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Original Article

Intelligent Tool Wear Classification of a CNC Drill Bit Using Feature Fusion and a Family of Lazy Classifiers

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Abstract *- On the shop floor, CNC machining is used for batch production, and it is essential to maintain a trouble-free CNC machine to avoid downtime and increase its practical usage. Among CNC machines, CNC drill maintenance is more complex due to the intricate structure of the drill bits. CNC drilling tool wear affects the accuracy of the system's dimensions, surface finish, and productivity. This paper proposes a method of multidomain feature fusion and a family of lazy classifiers for improved drill bit wear classification. During the controlled drilling processes, Acoustic Emission (AE) signals were recorded for the following wear states: Healthy Tool (HT), Low Wear (LW), Medium Wear (MW), and Severe Wear (SW). The Low, Medium, and Severe wear were created using Electro Chemical Machining (ECM) on the drill bit diameters of 3mm, 3.2mm, 3.4 mm,3.6 mm, and 3.8 mm, and the data acquisition was done using National Instruments (NI) Hardware and LabVIEW software. Features were extracted from the time-domain, frequency-domain, and time–frequency domain, and Wavelet Packet Decomposition (WPD) was used. Lazy classifiers, such as k-Nearest Neighbours (k-NN), Weighted k-NN (WKNN), Locally Weighted Learning (LWL), Instance-Based k (IBk), and LazyBayes, were used after the classifiers were trained on feature vectors describing the previously mentioned signals. Using a 10-fold cross-validation, the best classification rate of 98.7% was attained using WKNN, which outperformed other methods in precision and robustness. The proposed tool wear framework offers high accuracy and low computation for real-time CNC tool wear estimation.*

Keywords - *CNC tool wear, Feature fusion, Acoustic emission, Lazy classifiers, k-NN, Wavelet packet decomposition.*

1. Introduction

In recent years, Computer Numerical Control (CNC) machining has been widely accepted and used as a fundamental technology in the manufacturing industry for batch production, as it can help produce high-precision parts in a very repeatable and efficient manner. Among the numerous CNC processes, drilling is one of the most prevalent machining operations and a must in the aerospace, automotive, electronics, and medical manufacturing industries [1]. In drilling operations, the drill bit condition is critical and influences the quality and efficiency of the operations. Tool wear in CNC drill bits is a specific type due to the mechanical contact between the drill bit and the workpiece material. In the long term, wear can lead to dimensional inaccuracies, diminished surface quality, increased radial forces, and ultimately dangerous tool failure, all weakening product quality and raising manufacturing expenses.

Accurate and timely tool wear monitoring is critical to sustain stability in processes, trim, and manufacturing [2]. Traditional methods of monitoring the condition of a tool still rely on the estimation of cut forces, spindle power, and surface roughness measurement, which have their shortcomings as they are either too costly, time-consuming, or require dismantling equipment, or can only be done after a process is completed, causing a further delay [3].

1.1. Real-Time Monitoring of Tool Wear with Acoustic Emission Signals

Tool wear is a critical industrial concern in the production sector. Monitoring it in real-time is now feasible with Acoustic Emission (AE) sensing technology. AE signals are transient elastic waves produced by the quick release of energy within a material. They can capture very minute phenomena like cracking, sliding, and the plastic deformation of workpieces over tools. This makes AE a valuable means for condition monitoring. AE signals are also nonlinear and non-stationary, often burdened with noise, making robust feature extraction and classification quite arduous. Transient elastic waves can reveal a wealth of information [4].

AE data is indispensable in real-time monitoring of tools, making its extraction a significant focus of recent research. Time-domain statistical features, such as Root Mean Square (RMS), kurtosis, skewness, and entropy, are pretty simple, yet informative regarding the information they provide.

Fourier transforms also offer insight into the different wear states of the tools by revealing the dominating frequency components [5]. In addition to the aforementioned, Wavelet Packet Decomposition (WPD) permits the multiresolution analysis of signals, allowing for analysis of transient events in both time and frequency.

Feature fusion, which integrates different types of information from different feature domains, has enhanced the accuracy and robustness of tool wear classification. In classifiers, the time, frequency, and time-frequency features of wear progression are combined into one distinguishing feature vector so that they can capture complex patterns associated with wear progression.

Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), and Random Forests are examples of machine learning techniques used for tool condition monitoring [6]. These methods achieve promising accuracy but often require extensive training, careful hyperparameter tuning, and substantial computational resources, rendering them impractical for online monitoring in resource-constrained environments.

Lazy learning algorithms, such as k-Nearest Neighbours (k-NN), are nonparametric instance-based methods that postpone generalisation until query time. Due to their simplicity and adaptability, these classifiers have been helpful for small to moderate datasets, especially in fault diagnosis. Furthermore, weighted k-NN versions and locally weighted learning techniques improve classification outcomes by incorporating relevance-based weighting, fine-tuning the decision boundaries in highly intricate feature spaces.

This paper introduces an integrated system for classifying tool wear of CNC drill bits based on the AE signals using multidomain feature fusion and a set of lazy classifiers. This has analyzed the effectiveness of the method on four distinct wear states: Healthy Tool (HT), Low Wear (LW), Medium Wear (MW), and Severe Wear (SW). The method is designed for high accuracy and efficiency in computation and is robust, making it suitable for real-time industrial monitoring of the tools' condition.

The rest of the document is organized as follows: Section 2 contains the literature review of the AE-based tool wear monitoring and the lazy classifiers. Section 3 includes the research methodology, including data collection, feature extraction, and a classification framework. Section 4 presents the experimental framework and dataset construction. Section 5 presents the results and the discussion, and Section 6 presents the conclusions and the proposed future work.

1.2. Research Gap in the Existing Work

1. Feature fusion research requires multiple sensor data sets, which is time-consuming with accelerometer, force, current, and AE sensors [7].
2. Previous studies are based on a single type of feature set in AE signals
3. Very few works concentrate on intra-signal feature fusion, which means time, frequency, and time-frequency domains.
4. Lazy classifiers are rarely used in tool wear condition monitoring, particularly for CNC drill bit wear.
5. Deep learning requires a large data set, which is challenging to collect practically due to the time-consuming and extensive cost of computation.
6. Many ML and DL methods have practical difficulties when applied to real-time environments.

1.3. Novelty in the Proposed Methodology

The main novelty is using a single AE sensor through intra-signal feature fusion and a family of lazy classifiers. The conventional type of approach uses multisensor usage, which is more complex than a single sensor.

This work integrates the complementary features extracted from the AE signal's time, frequency, and time-frequency domains to form a unified feature representation of different tool wear states. The multidomain fusion enhances AE features' discriminative capability without additional sensor assistance.

The second novelty uses k-Nearest Neighbors (k-NN), Weighted k-NN, and Case-Based Reasoning for wear classification. The proposed method will combine feature-level fusion and efficient lazy learners, which offer a lightweight alternative to conventional deep learning models and are highly suitable for real-time industrial environments.

2. Literature Review

The impact of tool wear monitoring on product and process efficiency has made it one of the focus areas of research in manufacturing. Older approaches to wear detection utilised direct measurement techniques like optical and scanning electron microscopy and profilometry. However, such methods are often destructive, unsuitable for real-time monitoring, and tend to be time-intensive. This has made it easier for indirect sensing techniques like tool vibration, cutting forces, temperature, and Acoustic Emission (AE) to be used for online tool condition evaluation.

2.1. Acoustic Emission in Tool Wear Monitoring

A material's deformation and crack propagation generate local energy, emitting AE signals. In machining, AE monitors events associated with the tool and workpiece, such as chip generation, friction, and wear particle removal. As noted in the work of Aggarwal and Suri, AE features strongly indicate tool wear, which provides a non-invasive diagnostic option [8].

Later studies emphasized the extraction of relevant features from AE signals. Statistical metrics such as RMS, standard deviation, and kurtosis were commonly computed in the Time Domain for ease and interpretability. FFT, RMS, and kurtosis can be calculated in the Frequency Domain and are associated with different wear stages. AE signals, however, are non-stationary. Thus, time–frequency analysis methods such as Wavelet Transform (WT) and Wavelet Packet Decomposition (WPD) were favoured. Chen et al. showed that WPD could better isolate wear-related components in AE signals than FFT, showcasing its effectiveness in sub-band decomposition of AE signals [9].

2.2. Feature Fusion Approaches

Studies have indicated that complex signal behaviours are better captured when features of different domains are combined. As with feature-level fusion techniques, these features are considered comprehensive feature vectors that are more effective and robust in classification. With tool wear classification, Zhang et al. used time domain, frequency domain, and wavelet features alongside PCA for feature reduction. They reported a significant improvement in classification accuracy [10].

Multisensor fusion indeed improves diagnostic performance, as shown by Liu and Wang, who used a hybrid fusion approach of AE and vibration signals [11]. Wang Z. et al examined a multidomain feature fusion using AE signal for tool wear identification by combining statistical and spectral features into a single vector with the support of SVM to improve accuracy in classification [12].

Rao et al. fused Acoustic Emission signal features from time-domain and wavelet packet decomposition for milling tool wear prediction. They stated that fused features performed well in single-domain features [13]. Zhou et al. used entropy and wavelet-based AE feature fusion to improve the effectiveness of drill wear prediction accuracy with the support of CNN [14].

2.3. Machine Learning and Tool Wear Classification

Tool wear has been classified using different machine learning classifiers. Support Vector Machines (SVMs) are among the most popular because of their generalisation capabilities and competence with high-dimensional data [15]. Also gaining popularity with feature learning are Artificial Neural Networks (ANN), intensive learning structures, because of their accurate results. However, their demand for large datasets and computation is a downside [16]. Other previously mentioned classifiers, such as Random Forests (RF) and Gradient Boosting Machines, have also been efficient as they provide interpretability through feature importance ranking [17]. A common drawback with these classifiers is the need for offline training, making them inflexible to change, whether it be new or evolving data.

2.4. k-NN Based Fault Diagnosis and Lazy Classifiers

For fault classification, lazy learning algorithms such as k-Nearest Neighbours (k-NN) can be good options. Lazy classifiers, unlike eager learners, do not construct a model during training; they wait until a query is made. Because of this, such classifiers can easily adjust to new data without needing to be retrained [18].

Weighted k-NN (WKNN) enhances the basic k-NN algorithm by modifying the weighting scheme to be inverse proportional to distance, thereby fine-tuning neighbour contribution for more accurate classification [19]. Locally Weighted Learning (LWL) fits local models using proximity-based weighting, capturing more complex, nonlinear decision boundaries more accurately [20]. The performance of lazy classifiers in tool condition monitoring has been encouraging. For example, Bousbaa et al. used WKNN for bearing fault classification and reported better performance than SVM and ANN, although these models were trained on small datasets [21]. Still, their utilisation in CNC drill bit wear classification with fused AE feature is lacking, which motivates this study.

3. Methodology

The framework for classifying CNC drill bit tool wear proposes integrating AE signal acquisition, multidomain feature extraction, feature fusion, and classification with a range of lazy classifiers. This section systematically explains the methodology and components used in this work. It also gives information about the use of sensors, signal conditioning, a Data acquisition system, and software for data collection.

3.1. Dataset Collection

AE signals were obtained from CNC drilling tests meant to demonstrate four tool wear conditions: Healthy Tool (HT), Low Wear (LW), Medium Wear (MW), and Severe Wear (SW). To elicit drilling elastic wave emissions, a high-sensitivity wideband piezoelectric Acoustic Emission (AE) sensor was placed adjacent to the spindle of the CNC machine. AE signals were sampled at a rate of 2 MHz with 16-bit resolution to capture transient events from interactions between the tool and the workpiece. To capture the desired dataset, several drilling runs were conducted on a standard workpiece (e.g., AISI 1045 steel) for each wear condition, maintaining cutting parameters of spindle speed, feed rate, and depth of cut as constant to reduce noise from extraneous variables.

The AE signal was divided into 100-ms intervals and segmented according to the tool wear conditions. This procedure improved the performance of the supervised machine learning algorithm by ensuring the maintenance of dataset balancing.

3.2. Feature Extraction

Feature extraction is essential to reducing the classification complexity. The AE signals extracted from the drill bit condition monitoring procedure and the features extracted from AE signals were comprehensively utilised in time, frequency, and time-frequency domains. This approach exploits the advantages of each representation.

Rationale for WPD and AE Signal Processing

In this work, WPD was selected to analyse the AE signal because of its superior capability of handling non-stationary and transient signal characteristics during the drilling period. WPD fully decomposes approximation and detail coefficients, enabling enhanced time frequency resolution and finer sub-band analysis. This allows a more precise representation of the AE signal energy distribution, thereby capturing refined variations corresponding to tool wear intensity.

AE Signal Preprocessing

Before feature extraction, AE signals are preprocessed for signal reliability and consistency. This includes filtering and amplification. The NI-Hardware signal conditioning device acquired the signal using LabVIEW software. The NI Signal conditioning is used for real-time sampling, amplification, and noise suppression during data acquisition and maintaining integrity across all experiments. This data pre-processing includes band pass filtering within the range of 100kHz-1 MHz to eliminate background and mechanical noise, amplitude normalization to standardize the signal scale, and segmentation into fixed-length frames to maintain uniform temporal resolution. Also, additional outlier removal and envelope detection were applied to minimize the transient spikes and spurious bursts caused by the impact between the tool and the workpiece during the initial touch for drilling.

3.2.1. Time-Domain Features

The time-domain statistical features capture the amplitude variability of the AE signals. The following eight features were derived from each segment:

- Root Mean Square (RMS): Measures the energy of the signal
- Peak Value: The absolute maximum amplitude for the given segment.
- Peak-to-Peak (P2P): Value of maximum amplitude minus minimum amplitude value.
- Skewness: Measures the asymmetry of the referred signal distribution.
- Kurtosis: Measures the signal's impulsiveness.
- Standard Deviation (STD): Measures of signal values, the output will be dispersed.
- Variance: It is the square of the standard deviation.
- Entropy: Measures of the signal, including its complexity and randomness quantification.

3.2.2. Frequency-Domain Features

Frequency-domain features extract the spectrum information from AE signals that may define specific resonant frequencies associated with the wear mechanisms. Each segment has been processed using the Fast Fourier Transform (FFT), and the features listed below were obtained [22] :

- Spectral Centroid: the “centre of mass” of the spectrum.
- Bandwidth: the dispersion of the spectrum, centered at the centroid.
- Dominant Frequency: the frequency having the highest magnitude.
- Power Spectral Density (PSD): energy distribution as a frequency function.

3.2.3. Time–Frequency Domain Features

AE signals exhibit non-stationary behaviour; thus, time–frequency methods are better at identifying transitory phenomena. We performed Wavelet Packet Decomposition (WPD) up to level 3 using Daubechies-4 wavelet, which enabled us to derive the following features:

- Sub-band Energy: The energy associated with each sub-band is calculated as the sum of squared coefficients.
- Shannon Entropy: Quantifies the uncertainty associated with the sub-band.

The complete feature vector from all domains is the AE signals associated with the tool wear, which provides a rich representation.

3.3. Feature Fusion and Normalization

The time, frequency, and time-frequency domains features were concatenated for each AE segment to create a single feature vector. To address the problem of differing scales, all features underwent Min-Max normalisation to the [0,1] range:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Where x is the original feature value, and x_{min} *and* x_{max} are the minimum and maximum values of that feature across the dataset. The resulting vector after normalisation and fusion is used to train the classifiers.

3.4. Family of Lazy Classifiers

The objective of the classification problem is to assign each fused feature vector to one of the four wear classes (Healthy Tool (HT), Low Wear (LW), Medium Wear (MW), Severe Wear (SW)). To solve this problem, we analyze a family of lazy classifiers to evaluate and improve them. The Lazy classifiers are as follows.

1. K-Nearest Neighbours (k-NN): Classifies according to the majority class of the k Euclidean nearest neighbours in the feature space.
2. Weighted k-NN (WKNN): Neighbour distance-based weighting is applied inversely, where nearer neighbours have more influence.
3. Locally Weighted Learning (LWL): Models are created based on the locality of the query point, enabling some degree of non-linearity in the boundaries of decision functions.
4. Instance-Based k (IBk): This works more like k-NN, with further refinements in instance selection distance weighting.
5. Lazy Bayes: This method uses posterior Bayesian inference to estimate probabilities for classification by combining lazy learning and Bayesian inference.

Some hyperparameters, like k for the k-NN variants, were tuned using grid search with cross-validation.

3.5. Mathematics for Lazy Classifiers

1. k- Nearest Neighbours (k-NN)

This algorithm, k-NN, gives the new sample point x_p in the feature space.

The Euclidean distance for the feature is given by

$$D(x_p, x_i) = \sqrt{\sum_{j=1}^{d} (x_{pj} - x_{ij})^2} \tag{1}$$

Where the feature vector at each instance is given as

$$x_i = [x_{i1}, x_{i2}, \dots, x_{id}], i = 1,2, \dots, N$$

The local set $N_k(x_p)$ for k training instances can be found. The decision rule,

$$\hat{y}_p = arg \max_{c \in C} \sum_{x_i \in N_k(x_p)} \delta(y_i, c) \tag{2}$$

Where C is the set of all class labels and

$$\delta(y_i, c) = \begin{cases} 1, & if\ y_i = c \\ 0, & otherwise \end{cases} \tag{3}$$

2. Weighted k-Nearest Neighbours (WkNN)

When some weights are allotted to each neighbour depending on their distances in the k-NN algorithm, it transforms into a weighted k-NN algorithm.

The weighting function is the inverse of Euclidean distance with a constant ∈,

$$w_i = \frac{1}{D(x_p, x_i) + \in} \tag{4}$$

The decision rule becomes,

$$\hat{y}_p = arg \max_{c \in C} \sum_{x_i \in N_k(x_p)} w_i \cdot \delta(y_i, c) \tag{5}$$

The weighting function, including Gaussian weighting with σ controls, is given as

$$w_i = exp\left(-\frac{D(x_p, x_i)^2}{2\sigma^2}\right) \tag{6}$$

3. Locally weighted Learning (LWL)

LWL forms a local model for each query point with locally weighted linear regression for the training data $\{(x_i, y_i)\}_{i=1}^{N}$.

$$\hat{y}_p = \theta_p^T x_p$$

The weight matrix is given as

$$w_{ii} = K\left(\frac{D(x_p, x_i)}{h}\right) \tag{7}$$

$K(\cdot)$ is the kernel function and
h is the bandwidth
$\theta_p$is obtained from

$$\theta_p = (X^T W X)^{-1} X^T W y$$

X is the matrix training feature,
W is the diagonal weight matrix, and
y is the vector of target labels.
LWL is also known as Locally Weighted Regression (LWR).

4. Instance-based k (IBk)

In the enhanced implementation of kNN, the decision rule becomes

$$\hat{y}_p = arg \max_{c \in C} \sum_{x_i \in N_k(x_p)} f\left(D(x_p, x_i)\right) \cdot \delta(y_i, c) \tag{8}$$

Where
$f(\cdot)$ is the user-selected weighting function

5. Lazy Bayes

For a sample point x_p in the feature space, the local set $N_k(x_p)$ with k training instances, the Posterior probability $P(c \mid x_p)$

$$P(c \mid x_p) = \frac{P(c)\, P(x_p \mid c)}{P(x_p)} \tag{9}$$

$P(x_p \mid c)$ is estimated from

$$P(x_p \mid c) \approx \frac{1}{Z_c} \sum_{x_i \in N_k(x_p), y_i = c} K\left(\frac{D(x_p, x_i)}{h}\right) \tag{10}$$

Z_c is the normalization constant
The classification rule becomes

$$\hat{y}_p = arg \max_{c \in C} P(c \mid x_p) \tag{11}$$

4. Experimental Setup

This chapter describes the specific experiments, including the workflows, data preparation, and metrics used to evaluate the proposed CNC drill bit tool wear classification framework.

4.1. CNC Drilling Experiments and AE Data Collection

The experiments were carried out with the CNC drilling machine, which mounted an ultrasonic AE sensor (Model XYZ-1000, frequency response 100 kHz–1 MHz).

The sensor was placed towards the spindle using a magnet adapter to ensure repeatable mechanical coupling and reliable signal transmission. The CNC drilling machine specification is given in Table 1.

Table 1. Specification of CNC drilling machine

S.No	Description	Dimensions/ Details
	Work area	500*500*150mm (X, Y, Z)
	Outer Size	6.4*6.2*6.5 Ft (X, Y, Z)
	Speed, Power, and Cooling	24,000 RPM 2.2kW ATC, Water-Cooled spindle
	Weight on the table	20 Kg
	Linear Rail	20mm
	Motor	Hybrid Servo Motors
	Collet size	ER20
	Drilling hits/min	80 hits/min
	Resolution µm	50µ, Accuracy: 50µ
	Rapid Traverse	7000 mm/min
	Machine weight	600KG ex. accessories
	Software	Millsoft V1.12
	Power supply	220v 50Hz 20A single-phase

The workpiece material's dimensions are 100 mm × 50 mm × 20 mm. Its workpiece material is AISI 1045 medium carbon steel. The drilling used HSS drill bits of 3mm to 3.8 mm diameter. The cutting parameters for the experiments included:

- Spindle speed: 1200 RPM; • Feed rate: 0.1 mm/rev
- Depth of cut: 10 mm

Tool wear states were induced using Electrochemical machining bits for the following conditions, following industrial standards

- Healthy Tool (HT) - New or near-new drill bits.
- Low Wear (LW) - Introduced 0.3 mm wear
- Medium Wear (MW) - Introduced 0.6mm wear
- Severe Wear (SW) - Introduced 0.9 mm wear

Drilling operations were conducted 20 times for each category, including drilling passes for healthy, low, medium, and severe wear conditions. Each drilling pass's AE signal was continuously recorded at 2 MHz with 16-bit resolution. The total data collection includes. So, the data collection for 3mm in 4 categories (healthy, low, medium, and severe) was 4x50 = 200 data points for 3mm. Similarly, 3.2, 34,3.6, and 3.8 sets were collected. So, the total data set was 200 x5 = 1000 datasets were collected for the analysis. The data collection table is given in Table 2.

4.2. Data Labelling and Segmentation

AE signals were collected for 100ms with non-overlapping segments. Each segment was labelled with tool wear types, with the datasets of 1000 (250 for each wear class)

4.3. Feature Extraction and Fusion

Section 3 described the multidomain features obtained from each AE signal segment created over 100 ms. Eight features were captured in the time domain's statistical features, four spectral features in the frequency domain, and 12 features from sub-band features using WPD. This resulted in a combined feature vector of 24 features for each segment. Before classification, feature vectors were normalised using Min-Max scaling to a range of [0,1].

4.4. Classification and Validation

Using custom extensions and the scikit learn library in Python, five lazy classifiers were constructed:

- Weighted k-NN (WKNN)
- Locally Weighted Learning (LWL)
- k-NN
- LazyBayes
- Instance-Based k (IBk)

The number of neighbours, k, was preset to k=15 and optimised down through grid search. The best-performing k values were selected for the final evaluations.

For performance evaluation, the entire dataset was subjected to 10-fold cross-validation for unbiased estimation. In each fold, 90% was allocated for training the model, and 10% was reserved for testing it. This was done for all possible rotations of the folds to ensure all data points were used.

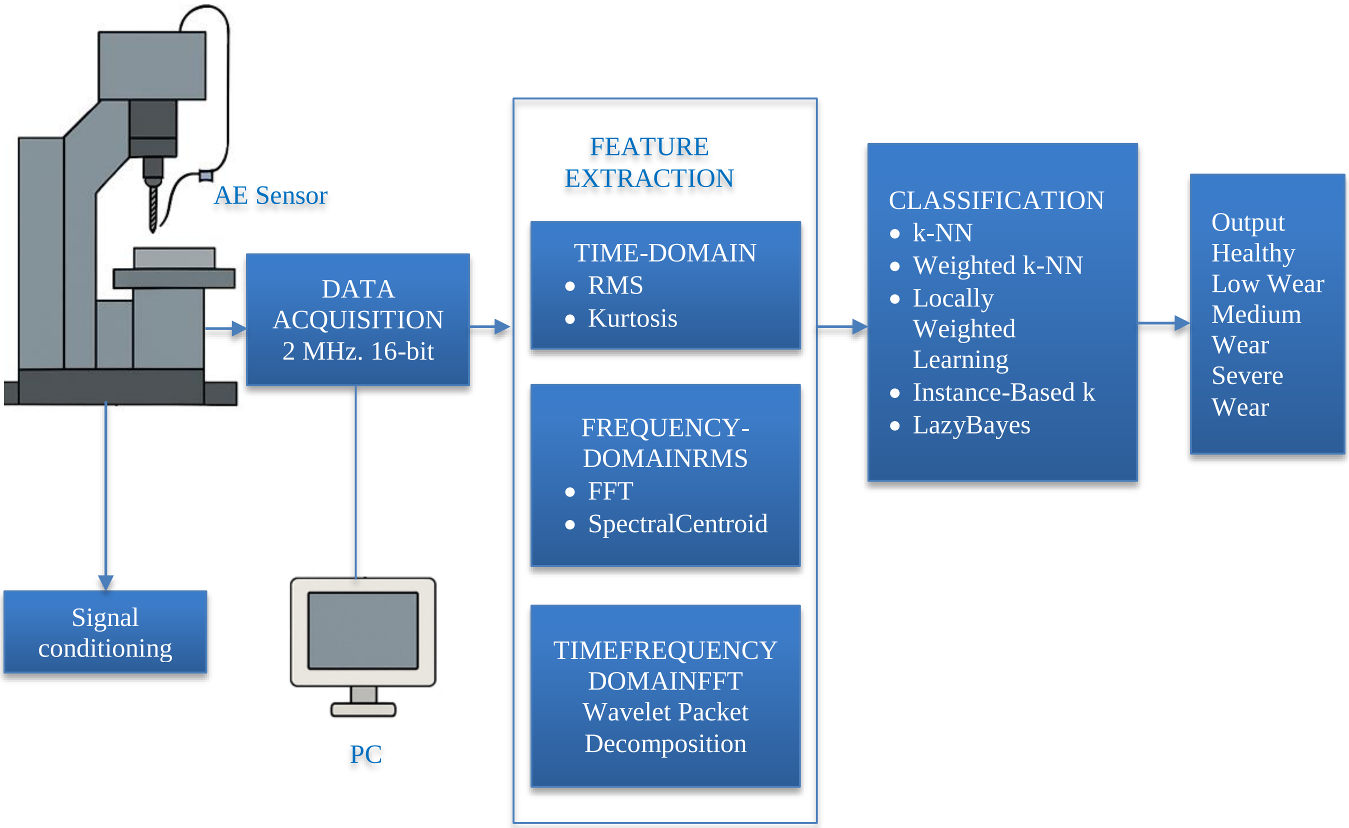

Fig. 1 Schematic diagram of the experimental setup and the proposed methodology

Fig. 2 Signal collection from the CNC drilling machine

4.5. Performance Metrics

The performance of the classifiers was assessed according to these five principles:

- Accuracy: the rate of correct classifications
- Precision: for every class, the fraction of its samples predicted to be that class that was predicted correctly
- Recall (Sensitivity): for every class, the fraction of its samples predicted to be that class
- F1-Score: the mean of precision and recall with an additional balance to false positives and false negatives.
- Cohen's Kappa: Evaluates the agreement of predicted and actual values and adjusts for the agreement that may happen by chance.

Class-wise performance, general misclassification trends, and class-wise performance errors were also assessed using confusion matrices.

Table 2. Data set collection

Drill bit condition / Drill diameter	Healthy	Low	Medium	Severe	Total
3.0 mm	50	50	50	50	200
3.2 mm	50	50	50	50	200
3.4 mm	50	50	50	50	200
3.6 mm	50	50	50	50	200
3.8 mm	50	50	50	50	200
Total	250	250	250	250	
Overall datasets					1000

Table 3. Classification performance comparison of lazy classifiers

Classifier	Accuracy (%)	Precision	Recall	F1-Score	Cohen's Kappa
k-NN	96.8	0.97	0.97	0.97	0.96
WKNN	98.7	0.99	0.99	0.99	0.98
LWL	95.4	0.96	0.95	0.95	0.94
IBk	97.2	0.97	0.97	0.97	0.96
LazyBayes	94.6	0.95	0.94	0.94	0.93

5. Results and Discussion

This subsection encompasses the classification outcomes acquired from applying lazy classifiers concerning the fused AE features for monitoring the tool wear of CNC drill bits. Results are presented as performance metrics, and classifier behaviour is analysed in detail.

5.1. Classification Metrics and Accuracy

Table 3 presents each classifier's average classification accuracy, precision, recall, F1-score, and Cohen's Kappa. It was calculated for a 10-fold cross-validation. Figures 3 to 7 show the confusion matrix derived during the computation of various lazy classifiers.

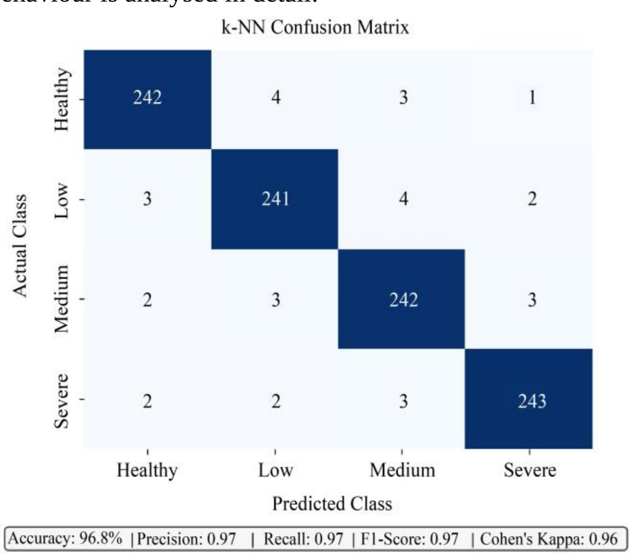

Fig. 3 Confusion matrix for k-NN

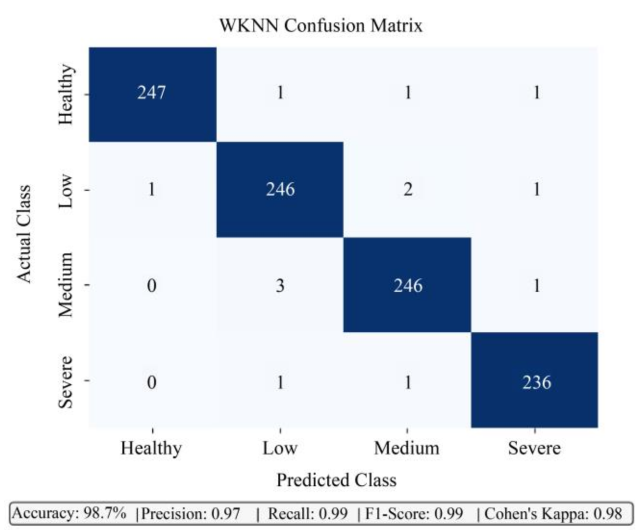

Fig. 4 Confusion matrix for WKNN

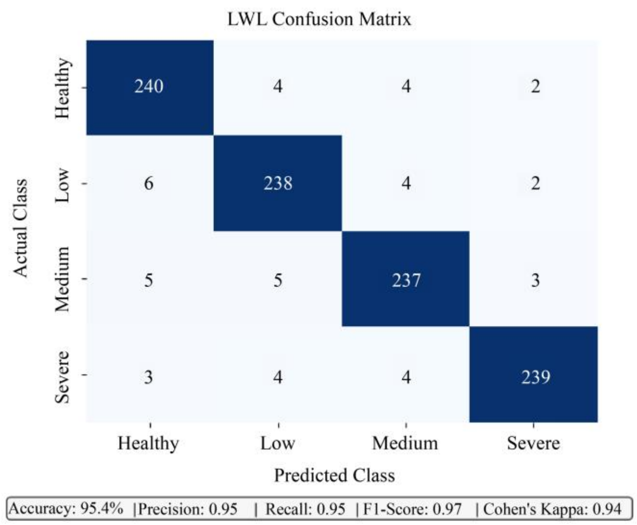

Fig. 5 Confusion matrix for lwl

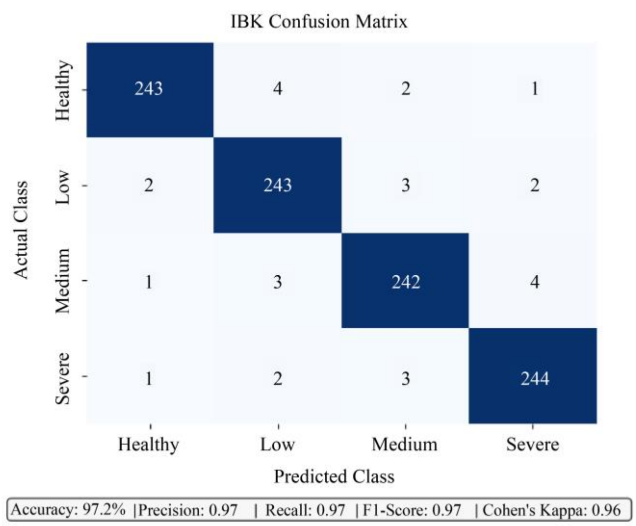

Fig. 6 Confusion matrix for IBk

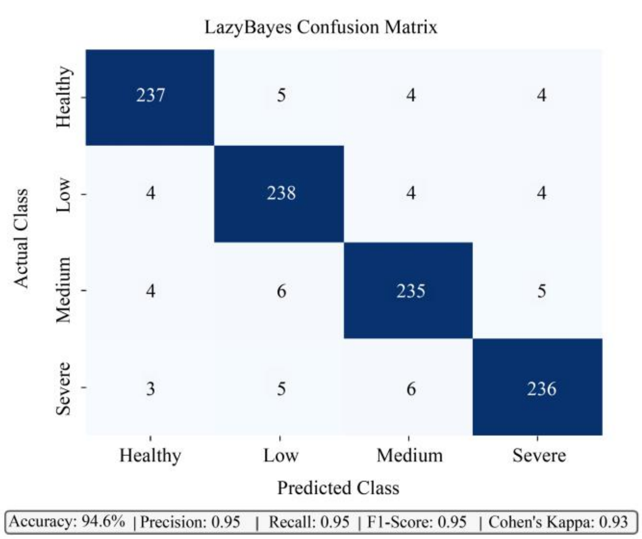

Fig. 7 Confusion matrix for LazyBayes

With an accuracy of 98.7%, the Weighted K-Nearest Neighbours classifier (WKNN) outperformed all other classifiers, earning the highest precision, recall, F1 score, and Cohen's Kappa. WKNN's improvement in performance over other classifiers is likely due to the neighbour weighing feature it employs, which considers the distance of the sample to the classifying neighbour, lessening the impact of far-off and irrelevant neighbours upon classification.

5.2. Analysis of Confusion Matrices

Table 4 presents the confusion matrix for WKNN, highlighted as the top classifier. Each sample is classified into its appropriate category, and corrections and errors are calculated as percentages of the total for each class.

Table 4. Normalised confusion matrix for WKNN classifier

Actual \ Predicted	HT	LW	MW	SW
HT	99.1%	0.6%	0.2%	0.1%
LW	0.7%	98.8%	0.4%	0.1%
MW	0.2%	0.5%	98.6%	0.7%
SW	0.1%	0.2%	1.0%	98.7%

The classifier demonstrated excellent discrimination among the four wear states. Most misclassifications occurred between adjacent wear states (e.g., LW and MW), likely due to subtle signal feature variations during intermediate wear stages.

5.3. Feature Importance and Analysis

Although lazy classifiers do not explicitly provide feature importance scores, exploratory analysis using Principal Component Analysis (PCA) on the fused features indicated that sub-band energies from WPD and entropy-based features contributed significantly to class separation. Time-domain features such as RMS and kurtosis are also strongly correlated with wear progression, which is consistent with the literature's findings.

5.4. Cross-Validation of the Proposed Methodology

To give generalizability and reliability of the classification performance, 10-fold cross-validation was used. In this method, the dataset was randomly partitioned into ten equal folds. For each iteration, nine folds were used to train the model, and the remaining one was used for testing. This process was repeated 10 times, so each fold served once as a validation subset. The average performance across all folds was then computed. The overall cross-validation accuracy, AccCV, is calculated as

$$Acc_{CV} = \frac{1}{k}\sum_{i=1}^{k} Acc_i \tag{12}$$

Where k=10 represents the number of folds, and Acci is the accuracy obtained in the ith fold.

This approach balances computational cost, reliable performance, and stability to reduce bias and variance in a single-train test split. This method was also considered across the different wear categories, including healthy tools, to ensure robustness. This stratification maintains proportionality in both training and testing datasets, improving the reliability of performance comparison among different classifiers.

5.5. Comparison with Existing Methods

The proposed feature fusion, combined with lazy classifiers, compares favorably with traditional machine learning approaches reported in the literature. For example, SVM-based methods typically achieve 95-97% accuracy on similar datasets, often with higher computational overhead. Deep learning models may reach higher accuracy but require significantly larger datasets and training times.

The proposed approach balances high accuracy, interpretability, and computational efficiency, making it suitable for real-time tool condition monitoring applications in industrial CNC environments. Table 5 compares the proposed classification with the prediction accuracy of the other classifiers based on the literature.

Table 5. Comparison of the proposed methodology with previous research works using ML and DL

Reference	Methodology used / Core application	Obtained Accuracy
Zhang, Y et.al. (2023) [23]	CNN based	Above 90%
Li,Z et.al. (2019) [24]	Used CART, RF, KUN, and SVM (tool wear without audio signal)	Overall accuracy in SVM is 99% on 90% of the dataset.
Drew,D et.al. (2025) [25]	CNN (TCM)	Min 92.09% Max of 100%
Hung,Y.H., et al. (2024) [26]	Used SVM and CNN for tool wear	CNN – 93% SVM – 89.8%
Vu, VQ (2025) [27]	Used ANN	Exceeds 90%
Kaliyannan,D et.al. (2024) [28]	Used LSTM, FFNN, Q-learning, and SARSA	LSTM – 94.85% FFNN – 98.16% Q-learning – 98.50% SARSA – 98.66%
Chen,M et.al. (2023) [29]	Used the TCM model	Recognition accuracy 96.11%
Proposed methodology	Lazy classifiers (WKNN) with WPD	98.7%

5.6. Limitations and Future Considerations

Despite promising results, this study used datasets reflecting controlled wear conditions. This does not consider the noise, varying cutting parameters, and tool types, which may affect model generalizability. Future work should include testing diverse tool geometries, materials, and dynamic cutting conditions, as well as exploring adaptive online learning methods. Also, the datasets are medium, which might be one of the reasons for the good performance of the Lazy classifiers. Large datasets are required to depend on deep learning-based algorithms.

5.7. Practical Application of the Proposed Methodology

The proposed methodology is highly relevant for modern manufacturing, focusing on automation, quality assurance, and predictive maintenance. By relying on AE signals, the methodology eliminates multiple sensors and makes it suitable for real-time, non-invasive monitoring of CNC drilling machines. The combination of feature fusion and lazy classifiers offers fast retraining and adaptive decision-making capabilities suitable for dynamic production settings. This can be implemented in smart manufacturing to detect tool wear progression. Furthermore, the industrial IoT platforms can be integrated with the proposed methodology, enabling deployment on edge devices within the cyber-physical production system and supporting Industry 4.0-driven intelligent manufacturing.

6. Conclusion

In this work, WPD is more effective for complex time domain signals generated from acoustic emission signals. Various statistical time-domain features are extracted from the signals of healthy and worn-out tools by processing AE signals. Then, Lazy classifiers were applied using the extracted feature as input to have fault classification by relating tool wear generated in various categories.

The integration of WPD and WKNN shows 98.7% accuracy with a significant promise in monitoring tool wear in CNC drilling machines. The combination can be applied to any nonlinear and non-stationary signal. The combination of WPD and lazy classifiers gave an excellent result with an accuracy above 95%. So, we can conclude that the WKNN has exceptional proficiency in signal processing of Time domain data and advanced predictive capabilities. A different combination of feature extraction techniques and WKNN can be implemented in future work on the tool wear prediction of CNC drilling machines using acoustic emission sensors. As per the theory, Lazy classifiers are suitable for smaller and medium datasets and handle nonlinear data, which is common in the condition monitoring of drill bits. Deep learning algorithms are highly suitable for large datasets, and it is possible to use hybrid and ensemble algorithms for more accuracy in classification. However, this research work will open a path for future researchers to move ahead through Lazy classifiers with the support of the proper feature extraction techniques.

Consent for Publication

All authors have been informed and have consented to publication.

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