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Combining Sensor Fusion and a Machine Learning Framework for Accurate Tool Wear Prediction During Machining

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Abstract: Effective cutting tool condition monitoring (TCM) is critical for achieving precision, cost efficiency, and minimizing unplanned downtime. This study proposes a sophisticated sensor fusion framework for accurate tool fault prediction during machining. Experimental data were collected while turning AISI 410-grade steel bars with uncoated carbide inserts under dry-cutting conditions. Force and vibration signals were captured across five tool health states (one healthy and four faulty) using a sensor network and data acquisition systems. The raw signals were decomposed using discrete wavelet transform, and key statistical features were extracted. Three distinct input datasets are constructed: Dataset I comprises statistical parameters extracted exclusively from the force signals, Dataset II consists of statistical parameters derived from the vibration signals, and Dataset III integrates the individual statistical parameters from both force and vibration signals through feature-level fusion. These datasets are then utilized for training ML classifiers (Support Vector Machine, Random Forest, and Naive Bayes) to perform feature learning and subsequent classification. Among the considered classifiers, the RF classifier yielded better classification accuracies of 96% and 97% while discriminating among the tool health scenarios through dataset I and II. Also, the RF and SVM classifiers achieved a classification accuracy of 98% and 88% in distinguishing tool health scenarios for dataset III. This method demonstrates exceptional suitability for real-time, in situ fault diagnostics and provides a strong foundation for developing online TCM systems, advancing the objectives of Industry 4.0 and smart manufacturing.

Keywords: CNC cutting tool; condition monitoring; sensor fusion; machine learning

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1. Background and Motivation

Industry 4.0 signifies integrating cyber-physical systems, advanced digital technologies, and data analytics into modern manufacturing, forming the foundation for next-generation paradigms such as Society 5.0 and Industry 5.0 [1]. Society 5.0 envisions a human-centered societal model leveraging technology to address environmental and social challenges. In contrast, Industry 5.0 extends beyond the technology-centric approach of Industry 4.0, fostering a sustainable, human-centric ecosystem within the industrial landscape [2]. The technological advancements of Industry 4.0 have enabled real-time data acquisition and analysis through sensors embedded in machine tools. These systems uncover actionable patterns and trends by employing artificial intelligence (AI) and advanced analytics, enhancing operational efficiency [3]. Among these innovations, CNC

machines are indispensable and renowned for their versatility in manufacturing complex components with exceptional precision and finish. These machines are pivotal in metal-cutting operations and central to modern manufacturing systems. According to a 2023 report by Fortune Business Insights, the global CNC machine market, valued at USD 71.88 billion in 2022, is projected to grow at a compound annual growth rate (CAGR) of 5.0%, reaching USD 105.7 billion by 2030 [4]. Tool wear, a critical issue in CNC machining, is the progressive degradation of cutting tools due to mechanical, thermal, and chemical interactions. It directly impacts tool life, machining quality, and production costs, accounting for approximately 20% of total production downtime [5,6]. Tool wear manifests in flank wear, crater wear, and notch wear, influenced by cutting speed, feed rate, material hardness, and lubrication conditions. Continuous machining exacerbates wear, leading to suboptimal surface finishes and necessitating timely tool replacement. Accurate tool wear estimation is crucial for proactive maintenance, minimizing downtime and reducing associated costs [7]. Many industries adopt advanced preventive maintenance strategies to mitigate the effects of tool wear. These include sensor-based detection models capable of identifying anomalous behavior in machine tools. Such methodologies enhance system reliability, reduce production lifecycle costs, and align with the overarching objectives of sustainable, intelligent manufacturing under Industry 4.0 and Industry 5.0 frameworks.

Machine Tool Condition Monitoring (TCM) employs external sensory data to detect faults, delivering critical benefits such as optimized maintenance scheduling, mitigation of catastrophic failures, and enhanced operational availability. TCM methodologies commonly leverage parameters like vibration, acoustics, temperature, and force to estimate tool wear and system health [8,9]. Data-driven fault detection methods harness statistical and nonstatistical algorithms to analyze complex, nonlinear data, uncovering latent patterns and trends that are challenging to discern through conventional methods. These approaches are particularly effective for systems where developing first-principles models is infeasible. Researchers have applied techniques such as vibration analysis, acoustic analysis, lubrication oil analysis, force analysis, and thermography to identify tool wear defects in machine tools [6,10]. Furthermore, the integration of multi-sensor signals offers multidimensional and comprehensive perspectives on the cutting status [11]. Sensor fusion emerges as a superior approach for achieving heightened accuracy and robustness, employing sophisticated algorithms and methodologies to effectively amalgamate data from diverse sensors. Within the framework of data fusion, multi-sensory inputs are concatenated into a unified representation, preserving the integrity of the original information. This is typically achieved by structuring each sensor's data as a distinct row in a matrix, contingent upon the uniformity of dimensionality across all sensors [12,13]. Alternatively, feature fusion synthesizes data representations rather than raw input, leveraging features that may be handcrafted, statistically derived, or extracted as latent representations through advanced machine learning models. Integrating multiple diagnostic modalities, such as vibration, thermal, and acoustic analyses, has been proposed to achieve superior fault detection capabilities with unprecedented precision [14,15]. Zhang et al. [16] proposed a sophisticated tool wear monitoring system for a milling cutter by embedding tri-axial cutting force, tri-axial vibration, and torque signal information, achieving a prediction accuracy of 97.5%. Zhang et al. [17] introduced an intelligent tool wear monitoring methodology leveraging multi-channel hybrid information and deep transfer learning, which demonstrated superior predictive performance compared to single-sensor approaches, enabling robust and effective tool wear monitoring for milling machines. Wang et al. [11] integrated accelerometer, acoustic emission, and dynamometer signal information to facilitate tool wear condition monitoring in a vertical milling machine, attaining a remarkable accuracy of 99.9%. Furthermore, Peng et al. [18] implemented a multi-sensor information fusion

framework, combining vibration and force signal data to predict tool wear values with an accuracy of 96.1%. Despite these advancements, raw sensor signals are often susceptible to background noise, complicating the extraction of defect-sensitive information. Developing robust methodologies to denoise and extract meaningful insights from raw data remains a critical challenge in advancing the reliability and efficacy of TCM systems.

Signal processing plays a pivotal role in analyzing, modifying, and synthesizing various forms of signals, using techniques like discrete Fourier transforms, fast Fourier transforms, filtering, and quantization. Despite its versatility, signal processing faces notable challenges such as noise interference, real-time operational constraints, and data compression [19]. The synergistic combination of AI and machine learning (ML) offers an intelligent and efficient framework for fault analysis and CNC machine tool lifespan prediction through data-driven simulation approaches. Advanced research has demonstrated the efficacy of signal processing in online tool wear monitoring. Techniques such as self-organizing maps with neural networks and supervised learning models (including multi-layer perceptron and artificial neural networks) have been deployed to detect tool wear and enable adaptive control systems for early fault detection [20]. These methods effectively analyze impulse responses to capture dynamic properties. Furthermore, an empirical-numerical hybrid approach employing a short-time Fourier transform has achieved remarkable accuracy, with a classification performance of 92.6% when integrated with the Random Forest algorithm [21]. The Discrete Wavelet Transform (DWT) facilitates the multiresolution analysis of time-domain signals by decomposing them into coarse approximations and fine details across distinct frequency bands. This is achieved by applying scaling and wavelet functions corresponding to low-pass and high-pass filters, respectively, enabling progressive signal decomposition via successive filtering [22]. Extensive research on DWT has underscored its utility in fault detection and diagnosis, particularly in identifying and classifying rolling bearing anomalies and fault diagnosis in industrial gearboxes [23,24]. The integration of DWT with advanced ML algorithms has significantly advanced the development of intelligent tool condition monitoring systems, enhancing operational reliability and performance in complex industrial applications [25]. Random Forest (RF) is a robust supervised ML algorithm widely employed for classification and regression tasks. By constructing multiple decision trees on distinct subsets of training data and aggregating their predictions via majority voting, RF achieves high reliability and accuracy. Its ensemble-based structure excels in handling large, high-dimensional datasets and evaluates splits by measuring impurity reduction (e.g., Gini impurity or entropy), weighted by the number of samples reaching each node [26,27]. On the other hand, Support Vector Machine (SVM) is a hyperplane-based supervised learning algorithm effective for classification and regression. It identifies the optimal hyperplane that maximizes the margin between data classes, ensuring robust separation. While computationally demanding with memory usage influenced by kernel size, SVM leverages kernel functions—such as linear, polynomial, radial basis function, and sigmoid—to map input features into higher-dimensional spaces, enabling the resolution of nonlinear decision boundaries [28]. Naive Bayes is a probabilistic classifier that assumes conditional independence among features. Despite its simplicity, it is extensively utilized in diverse applications, including fault diagnosis in condition monitoring systems. By applying Bayes' theorem, Naive Bayes computes posterior probabilities for each class given the input features, offering efficient and interpretable classification. Schueller and Saldana [29] utilized sound signal data, extracting key features and applying them to various ML classifiers, achieving a mean accuracy of 92.6% through RF classifier. Patange et al. [30] extracted a range of statistical features from vibration signals, and subsequently, employed these features in various ML-based classification models, achieving the highest classification accuracy of 92.6% in

effectively discriminating between different tool conditions. Integrating sensor data with novelty detection algorithms and learning vector quantization neural networks has proven highly effective, enhancing system reliability and reducing monitoring systems' design complexity. Additionally, novel approaches involving abscissa stretching and compressing have been developed to model and predict tool wear with greater precision [31].

ML algorithms are trained using input data to construct models that perform specific tasks. In the manufacturing industry, ML techniques are increasingly employed to analyze and interpret substantial production data volumes, resulting in process optimization and enhanced overall efficiency [32,33]. By harnessing these methods, manufacturers can elevate productivity, quality, and operational efficiency while addressing complex challenges through data-driven solutions. Recent advancements in ML have demonstrated significant promise in tool wear detection. Image-based methods utilizing pixel data have proven particularly effective, with certain models achieving an impressive accuracy rate of 97% in specific studies [34,35]. These techniques enable early detection of potential catastrophic tool failures, facilitating timely interventions. However, a comprehensive review of existing literature reveals a few research gaps. Although studies on tool life prediction using individual 1D signals have been conducted, the synergistic integration of multi-sensor data (whether at the data fusion or feature fusion level) remains insufficiently investigated. While tool wear prediction based on single-sensor data has received considerable attention, the efficacy of combining multi-sensor data with data-driven methodologies warrants further exploration. Research in ML has exhibited remarkable efficacy in leveraging advanced methodologies for machining hard materials, thereby mitigating the risk of catastrophic tool failures and ensuring superior quality assurance by rectifying manufacturing defects [36]. Simultaneously, to address the inherent complexities in constructing real-time predictive models, contemporary advancements focus on developing sensor-driven ML frameworks. These models deliver a synergistic combination of high predictive accuracy and operational simplicity, aligning seamlessly with the stringent requirements of modern industrial manufacturing processes [37].

This study seeks to bridge these research gaps by integrating multi-sensor data with state-of-the-art machine learning algorithms for enhanced fault detection in cutting tools during turning operations. Experimental data were acquired during turning AISI 410-grade steel bars using uncoated carbide inserts under dry-cutting conditions. The data acquisition system, equipped with a network of force and vibration sensors, captured signals across five distinct tool health states, comprising one healthy and four faulty scenarios. The raw force and vibration signals were individually processed through DWT to extract salient statistical features. Subsequently, a feature-level fusion methodology was employed to consolidate these features into a unified dataset, which was then analyzed using ML techniques for fault diagnostics. The key contributions of this investigation are as follows:

- Development of a novel, integrated, real-time monitoring framework for advanced fault diagnosis;
- Validation of the proposed model using real-world machine tool sensor datasets, thereby demonstrating its practical applicability;
- Establishment of the model's robustness in feature extraction through applying ten distinct mother wavelets, ensuring comprehensive signal analysis across a diverse range of inputs.
- Empirical evidence showing that the fusion of force and acceleration data significantly enhances classifier performance, with SVM emerging as the most robust classifier across all metrics when leveraging combined sensor data;
- The findings underscore the effectiveness of the proposed signal processing-based fault classification framework, which accurately predicts tool wear stages by integrating

accelerometer and dynamometer data. This approach presents a robust and scalable solution for real-time monitoring in industrial applications.

2. Experimentation and Data Acquisition

The machining experiments were conducted on a three-axis CNC turning machine, as depicted in Figure 1, utilizing an uncoated cemented carbide insert (CNMG 120408, WIDIA make). The turning insert used in the present study is cemented carbide insert (CNMA 120408-THM ISO). Inserts made of this material have a resistance of up to 100 degrees. The cutting insert geometry in the present study is WIDIA make CNMA 120408-THM ISO turning insert uncoated cemented carbide without chip braker (Plain). The nose radius is 0.8 mm and the rake angle is −5 degrees. The work piece material was AISI 410-grade steel, with dimensions of 25 mm in diameter and 150 mm in length. The machining parameters employed included a feed rate of 0.2 mm/rev, a cutting speed of 100 m/min, and a depth of cut of 0.6 mm. While these parameters represent moderate cutting conditions, as referenced in [35], extending the parameter range (encompassing varied speeds, feeds, and depths of cut) could enhance the model's robustness and provide a more comprehensive dataset for training and validation. To measure cutting forces, a three-axis piezoelectric dynamometer (MI instruments make, MCLNL 2020K12 WIDIA) with a ±4 kN capacity was affixed to the lathe turret. This dynamometer captured forces in the F_x, F_y, and F_z directions. Additionally, a tri-axial accelerometer (PCB 356B21), with a sensitivity of 10 mV/g (±10%), was mounted on a metal spacer plate beneath the cutting tool to record vibration signals in the radial (*X*-axis), longitudinal (*Y*-axis), and transverse (*Z*-axis) directions. Data acquisition was facilitated through an NI 9352 input module integrated with LabVIEW software (2024 Q1). Signals (both force and acceleration) were sampled at a frequency of 10 kHz and stored as discrete files. Cutting force data, recorded via Manuware software, were collected on a dedicated PC connected to the dynamometer. Simultaneously, vibration signals were captured on a separate PC configured with LabVIEW software and the mDAQ driver. Data logging commenced with the initiation of the turning process and concluded upon tool retraction from the workpiece, with individual machining cycle data securely stored.

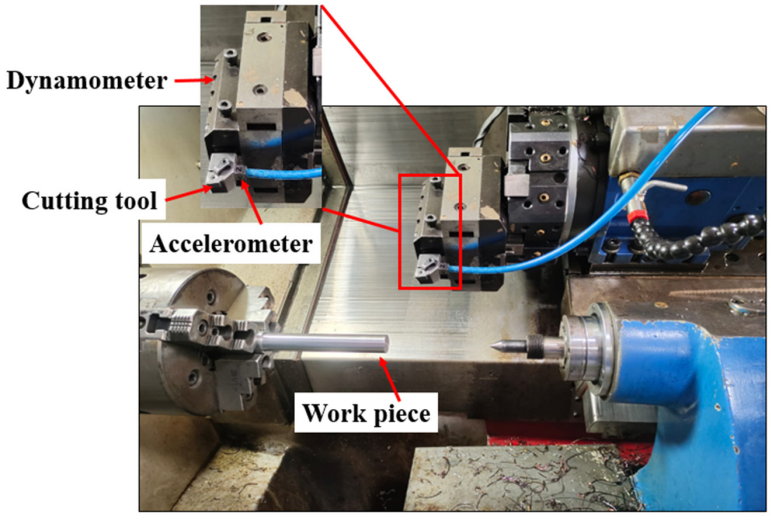
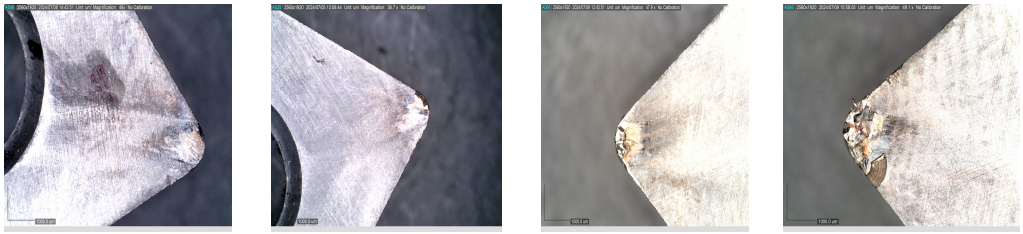


Figure 1. CNC turning machine test setup consisting of a dynamometer and accelerometer.

A portable digital microscope (Dino-Lite 2.0) was employed to monitor and measure tool wear at consistent intervals following each machining cycle. These measurements were synchronized with machining cycle times to ensure accurate monitoring. The surface roughness of the machined surface was evaluated using a profilometer, with its values serving as a critical parameter for the classification of machining conditions. A vision

measuring machine was also utilized to quantify various tool wear types, including flank wear, crater wear, and chipping. During each turning cycle of 30 mm in length, data from the accelerometer and dynamometer were captured and stored in discrete files. Machining time was meticulously recorded, while surface roughness and tool wear were measured after every three complete machining cycles. This methodology was systematically applied to both the healthy tool condition and four distinct faulty tool conditions; see Figure 2. The fault classifications for the tool are outlined in Table 1. The vision measuring machine provided detailed quantification of tool wear characteristics after each machining cycle, categorizing the wear as flank wear, crater wear, chipping, or a combination thereof. This process was repeated for all tool conditions until the tool reached its ultimate failure point. Additional datasets were collected beyond the breaking point to analyze the post-failure behavior of signals, offering insights into the tool's response under extreme wear conditions. This study utilized an NI DAQ system to acquire high-precision real-time sensor signals. Data acquisition was performed continuously until the tool reached its failure point, ensuring a comprehensive dataset across all operational stages.



(**a**) (**b**) (**c**) (**d**)

Figure 2. The classification of tool wear observed in the current study along with class labels: (**a**) Faulty tool without chipping—C2; (**b**) Faulty tool without chipping—C3; (**c**) Faulty tool with chipping—C3; (**d**) Faulty tool with chipping—C4.

Table 1. Various health scenarios of the cutting tool (artificially seeded) along with their class labels.

S.No	Nature of the Tool	Flank Wear Vb (mm)	Crater Wear Km (mm)	Characteristics	Dataset Size	Class Label
1	Healthy	0	0	Fresh cutting edge	60 × 2048	C0
2	Damaged tool	0.2	0	No chipping observed	30 × 2048	C1
3	Damaged tool	0.4	0.2	No chipping observed	30 × 2048	C2
4	Damaged tool	0.511	0.243	Chipping observed	30 × 2048	C3
5	Damaged tool	0.724	0.421	Chipping observed	30 × 2048	C4

3. Methodology

3.1. Signal Processing and Feature Extraction

Real-time acceleration and vibration data were recorded for each tool condition, encompassing healthy and faulty stages. Data were converted into time-series format, with unstable machining regions trimmed to ensure consistency, and subsequently stored in Excel files. Figure 3 illustrates sample accelerometer signals captured for healthy and faulty tools. Discrete wavelet transform has been instrumental in analyzing the abrupt changes in the nonlinear signals by transforming the time-domain using appropriate scaling/basis function [38]. This transformation involves the scaling and contraction through mother wavelets or basis function. DWT was employed to decompose the signals (both force and

acceleration) into multiple frequency components, capturing both high- and low-frequency dynamics. In this study, initially, four mother wavelets, such as haar, db4, and sym4 were used for signal decomposition. The raw signals (both force and acceleration) were decomposed into low-frequency and high-frequency subbands. Four-level decomposition was performed and the raw signals (vibration and force) were decomposed individually using ten wavelet basis functions, such as haar, db2, db4, db6, db8, sym2, sym4, sym6, sym8, and coif2. Four statistical features, such as mean, sample variance, kurtosis, and Shannon entropy, were extracted from each of the wavelet coefficients. The resulting features were organized into a comprehensive feature dataset and fault class type. The dataset was partitioned into training and testing subsets and subjected to feature scaling to normalize data. The training data were normalized using the StandardScaler method, which transforms the features to having mean equal to zero, with unit variance. This method was chosen as it was observed that a few of the features have followed a normal distribution. Three distinct input datasets were generated for analysis. Dataset I comprises feature vectors extracted from the time-domain force sensor signals, resulting in a dataset with 8 columns (4 statistical features + 1 type of mother wavelet + 1 level of wavelet coefficient + 1 axis of force + 1 output class) and 900 rows (180 observations × 5 health conditions). Dataset II contains feature vectors derived from the time-domain accelerometer signals, resulting in a dataset with 8 columns (4 statistical features + 1 type of mother wavelet + 1 level of wavelet coefficient + 1 axis of vibration + 1 output class) and 900 rows (180 observations × 5 health conditions). To construct Dataset III, a feature-level fusion approach was employed, integrating the feature vectors from both the vibration (Dataset II) and force (Dataset I) signals [39]. Consequently, Dataset III consists of 16 columns (8 columns of vibration signal dataset and 8 columns of force signal dataset) and 900 rows (180 observations × 5 health conditions). These comprehensive feature vector sets, representing health indicators, are subsequently input into conventional ML algorithms for defect diagnostics; see Figure 4.

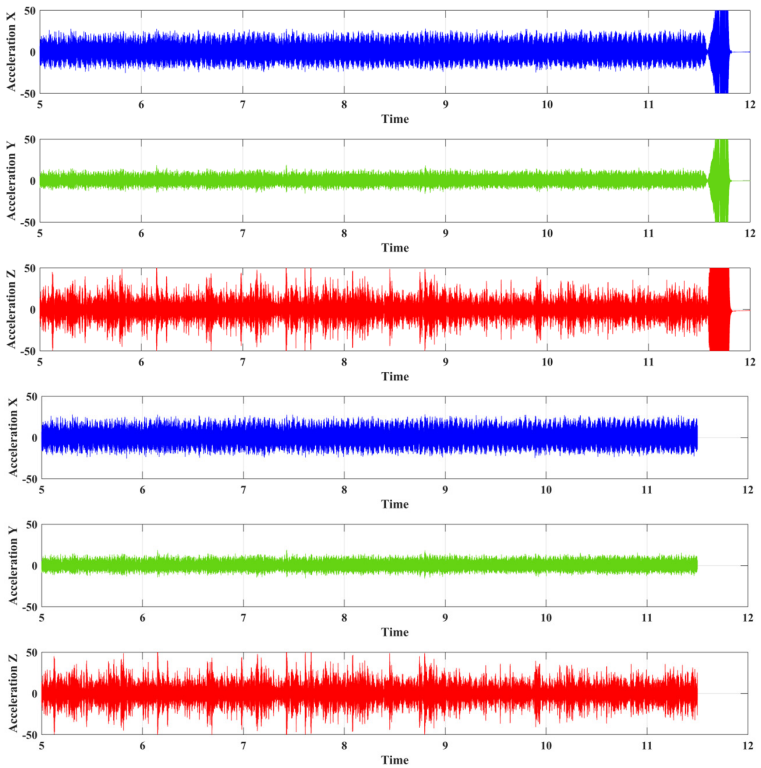


Figure 3. The vibration signals (3-axis) captured for health scenarios of the cutting tool: (**a**) for a healthy cutting tool—C1; (**b**) for a faulty tool with chipping—C4.

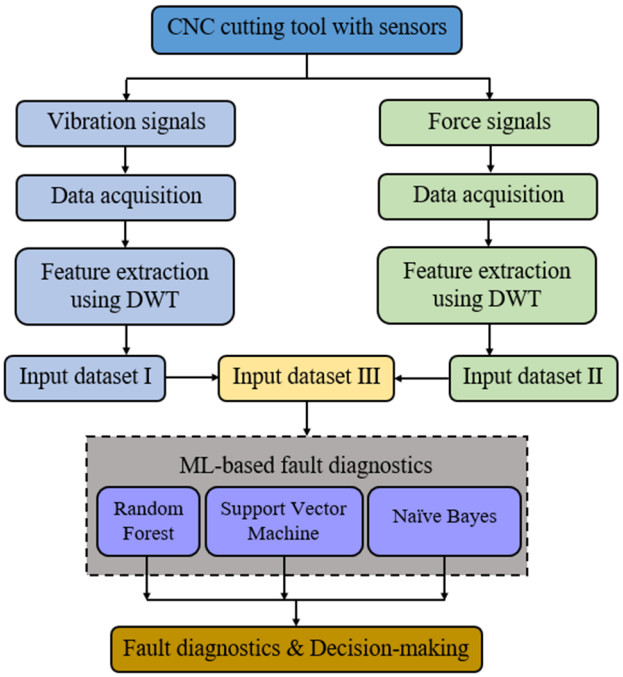


Figure 4. Schematic diagram of the framework employed in the current investigation for achieving the tool wear classification based on DWT feature extraction, feature-level fusion, and ML algorithms.

3.2. ML Framework and Classifiers

The ML framework employed in this study incorporates three supervised classification algorithms: Random Forests (RF), Naive Bayes, and Support Vector Machines (SVM). These classifiers are used to identify fault conditions in worn tools by leveraging features extracted from sensor data, such as force and acceleration signals.

RF classifiers form a core component of the condition monitoring system, employing an ensemble learning approach for fault classification. This method constructs a collection of decision trees, each independently trained on a randomly sampled subset of the training data. Additionally, a random subset of features is selected at each decision node split during the training process. These randomizations reduce correlations among the trees, mitigating overfitting while improving generalization performance. A distinct advantage of RF lies in its capability to assess feature importance. This is achieved by evaluating the reduction in impurity (e.g., Gini impurity or entropy) at each split across all decision trees, weighted by the number of samples reaching the node. Features that contribute to greater impurity reduction are deemed more significant for classification tasks. This ability to quantify feature importance is instrumental in identifying the most relevant attributes from the sensor data and linking them to specific tool wear stages. Such insights enhance the interpretability of the classification results and provide a deeper understanding of the tool wear process. The system achieves robust classification accuracy by incorporating an RF classifier while offering valuable process-level insights. These attributes position the framework as a sophisticated solution for real-time fault diagnosis and condition monitoring in machining operations. The proposed methodology deploys the RF algorithm as a key classification model, trained on features derived through the DWT. This study employed the RF classifier to address the multi-class classification problem by training on three distinct input datasets (I, II, and III), each corresponding to a unique output class. For model training, 70% of the data was utilized, with 30% reserved for testing.

Naive Bayes classifiers embody a probabilistic framework that assumes conditional independence among features. Despite their simplicity, these classifiers are extensively employed in various classification tasks, including fault diagnosis within our integrated

condition monitoring system. Leveraging Bayes' theorem, Naive Bayes classifiers compute the posterior probability of each class, conditioned on the input features. The "Naive" feature independence assumption facilitates the efficient computation of conditional probabilities, thereby streamlining the modeling process. These classifiers yield probabilistic predictions by estimating the posterior probability for each class given the input features. The class with the highest posterior probability is selected as the predicted label. In our approach, Naive Bayes classifiers are utilized as one of the core classification models, trained on features extracted using the DWT. The statistical features derived from wavelet coefficients, combined with wavelet type, decomposition level, signal channel, and fault type, collectively form the input dataset for training the classifier. We specifically employ the Gaussian Naive Bayes variant, which is well-suited for handling continuous, numerical data. In this study, the Naive Bayes classifier addressed the multi-class classification problem by training on three distinct input datasets (I, II, and III), each corresponding to a unique output class. For model training, 70% of the data was utilized, with 30% reserved for testing.

SVM is a prominent supervised learning algorithm extensively applied in classification tasks across various domains, including within our integrated condition monitoring system. In this framework, SVMs function as a pivotal classification model for fault diagnosis, utilizing features derived from force and acceleration signals. SVMs seek to identify the hyperplane that optimally separates distinct classes in the feature space while maximizing the margin between the closest data points from each class, referred to as support vectors. This approach ensures robust and accurate classification performance. Using kernel functions, SVMs can efficiently manage nonlinear decision boundaries by mapping input features into a higher-dimensional space, thereby facilitating the separation of data that are not linearly separable in the original feature space. To address nonlinearity, SVMs employ kernel functions to implicitly transform the input features into a higher-dimensional space, where a linear decision boundary can be more easily established. Various kernel functions, such as linear, polynomial, radial basis function, and sigmoid, can be utilized, each tailored to accommodate the data's specific nature and the decision boundary's desired form. This study employed the SVM algorithm to address the multi-class classification problem by separately training on three distinct input datasets (I, II, and III), each corresponding to a unique output class. For model training, 70% of the data was utilized, with 30% reserved for testing.

4. Results and Discussion

The classification models were trained using the framework and algorithms outlined in the preceding sections. For each fault category, stratified sampling was applied to ensure a balanced distribution of samples across each class in both the training and testing datasets. This method mitigates the potential issues of class imbalance, which can lead to biased model training, poor generalization to unseen data, and distorted evaluation metrics. To evaluate the performance of the various algorithms, several metrics were employed, including the confusion matrix, accuracy, precision, recall, and F1 score. Grid search was coupled with five-fold cross-validation to determine the optimal hyperparameters for each model. The evaluation metrics used to assess the model's classification performance for different tool wear stages, along with their respective interpretations, are as follows:

- *Accuracy:* Reflects the proportion of correctly classified instances relative to the total number of samples. While a high accuracy indicates the model's general effectiveness, it can be misleading when working with imbalanced datasets, where the model may predominantly predict the majority class.

- *Precision:* Quantifies the accuracy of positive predictions. High precision minimizes false positives, which is essential for ensuring the reliability of fault detection.
- *Recall:* Measures the model's ability to correctly identify all relevant instances. A high recall ensures comprehensive detection of faults, reducing the likelihood of overlooking critical failures.
- *F1 Score:* Provides a harmonic mean of precision and recall, offering a balanced metric for evaluating model performance. A high F1 score indicates an effective trade-off between precision and recall, critical for reliable and dependable fault diagnosis.

Tables 2–4 illustrate the confusion matrix pertaining to the ML classifiers considered in this investigation. It can be inferred that the RF classifier has yielded better discrimination among the various health scenarios considered in the tool wear. Among the classifiers, the RF classifier exhibited the highest accuracy, precision, recall, and F1 score across all datasets; see Tables 5–7. With acceleration data, the RF classifier achieved an accuracy of 97.2%, while force data resulted in an accuracy of 96.1%. The combination of both data types, i.e., dataset III, delivered the highest performance metrics, with an accuracy of 98.3%; see Figure 5. Therefore, the proposed integrated sensor fusion approach can classify the faults of machine tools, making it exceptionally well-suited for practical applications. In contrast, Naive Bayes exhibited the lowest performance among the classifiers. With acceleration data, i.e., dataset II, it achieved a modest accuracy of 33.9%, while force data, i.e., dataset I, yielded an accuracy of 45%, and the combination of both data types, i.e., dataset III, resulted in an accuracy of 50%. This can be due to their probability prediction ability, which is hardly suitable for analyzing complex and nonlinear datasets. Besides, the SVM classifier demonstrated solid performance, particularly with force dataset I (accuracy of 86.6%) and with the combined dataset III (accuracy of 88%). Although slightly lower than the RF classifier, SVM consistently maintained high precision, recall, and F1 scores, indicating its reliable ability to classify faults accurately; see Tables 5–7.

Table 2. Confusion matrix for the RF classifier.

C0	C1	C2	C3	C4	Class
60	0	0	0	0	C0
0	30	0	0	0	C1
0	0	30	0	0	C2
0	0	0	30	0	C3
2	0	1	0	27	C4

Table 3. Confusion matrix for the Naive Bayes classifier.

C0	C1	C2	C3	C4	Class
30	11	12	7	0	C0
5	8	17	0	0	C1
0	14	16	0	0	C2
15	1	9	5	0	C3
10	7	11	0	2	C4

Table 4. Confusion matrix for the SVM classifier.

C0	C1	C2	C3	C4	Class
55	3	1	1	0	C0
1	25	4	0	0	C1
5	1	24	0	0	C2
2	0	0	28	0	C3
1	1	1	0	28	C4

Table 5. Evaluation metrics for the classification of cutting tool wear through various ML algorithms for dataset I.

S.No	ML Classifier	Accuracy	Precision	Recall	F1 Score
1	RF	0.96	0.96	0.96	0.96
2	Naive Bayes	0.45	0.70	0.45	0.46
3	SVM	0.87	0.87	0.87	0.86

Table 6. Evaluation metrics for the classification of cutting tool wear through various ML algorithms for dataset II.

S.No	ML Classifier	Accuracy	Precision	Recall	F1 Score
1	RF	0.97	0.97	0.97	0.97
2	Naive Bayes	0.34	0.48	0.32	0.32
3	SVM	0.80	0.80	0.79	0.79

Table 7. Evaluation metrics for the classification of cutting tool wear through various ML algorithms for dataset III.

S.No	ML Classifier	Accuracy	Precision	Recall	F1 Score
1	RF	0.98	0.98	0.98	0.98
2	Naive Bayes	0.50	0.68	0.50	0.51
3	SVM	0.88	0.89	0.89	0.89

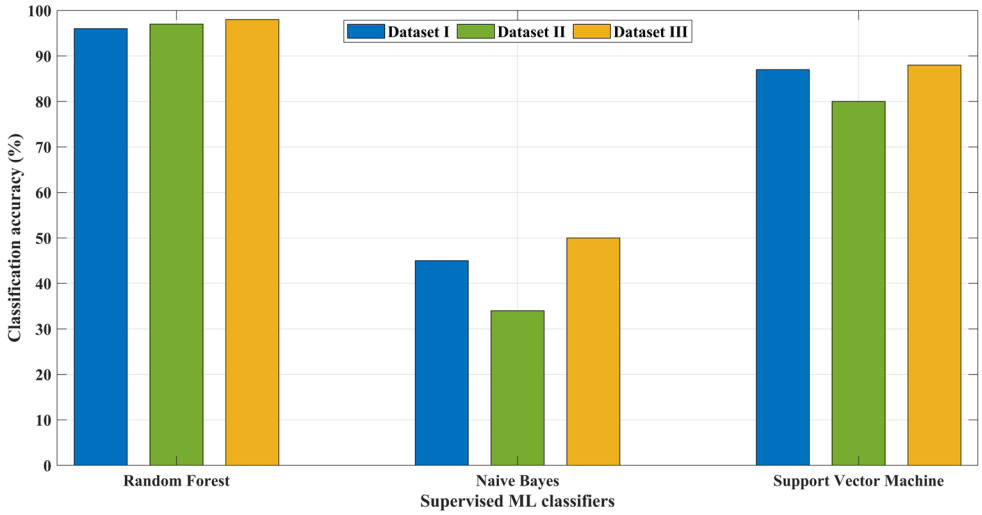


Figure 5. Classification accuracies of the formulated input datasets computed through various ML algorithms.

The classification accuracies achieved by the ML classifiers are presented in Figure 5. Notably, when performing multi-class classification, it was observed that feature vectors derived solely from force sensor signals (input dataset I) resulted in highly favorable classification accuracies. Specifically, the accuracies were 96%, 45%, and 87% for RF, Naive Bayes, and SVM classifiers, respectively. This enhanced performance can be attributed to the sensitivity of the dynamometer force to changes in the critical operational parameters of the machine tool, which significantly aids in the discrimination of various health scenarios. Also, input dataset II, based solely on vibration signals, exhibited favorable classification accuracies akin to dataset I across the various health conditions. Furthermore, the fusion of vibration and force signal feature vectors (input dataset III) resulted in even better classification performance. This improvement is due to the complementary nature of the two signal types, with vibration signals excelling at detecting early-stage failure, while

force signals are particularly responsive to more severe failures. As a result, input dataset III achieved superior classification accuracies of 98%, 50%, and 88% for the RF, Naive Bayes, and SVM classifiers, respectively, as illustrated in Figure 5. It is worth noting that acceleration data yielded superior results for the RF classifier, while force signal data produced better outcomes for SVM and Naive Bayes classifiers. This highlights the robustness of the proposed integrated sensor fusion approach compared to traditional single-sensor methods. Thus, the multi-health condition diagnosis of the machine tool can be effectively performed and accurately distinguished using statistical features derived from the time-domain force and vibration. The performance evaluation of the proposed framework is compared with the existing work reported in the literature; see Table 8. It can be observed that the proposed framework has registered favorable classification accuracies while classifying across the various health states of the tool wear. The input dataset III-infused RF classifier produced 98% accuracy, whereas the input dataset III-infused SVM classifier produced 88% accuracy. Thus, the proposed framework contributes in a novel way to higher classification accuracy and can perform multi-health condition diagnosis of the machine tool.

Table 8. Performance comparison of the proposed framework with the existing works.

Author Reference	Machining Process	Signals Considered	Classifier/Model	Accuracy
Patange et al. [30]	Turning	Vibration	ML classifier—Random Forest	92.6%
Zhang et al. [17]	Milling	Force, Vibration, torque	DL classifier—improved residual network	97.5%
Schueller and Saldana [29]	Milling	Sound signals	ML classifier—Random Forest	92.6%
Peng et al. [18]	Turning	Force, vibration	DL model—multi-kernel weighted Gaussian process	96.1%
Proposed work	Milling	Force, Vibration	ML classifier—Random Forest	98%

5. Conclusions

The signals obtained from machine tools, encompassing both vibration and force signals, are inherently nonstationary and aperiodic, presenting significant challenges in extracting health indicators that effectively capture defect-related information during post-processing. This research aims to extract the various health indicators derived from vibration and force signals for performing CNC machine tool wear defect diagnostics subjected to fluctuating operating conditions. Five distinct health scenarios are considered, with raw data, time-domain force (3-axis), and vibration signals (3-axis) collected from a CNC machine tool. Statistical parameters are computed separately for each health scenario's force and vibration signals. Three distinct input datasets are constructed: Dataset I comprises statistical parameters extracted exclusively from the force signals, Dataset II consists of statistical parameters derived from the vibration signals, and Dataset III integrates the individual statistical parameters from both force and vibration signals through feature-level fusion. These datasets are then utilized for training ML classifiers (SVM, RF, and Naive Bayes) to perform feature learning and subsequent classification. The results of the analysis are summarized as follows:

- The fusion of force and acceleration data, i.e., dataset III, led to notable improvements across all performance metrics for each classifier, underscoring the advantages of multi-sensor integration. This improvement is due to the complementary nature of the two signal types, with vibration signals excelling at detecting early-stage failures, while force signals are particularly responsive to more severe failures.

- The RF classifier yielded the highest classification accuracies in most scenarios, offering enhanced generalization capabilities, particularly when working with smaller datasets.
- The RF classifier consistently outperformed other models, achieving superior accuracy and precision, affirming its fault classification reliability. Besides, the SVM classifier also demonstrated strong performance, particularly when utilizing the combined dataset.
- These findings highlight the effectiveness of our signal processing-based fault classification framework, which accurately predicts tool wear stages by leveraging integrated accelerometer and dynamometer data, positioning it as a valuable tool for advanced, real-time monitoring and diagnostic applications within industrial settings.

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