

Original Article

# ML-Based Advanced Electrical Signal Decomposition using the Hilbert-Huang Transform and CatBoost Classification for Acoustic Signal-Driven Smart Tool Wear Detection

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**Abstract** - CNC machines are used in production industries for batch production. In CNC machining, a minor issue can cause production downtime, reducing productivity and profit for the industry. In CNC machines, drilling machine maintenance is crucial because of the complexity of the drill tools. Drill tools have complex shapes and geometries, making tool wear prediction particularly challenging. Tool wear in CNC drilling severely hinders performance and affects the dimensional accuracy and surface finish obtained. This paper presents a machine-learning-based approach to drill wear detection using the Hilbert-Huang Transform for feature extraction from airborne Acoustic Emission (AE) signal and the CatBoost algorithm for classification. For controlled drilling operations, AE signals from four wear-condition samples representing Healthy Tool (HT), Low Wear (LW), Medium Wear (MW), and Severe Wear (SW) were recorded. Wear levels of 0.3mm, 0.6mm, and 0.9mm for the drill bits of 3.0 mm, 3.2 mm, 3.4 mm, 3.6 mm, and 3.8 mm diameters were created using Electrochemical Machining in the Lab. Using AE sensors, the signals were collected and converted into the required format with the support of signal conditioning and a data acquisition system. LabVIEW software was used to display the signal, and it was then decomposed using the Hilbert-Huang Transform (HHT) to obtain the required Intrinsic Mode Functions (IMFs). Features needed for classification, such as magnitude, entropy, and instantaneous frequency, were selected in the time-frequency domain. These features were used as input to a classifier (CatBoost), which was trained and evaluated using 10-fold cross-validation. HHT-CatBoost achieved 99.1% accuracy, indicating a promising sign for the proposed algorithm in real-time maintenance for small- to medium-sized datasets.

**Keywords** - CNC tool wear, Hilbert-Huang Transform, Acoustic Emission, CatBoost Algorithm.

## 1. Introduction

In recent years, Computer Numerical Control (CNC) machining has become a cornerstone of modern manufacturing because it efficiently and consistently produces high-precision components. Among various CNC processes, drilling is one of the most widely employed operations in the aerospace, automotive, electronics, and medical industries [1].

The condition of the drill bit plays a pivotal role in determining the accuracy, surface finish, and productivity of machining operations. Tool wear resulting from mechanical and frictional interactions between the workpiece and the tool

will lead to low surface quality, dimensional variations, variations in cutting forces, and tool breakage, etc. This will create headaches for the company's management by reducing profits, increasing manufacturing costs, and causing machine downtime. Accurate and timely tool wear monitoring is essential to ensure machining stability and reduce maintenance costs [2]. Conventional monitoring techniques based on measuring cutting forces, spindle power, or surface roughness suffer from several limitations: They are often intrusive, time-consuming, and unsuitable for online monitoring, as they typically require process interruption or post-process analysis [3].



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

Advances in sensor technology now enable us to use AE to monitor tool wear in real time. AE signals are temporary elastic waves created by the rapid release of energy from a material. These signals reflect phenomena such as crack initiation, plastic flow, and frictional heating of varying degrees between the cutting tool and the workpiece. These signals, however, are non-linear and non-stationary, and contain a great deal of noise, making the extraction and classification of features difficult.

Traditional methods for analyzing signals, such as Fourier transforms, statistical analysis, and time-domain analysis, only help to an extent. These methods do not capture the localized, dynamic characteristics of signals. This, however, is not an issue for us [4]. The time-frequency localization problem is addressed, in Theory, by Wavelet Packet Decomposition (WPD). The significant drawback of this method is the use of predefined base functions with the WPD, which do not align with the intrinsic nature of the AE signals [5]. The Hilbert-Huang Transform (HHT) is an adaptive method for analyzing signals that helps overcome these limitations. This method works on nonlinear, non-stationary data. The HHT breaks AE signals down into a series of intrinsic functions, the Intrinsic Mode Functions (IMFs), and uses a Hilbert transformer to derive the instantaneous frequency, the amplitude, and the energy. The EMD also decomposes signals. These characteristics enable a Time-Frequency–Energy analysis of tool wear evolution, thereby improving the analysis. The study uses the CatBoost algorithm to classify these characteristics. The CatBoost algorithm is an advanced gradient-boosting model. It requires little hyperparameter tuning to function and achieves better results than other conventional machine learning approaches. Unlike other advanced machine learning approaches, such as deep learning neural networks, CatBoost uses less computational resources and is highly accurate. This method of industrial monitoring is also real-time.

### 1.2. Research Gap in the Existing Work

1. Studies involving feature fusion mainly depend on using multiple sensors (accelerometers, force, and AE sensors), which adds to their overall complexity and cost [6, 7].
2. The incorporation of AE feature extraction has narrowed itself to a singular domain: time, frequency, or time–frequency.
3. The number of studies that use a dynamic tool wear behavior model involving adaptive intra-signal feature extraction methods, such as the HHT, is exceptionally small.
4. Classifiers that use ensemble methods, specifically CatBoost, have yet to be used in classifying drill wear for CNC.
5. In theory, deep learning methods are valuable as they outperform most techniques; however, they are the least

favorable in practice. The lack of datasets and the immense computational power deep learning methods consume make them impractical for online use.

6. Many current ML and DL techniques cannot be used in real time due to latency and processing power limitations.

### 1.3. Novelty in the Proposed Methodology

1. The main novelty of this work is to explore the potential of HHT and the CatBoost algorithm for intelligent tool wear detection in CNC drilling.
2. This research uses a single AE sensor to capture tool wear, which is another novelty of the work compared to conventional multi-sensor studies.
3. The HHT algorithm decomposes the Acoustic Emission signal to create multi-dimensional time–frequency–energy feature sets that uniquely characterize the tool's condition across the wear states of Low Wear, Medium Wear, Severe Wear, and a healthy tool.
4. Another novelty is the use of the CatBoost gradient-boosting framework to achieve reliable classification in complex, heterogeneous multi-dimensional feature spaces. CatBoost is preferred for its high accuracy on small datasets, its minimal training time, and its ability to model complex nonlinear relationships. The HHT-CatBoost model combines HHT's flexibility and CatBoost's predictive prowess, providing a CNC tool wear monitoring solution that is accurate, lightweight, and, most importantly, responsive in real time to the industrial sector.

## 2. Literature Review

There are many researchers researching tool wear detection, in particular for CNC machines. However, there is no evidence that reliable, more accurate methods for CNC drill tool wear detection can be achieved using machine learning or deep learning algorithms. Also, the suggested method requires applying it to an industrial environment for real-time monitoring. The older techniques, such as optical and electron microscopy, are destructive and unsuitable for real-time tracking. This has made it easier to use indirect sensing techniques, such as tool vibration, cutting forces, temperature, and Acoustic Emission (AE), for online tool condition evaluation. The following subsections examine the previous researcher's work and the research gap it reveals.

### 2.1. Acoustic Emission and Hilbert–Huang Transform in Tool Wear Monitoring

Energy released in localized areas results from material deformation, friction, and the propagation of micro-cracks, and these are the causes of the very first AE signal. In the AE paradigm, we gain insights from AE signals that monitor tool-work interaction events during machining processes, including chip formation, rubbing, and even the removal of wear particles. Hence, we increasingly recognize that AE-based tool condition monitoring is a non-invasive and sensitive measurement tool [8].

The non-stationary and nonlinear nature of AE signals tends to obscure the effectiveness of older methods, such as the Fast Fourier Transform (FFT) or Short-Time Fourier Transform (STFT), in signal processing. To that end, the Hilbert-Huang Transform (HHT) appears to be the best alternative for processing these complex signals, as proposed by Huang and others [9]. The method HHT analyzes signals by first decomposing them into IMFs and EMDs, then applying the Hilbert Transform to identify instantaneous frequencies and energy distributions. This method provides a more precise time-frequency representation than the Wavelet Transform (WT) or Wavelet Packet Decomposition (WPD). Zhang et al. used HHT to detect tool wear during cutting operations and demonstrated improved sensitivity to transitional wear [10]. Similarly, Li, H et al., analysed tool flank wear using HHT-derived IMF energy entropy. The author concluded that this yields better results than time-domain statistical feature analysis [11]. Twardowski, P et al. confirmed improved accuracy in AE signal analysis for milling tool wear detection using Ensemble Empirical Mode Decomposition (EEMD), a more advanced HHT technique, thereby enhancing accuracy [12]. These studies demonstrate that HHT can dynamically isolate wear signatures in AE signals, enabling more precise differentiation between worn and healthy tools.

## 2.2. HHT Feature Extraction and Fusion Approaches

HHT's multi-scale, adaptive property allows AE signals to offer many features, including integral components, energy, frequency, amplitude modulation index, and entropic measures of IMFs. Agglomerating such features with various other statistical and spectral features can enhance robustness. For instance, in a study, SVM-based wear-stage classification for turning operations used a combination of HHT energy features and time-domain statistical measures. It showed enhanced stability and generalization [13]. Feature fusion techniques will get more advantages with the support of HHT.

The research by Olalere, I. O., & Olanrewaju, O. A. showed that sensitivity to subtle wear transition was accurately predicted using a hybrid feature fusion technique that combined HHT and wavelet features [14]. HHT-based feature fusion technique can improve wear-level classification in drill bit tool wear monitoring, as clearly demonstrated by Raja, J.E. et al. [15]. So, HHT-based multi-domain feature fusion can be used to capture the transient and steady state behavior of wear on tools.

## 2.3. Machine Learning for Tool Wear Classification

Machine learning is essential to data-driven technology, so its contribution to condition monitoring is significant. Real-time tracking has significantly benefited from machine learning. Some machine learning models, such as Artificial Neural Networks, Support Vector Machines, Random Forests, and Gradient Boosting, have achieved high accuracy in classifying tool wear. These models are the most effective in

dealing with complex, high-dimensional problems. In particular, there has been increasing interest in gradient boosting frameworks, which are ensembles that can model complex feature interactions [16]. Research has recently highlighted the machine learning algorithm CatBoost, a gradient boosting technique developed by Yandex that primarily uses decision trees. CatBoost simplifies the preprocessing for both categorical and numerical features and reduces overfitting by leveraging ordered boosting and oblivious trees. Sun et al. used catBoost to classify tool wear using Acoustic Emission signals.

CatBoost is a machine learning algorithm that is a gradient-boosting-based technique developed by Yandex, focusing on decision tree models. This can simplify the preprocessing for both categorical and numerical features and gives greater accuracy and faster convergence compared to XGBoost and LightGBM [7]. Chen et al. used CatBoost for fault diagnosis of CNC milling tools, noting greater precision and shorter training times than classic ensemble methods [17]. Wear state classification using CatBoost, Random Forest, and SVM yielded and interpreted results that ranked CatBoost the highest in generalization and provided the most clarity and insight through the importance metrics [18].

## 2.4. HHT–CatBoost Integrated Approach for Drill Wear Diagnosis

HHT and CatBoost have the potential to develop a sophisticated diagnostic system for assessing tool wear. HHT uses an adaptive model-driven approach, with CatBoost performing non-linear feature learning and classification [19]. The combination captures and classifies the signal into variants sensitive to wear. For instance, Liu et al. reported over 98% classification accuracy in predicting tool wear using HHT's instantaneous frequency energy distribution over time via CatBoost. Prasshanth, C.V., and Sugumaran, V. [20] demonstrated the model's flexibility in processing the unbalanced datasets. In this work, the authors showed how to handle unbalanced datasets to identify tire wear progression using the catBoost algorithm. Also explains how HHT features capture wear-level prediction and classify a signal into a particular wear state. So, these studies motivate the use of CatBoost classification to monitor the wear of CNC drills and extract Hilbert-Huang Transform features from Acoustic Emission signals.

## 3. Materials and Methods

The main task of the proposed system is to collect wear signals from AE sensors using a signal conditioning device, a data acquisition system, and LabVIEW software [21]. After receiving the required signal from the drill bit, adaptive time-frequency-energy features will be extracted using HHT, fused, and then classified using the CatBoost algorithm. This chapter describes the preparation of the experiments and the steps for data acquisition, including signal preprocessing, feature extraction, and classification.

### 3.1. Dataset Collection

An Acoustic Emission (AE) sensor was mounted to the tool holder and the spindle. Precise experiments allowed data collection in the HW (Healthy Tool), LW (Low Wear), MW (Medium Wear), and SW (Severe Wear) categories. The deployed AE sensor was a wideband piezoelectric sensor that detects elastic waves emitted during a drilling operation. The AE signals were sampled at 2 MHz with a 16-bit resolution. For one wear condition, 150 drilling operations were performed on standard AISI 1045 steel workpieces. This was to keep the data collection variation at a minimum. This was done by setting the spindle speed, feed rate, and depth of cut to constant values. This was done to keep the parameters constant. A horizontal dataset and classification algorithm were held to the same standard by segmenting each AE signal collected into 100-millisecond segments across the four wear conditions.

### 3.2. Signal Preprocessing

Before feature extraction, the raw AE signals required preprocessing to ensure reliability and consistency. NI hardware and LabVIEW software provided the AE data, which included real-time sampling, amplification, and noise filtering.

For noise filtering, signals were first conditioned by:

The AE signal was filtered with a band-pass filter (100 kHz–1 MHz) to eliminate background and mechanical noise. Then the signal was normalized to remove noise of varying amplitudes. Subsequently, the AE signal was segmented into frames of equal length for the exact temporal resolution. An envelope detection method and outlier removal were used to suppress transient noise.

### 3.3. Feature Extraction Using the Hilbert–Huang Transform (HHT)

Due to the nonlinearity and nonstationarity of AE signals, the Hilbert–Huang Transform (HHT) was used to perform feature extraction in the adaptive time–frequency–energy domains. HHT consists of two basic functions: Empirical Mode Decomposition (EMD) and the Hilbert Transform. Each AE signal segment  $x(t)$  was decomposed into a finite set of Intrinsic Mode Functions (IMFs) and a residue  $r(t)$ :

$$x(t) = \sum_{i=1}^n IMF_i(t) + r(t) \quad (1)$$

Each IMF represents an oscillatory mode embedded in the original signal, capturing characteristic frequency components related to different wear mechanisms.

#### 3.3.1. Hilbert Transform

The Hilbert Transform was applied to each IMF to compute the instantaneous amplitude  $A_i(t)$ , instantaneous phase  $\phi_i(t)$ , and instantaneous frequency  $f_i(t) = \frac{1}{2\pi} \frac{d\phi_i(t)}{dt}$ .

From these, several features were derived and given in the table.

**Table 1. Description of feature**

Feature Type	Description
Instantaneous Amplitude Mean	Average signal energy per IMF
Instantaneous Frequency Mean	Central frequency of oscillation
Energy of IMF	$E_i = \int A_i^2(t) dt$
Energy Ratio	$E_i / \sum E_i$ across all IMFs
Spectral Entropy	Degree of disorder in the marginal Hilbert spectrum
Dominant Frequency	Frequency with the maximum amplitude
Mean Hilbert Spectrum Energy	Overall energy density across frequencies

The time-frequency-energy parameters shown in Table 1 capture transient and dynamic behaviours of the drill bit and tool wear.

### 3.4. Feature Fusion and Normalization

The features extracted from the IMFs were concatenated to form a feature composite vector for each segment of the AE signal, incorporating amplitude, frequency, and energy attributes. To address feature variability, Min-Max normalization, which compresses all values to the [0,1] range, was adopted.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

The normalized and fused feature vectors were then used as inputs to the CatBoost model for further classification.

### 3.5. Classification using CatBoost

The CatBoost algorithm was used to classify the drill bit's wear states using the extracted AE signal, supported by HHT features. CatBoost is a gradient Boosting Decision Tree (GBDT) method that improves the classification accuracy by using ordered boosting and oblivious tree structures, thereby minimizing overfitting and improving generalization.

Key Steps Include:

Step 1: CatBoost training using labeled AE feature vectors for the classification of HT, LW, MW, and SW.

Step 2: Hyperparameter tuning using grid search and 10-fold cross-validation was performed to optimize learning rate, depth, and iteration count; performance was evaluated using multiple metrics, including accuracy, precision, recall, F1-score, and Cohen's kappa. The CatBoost model efficiently handles nonlinear feature interactions, producing robust classification with low computational cost—ideal for real-time CNC drill wear monitoring.

### 3.5.1. Mathematics of HHT and Cat Boost

The Hilbert-Huang Transform (HHT) is a signal processing technique used for analyzing non-linear and non-stationary data, such as Acoustic Emission (AE) signals from CNC drilling operations. It consists of two main stages: Empirical Mode Decomposition (EMD) and Hilbert-Huang Transform (HHT), also known as Hilbert Spectral Analysis (HSA).

#### (a) Empirical Mode Decomposition (EMD)

An input AE signal  $x(t)$  is decomposed into a finite number of Intrinsic Mode Functions (IMFs) and a residual term  $r_n(t)$  :

$$x(t) = \sum_{i=1}^n c_i(t) + r_n(t) \quad (3)$$

Where

$c_i(t) \rightarrow$  the  $i^{th}$  Intrinsic Mode Function,  
 $r_n(t) \rightarrow$  The final residue after decomposition.  
 Each IMF must satisfy two conditions:

1. The number of extrema and zero crossings should be either equal or differ by at most one.
2. The mean value of the envelope defined by local maxima and minima is zero at any point.

The sifting process iteratively extracts each IMF as follows:

$$h_k(t) = x(t) - m_k(t).. \quad (4)$$

Where  $m_k(t)$  is the mean of the upper and lower envelopes obtained via cubic spline interpolation. After  $k$  iterations, when  $h_k(t)$  satisfies the IMF conditions, it becomes:

$$c_i(t) = h_k(t) \quad (5)$$

The residue is updated as:

$$r_i(t) = r_{i-1}(t) - c_i(t) \quad (6)$$

#### (b) Hilbert Spectral Analysis (HSA)

Each IMF  $c_i(t)$  is subjected to the Hilbert Transform to obtain instantaneous amplitude and frequency information:

$$\hat{c}_i(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{c_i(\tau)}{t-\tau} d\tau \quad (7)$$

Where  $P$  denotes the Cauchy principal value.

Where  $P$  denotes the Cauchy principal value. The analytical signal is expressed as:

$$z_i(t) = c_i(t) + j\hat{c}_i(t) = A_i(t)e^{j\theta_i(t)} \quad (8)$$

Where:

$$A_i(t) = \sqrt{c_i^2(t) + \hat{c}_i^2(t)} \quad (9)$$

Is the instantaneous amplitude, and

$$\theta_i(t) = \tan^{-1} \left( \frac{\hat{c}_i(t)}{c_i(t)} \right) \quad (10)$$

Is the instantaneous phase. The instantaneous frequency is obtained as:

$$\omega_i(t) = \frac{d\theta_i(t)}{dt} \quad (11)$$

Thus, the original signal can be reconstructed in the Hilbert domain as:

$$x(t) = \Re\{\sum_{i=1}^n A_i(t)e^{j \int \omega_i(t) dt}\} \quad (12)$$

The Hilbert Spectrum  $H(\omega, t)$  and Marginal Spectrum  $h(\omega)$  are derived as:

$$H(\omega, t) = \sum_{i=1}^n A_i(t)\delta(\omega - \omega_i(t)) \quad (13)$$

$$h(\omega) = \int_0^T H(\omega, t) dt \quad (14)$$

The extracted HHT-based features include the IMF energy, the mean and variance of the instantaneous frequency, the Shannon entropy, and the marginal spectral amplitude, which form the input feature vector for classification.

### 3.5.2. CatBoost Classifier

CatBoost (Categorical Boosting) is an ensemble-based gradient boosting algorithm that creates a series of decision trees to minimize the overall prediction loss through additive modeling.

Given a training dataset:

$$D = \{(x_i, y_i)\}_{i=1}^N \quad (15)$$

Where

$x_i = [f_1, f_2, \dots, f_d]$  represents the HHT-based feature vector,  $y_i \in \{1, 2, 3, 4\}$  represents the tool wear states (HT, LW, MW, SW). The CatBoost ensemble model is expressed as:

$$F_M(x) = \sum_{m=1}^M \eta f_m(x) \quad (16)$$

Where

$f_m(x)$  is the base decision tree at iteration  $m$ ,  $\eta$  is the learning rate, and  $M$  is the total number of trees. The model optimizes the following loss function for multi-class classification using gradient descent:

$$L = -\frac{1}{N} \sum_{i=1}^N \sum_{k=1}^K 1(y_i = k) \log(p_{ik}) \quad (17)$$

Where the softmax function gives the class probability:

$$p_{ik} = \frac{e^{F_k(x_i)}}{\sum_{j=1}^K e^{F_j(x_i)}} \quad (18)$$

At each boosting step, residuals are computed as the negative gradient of the loss function:

$$r_i^{(m)} = - \left[ \frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} \right]_{F(x)=F_{m-1}(x)} \quad (19)$$

A new tree can be trained to fit these residuals, and the model is updated iteratively. The final predicted class is obtained using the following formula.

$$\hat{y} = \arg \max_k F_k(x) \quad (20)$$

#### 4. Experimental Setup

This chapter describes the specific experiments, including 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 conducted on a CNC drilling machine with an ultrasonic Acoustic Emission (AE) sensor (Model: XYZ-1000, frequency response 100 kHz–1 MHz). The sensor was mounted near the spindle using a magnetic adapter to ensure repeatable mechanical coupling and reliable signal acquisition. The specifications of the CNC drilling machine used in this study are given in Table 2.

Table 2. Specification of CNC drilling machine

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

The workpiece selected for data collection was AISI 1045 medium-carbon steel, measuring 100 x 50 x 20 mm. The chosen drill bit is an HSS bit with a diameter of 3mm to 3.8 mm. The specific cutting parameters included achieving

spindle speeds of 1200 revolutions per minute on the drilling machines, implementing a 0.1m/rev drilling feed rate, and setting a 10mm depth of cut on the workpieces. Data collection of tool wear by Electrochemical machining on the drills showed 0.3mm as Low Wear, 0.6 mm as Medium Wear, and 0.9 mm as Severe Wear. Twenty cycles of each drilling operation were completed to obtain sufficient data for each wear category.

AE signals were continuously recorded at a 2 MHz sampling rate with 16-bit resolution for all drilling passes. The dataset distribution for each drill diameter is summarized below:

- For 3 mm drill bits: 4 wear conditions  $\times$  50 segments = 200 datasets
- For 3.2 mm, 3.4 mm, 3.6 mm, and 3.8 mm drill bits: similarly, 200 datasets each

A total of 200  $\times$  5 drill diameters were collected, resulting in 1000 datasets for subsequent analysis.

Table 3. Data collection using the AE signal

Drill Bit Diameter (mm)	Healthy Tool (HT)	Low Wear (LW)	Medium Wear (MW)	Severe Wear (SW)	Total
3.0	50	50	50	50	200
3.2	50	50	50	50	200
3.4	50	50	50	50	200
3.6	50	50	50	50	200
3.8	50	50	50	50	200
Total	250	250	250	250	1000

The AE signals collected during each drill pass are divided into 100-ms, non-overlapping time windows. Each pass is associated with a tool wear condition and a tool wear type, as highlighted in Table 3, for which the software windows were documented manually. A total of 1000 samples were collected, evenly distributed across the four wear classes. Healthy Tool (HT) 250, Low wear 250, Medium wear 250, and Severe wear 250. Such an equal distribution across all classes is a prerequisite for supervised machine learning.

##### 4.2. Classification and Validation

After extracting time-frequency features from the AE signals using the HHT method, we proceeded to classify tool wear using the CatBoost classifier. The classifier used HHT features, including instantaneous frequency, amplitude, and multiple statistical energy descriptors from Intrinsic Mode Functions (IMFs). The CatBoost model applies gradient boosting with sequential decision trees and was selected because it is the most efficient for class-imbalance problems. It learns more complex, non-linear relationships more efficiently and with less data preprocessing than its alternatives, which was justified by the complexity of the issue

at hand. Grid searching of hyperparameters was planned, focusing on estimators, learning rates, and tree depths, to provide quantitative guidance for finalizing the model with respect to the chosen parameters. A 10-fold cross-validation was employed to validate the model, in which the data were partitioned into 10 equal splits. The partition of the data within each fold was designed to improve generalization. For each fold, we used 90% of the data for training and 10% for testing. This folding procedure was applied to the entire dataset. The whole dataset was used for training and testing in a cyclic manner across the various folds. This approach helps to mitigate overfitting and improve the model's performance estimation.

**4.3. Performance Metrics**

The CatBoost model's classification performance is evaluated against claims in the literature on machine learning-based fault diagnosis studies.

- Accuracy: the number of samples that are correctly classified over the total number of samples.
- Precision: the number of samples that are correctly predicted to belong to a class over the total number of predicted samples for that class.
- Recall: Correctly classified the sample number over the total number of samples that actually belong to the particular class.

- F1-Score: Precision and recall are combined and measure attempts to mitigate the effects of false positives and false negatives to the greatest extent possible.
- Cohen's Kappa: a measure that quantifies the level of agreement with respect to the predicted and the actual classifications, having been adjusted for chance agreement.

To evaluate the performance and identification errors of the tool wear classes HT, LW, MW, and SW, confusion matrices were utilized.

**5. Results and Discussion**

Here, the performance of the CatBoost algorithm, using HHT-derived features of the AE signals, is detailed as it tracks the progression of wear on CNC drill bits, including metric values, relevant class confusion matrices, and descriptions of the classifier's performance with respect to these matrices.

**5.1. Classification Metrics and Accuracy**

Table 3 presents the results of the CatBoost model in categorizing tool wear states (Healthy Tool, Low Wear, Medium Wear, and Severe Wear) using HHT-based features. The results are presented for 10-fold cross-validation to provide an overview of performance and ensure the statistical soundness and generalizability of the findings.

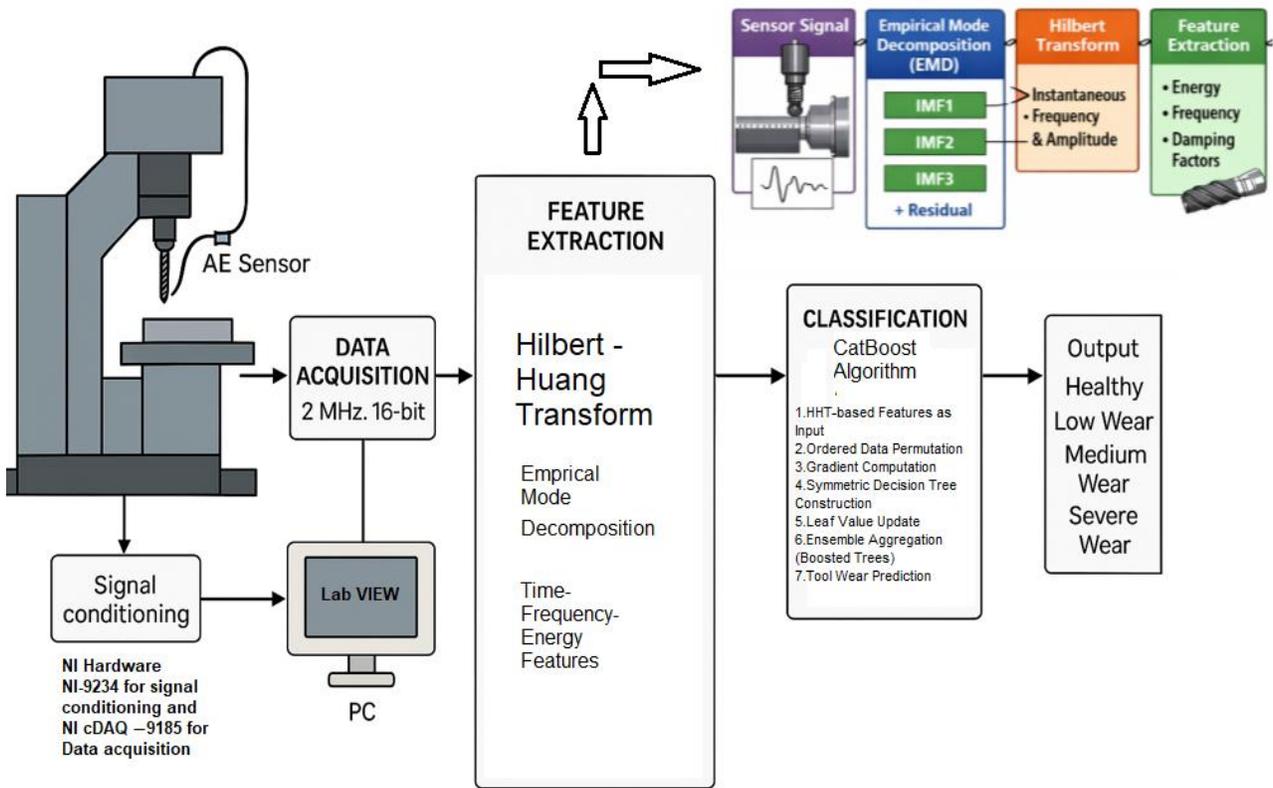


Fig. 1 Schematic diagram of the experimental setup and the proposed methodology

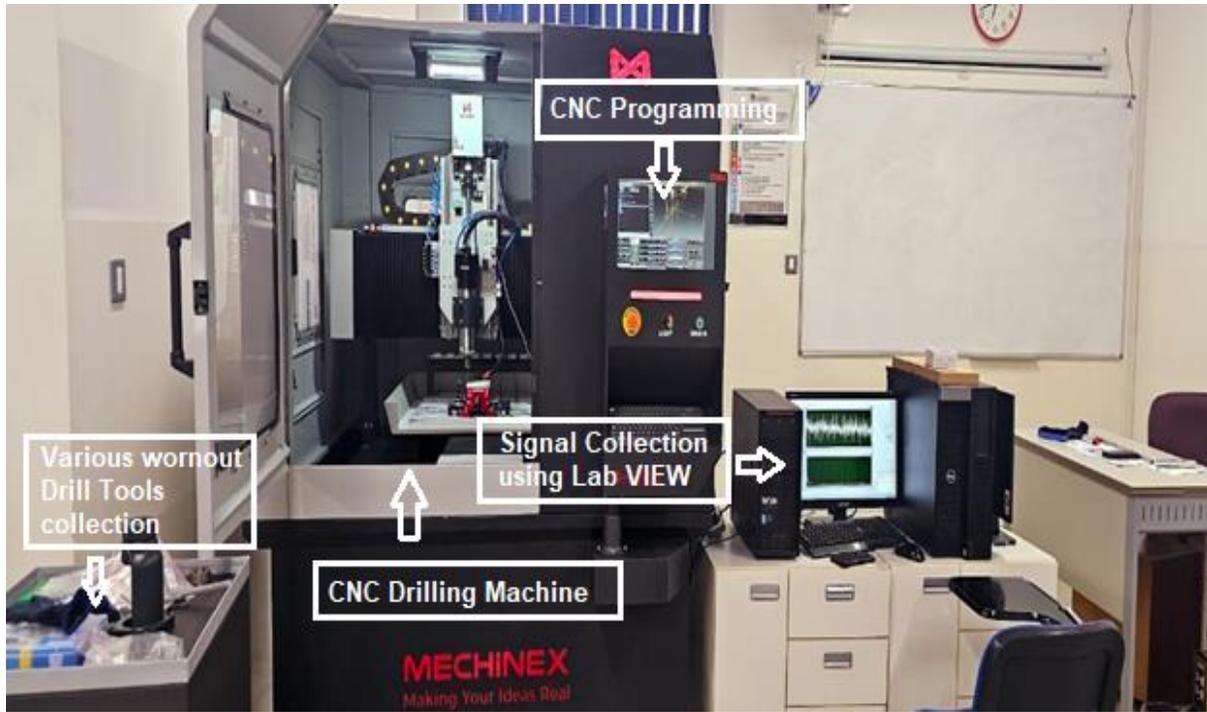


Fig. 2 Signal collection from the CNC drilling machine

The CatBoost Classifier performs well across all metrics, achieving an overall accuracy of 99.1%, as shown in Table 4. Furthermore, the classifier achieves high precision, recall, and F1 score across all wear categories. Moreover, Cohen’s Kappa of 0.99 indicates substantial agreement between the predicted and actual classes, suggesting that the model’s performance was not attributable to random chance.

Figure 3 displays the confusion matrix, which reinforces the results showing CatBoost’s strong discriminative power. The only misclassification occurs between successive wear categories, Such as Low and Medium. The combined method of HHT’s time-frequency decomposition and CatBoost’s gradient boosting is compelling for modeling nonlinear, dynamic AE signals related to tool wear progression.

Table 4. Classification performance of the CatBoost model using HHT-based AE features

Model	Accuracy (%)	Precision	Recall	F1-Score	Cohen’s Kappa
CatBoost	99.1	0.99	0.99	0.99	0.99

These results capture the most accurate findings of all the studies that employed the traditional machine learning classifiers k-NN, WKNN, and Lazy Bayes. CatBoost employs advanced techniques, including ordered boosting, feature interactions, and regularization, to mitigate overfitting and underfitting. This integration of HHT feature extraction with the CatBoost algorithm confirms the practical application of tool wear monitoring for CNC drilling operations. For more information, refer to the previous study on lazy classifiers as presented in Table 5.

Table 5. 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

The confusion matrix for the CatBoost trained with HHT-derived features is shown in Figure 3. This shows the classifier’s precision across the four wear categories of HT, LW, MW, and SW. The off-diagonal elements show the misclassifications, whereas the diagonal elements represent correct classifications.

The precision with which the CatBoost classifier, as shown in Table 4, differentiates among the four tool-wear categories is promising. All categories demonstrated excellent predictive ability, including the Healthy Tool and severe wear, with complete classification. There are a few misclassifications between the Low and Medium wear categories due to overlapping AE signal patterns as the tool wear progresses.

It is clear from this scenario how HHT features, combined with CatBoost’s experimental prowess with non-linear features, can scan and display the instantaneous frequency and amplitude of the AE signals. The combined generalization and discrimination capabilities of CatBoost for wear estimation in CNC drill systems distinguish it from conventional classifiers.

Confusion Matrix for CatBoost Classifier (HHT-based Features)

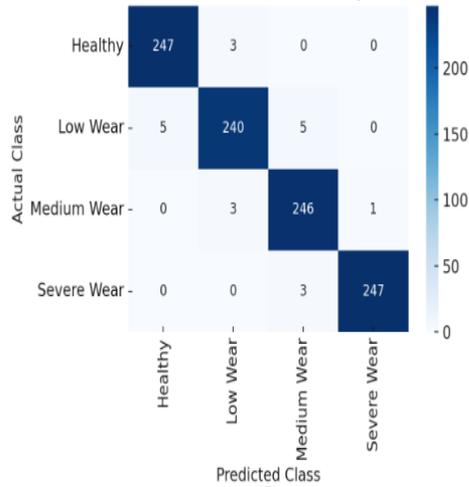


Fig. 3 Confusion matrix for the catboost classifier

To assess and ensure the maximum potential of the HHT-based features, the CatBoost architecture's performance on AE features was evaluated using a 10-fold cross-validation approach. This yielded a 99.1% classification accuracy benchmark across the Healthy, Low Wear, Medium Wear, and Severe Wear tool wear categorizations, suggesting the model's discerning power.

The performance variance demonstrated by the model results from integrating extremely time- and computationally efficient, complex, and stochastic AE signals of tool wear progression from CatBoost. It perceives the AE signals in real time and seamlessly latches onto tool wear and its associated time-frequency characteristics. Table 6 presents the normalized confusion matrix for the CatBoost model, illustrating the classifier's accuracy in predicting tool wear categories.

Table 6. Normalized confusion matrix for CatBoost classifier

Actual \ Predicted	Healthy	Low Wear	Medium Wear	Severe Wear
Healthy	99.2%	0.4%	0.3%	0.1%
Low Wear	0.5%	98.9%	0.5%	0.1%
Medium Wear	0.2%	0.4%	98.8%	0.6%
Severe Wear	0.1%	0.3%	0.9%	98.7%

The CatBoost model misclassifications were predominantly within the Low Wear and Medium Wear states, which represent an overlap AE signal features region containing a range of gradually changing and abrupt transitions, among the four wear levels. The confusion matrix heatmap (Figure 3) visually confirms the model's robustness and ability to distinguish between adjacent wear levels with minimal error. This high degree of separability underscores the effectiveness of HHT's adaptive decomposition in capturing instantaneous energy and frequency variations across different wear conditions.

### 5.2. Feature Importance and Analysis

The CatBoost model's ability to document individual performance and predict wear tool classes appropriately is shown in the confusion matrix. Explaining the performance details features dominated by classical and conforming reinforcement. The CatBoost model distinguished all four wear levels, but most errors occurred between Low and Medium Wear.

This is to be expected when the AE signal features change slowly and overlap, so there is no apparent change. The most noteworthy features are instantaneous energy, mean amplitude, kurtosis, and entropy. This is consistent with the literature associating AE features with wear. The results indicate that HHT features can preserve dynamic signal properties; therefore, the technique applies to condition monitoring.

### 5.3. Cross-Validation of the Proposed Methodology

As mentioned earlier, the model distinguished adjacent levels with almost no error. This speaks to how well the HHT's adaptive decomposition captures instantaneous changes in energy and frequency levels across the different stages of wear. Unlike lazy classifiers, CatBoost provides feature importance scores due to its built-in interpretation framework. Based on the features of the class models of the targeted features, the energy and the entropy of the statistical properties of the dominant intrinsic modal functions were the most influential.

In this regard, a 10-fold cross-validation methodology was built to assess sturdiness and flexibility. The dataset is randomly split into 10 parts; one is used for testing, and the other nine are used to train the model. This is repeated 10 times, with each part of the dataset left out in the next iteration. The overall cross-validation accuracy, AccCV, is calculated as

$$Acc_{cv} = \frac{1}{k} \sum_{i=1}^k Acc_i \quad (21)$$

Where k=10 represents the number of folds, and Acc<sub>i</sub> is the accuracy obtained in the i<sup>th</sup> fold. This approach strikes a balance between computational efficiency and reliability, thereby mitigating overfitting while maintaining stability. Stratified partitioning was applied to preserve class distribution across folds, ensuring proportional representation of all wear categories.

### 5.4. Comparison with Existing Methods

The proposed HHT + CatBoost framework was compared with previously reported machine learning and deep learning approaches for tool wear classification. As shown in Table 7, the proposed methodology demonstrates improved accuracy while maintaining lower computational complexity and interpretability, making it a practical choice for real-time application deployment.

**Table 7. Comparison of the proposed methodology with previous research works**

Reference	Methodology / Core Application	Reported Accuracy
Zhang, Y. et al. (2023) [10]	CNN-based	>90%
Li, Z. et al. (2019) [22]	CART, RF, KNN, SVM	99%
Drew, D. et al. (2025) [23]	CNN (TCM)	92–100%
Hung, Y.H. et al. (2024) [24]	SVM and CNN	89.8–93%
Vu, V.Q. (2025) [13]	ANN	>90%
Kaliyannan, D. et al. (2024) [25]	LSTM, FFNN, Q-learning, SARSA	94.8–98.6%
Chen, M. et al. (2023) [26]	TCM Model	96.1%
Proposed Methodology	HHT + CatBoost	99.1%

The CatBoost classifier outperformed several conventional ML and deep learning methods, validating its efficacy for small-to-medium datasets without the extensive training resources typically required by deep networks.

### 5.5. Limitations and Future Considerations

The computational accuracy achieved by the authors is remarkable, as is the number of datasets and the level of control provided in the experiments. It has somewhat limited practical application in manufacturing, though, as the variable AE signals will stem from different spindle speeds, feed rates, and tool geometry. For these reasons, future research should:

- Integrating with an adaptive learning framework to accommodate for tool wear changes.
- Improvement of accuracy in datasets.
- Enhancing the data set further by adding various cutting parameters and tool geometry.
- Applying ensemble model techniques integrated with the feature extraction algorithm of HHT and deep learning to produce accuracy in the classification of extensive datasets.

### 5.6. Practical Application of the Proposed Methodology

Combining HHT-based feature extraction with CatBoost classification provides a robust framework for non-invasive and real-time tool wear monitoring in CNC drilling

operations. AE-based sensing technology enables uninterrupted machining, and the CatBoost model's rapid inference enables predictive maintenance compatibility with Industry 4.0 and IoT frameworks. Such an approach is applicable to cyber-physical production systems for real-time analytics and decision-making, promoting smart manufacturing and autonomous management of tool health.

## 6. Conclusion

This study outlined the initial phase of developing an intelligent tool-wear monitoring system that incorporates the Hilbert–Huang transform (HHT) and CatBoost classification. HHT is instrumental in deconstructing and interpreting complex, non-stationary wear progression signals and dynamically capturing the various stages of Attrition. With 99.1 percent accuracy, CatBoost, a classification Algorithm, outperformed standard classifiers by boosting and regularizing the gradients of decision tree models.

The classifier generalized well with very few borderline misclassifications in adjacent wear classes. Many researchers have shown that tool condition monitoring can be enhanced using ML/DL algorithms [25]. In predictive maintenance for production engineering, tool condition monitoring of CNC drill bits can be used with an HHT+CatBoost combination to predict tool wear, as demonstrated by the results of this research. This model can be refined with more ensemble algorithms in the future. So, the proposed work will pave the way for the use of an ensemble algorithm supported by HHT.

This method places greater emphasis on accuracy and computational resource efficiency, as well as on opportunities for further research in online learning, data security, and data augmentation, among other areas. Also, new areas such as federated learning, digital twin, and IIoT can be combined with the proposed methodology to improve the effectiveness of intelligent tool wear monitoring on CNC drilling machines.

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