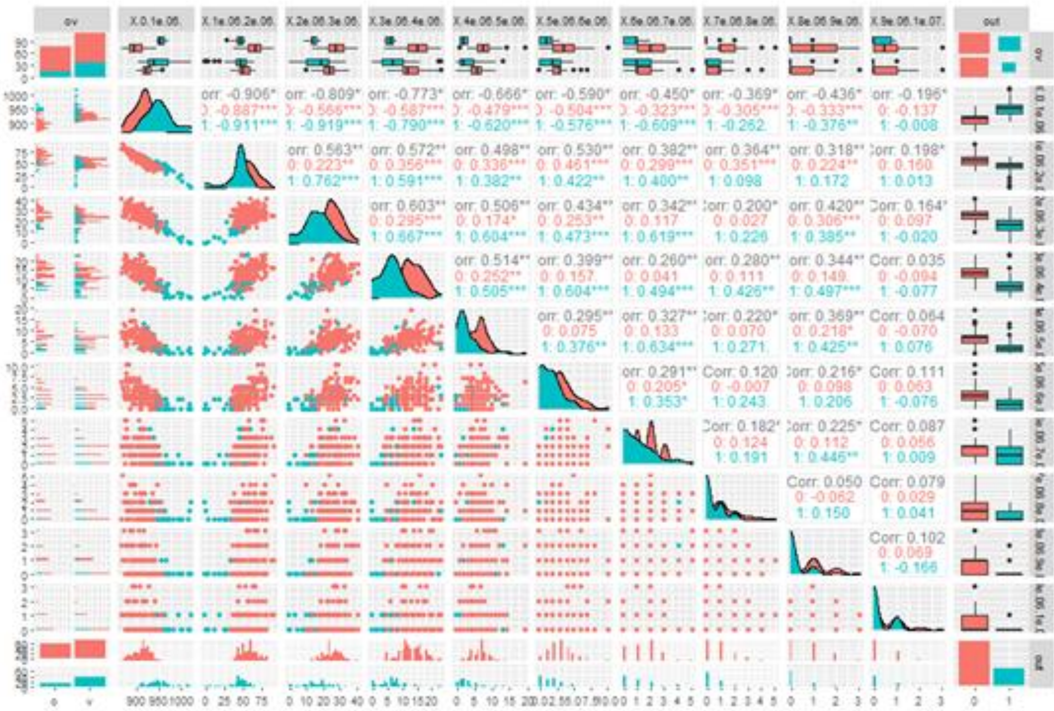


Figure 7. Spectral distributions for the 1st–10th decile quantiles based on Measurement #300 (0: normal operation; 1: tool failure).

The extracted features were used to train ten supervised learning models under identical data partitions and preprocessing. Each algorithm was evaluated using repeated cross-validation, and the results were summarized by the minimum, first quartile, median, mean, third quartile, and maximum values of classification accuracy and Cohen's κ. Table 1 A and B provide a comparative overview for Measurements #296 and #300.

Table 1. Descriptive statistics ((minimum, median, mean, maximum, 1st and 3rd quartiles) of classification accuracy and Cohen's κ for ten algorithms based on A: Measurement #296. B: Measurement #300: Random Forest (RF), Support Vector Machine with linear, and polynomial kernels as well as kernel-based regression (SVML, SVMR, SVMP), k-Nearest Neighbours (KNN), Generalized Linear Models (GLM), Linear and Quadratic Discriminant Analysis (LDA, QDA), Artificial Neural Network (ANN), Logistic Regression (LogReg).

A	Accuracy						Cohen's κ					
Model	Min.	1st Q	Median	Mean	3rd Q	Max.	Min.	1st Q	Median	Mean	3rd Q	Max.
RF	0.63	0.80	0.87	0.87	0.93	1.00	0.02	0.44	0.59	0.63	0.81	1.00
SVML	0.64	0.80	0.87	0.86	0.93	1.00	0.00	0.44	0.59	0.58	0.81	1.00
SVMR	0.60	0.80	0.87	0.85	0.93	1.00	0.00	0.44	0.59	0.57	0.81	1.00
SVMP	**0.71**	**0.80**	**0.87**	**0.87**	**0.93**	**1.00**	**0.00**	**0.44**	**0.59**	**0.61**	**0.81**	**1.00**
KNN	**0.73**	**0.80**	**0.87**	**0.86**	**0.89**	**1.00**	**0.00**	**0.44**	**0.59**	**0.60**	**0.74**	**1.00**
GLM	0.67	0.80	0.87	0.86	0.93	1.00	0.07	0.48	0.66	0.63	0.81	1.00
LDA	0.60	0.80	0.87	0.86	0.93	1.00	0.00	0.44	0.59	0.62	0.81	1.00
QDA	0.67	0.79	0.87	0.83	0.87	1.00	0.00	0.41	0.59	0.55	0.71	1.00
ANN	0.64	0.80	0.87	0.85	0.93	1.00	0.00	0.33	0.59	0.56	0.81	1.00
LogReg	0.60	0.80	0.87	0.86	0.93	1.00	0.00	0.51	0.66	0.63	0.81	1.00

B	Accuracy						Cohen's κ					
Model	Min.	1st Q	Median	Mean	3rd Q	Max.	Min.	1st Q	Median	Mean	3rd Q	Max.
RF	0.67	0.80	0.87	0.85	0.93	1.00	0.00	0.44	0.59	0.57	0.81	1.00
SVML	0.71	0.80	0.87	0.85	0.89	1.00	0.00	0.33	0.59	0.54	0.71	1.00
SVMR	0.57	0.80	0.87	0.85	0.93	1.00	0.00	0.33	0.59	0.57	0.81	1.00
SVMP	**0.67**	**0.80**	**0.87**	**0.87**	**0.93**	**1.00**	**0.00**	**0.44**	**0.59**	**0.60**	**0.81**	**1.00**
KNN	**0.71**	**0.80**	**0.87**	**0.86**	**0.93**	**1.00**	**0.00**	**0.44**	**0.59**	**0.60**	**0.81**	**1.00**
GLM	0.53	0.79	0.86	0.83	0.93	1.00	0.00	0.39	0.59	0.56	0.81	1.00
LDA	0.60	0.80	0.86	0.84	0.93	1.00	0.00	0.44	0.59	0.57	0.81	1.00
QDA	0.64	0.78	0.81	0.83	0.88	1.00	0.00	0.41	0.53	0.54	0.71	1.00
ANN	0.67	0.80	0.87	0.84	0.87	1.00	0.00	0.33	0.59	0.51	0.59	1.00
LogReg	0.64	0.75	0.83	0.83	0.93	1.00	0.00	0.34	0.56	0.56	0.81	1.00

All tested models demonstrated overall stable generalization behaviour. Across both measurements (#296 and #300), the machine learning models demonstrated strong predictive performance, with mean accuracies typically ranging from 83% to 87%. The median accuracy for most algorithms was consistently high at 87%, indicating that in a typical scenario, most models perform very well.

Two models stand out for their superior and consistent performance across both measurements. The Support Vector Machine with Polynomial Kernel (SVMP) achieved the highest or joint-highest mean accuracy on both measurements (0.87 on both #296 and #300). It also maintained a high mean Cohen's Kappa, suggesting its classifications are reliable.

The k-Nearest Neighbours (KNN) is another robust performer. It had a high mean accuracy (0.86 on both measurements) and, most notably, the highest minimum accuracy on measurement #296 (0.73) and was tied for the highest on measurement #300 (0.71). This indicates that KNN is the most reliable model, with the best worst-case performance.

The high κ values of both models confirm robust agreement between predicted and actual tool states, implying good generalization despite moderate dataset size.

Though the performances of SVMP and KNN models are slightly better and more consistent on measurement #296 compared to measurement #300, the similarity of the results for the two measurements indicates strong reproducibility across separate cutting trials, suggesting that the extracted features capture stable vibration patterns independent of the specific workpiece or tool-condition sequence.

The RF, GLM and LDA models performed exceptionally well on measurement #296, rivalling the top-tier models, but showed a noticeable drop in performance on measurement #300. This suggests they may be less robust to variations in the data.

SVML and ANN models delivered solid, acceptable performance across both measurements but never reached the top of the rankings while QDA consistently ranked at or near the bottom across both measurements.

Discussion and Conclusions

The experimental results confirm that vibration- and AE-based features can effectively distinguish between normal and abnormal tool states. While most of the tested algorithms are effective for these tasks, the SVMP and KNN models are the most distinguished showing that the task associated with measurement #300 appears to be slightly more difficult than that of #296. SVMP consistently delivered the highest average classification accuracy and agreement values, while KNN proved to be the most reliable and robust model, making it a safe choice to avoid poor outcomes, and indicating strong suitability for fault detection tasks. In contrast, discriminant analysis consistently underperformed, making it the least suitable choice for these classification tasks. The ANN model with its higher computational demands and not outstanding performance is less practical for real-time monitoring. RF, GLM, LogReg, and LDA demonstrated high potential, even outperforming others however, their sensitivity to data variations makes them less reliable choices.

Although the models demonstrated consistent performance across independent measurements, the results are still conditioned on the specific machine setup and material parameters used during the trials. Variations in spindle speed, feed rate, or workpiece material could alter the vibration response, requiring re-validation or retraining of the models for new conditions. Furthermore, the size of the available dataset limited the statistical robustness of the evaluation. Expanding the database with additional cutting trials, different tool geometries, and varying operational regimes would strengthen the model’s generalizability and facilitate adaptive learning approaches.

It is also important to note that the neural network model, despite its potential for nonlinear representation, proved less efficient under limited data availability. Future work could explore hybrid or ensemble learning architectures that combine the interpretability of tree-based models with the adaptability of neural methods while maintaining computational efficiency.

Future research will focus on extending the developed diagnostic framework toward real-time implementation and autonomous decision support. Integration with edge-computing devices would enable continuous in-process monitoring without interrupting production cycles. Additionally, incorporating online learning or transfer learning mechanisms could allow the system to adapt to gradual changes in machine dynamics and cutting environments.

Beyond technical development, further studies will assess the long-term sustainability benefits of predictive maintenance—including reductions in waste, tool consumption, and carbon footprint—to quantify the environmental impact of intelligent diagnostics in industrial machining.

From an application standpoint, the combination of Fourier-based spectral analysis and classical machine learning models provides a compact yet powerful diagnostic framework. The present work demonstrates that vibration- and AE-based feature extraction combined with classical machine learning models provides a reliable and scalable foundation for predictive maintenance.

The ability to detect the early onset of tool degradation enables proactive replacement before catastrophic failure, thereby reducing scrap rates, tool expenditures, and unplanned production downtime. These advancements directly contribute to the objectives of sustainable manufacturing by decreasing energy usage and material waste, while simultaneously supporting the broader framework of green innovation and Industry 4.0-driven process optimization.

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