

## **Automated CNC Tool Wear Detection System Using Multi-Domain Signal Processing and Machine Learning**

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### **ABSTRACT**

Remaining Useful Life (RUL) prediction and machine accuracy monitoring are critical components of predictive maintenance in CNC machining systems. However, many existing approaches rely heavily on labeled datasets, computationally expensive models, and complex feature engineering, which restrict their deployment in real industrial environments, particularly on resource-constrained IoT and edge devices. This paper presents an efficient multi-domain signal processing and machine learning framework for CNC machine accuracy prediction.

The proposed system follows a five-stage methodology. First, multi-sensor data are acquired from vibration, current, temperature, and cutting force sensors. Second, data preprocessing is performed through cleaning, noise reduction using Mean, Median, Gaussian, Wiener, Wavelet, and Kalman filters, and normalization using Min-Max, Z-Score, and L2 methods. Third, multi-domain signal analysis is conducted in the time domain, frequency domain using Fast Fourier Transform (FFT), and time-frequency domain using Maximal Overlap Discrete Wavelet Transform (MODWT). Fourth, a total of 49 discriminative features are extracted, including statistical features such as mean, variance, skewness, kurtosis, and wavelet-based descriptors. Finally, multiple machine learning models, including Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, and Artificial Neural Network (ANN), are employed for classification.

A significant contribution of this work is the development of a node-based visual interface using React and ReactFlow, enabling users to construct analytical pipelines through drag-

and-drop operations without programming expertise. The platform supports both manual and automatic modes to enhance usability and flexibility.

Experimental evaluation using the PHM 2010 dataset demonstrates strong predictive performance, where the Random Forest model achieved 94.8% classification accuracy. Results further indicate that sensor fusion and multi-domain feature extraction significantly improve prediction performance, with wavelet-based features providing the highest contribution.

The proposed framework offers a scalable, cost-effective, and interpretable solution for Industry 4.0 predictive maintenance applications. Future work will focus on real-time deployment, edge-device integration, and cloud-based monitoring systems.

**KEYWORDS:** Remaining Useful Life (RUL), Predictive Maintenance, CNC Machine Monitoring, Machine Accuracy Prediction, Multi-Sensor Data Fusion, Signal Processing, Feature Extraction, Machine Learning, Random Forest, Industry 4.0, IoT, Edge Computing, PHM 2010 Dataset.

## **1.INTRODUCTION**

Computer Numerical Control (CNC) machines are fundamental to modern manufacturing industries because of their ability to deliver high precision, repeatability, and automated machining operations. They are extensively used in sectors such as automotive, aerospace, medical device manufacturing, and heavy engineering, where dimensional accuracy and production efficiency are critical. However, prolonged machine operation often results in tool wear, spindle degradation, vibration abnormalities, thermal expansion, and alignment errors, which can reduce machining quality and overall system performance. Unexpected failures of CNC machines may lead to costly downtime, reduced productivity, and increased maintenance expenses.

To minimize such risks, predictive maintenance has become an essential strategy in Industry 4.0 manufacturing environments. Unlike reactive maintenance, which is performed after machine failure, and preventive maintenance, which follows fixed schedules, predictive maintenance utilizes real-time sensor data and intelligent analytics to estimate machine health conditions and forecast failures before they occur. Among the major objectives of predictive maintenance, Remaining Useful Life (RUL) prediction and machine accuracy monitoring are particularly important, as they enable timely maintenance decisions, improve operational efficiency, and extend equipment lifespan.

Recent developments in industrial sensing technologies have enabled CNC machines to be equipped with multiple sensors such as vibration, current, temperature, and cutting force sensors. These sensors continuously generate valuable condition-monitoring data that can be analyzed using machine learning techniques. Nevertheless, many existing approaches rely heavily on large labeled datasets, computationally expensive deep learning models, and complex handcrafted feature extraction methods. Such requirements limit their practical deployment in real industrial settings, especially on resource-constrained edge and IoT devices.

To address these challenges, this paper proposes an efficient multi-domain signal processing and machine learning framework for CNC machine accuracy prediction. The proposed

methodology combines multi-sensor data acquisition, preprocessing, noise filtering, normalization, and feature extraction within a unified pipeline. Signal characteristics are analyzed in the time domain, frequency domain using Fast Fourier Transform (FFT), and time-frequency domain using Maximal Overlap Discrete Wavelet Transform (MODWT). A comprehensive set of statistical and wavelet-based features is extracted and used to train multiple machine learning classifiers, including Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, and Artificial Neural Network (ANN).

In addition to predictive modeling, a node-based visual workflow interface is developed using React and ReactFlow, enabling users to construct data-processing pipelines through drag-and-drop operations without requiring programming expertise. This improves usability and accessibility for industrial engineers, researchers, and maintenance personnel.

Experimental validation is conducted using the PHM 2010 dataset, where the proposed framework demonstrates strong classification performance. The results indicate that sensor fusion and multi-domain feature extraction significantly enhance prediction accuracy, with the Random Forest classifier achieving the best performance. The proposed system offers a scalable, interpretable, and cost-effective solution for smart manufacturing and next-generation predictive maintenance applications.

## **1.1 Background of the Study**

Computer Numerical Control (CNC) machines play a crucial role in modern manufacturing industries by enabling precise, repeatable, and automated machining of complex components used in automotive, aerospace, defense, medical, and general engineering sectors. Among the various machine components, the cutting tool is one of the most critical elements, as it directly affects machining accuracy, surface finish, productivity, and overall operational cost.

During machining operations, the cutting tool is subjected to continuous mechanical friction, high temperatures, and cutting stresses at the tool–workpiece interface. These conditions lead to progressive tool wear, which gradually reduces cutting efficiency and machining quality. If tool wear is not detected at an early stage, it can result in dimensional inaccuracies, poor surface quality, defective products, unexpected machine stoppages, material wastage, financial losses, and potential safety risks. In severe cases, sudden tool failure may also damage the spindle, fixtures, or other machine components.

Traditionally, tool condition monitoring has been performed through manual inspection by experienced operators or by replacing tools after fixed operating intervals. However, manual inspection is time-consuming, subjective, interrupts production processes, and depends heavily on operator expertise. Similarly, scheduled tool replacement may cause premature disposal of usable tools or delayed replacement of worn tools, leading to increased maintenance costs or quality issues. These conventional approaches do not provide real-time information regarding the actual health condition of the cutting tool.

Recent advancements in sensor technology, Industrial Internet of Things (IIoT), signal processing, and machine learning have enabled the development of intelligent tool condition monitoring systems. Sensors such as vibration, motor current, temperature, and cutting force sensors can continuously capture machine condition data during operation. When these signals are analyzed effectively, they can reveal hidden patterns associated with wear progression and machine degradation.

Despite these developments, several limitations remain in existing data-driven approaches for tool wear monitoring and Remaining Useful Life (RUL) prediction. First, many supervised learning methods require labeled wear data, which is difficult and expensive to obtain in industrial environments. Second, deep learning models often demand high computational resources, limiting their use on low-cost edge or IoT devices. Third, complex black-box models offer limited interpretability, reducing trust and adoption in practical manufacturing systems.

To overcome these challenges, this study proposes an efficient multi-domain signal processing and machine learning framework for CNC machine accuracy prediction and tool condition monitoring. The proposed system integrates multi-sensor data analysis, feature extraction, and classification with a node-based visual interface that enables users to design custom analytical pipelines through drag-and-drop interactions without programming expertise.

## **1.2 Problem Statement**

In practical manufacturing environments, CNC machines frequently operate continuously over multiple shifts, while operators often lack a reliable method to determine the actual health condition of cutting tools. Unexpected tool failure can damage the workpiece, fixture, spindle, and associated machine components, resulting in costly repairs and significant production downtime. Even without catastrophic failure, gradual tool wear can produce dimensional deviations and poor-quality parts, which may remain undetected until final inspection. By that stage, a large number of defective components may already have been manufactured, causing material loss, rework effort, delayed deliveries, and customer dissatisfaction.

This challenge is particularly severe for small and medium enterprises (SMEs), which may not have the financial capacity to adopt expensive commercial monitoring systems that require specialized sensors such as dynamometers or acoustic emission devices, along with proprietary software solutions. At the same time, they cannot afford the losses caused by sudden tool failures or inefficient maintenance practices. As a result, many industries still depend on operator experience or fixed tool replacement schedules, both of which are inefficient and inconsistent.

Existing intelligent monitoring systems also face practical limitations, including poor adaptability to varying machining conditions, high computational complexity, dependence on labeled datasets, and lack of user-friendly interfaces suitable for shop-floor personnel. These constraints reduce their real-world applicability, especially in resource-constrained industrial settings.

Therefore, there is a strong need for an accurate, cost-effective, interpretable, and easy-to-use tool condition monitoring system that utilizes commonly available sensors such as vibration, current, and temperature sensors. Such a system should support real-time monitoring, minimize dependence on labeled wear data, and provide accessible operation without requiring advanced programming knowledge.

### **1.3 Objectives of the Study**

The main objective of this research is to develop an effective multi-domain signal processing and machine learning system for predicting CNC cutting tool wear. The proposed framework also includes a node-based visual interface to simplify workflow creation, analysis, and model execution for users with different technical backgrounds.

The specific objectives are listed below:

1. To create an interactive node-based graphical interface with Manual Mode and Auto Mode, allowing users to build customized processing workflows without programming skills.
2. To apply signal preprocessing methods such as data cleaning, denoising filters including Mean, Median, Gaussian, Wiener, Wavelet, and Kalman filters, along with normalization techniques like Min-Max, Z-Score, and L2 normalization.
3. To generate a detailed set of 49 features from time-domain, frequency-domain, and time-frequency-domain signals for effective representation of tool wear behavior.
4. To design and evaluate multiple machine learning algorithms, including Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, and Artificial Neural Network (ANN), for identifying tool condition classes.
5. To assess the performance of the proposed framework using the PHM 2010 benchmark dataset through cross-validation and performance metrics such as accuracy, precision, recall, and F1-score.
6. To determine the most significant predictive features through feature importance analysis using the Random Forest algorithm.

### **1.4 Scope of the Study**

This research is centered on developing a machine learning and signal processing framework for CNC tool wear prediction using industrial sensor data such as vibration, current, temperature, and cutting force signals.

The study covers the following areas:

1. Collection and utilization of CNC machine sensor datasets available in CSV and Excel formats for analysis and model development.
2. Improvement of raw sensor data quality through preprocessing operations such as missing value handling, noise filtering, and normalization.
3. Extraction of 49 informative features from time-domain, frequency-domain, and time-frequency-domain analyses using methods such as FFT, Continuous Wavelet Transform (CWT), Hilbert Transform, Wavelet Packet Transform, Scalogram, and Wigner–Ville Distribution (WVD).
4. Implementation and comparative evaluation of five classification algorithms: Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, and Artificial Neural Network (ANN), to classify tool condition as Good or Worn.

5. Development of a graphical node-based interface with Manual Mode for advanced users and Auto Mode for beginners, enabling workflow creation through drag-and-drop operations without coding.
6. Validation of the proposed model using the PHM 2010 high-speed milling dataset with suitable cross-validation techniques.

This study does not address live sensor streaming from operating CNC machines, deployment on embedded edge hardware, cloud monitoring systems, robotic automation integration, Remaining Useful Life (RUL) regression modeling, or multi-level wear stage classification. However, the proposed architecture is flexible and can be extended in future work for real-time industrial applications and smart factory environments.

## **2.RELATED WORK**

Tool condition monitoring and predictive maintenance in CNC machining have been extensively researched over the past several decades due to their critical role in enhancing manufacturing efficiency, minimizing machine downtime, and maintaining consistent product quality. Researchers have investigated a wide range of techniques, starting from classical signal processing methods to modern machine learning and deep learning-based approaches.

In the initial stages of research, tool wear monitoring mainly depended on traditional condition monitoring techniques. These approaches utilized signals such as vibration, cutting force, acoustic emission, and spindle motor current. From these signals, time-domain statistical parameters including mean, standard deviation, root mean square (RMS), skewness, kurtosis, and crest factor were extracted to identify tool degradation patterns. In addition, frequency-domain analysis using Fast Fourier Transform (FFT) was widely employed to observe variations in signal frequency characteristics that correlate with tool wear progression.

With the advancement of artificial intelligence, machine learning techniques became increasingly popular for tool condition classification and prediction. Methods such as Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbors (KNN), Random Forest, and Artificial Neural Networks (ANN) have demonstrated strong performance in identifying tool wear conditions. Among these, ensemble learning approaches like Random Forest and boosting algorithms have been found to be more robust, especially when dealing with noisy and high-dimensional industrial datasets.

More recently, deep learning techniques have shown significant improvements in this domain. Convolutional Neural Networks (CNNs) are widely used for automatic feature extraction from raw sensor data, while Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) models are effective in capturing temporal dependencies in sequential machining signals. Hybrid models combining CNN and LSTM architectures have further enhanced prediction accuracy by learning both spatial and temporal patterns. However, these methods often require large labeled datasets, substantial computational resources, and are not always suitable for real-time industrial deployment.

Several studies have also emphasized the effectiveness of multi-sensor data fusion techniques. Integrating signals such as vibration, current, temperature, and cutting force provides a more comprehensive and reliable assessment of tool health compared to single-sensor systems. Furthermore, multi-domain feature extraction approaches that include time-domain,

frequency-domain, and time-frequency-domain analysis have proven effective in capturing both steady-state and dynamic tool wear behaviors.

Despite these advancements, existing systems still have certain limitations. Many approaches rely heavily on labeled datasets, which are often difficult and costly to obtain in real manufacturing environments. Some models also involve high computational complexity, making them unsuitable for edge or IoT-based real-time applications. In addition, a lack of interpretability and user-friendly interfaces limits their practical usability on the shop floor.

To address these challenges, the proposed work introduces a multi-domain signal processing and machine learning framework integrated with a node-based visual interface. This system facilitates efficient feature extraction, accurate tool condition classification, and intuitive pipeline design without requiring programming expertise, thereby making it more suitable for real-world industrial predictive maintenance applications.

### **3.PROPOSED SYSTEM**

#### **3.1 Existing System**

Existing tool condition monitoring and tool wear prediction systems in CNC machining mainly rely on traditional maintenance practices, sensor-based monitoring methods, and data-driven machine learning approaches. In many industries, tool condition is still assessed through manual inspection by skilled operators or by replacing tools after fixed machining intervals. Although these methods are simple to implement, they are inefficient, subjective, and unable to provide real-time information about the actual health condition of the cutting tool.

With the advancement of Industry 4.0 technologies, several automated monitoring systems have been introduced using sensors such as vibration, acoustic emission, motor current, temperature, and cutting force sensors. These systems collect machining data and apply signal processing techniques to identify patterns related to tool wear, chatter, spindle faults, and machining abnormalities. Time-domain and frequency-domain analysis methods, such as statistical analysis and Fast Fourier Transform (FFT), are commonly used for feature extraction.

Recent studies have also applied machine learning and deep learning models for tool wear prediction and classification. Algorithms such as Support Vector Machine (SVM), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Random Forest, and Long Short-Term Memory (LSTM) networks have shown promising results in predicting tool condition. These systems can improve maintenance planning, reduce downtime, and increase production efficiency.

However, existing systems still face several practical limitations. Many approaches require large volumes of labeled training data, which are difficult and expensive to obtain in real manufacturing environments. Deep learning models often require high computational resources and specialized hardware, making them unsuitable for low-cost IoT or edge devices. Some methods depend on expensive sensors such as acoustic emission sensors and dynamometers, which are not affordable for small and medium industries. In addition, many

existing solutions provide limited interpretability and lack user-friendly interfaces, making them difficult for shop-floor operators to use effectively.

Therefore, although current systems have improved tool condition monitoring, there remains a need for a cost-effective, accurate, scalable, and easy-to-use solution that can operate with standard sensors and simplified deployment in industrial environments.

### **3.2 Proposed Method**

The proposed system presents a smart and efficient approach for monitoring CNC cutting tool condition through the integration of signal processing methods and machine learning algorithms. It is developed to address the drawbacks of traditional maintenance practices by offering timely prediction of tool wear, improved machining reliability, and simplified operation for industrial users.

The system utilizes sensor data obtained from standard industrial sources such as vibration, motor current, temperature, and cutting force measurements. These signals contain valuable information related to tool health, machining stability, and performance changes during operation. By using commonly available sensors, the proposed framework reduces implementation cost and increases suitability for practical manufacturing environments.

The first stage of the framework focuses on preprocessing the collected sensor signals. Raw data are examined for missing values, abnormal readings, and inconsistencies. Signal noise is minimized using filtering methods such as Mean, Median, Gaussian, Wiener, Wavelet, and Kalman filters. After cleaning, normalization techniques including Min-Max scaling, Z-Score standardization, and L2 normalization are applied to produce consistent input data for further analysis.

The second stage performs feature extraction from multiple signal domains in order to capture complete information about tool wear progression. Time-domain analysis provides statistical indicators such as mean, standard deviation, variance, skewness, kurtosis, and root mean square values. Frequency-domain features are obtained through Fast Fourier Transform (FFT), while time-frequency characteristics are derived using wavelet-based methods such as MODWT and Continuous Wavelet Transform (CWT). In total, 49 relevant features are generated for classification.

The processed features are then supplied to several machine learning models, including Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, and Artificial Neural Network (ANN). These models are trained to classify tool condition into operational states such as healthy or worn. Comparative analysis is carried out to identify the best-performing model for prediction accuracy and reliability.

An important component of the proposed system is the graphical node-based user interface built with React and ReactFlow. This interface allows users to design complete analysis workflows using drag-and-drop nodes instead of coding. Manual Mode provides full control for experienced users, while Auto Mode automatically creates optimized workflows for beginners.

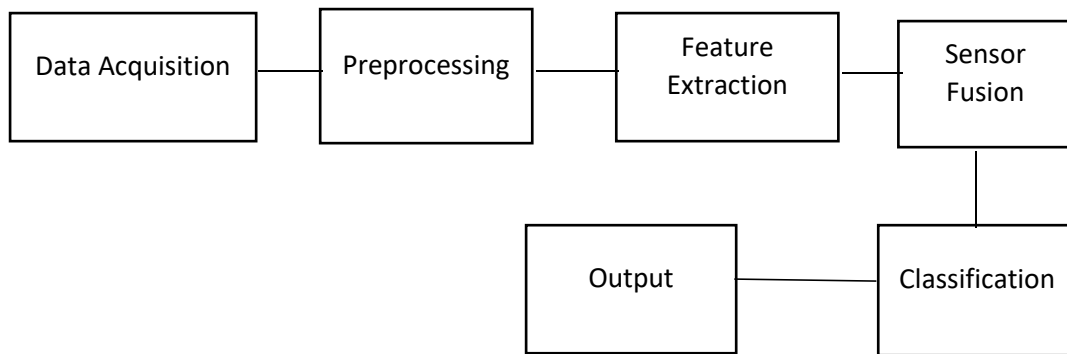
The framework is evaluated using the PHM 2010 benchmark dataset and demonstrates strong predictive capability. Overall, the proposed system provides a practical, low-cost, scalable,

and interpretable solution for predictive maintenance in modern smart manufacturing industries. Its modular architecture also supports future enhancement for real-time monitoring, edge deployment, and cloud connectivity.

Features	Existing System	Proposed System
Monitoring	Manual inspection or periodic checking by operators	Continuous sensor-based real-time monitoring
Prediction	Failure identified after wear or breakdown occurs	Early tool wear prediction using machine learning
Alerts	Limited or no automatic warning system	Automatic alerts for worn tool condition
Accuracy	Depends on operator experience and fixed schedules	High prediction accuracy using multi-domain features
Automation	Low automation, human dependent process	High automation with smart pipeline execution

### 3.3 System Architecture

The proposed system architecture is organized as a modular processing pipeline consisting of five sequential stages. Each stage performs a dedicated function and transfers its processed output to the next stage. The final outcome of the framework is the prediction of CNC cutting tool condition, enabling timely maintenance decisions and improved machining reliability.



**Fig. Overall System Architecture**

#### Stage 1: Data Acquisition

The first stage is responsible for collecting raw input data from different sources. Sensor data are imported through CSV or Excel files generated from CNC machining operations. The framework supports signals obtained from vibration sensors, motor current sensors, temperature sensors, and cutting force sensors. During this stage, the system verifies the file format, identifies available columns, and presents a preview of the dataset to ensure correct data loading.

#### Stage 2: Preprocessing

The second stage focuses on improving data quality before analysis. Industrial sensor signals may contain noise, incomplete values, or inconsistent measurements. Therefore, preprocessing is carried out through three main operations. Data cleaning is performed to manage missing values using methods such as zero replacement, neighboring mean estimation, or neural network-based imputation. Noise reduction is achieved using filters such as Mean, Median, Gaussian, Wiener, Wavelet, and Kalman filters. Finally, normalization methods including Min-Max scaling, Z-Score standardization, and L2 normalization are applied to bring all features into a comparable numerical range.

#### Stage 3: Feature Extraction

In this stage, the processed sensor signals are transformed into informative numerical descriptors suitable for machine learning models. Feature extraction is conducted across multiple signal domains to capture comprehensive wear characteristics.

- **Time-Domain Features:** Statistical measures such as mean, variance, RMS, skewness, kurtosis, crest factor, and impulse factor.
- **Frequency-Domain Features:** Spectral characteristics derived from Fast Fourier Transform (FFT), including spectral energy and spectral centroid.
- **Time-Frequency Features:** Advanced descriptors generated from wavelet coefficients, Continuous Wavelet Transform (CWT), Hilbert Transform, and scalogram representations.

A total of 49 features are generated from all domains.

#### Stage 4: Sensor Fusion

Features extracted from individual sensors are merged into a single unified feature vector through feature-level concatenation. This fusion strategy combines information from multiple sensing sources and provides a more complete representation of tool condition than any single sensor alone.

#### Stage 5: Machine Learning Classification

The fused feature vector is supplied to machine learning algorithms for tool condition classification. The implemented models include Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, and Artificial Neural Network (ANN). Based on the learned patterns, the system predicts whether the tool condition is **Good** (acceptable wear state) or **Worn** (replacement required).

#### Visual Workflow Interface

The complete pipeline is integrated into a node-based graphical user interface. Users can drag and drop nodes representing each processing stage, connect them visually to create customized workflows, and execute the entire pipeline with minimal effort. This design improves accessibility for both technical users and shop-floor operators without requiring programming knowledge.

## 4. METHODOLOGY

The proposed methodology for CNC machine tool wear prediction is developed as a structured pipeline that integrates data acquisition, signal preprocessing, feature extraction, sensor fusion, and machine learning classification. The objective of this methodology is to

provide an accurate, efficient, and user-friendly solution for predictive maintenance in CNC machining environments.

#### Step 1: Data Acquisition

The first step involves collecting raw sensor data from CNC machining operations. The system accepts input data from vibration, motor current, temperature, and cutting force sensors. Historical datasets stored in CSV or Excel format are used for training, testing, and validation. In this study, the PHM 2010 high-speed milling dataset is used as the benchmark dataset.

#### Step 2: Data Preprocessing

Raw industrial sensor data may contain noise, missing values, and inconsistent measurements. Therefore, preprocessing is performed to improve data quality before analysis. Missing values are handled using suitable imputation methods. Noise reduction is carried out using Mean, Median, Gaussian, Wiener, Wavelet, and Kalman filters. After denoising, normalization methods such as Min-Max scaling, Z-Score normalization, and L2 normalization are applied to standardize the data.

#### Step 3: Multi-Domain Feature Extraction

After preprocessing, informative numerical features are extracted from the sensor signals. Feature extraction is performed across three signal domains:

- **Time Domain:** Mean, variance, standard deviation, RMS, skewness, kurtosis, crest factor, impulse factor, and related statistical measures.
- **Frequency Domain:** Spectral features obtained using Fast Fourier Transform (FFT), such as spectral energy and frequency centroid.
- **Time-Frequency Domain:** Features derived from MODWT, Continuous Wavelet Transform (CWT), Hilbert Transform, Scalogram, and Wavelet Packet methods.

A total of 49 features are generated to represent tool condition comprehensively.

#### Step 4: Sensor Fusion

Features extracted from multiple sensors are combined into a single feature vector through feature-level fusion. This process integrates complementary information from vibration, current, temperature, and force sensors, resulting in improved prediction capability compared to individual sensor analysis.

#### Step 5: Machine Learning Classification

The fused feature set is used to train and evaluate multiple machine learning models, including:

- Logistic Regression
- Support Vector Machine (SVM)
- Random Forest
- XGBoost
- Artificial Neural Network (ANN)

These models classify the tool state into two categories: **Good** and **Worn**.

#### Step 6: Performance Evaluation

The developed models are evaluated using the PHM 2010 dataset through cross-validation techniques. Performance is measured using standard metrics such as accuracy, precision, recall, and F1-score. Comparative analysis is performed to identify the best-performing classifier.

#### Step 7: User Interface Integration

A node-based graphical interface developed using React and ReactFlow is integrated into the system. Users can visually construct processing pipelines through drag-and-drop nodes. Manual Mode allows full customization, while Auto Mode generates optimized workflows automatically.

The proposed methodology provides an interpretable, scalable, and cost-effective framework for CNC tool wear monitoring and predictive maintenance, suitable for Industry 4.0 manufacturing applications.

### **5.PROCEDURE**

The procedure adopted for the proposed CNC tool wear prediction system consists of a series of systematic steps starting from data collection and ending with prediction of tool condition. Each step is designed to ensure reliable analysis and accurate classification.

#### Step 1: Data Collection

Sensor data are collected from CNC machining operations using vibration, motor current, temperature, and cutting force sensors. The system also accepts historical datasets stored in CSV or Excel file formats. In this study, the PHM 2010 dataset is used for experimentation and validation.

#### Step 2: Data Loading and Inspection

The selected dataset is loaded into the system. File format, column names, and data structure are verified. A preview of the dataset is displayed to confirm successful data import and identify any missing or inconsistent values.

#### Step 3: Data Preprocessing

The raw sensor signals are cleaned to improve quality. Missing values are handled using suitable replacement techniques. Noise present in the signals is reduced using filters such as Mean, Median, Gaussian, Wiener, Wavelet, and Kalman filters. After filtering, normalization methods such as Min-Max, Z-Score, or L2 normalization are applied.

#### Step 4: Feature Extraction

Relevant features are extracted from the processed signals to represent tool condition. Features are generated from:

- **Time Domain:** Mean, variance, RMS, skewness, kurtosis, and related measures
- **Frequency Domain:** FFT coefficients, spectral energy, spectral centroid
- **Time-Frequency Domain:** Wavelet coefficients, CWT features, Hilbert features, scalogram descriptors

A total of 49 features are extracted.

#### Step 5: Feature Fusion

The extracted features from different sensors are combined into a single feature vector. This fusion process integrates multiple sources of information and improves the overall prediction capability of the system.

#### Step 6: Model Training and Testing

The fused dataset is divided into training and testing sets. Machine learning algorithms such as Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, and Artificial Neural Network (ANN) are trained using the training data and tested using unseen data.

#### Step 7: Tool Condition Prediction

The trained model predicts the condition of the cutting tool into two categories:

- **Good** – Tool is in acceptable working condition
- **Worn** – Tool requires replacement or maintenance

#### Step 8: Performance Evaluation

The prediction results are evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Comparative analysis is performed to determine the best-performing model.

#### Step 9: User Interface Execution

The complete procedure is implemented through a node-based graphical user interface. Users can drag and drop nodes representing each stage, connect them, and run the pipeline easily through Manual Mode or Auto Mode.

The procedure provides an efficient workflow for intelligent CNC tool monitoring, enabling early wear detection, reduced downtime, and improved machining productivity.

## **6.SYSTEM DESIGN**

The proposed system is designed as an integrated and modular framework for CNC tool wear monitoring and prediction. The design combines signal processing techniques, machine learning models, and a graphical user interface to provide an efficient and practical predictive maintenance solution. Each module of the system performs a specific function and communicates with other modules in a sequential workflow.

### 1. Input Module

The input module is responsible for receiving raw data from different sources. The system accepts sensor readings collected from vibration, motor current, temperature, and cutting force sensors installed on CNC machines. In addition, historical datasets stored in CSV and Excel formats can be uploaded for offline analysis, training, and testing.

### 2. Data Management Module

This module manages imported datasets and organizes them for processing. It verifies file structure, detects available columns, handles missing records, and stores the processed data in a structured format. Data preview and validation functions are also included to ensure input correctness.

### 3. Preprocessing Module

The preprocessing module improves the quality of raw sensor signals before feature generation. It performs data cleaning, missing value handling, and noise suppression. Different filtering methods such as Mean, Median, Gaussian, Wiener, Wavelet, and Kalman filters are incorporated. The module also applies normalization techniques including Min-Max scaling, Z-Score normalization, and L2 normalization to standardize numerical values.

### 4. Feature Extraction Module

This module converts processed signals into informative numerical descriptors. Features are extracted from multiple domains to capture different characteristics of tool wear.

- **Time Domain:** Mean, variance, RMS, skewness, kurtosis, crest factor, and impulse factor.
- **Frequency Domain:** Spectral energy, dominant frequency, spectral centroid, and FFT-based descriptors.
- **Time-Frequency Domain:** Wavelet coefficients, Continuous Wavelet Transform (CWT), MODWT, Hilbert Transform, and scalogram features.

A total of 49 features are generated and forwarded to the prediction engine.

### 5. Sensor Fusion Module

The sensor fusion module combines features extracted from different sensors into a single feature vector. This integrated representation improves prediction reliability by utilizing complementary information from multiple sensing sources.

### 6. Prediction Module

The prediction module contains machine learning algorithms used for tool condition classification. Implemented models include Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, and Artificial Neural Network (ANN). The output is generated as binary classes such as **Good** or **Worn**.

### 7. User Interface Module

A node-based graphical user interface is designed using React and ReactFlow. This module allows users to visually construct analysis pipelines by connecting blocks representing preprocessing, feature extraction, and classification stages.

- **Manual Mode:** Allows complete customization of workflow steps.
- **Auto Mode:** Automatically creates an optimized workflow for quick execution.

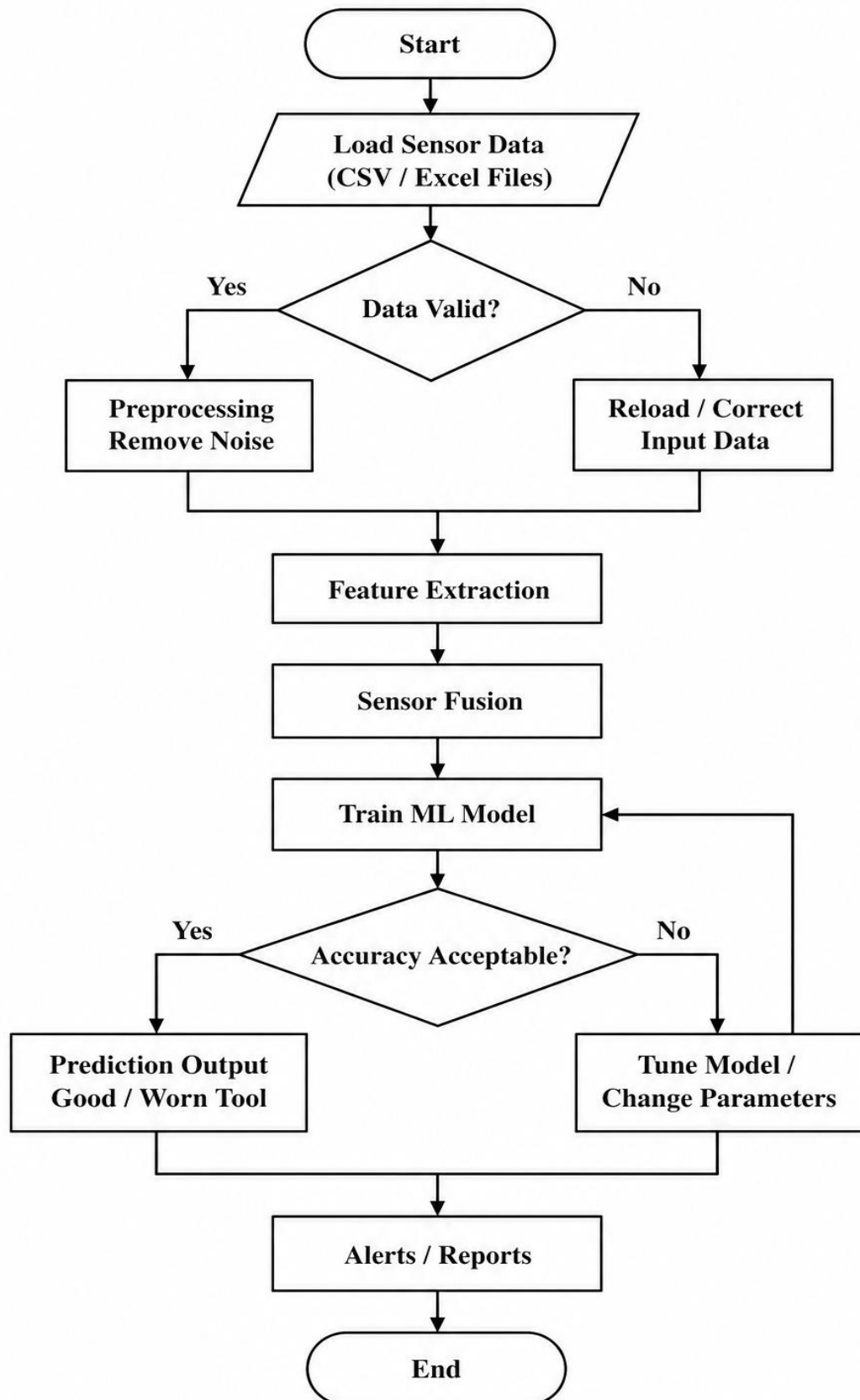
### 8. Output Module

The output module displays final prediction results and analytical insights. It presents tool condition status, classification metrics, feature importance rankings, and maintenance alerts. Results can also be exported for reporting and future reference.

### Design Advantages

The system design is modular, scalable, and easy to maintain. Each component can be upgraded independently without affecting the entire framework. The design supports future enhancements such as real-time monitoring, cloud connectivity, and edge deployment, making it suitable for Industry 4.0 manufacturing applications.

BLOCK DIAGRAM



## 6.1 Hardware components

The proposed system was developed and evaluated using a standard computing environment suitable for machine learning experimentation and application development. Since the framework primarily focuses on dataset-based tool wear prediction, no dedicated industrial hardware setup was required during model training and validation. A personal computer or workstation with moderate specifications is sufficient for executing the proposed pipeline.

The computing system includes a multi-core processor for data processing and model training, adequate RAM for handling sensor datasets, and storage devices for maintaining project files, datasets, and trained models. A standard display unit is used for visualization of results and interaction with the graphical user interface. The hardware environment is scalable and can be extended for future deployment on industrial computers or edge devices.

<b>Component</b>	<b>Specification</b>
Processor	Intel Core i5 / AMD Ryzen 5 or above
RAM	8 GB or higher
Storage	256 GB SSD or higher
Display	Standard HD Monitor
Operating System	Support Windows / Linux

## **6.2 Software Tools**

Several software tools and libraries were used to design, implement, and evaluate the proposed framework. Python was used as the primary programming language because of its extensive support for data analysis, signal processing, and machine learning. React and ReactFlow were used to develop the node-based visual interface for workflow construction.

Popular scientific and machine learning libraries were utilized for preprocessing, feature extraction, model development, and performance evaluation. These tools improved development speed, reproducibility, and system flexibility.

<b>Software Tool</b>	<b>Purpose</b>
Python	Core programming and model development
NumPy	Numerical computation
Pandas	Dataset handling and preprocessing
SciPy	Signal processing operations
Scikit-learn	Machine learning models
XGBoost	Gradient boosting classifier

<b>Software Tool</b>	<b>Purpose</b>
TensorFlow / Keras	Neural network implementation
React	Frontend user interface
ReactFlow	Node-based workflow design
Matplotlib / Seaborn	Data visualization

### 6.3 AI Models Used

The proposed system employs multiple machine learning and artificial intelligence models for tool condition classification. Different algorithms were selected to compare predictive performance and identify the most suitable model for CNC tool wear monitoring.

- **Logistic Regression** was used as a baseline linear classifier for binary prediction.
- **Support Vector Machine (SVM)** was employed for its ability to classify high-dimensional feature spaces effectively.
- **Random Forest** was used because of its robustness, interpretability, and strong performance on structured datasets.
- **XGBoost** was included as an advanced ensemble boosting method capable of high predictive accuracy.
- **Artificial Neural Network (ANN)** was applied to capture nonlinear relationships among extracted features.

These models classify the cutting tool into two conditions: **Good** and **Worn**. Comparative analysis based on accuracy, precision, recall, and F1-score was carried out to determine the best-performing model. Experimental results indicated that the Random Forest classifier achieved superior overall performance.

<b>AI Model</b>	<b>Role in System</b>
Logistic Regression	Baseline binary classifier
Support Vector Machine	Margin-based classification
Random Forest	Ensemble decision-tree classifier
XGBoost	Boosting-based high-accuracy model
Artificial Neural Network	Nonlinear pattern learning

### 6.4 SYSTEM WORKFLOW

The workflow of the proposed CNC tool wear prediction system is organized as a sequence of interconnected stages that transform raw sensor data into accurate tool condition predictions. Each stage performs a specific task, ensuring reliable processing, efficient analysis, and meaningful output for predictive maintenance applications.

The process begins with data acquisition, where sensor signals or historical machining datasets are collected from sources such as vibration, motor current, temperature, and cutting force measurements. The imported data are verified and prepared for further analysis.

In the second stage, preprocessing is performed to improve data quality. Missing values are handled using suitable replacement methods, while unwanted noise is reduced through filtering techniques such as Mean, Median, Gaussian, Wiener, Wavelet, and Kalman filters. Normalization methods including Min-Max scaling, Z-Score standardization, and L2 normalization are then applied to standardize feature values.

After preprocessing, the cleaned signals enter the feature extraction stage. Here, relevant characteristics are obtained from multiple domains. Time-domain features represent statistical behavior of signals, frequency-domain features capture spectral information using Fast Fourier Transform (FFT), and time-frequency features are generated through wavelet-based techniques to identify transient wear patterns.

The extracted features from multiple sensors are then combined through feature-level sensor fusion. This step creates a unified feature vector containing comprehensive information about tool condition, thereby improving prediction capability.

Next, the fused feature set is supplied to machine learning models such as Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, and Artificial Neural Network (ANN). These models classify the cutting tool state into categories such as healthy or worn.

Finally, the prediction results are displayed through the graphical user interface. The system provides tool condition status, performance metrics, alerts, and workflow visualization. Users can also modify or create custom pipelines using the node-based drag-and-drop interface.

## **7.IMPLEMENTATION**

The implementation of the proposed CNC tool wear prediction system was carried out through the integration of data processing modules, machine learning models, and a graphical user interface. The framework was developed to provide an efficient and user-friendly environment for analyzing sensor data and predicting tool condition.

### **Development Environment**

The system was implemented using Python as the core programming language due to its extensive support for machine learning, numerical computation, and signal processing. Frontend development was carried out using React and ReactFlow to create an interactive node-based interface for workflow construction. Supporting libraries such as NumPy, Pandas, SciPy, Scikit-learn, XGBoost, TensorFlow, and Matplotlib were used for data handling, model development, and visualization.

### **Data Input Module**

The implementation begins with a data input module that allows users to upload machining datasets in CSV or Excel format. The module reads the selected file, validates the structure, and displays column information with a preview of records. This ensures that the imported data are correctly formatted before processing.

#### Preprocessing Module

A dedicated preprocessing module was implemented to improve raw data quality. Missing values are handled using replacement strategies such as zero filling, neighboring mean estimation, or interpolation methods. Noise present in the sensor signals is reduced through filtering techniques including Mean, Median, Gaussian, Wiener, Wavelet, and Kalman filters. After filtering, normalization methods such as Min-Max scaling, Z-Score standardization, and L2 normalization are applied.

#### Feature Extraction Module

The cleaned sensor signals are passed to the feature extraction module. This module computes a set of informative descriptors from multiple signal domains. Time-domain statistical features, frequency-domain spectral features using Fast Fourier Transform (FFT), and time-frequency features using wavelet-based transforms are extracted. A total of 49 features are generated for each sample and stored for classification.

#### Sensor Fusion Module

Features extracted from different sensors are combined through feature-level fusion. The implementation uses concatenation of feature vectors obtained from vibration, current, temperature, and cutting force signals. This fused representation improves the ability of the classifier to detect wear-related patterns.

#### Machine Learning Module

The classification module includes Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, and Artificial Neural Network (ANN). Each model was trained using labeled tool condition data and evaluated on unseen samples. Hyperparameter tuning and comparative testing were performed to identify the most effective model.

#### User Interface Module

A node-based graphical interface was implemented to simplify workflow creation. Users can drag and connect nodes representing stages such as data loading, preprocessing, feature extraction, and classification. Manual Mode enables full customization of the pipeline, while Auto Mode automatically configures a recommended workflow for quick execution.

#### Output Module

The final implementation displays tool condition predictions as **Good** or **Worn**. In addition, the system presents performance metrics such as accuracy, precision, recall, F1-score, confusion matrix, and feature importance analysis. Results can be visualized through charts and exported for reporting purposes.

#### Implementation Outcome

The completed system successfully integrates data analytics, machine learning, and user interaction into a single platform. The modular implementation ensures easy maintenance, scalability, and future extension toward real-time deployment, cloud integration, and edge-based predictive maintenance applications.

## 8.RESULTS AND DISCUSSION

The proposed CNC tool wear prediction framework was evaluated using the PHM 2010 high-speed milling dataset. Multiple machine learning models were trained and tested using extracted multi-domain features obtained from vibration, current, temperature, and cutting force signals. Performance was measured using accuracy, precision, recall, and F1-score.

Among the implemented models, the Random Forest classifier achieved the best overall performance with an accuracy of **94.8%**. The model demonstrated strong generalization ability and consistent classification of healthy and worn tool conditions. XGBoost also produced competitive results, while Support Vector Machine and Artificial Neural Network achieved satisfactory performance under tuned conditions. Logistic Regression served as a baseline classifier with comparatively lower accuracy.

The results indicate that combining features from time-domain, frequency-domain, and time-frequency-domain analyses significantly improves prediction performance compared with single-domain feature sets. Sensor fusion further enhanced classification accuracy by integrating complementary information from multiple sensor sources. Feature importance analysis revealed that wavelet-based energy descriptors, RMS values, kurtosis, and spectral energy were among the most influential parameters.

The findings confirm that the proposed framework is suitable for predictive maintenance applications where early identification of tool wear is essential for reducing downtime and maintaining machining quality.

### **Advantages**

The proposed system offers several practical and technical advantages:

1. Provides early detection of tool wear before catastrophic failure occurs.
2. Improves machining quality and dimensional accuracy.
3. Reduces unplanned machine downtime and maintenance cost.
4. Uses standard industrial sensor data without expensive specialized equipment.
5. Integrates multi-domain feature extraction for improved prediction accuracy.
6. Supports multiple machine learning models for comparative analysis.
7. Includes a node-based graphical interface for non-programming users.
8. Scalable architecture suitable for future Industry 4.0 environments.

### **Limitations**

Despite its strong performance, the present study has certain limitations:

1. Validation was conducted mainly using benchmark datasets rather than continuous live industrial data.
2. The current framework focuses on binary classification (Good/Worn) instead of multiple wear severity levels.
3. Real-time deployment on edge devices was not implemented.
4. Model performance may vary under different machining parameters or unseen tool materials.
5. Additional calibration may be required before direct industrial adoption.

## **Future Scope**

The proposed framework can be extended in several directions:

1. Integration with live CNC machines for real-time monitoring.
2. Deployment on IoT edge devices for low-latency prediction.
3. Cloud-based dashboards for centralized industrial monitoring.
4. Multi-class wear level classification and Remaining Useful Life (RUL) estimation.
5. Deep learning models for automated feature learning.
6. Adaptive learning systems capable of handling changing machining conditions.
7. Integration with robotic and autonomous manufacturing systems.

## **9.CONCLUSION**

This study presented an intelligent and efficient framework for CNC machine tool wear prediction using multi-domain signal processing and machine learning techniques. The system combines preprocessing, feature extraction, sensor fusion, and classification into a unified workflow supported by a node-based visual interface. Experimental evaluation using the PHM 2010 dataset demonstrated strong predictive performance, with the Random Forest model achieving the highest accuracy of 94.8%.

The obtained results confirm that multi-sensor data and hybrid feature extraction significantly improve tool condition monitoring performance. The proposed system provides a practical, cost-effective, and interpretable solution for predictive maintenance in modern manufacturing environments. With further development toward real-time deployment and cloud integration, the framework has strong potential for future smart factory applications.

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