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Article

Comparative Analysis of Time, Frequency, and Wavelet Features for Tool Condition Monitoring Using Machine Learning under Cross-Tool Validation

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Abstract: Tool condition monitoring (TCM) is critical for ensuring high machining quality and preventing catastrophic tool failures in smart manufacturing. While data-driven approaches increasingly rely on complex machine learning architectures and hybrid feature extraction (combining time, frequency, and time-frequency domains), the specific computational and accurate contributions of each domain remain poorly understood—a critical bottleneck for real-time edge-computing deployment. This study presents a systematic benchmarking analysis comparing time-domain, frequency-domain (FFT), wavelet-based, and hybrid feature sets for tool wear classification using the standard PHM 2010 Data Challenge dataset. To ensure industrial relevance, model generalization is rigorously assessed through cross-tool validation using a robust leave-one-out approach. Operating under strict computational efficiency constraints, a Decision Tree and Random Forest framework is employed. The results demonstrate that simpler time-domain features perform exceptionally robustly, with the Random Forest model achieving 92.3% classification accuracy. Crucially, hybrid features offer only marginal improvements at the expense of high computational overhead, while standalone frequency and wavelet domains prove less effective under cross-tool constraints. Furthermore, our analysis reveals two critical pitfalls for practical TCM design: feature selection techniques fail to improve accuracy, and standard segment normalization severely degrades performance by inadvertently removing vital signal magnitude information linked to tool wear. These insights provide concrete, computationally efficient guidelines for deploying lean, high-accuracy machine learning models on real-time industrial edge devices.

Keywords :
Tool Condition Monitoring (TCM), Machine Learning, Feature Extraction, Time-Domain Features, Random Forest, Frequency-Domain Analysis, Wavelet Transform, Hybrid Features, Cross-Tool Validation, PHM 2010 Dataset

1. Introduction

In modern manufacturing, tool condition monitoring (TCM) is vital for maintaining machining precision, managing tool wear, and improving productivity. Tool wear reduces accuracy and surface finish, so early detection is essential for process stability and minimising downtime.

Industry 4.0 has increased the importance of data-driven methods in TCM. Monitoring systems use sensor signals such as vibration, cutting force, and acoustic emissions to track tool wear in real time. These signals provide valuable information for machine learning analysis. However, deploying these data-driven models onto the factory floor requires a shift toward real-time edge computing. Because CNC machinery generates high-frequency data streams, transferring massive raw sensor datasets to centralized cloud networks introduces severe bandwidth bottlenecks and latency issues that prevent immediate tool failure interventions. Consequently, modern smart manufacturing demands lightweight machine learning frameworks capable of local, low-latency deployment directly on edge sensors or shop-floor microcontrollers. Common algorithms for tool wear classification include Decision Trees and Random Forests, valued for their interpretability and stability, as well as Support Vector Machines (SVMs), which handle high-dimensional data and complex decision boundaries. Model effectiveness depends on feature quality, emphasising the importance of feature engineering. Sensor data are transformed into time-domain, frequency-domain, and time-frequency-domain features. Time-domain features capture statistical properties, while frequency-domain and wavelet-based features provide additional spectral and time-localised information. Many studies combine these domains into hybrid feature sets to improve classification accuracy. While complex deep learning models (such as deep Convolutional or Transformer networks) are frequently proposed to automatically process these massive hybrid feature sets, their high computational overhead and "black box" nature present major hurdles for resource-constrained edge hardware. This underscores the need to determine whether complex, computationally heavy feature transformations are truly necessary, or if leaner, traditional algorithms can achieve equivalent industrial reliability.

However, it remains unclear whether combining features from different domains significantly improves classification performance over simpler alternatives. Addressing this question is important for developing efficient and practical TCM systems. This study provides a comprehensive analysis of various feature domains using multiple machine learning models evaluated under realistic validation scenarios. To achieve this, the well-documented PHM 2010 Data Challenge dataset is utilized as a standardized baseline for a rigorous, controlled benchmarking analysis of independent feature domains. By assessing model generalization under a strict cross-tool validation framework, this study isolates the exact computational trade-offs of feature selection and normalization, providing concrete design guidelines for lean, practical TCM systems.

The paper is structured as follows: Section 2 reviews related work, Section 3 describes the methodology, Section 4 presents the results, Section 5 discusses the findings, and Section 6 outlines future research directions.

2. Literature Review

Extensive research has been conducted on data-driven and sensor-based tool condition monitoring. Initial methods relied on indirect signals such as vibration, force, and acoustic emissions to predict tool wear. These signals, which reflect interactions between the tool and workpiece, are widely utilised in machining process monitoring [2], [3], [4]. Notably, studies in computational intelligence emphasise the critical role of signal analysis in fault detection and diagnosis [15].

Benchmark datasets, such as the PHM 2010 Data Challenge [1], have enabled standardised evaluation of tool wear prediction methods. The PHM 2010 dataset provides multi-channel sensor data alongside corresponding wear measurements, facilitating the development and validation of machine learning models. Prior studies [21], [22] have demonstrated the application of machine learning for tool condition monitoring in both milling and turning processes.

Machine learning plays a significant role in modelling the relationship between sensor signals and tool wear. Algorithms such as Decision Tree and Random Forest are frequently employed due to their stability and interpretability [13], [14]. Random Forest enhances prediction accuracy by aggregating multiple decision trees, thereby reducing variance and mitigating overfitting. Ensemble learning methods have been adopted in tool condition monitoring (TCM) to increase model robustness and adaptability across diverse machining scenarios [16]. Support Vector Machine (SVM) is also used for wear classification, given its effectiveness with nonlinear and high-dimensional data.

Feature extraction constitutes a fundamental aspect of tool condition monitoring. Time-domain features, such as mean, standard deviation, and root-mean-square, are commonly used due to their simplicity and effectiveness. Frequency-domain features derived from Fourier analysis offer spectral information, while wavelet transforms capture both temporal and frequency characteristics of signals. Numerous studies indicate that integrating features from these domains can enhance classification accuracy [10], [11], [12].

Recent studies have investigated advanced data-driven approaches, such as deep learning and multi-sensor fusion, to enhance prediction performance [5], [6], [7], [8], [9], [17], [18], [19], [20]. While these methods demonstrate strong performance, they typically require large datasets and substantial computational resources, which may limit their practicality in industrial applications.

Despite the widespread adoption of hybrid features and advanced modelling techniques, several challenges persist. Many studies prioritise accuracy improvements without thoroughly investigating the individual contributions of each feature domain. The influence of feature selection within hybrid feature sets also remains underexplored. Furthermore, the widespread use of random data splitting does not reflect real industrial scenarios, in which models must be validated across different tools.

These considerations highlight the necessity for systematic analysis of feature domains under realistic validation conditions. Addressing this need constitutes the primary objective of the present study.

2.1 Research Gap and Contributions

Despite the widespread use of hybrid features and advanced modelling techniques, several challenges remain. Many studies focus on accuracy improvements without fully examining the individual contributions of each feature domain. The impact of feature selection within hybrid sets is also underexplored. Additionally, it is unclear whether the performance gains from integrating features across domains justify the added computational complexity.

The common use of random data splitting does not reflect real industrial scenarios, where models must be validated across different tools and varying process conditions. Although hybrid feature sets often include redundant or highly correlated indicators, the specific impact of feature selection on classification outcomes has not been sufficiently addressed in the literature.

These points highlight the need for systematic analysis of feature domains under realistic validation conditions. Evaluating the benefits of hybrid feature extraction and the effects of feature reduction is essential for improving data-driven monitoring strategies.

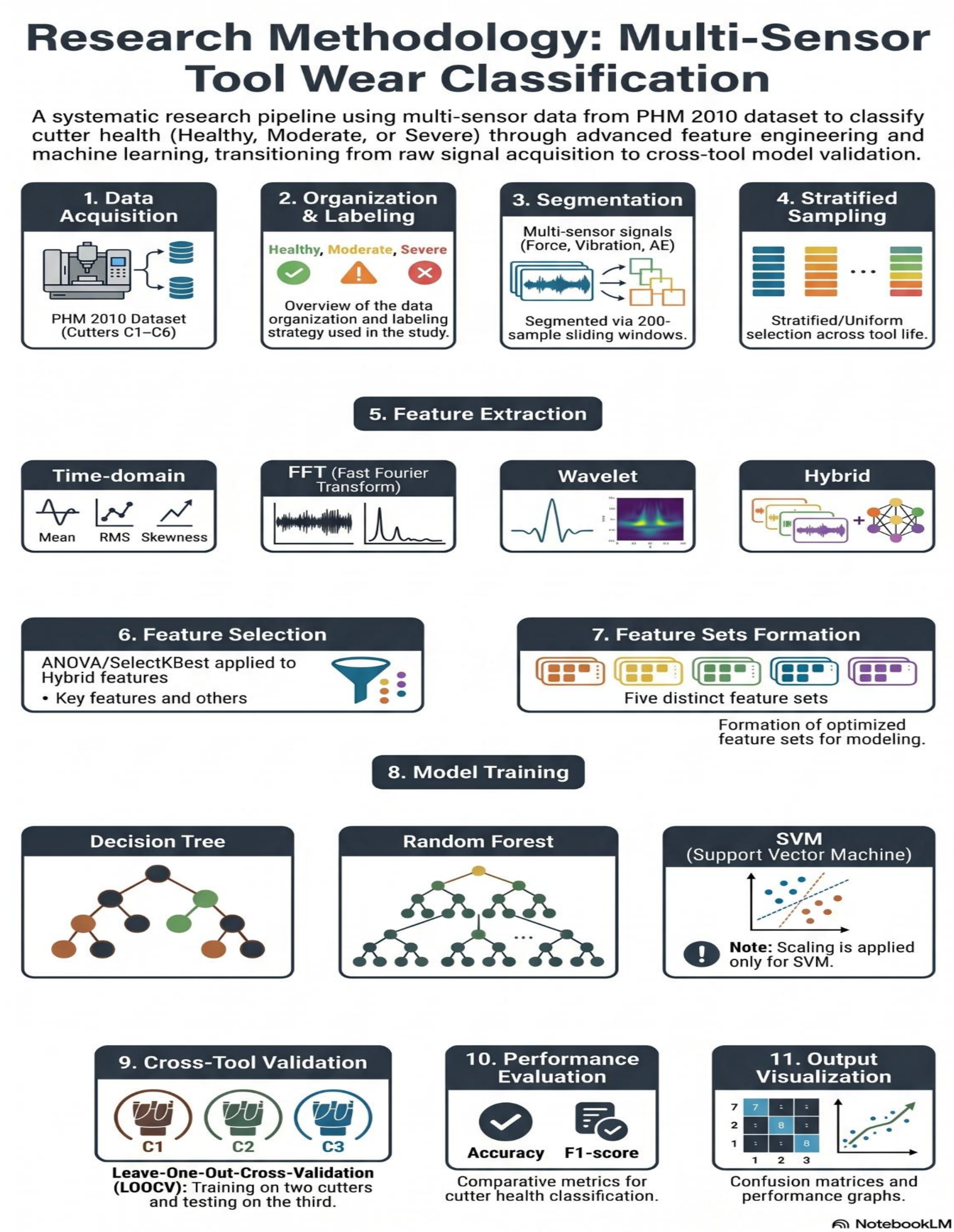
This study addresses these research gaps by rigorously evaluating feature domains using the PHM 2010 Data Challenge dataset. The main contributions are as follows:

- An assessment of various time-domain, frequency (FFT), wavelet-based, and hybrid features as indicators of tool wear.
- Adoption of a cross-tool validation technique, based on a leave-one-out scheme, to provide a realistic model evaluation.
- Exploration of the effect of feature selection on hybrid features, indicating redundancy.
- Evaluation of several machine learning algorithms, such as Decision Tree, Random Forest, and Support Vector Machine.
- Demonstration that time-domain features can achieve performance comparable to hybrid features, thereby challenging prevailing assumptions in the literature.

3. Methodology

3.1 Overview of Proposed Framework

The tool condition monitoring methodology involves sequential steps: data collection, segmentation, feature extraction, model training, and evaluation. Figure 1 illustrates this framework.



This process enables comparative evaluation of feature performance across time-domain, frequency-domain, wavelet-based, and hybrid features under realistic operational conditions.

3.2 Dataset Description

The PHM 2010 Data Challenge dataset [1] was selected as the benchmarking baseline for this study because its well-documented wear progression allows for a rigorous, controlled comparative analysis of independent feature domains. This open-source dataset includes multi-sensor data collected from a high-speed CNC milling process and contains the following components:

- Six cutters (C1–C6), each representing a complete tool life cycle
- Seven sensor channels:
    - Force signals (X, Y, Z)
    - Vibration signals (X, Y, Z)
    - Acoustic emission (AE-RMS)

All signals are sampled at a high frequency of 50 kHz to capture the micro-level dynamic information relevant to machining physics and progressive tool wear. Flank wear measurements are recorded for each cutting pass, enabling supervised machine learning and precise model validation.

3.3 Data Segmentation and Labeling

Sensor signals are segmented to extract local features using a sliding window approach with the following parameters:

- Window size: N=200 samples
- Step size: 4N, which reduces redundancy and computational load

Each window is assigned a label corresponding to the tool wear value:

$$\text{Label} = \begin{cases} 0, & \text{if } w < 0.1 \text{ (Healthy)} \\ 1, & \text{if } 0.1 \leq w < 0.3 \text{ (Moderate)} \\ 2, & \text{if } w \geq 0.3 \text{ (Severe)} \end{cases}$$

where w represents the flank wear in millimeters.

3.4 Stratified Sampling Strategy

A stratified sampling approach ensures representation of all stages of tool life while reducing computational cost. Instead of random sampling, samples are uniformly selected across the full range of machining passes:

$$i_k = \left\lfloor \frac{k \cdot (N_f - 1)}{K - 1} \right\rfloor, \quad k = 0, 1, \ldots, K - 1$$

where:

- N_f is the total number of files
- K is the number of selected samples

This strategy ensures representation of early, middle, and late stages of tool wear, enhancing model generalisation.

3.5 Feature Extraction

Feature extraction is performed independently for each signal segment, considering five distinct feature sets:

3.5.1 Time-Domain Features

Time-domain features characterise the statistical properties of the signal:

Mean: $\mu = (1/N)\, \Sigma(i = 1\ to\ N)\, x_i$

Standard Deviation: $\sigma = sqrt[(1/N)\, \Sigma(i = 1\ to\ N)\, (x_i - \mu)^2]$

RMS: $RMS = sqrt[(1/N)\, \Sigma(i = 1\ to\ N)\, x_i^2]$

These features are calculated for each of the seven sensor channels.

3.5.2 Frequency-Domain Features (FFT)

Frequency-domain features are extracted using the Fast Fourier Transform (FFT):

$$X(k) = \Sigma(n = 0\ to\ N - 1)\ x(n)\ e^\wedge(-j2\pi kn/N)$$

The maximum magnitude of the FFT spectrum is used as the representative feature:

$$f\_max = max\ |X(k)|$$

3.5.3 Wavelet Features

Wavelet decomposition is performed using the discrete wavelet transform (DWT) with the Daubechies (db4) wavelet. The total energy of wavelet coefficients is computed as:

$$E = \Sigma\Sigma\ c_{ij}^2$$

Where c_{ij} are the wavelet coefficients at different levels.

3.5.4 Hybrid Features

Hybrid features combine:

- Time-domain features
- Statistical features (skewness and kurtosis)
- FFT-based features
- Wavelet-based features

This approach provides a comprehensive feature representation that captures multiple characteristics of the sensor signals.

3.5.5 Feature Selection (Hybrid + FS)

Feature selection is applied to the hybrid feature set using the ANOVA F-test to reduce dimensionality and eliminate redundant features:

$$F = (variance\ between\ classes)\ /\ (variance\ within\ classes)$$

The top k = 20 features are selected based on their discriminative power.

3.6 Classification Models

Three machine learning models are used for tool wear classification: Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM). The Decision Tree serves as a simple, interpretable baseline. Random Forest improves performance through ensemble learning by reducing variance and overfitting. Support Vector Machine is a margin-based classifier that operates in high-dimensional feature spaces and can handle nonlinear decision boundaries.

For the SVM model, a radial basis function (RBF) kernel is used, and input features are standardised before training to reduce sensitivity to feature scaling. Tree-based models, such as Decision Tree and Random Forest, do not require feature scaling, so raw feature values are used. Class imbalance in tree-based models is addressed through class weighting to ensure balanced learning. Normalisation of raw signal segments is omitted, as it removes magnitude-based information essential for representing tool wear progression.

3.7 Cross-Tool Validation (LOOCV)

To simulate real industrial conditions, a leave-one-out cross-tool validation (LOOCV) strategy is implemented. In each iteration:

- Two cutters are used for training
- The remaining cutter is used for testing

This process is repeated for all cutter combinations, ensuring the model is evaluated on previously unseen tools. This strategy provides a more realistic assessment than random data splitting.

3.8 Performance Evaluation Metrics

Model performance is assessed using the following metrics:

Accuracy = (TP + TN) / (TP + TN + FP + FN)

$$Precision = TP / (TP + FP)$$
$$Recall = TP / (TP + FN)$$
$$F1\,Score = 2 \times (Precision \times Recall) / (Precision + Recall)$$

Additionally, confusion matrices are used to analyse prediction performance for each class.

4. Results and Discussion

4.1 Overview of Experimental Results

The proposed framework is evaluated using time-domain, frequency-domain (FFT), wavelet-based, and hybrid methods with feature selection. A leave-one-out cross-tool validation strategy ensures realistic generalisation.

Three machine learning models—Decision Tree, Random Forest, and Support Vector Machine—are used for classification. Performance is assessed using accuracy, precision, recall, and F1-score.

4.2 Comparative Performance Analysis

Table 1 summarises the average performance of all models across feature sets.

Table 1: Performance Comparison Across Feature Sets

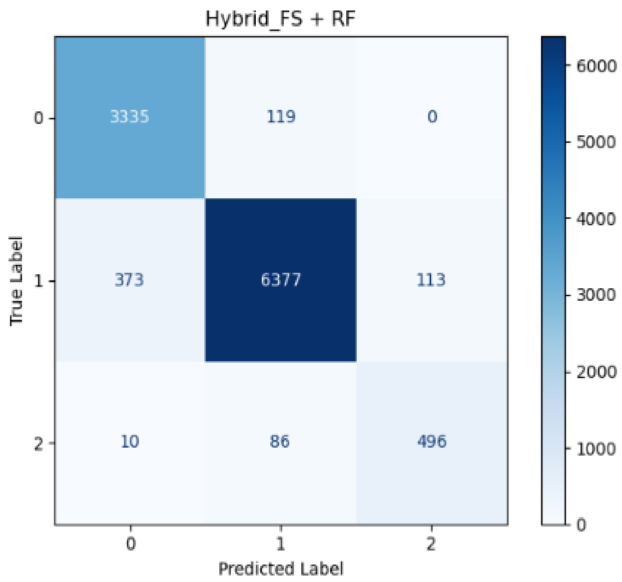
Feature Set	Model	Accuracy (%)	Precision	Recall	F1-score
Time	DT	88.31	0.89	0.88	0.87
Time	RF	**92.30**	0.93	0.92	0.92
Time	SVM	88.27	0.92	0.88	0.89
FFT	DT	85.09	0.85	0.85	0.85
FFT	RF	88.17	0.89	0.88	0.88
FFT	SVM	85.41	0.85	0.85	0.85
Wavelet	DT	85.51	0.87	0.86	0.85
Wavelet	RF	85.89	0.88	0.85	0.85
Wavelet	SVM	86.68	0.87	0.86	0.85
Hybrid	DT	88.09	0.89	0.88	0.87
Hybrid	RF	**92.92**	0.93	0.93	0.93
Hybrid	SVM	91.80	0.91	0.91	0.91
Hybrid+FS	DT	87.95	0.89	0.87	0.87
Hybrid+FS	RF	88.75	0.90	0.88	0.88
Hybrid+FS	SVM	85.68	0.90	0.85	0.87

4.3 Key Observations

- Random Forest demonstrates the highest performance across all feature sets, achieving a maximum accuracy of 92.92% with hybrid features.
- Time-domain features yield strong performance, with Random Forest attaining an accuracy of 92.30%.
- Hybrid features offer only a marginal improvement over time-domain features.
- FFT and wavelet features demonstrate comparatively lower performance.
- Support Vector Machine demonstrates competitive performance, particularly with hybrid features, achieving 91.80% accuracy.
- Feature selection reduces performance for both Random Forest and Support Vector Machine models.

4.4 Confusion Matrix Analysis

Confusion matrices for selected feature-model combinations are shown in Figure X. Time-domain and hybrid features demonstrate strong classification performance with clear diagonal dominance. In contrast, FFT and wavelet features exhibit higher misclassification rates, particularly between moderate and severe wear classes.



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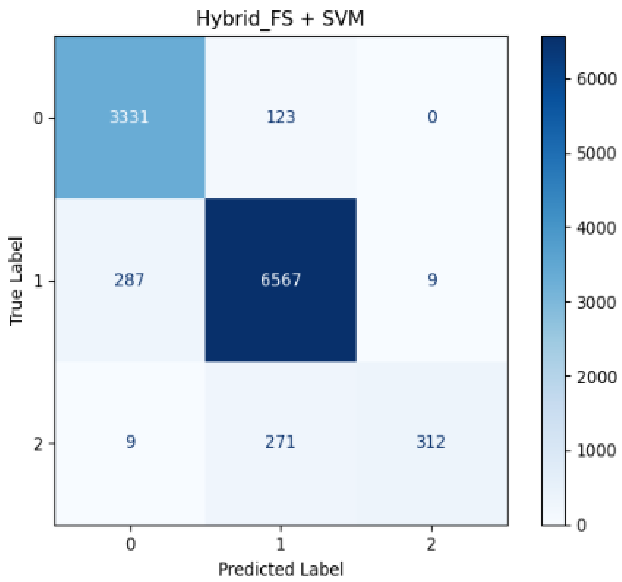

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5. Discussion

The results presented in this study provide several important insights into the effectiveness of different feature domains and machine learning models for tool condition monitoring.

5.1 Effectiveness of Feature Domains

A key finding is that time-domain features alone achieve performance comparable to hybrid feature sets. The Random Forest model reaches 92.30% accuracy with time-domain features, while hybrid features provide only a slight improvement to 92.92%. This minimal gain suggests that frequency-domain and wavelet-based features do not substantially enhance classification performance.

These results suggest that the statistical characteristics of sensor signals effectively capture the main patterns of tool wear progression. The magnitude and variability of the signals provide sufficient discriminative information, reducing the need for more complex feature representations. These findings challenge the common assumption that combining multiple feature domains always improves performance.

5.2 Limitations of Frequency and Wavelet Features

Frequency-domain (FFT) and wavelet-based features consistently perform worse than time-domain features. This is likely because tool wear progression in the dataset is mainly reflected in gradual changes in signal magnitude, not in distinct spectral patterns.

While FFT and wavelet transforms are effective for capturing periodic and transient behaviours, their contributions here are limited. When used alone, these features do not adequately capture key characteristics of tool wear, reducing classification accuracy.

5.3 Model Behavior and Comparative Analysis

Among the evaluated models, Random Forest consistently outperforms both Decision Tree and Support Vector Machine across all feature sets. This is due to its ensemble learning mechanism, which improves generalisation by aggregating multiple decision trees and reducing variance.

The Support Vector Machine model shows competitive performance, especially with hybrid features, achieving 91.80% accuracy. This suggests SVMs benefit from richer feature representations, which help build more effective decision boundaries. However, SVM performance declines with feature selection, highlighting its sensitivity to feature reduction and reliance on comprehensive feature information.

The Decision Tree model, used as a baseline, shows lower performance. This is expected due to its tendency to overfit and its limited ability to capture complex data relationships.

5.4 Impact of Feature Selection

Contrary to expectations, feature selection does not improve performance in this study. Instead, accuracy decreases for both Random Forest and Support Vector Machine models when feature selection is applied to hybrid features.

This suggests the hybrid feature set already provides a balanced representation of relevant information, and removing features may eliminate important discriminative characteristics. It also indicates that the feature space may not be overly redundant, or that the selection method does not effectively capture feature importance in this context.

5.5 Effect of Data Preprocessing

A key observation is the negative impact of normalising raw signal segments. Normalisation reduces classification performance by removing magnitude-based information critical for distinguishing different wear conditions.

This finding highlights the importance of preserving absolute signal characteristics in tool condition monitoring, where wear progression is closely linked to changes in signal amplitude. It emphasizes that preprocessing techniques must be carefully chosen based on the data and the underlying physical phenomena.

5.6 Practical Implications

These findings have significant implications for the design of practical tool condition monitoring systems. The results show that simpler time-domain features can achieve performance comparable to more complex hybrid approaches, reducing computational requirements and simplifying implementation.

The consistent performance of Random Forest suggests that ensemble methods provide a robust and reliable solution for tool wear classification. The limited benefit of feature selection indicates that additional preprocessing may not be necessary when feature extraction is already well-designed.

Overall, the findings indicate that efficient and accurate tool condition monitoring systems can be developed using relatively simple feature representations and robust machine learning models, thereby eliminating the need for computationally intensive feature engineering.

6. Conclusion

This study presented a systematic, benchmarking evaluation of feature-domain effectiveness for data-driven tool condition monitoring (TCM). A comprehensive comparative analysis was conducted across standalone time-domain, frequency-domain (FFT), wavelet-based, and combined hybrid feature spaces, evaluated under a rigorous cross-tool validation framework using the standardized PHM 2010 dataset.

The empirical results demonstrate that computationally lean time-domain statistical features capture the core physical characteristics of tool wear progression exceptionally well, enabling a Random Forest model to achieve a robust 92.30% classification accuracy. While high-dimensional hybrid feature extraction incorporates multi-signal representations, it yields only marginal performance gains. This indicates high feature redundancy and highlights a critical trade-off: the minimal accuracy increase from complex frequency and time-frequency transformations rarely justifies the massive computational overhead they introduce.

Furthermore, cross-model evaluations revealed that the Random Forest algorithm consistently outpaced Decision Trees and Support Vector Machines (SVMs) across varying feature configurations, establishing its stability for industrial classification tasks. Crucially, this study identified two major pitfalls for practical TCM system design:

1. Feature Selection Ineffectiveness: Automated feature selection failed to enhance model accuracy, confirming that traditional filtering algorithms can inadvertently disrupt highly correlated manufacturing data streams.
2. The Normalization Pitfall: Standard segment-level normalization severely degraded classification performance. By stripping away absolute signal magnitudes, normalization eliminates the vital, physical energy shifts caused by progressive tool-and-workpiece degradation.

Ultimately, these findings challenge the prevalent literature assumption that hybrid feature extraction and complex data preprocessing are mandatory for high-performance TCM. Instead, this research provides a concrete, computationally efficient architecture proving that raw time-domain features, paired with robust ensemble models and realistic validation strategies, offer a highly viable pathway for real-time edge computing deployment on resource-constrained shop-floor hardware.

Future work will focus on validating these edge-efficient guidelines across diverse machining parameters and varying cutting materials to further establish generalizability. Additionally, investigations into lightweight deep learning architectures, such as 1D-CNNs operating solely on raw time-series data, will be explored to balance computational efficiency with automated feature learning.

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