



Article

Classification of Tool Wear Condition During CNC Cutting Process from Spindle Motor Current Signal Monitoring

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Abstract

Tool wear in CNC milling increases friction and torque demand at the tool-workpiece interface, which is reflected in spindle motor current. This study develops a non-intrusive tool wear condition classification method using spindle motor current monitoring during practical CNC milling of commercial medium-carbon steel workpieces (JIS S50C/AISI SAE 1050-equivalent; as-received and non-heat-treated; nominal laboratory hardness approximately 4.3 HRC). Experiments were performed on a Tongtai MDV-508 vertical machining center at fixed cutting conditions (3000 rpm spindle speed, 2 mm axial depth of cut, 5 mm cutting width, and 300 mm/min feed rate) using eight TiAlN-coated fine-grain WC–Co solid carbide end mills (10 mm diameter, four flutes; nominal Co binder approximately 10 wt%). An oil-based HS Highstart/HS-SSHS-BH10 cutting fluid was applied through the machine external coolant nozzle in flood mode at an estimated nominal flow rate of approximately 3 L/min and near-room coolant temperature (25 ± 2 °C), and was used as supplied without dilution. A clamp-type AC current sensor was installed on one phase line supplying the spindle motor, and current was acquired using an NI-9221 module at 20 kHz. Cutting intervals were isolated by envelope-based segmentation, concatenated, and divided into 1 s windows (0.5 s overlap) for feature extraction. Three feature sets were evaluated: time-domain statistics, frequency-domain statistics, and an FFT→PCA hybrid representation. Tool states (New, Mid-life, Old) were labeled using post-process surface roughness R_a thresholds supported by microscope observation. The PCA transformation was fitted only on training data and then applied to the held-out test data. A logistic regression classifier achieved 97.44% test accuracy (152/156 windows; 95% Wilson CI: 93.59–99.00%) with the PCA-hybrid features, outperforming time-domain (89.74%) and frequency-domain (94.87%) models. The results support spindle current monitoring as a low-cost approach for quality-aligned tool condition monitoring, while the external validity remains limited to the tested machine, material, tool, coolant, and cutting-parameter combination.



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1. Introduction

Computer numerical control (CNC) machining remains one of the most widely adopted manufacturing routes for producing precision metal components in aerospace, automotive, mold and die, medical devices, and general machinery. In milling operations, cutting tool wear is inevitable due to severe thermo-mechanical loading and complex tribological interactions at the tool-chip and tool-workpiece interfaces. Wear progression deteriorates dimensional accuracy and surface integrity, increases cutting forces and energy consumption, and ultimately leads to tool failure (e.g., chipping, catastrophic fracture, or excessive flank wear), which can scrap parts and interrupt production. For this reason, robust tool condition monitoring (TCM) is widely recognized as a key enabler of machining quality, productivity, and sustainability in modern manufacturing systems [1–3].

The economic motivation for tool monitoring is straightforward: tool-related issues contribute a substantial fraction of unplanned downtime, while tool replacement and tool-change-related interruptions also account for a measurable share of machining costs. Recent reviews and surveys report that tool failure can account for a nontrivial portion of total machine downtime (often reported on the order of single- to low-double-digit percentages depending on the process and factory context), and tool changes can contribute several percent of total machining costs [4]. In practice, many manufacturers therefore adopt conservative tool replacement policies, replacing tools earlier than their true end-of-life to avoid failure risk. However, premature replacement wastes usable tool life, increases tooling costs, and can add unnecessary environmental burden through increased consumption of tool materials and associated upstream impacts. Conversely, “run-to-failure” behavior risks sudden breakage, secondary damage, and quality excursions. These competing pressures motivate a shift from time-based or rule-based tool replacement toward data-driven, condition-based decision-making [5,6].

From the broader perspective of maintenance strategy evolution, industrial facilities have transitioned from breakdown maintenance to scheduled preventive maintenance, and increasingly to predictive maintenance supported by real-time sensing and analytics [5–7]. Condition-based maintenance (CBM) and prognostics aim to infer degradation states from measurable signals, estimate remaining useful life (RUL), and schedule interventions to minimize total cost and disruption [6,7]. This paradigm aligns with Industry 4.0 and smart manufacturing, where ubiquitous connectivity, low-cost industrial sensors, and computational intelligence support continuous monitoring, anomaly detection, and decision support for production assets [8,9]. In machining, TCM is the analog of CBM for cutting tools: it seeks to infer tool condition and predict wear progression (or failure likelihood) during operation so that tool replacement can be triggered at an optimal time [1–3].

1.1. Tool Wear and Quality-Driven Labeling in Milling

Tool wear manifests in several modes (e.g., flank wear, crater wear, adhesion, abrasion, diffusion, and oxidation), and the dominant mode depends on workpiece material, cutting parameters, tool material/coating, and coolant strategy [2,3,10]. In end milling of steels, flank wear is often one of the principal modes affecting surface finish and dimensional accuracy because it alters the effective cutting geometry and increases rubbing contact on the newly generated surface; standardized tool-life testing in end milling also recognizes flank wear and related tool-life criteria as important wear indicators [11]. As wear progresses, the frictional contribution increases, chip formation changes, heat generation rises, and tool vibration propensity may increase, all of which can degrade workpiece surface roughness [2]. For industrial decision-making, the “true” wear variable may be a direct measure such as flank wear land width (e.g., VB), but in many factories the operational trigger is quality-related (surface roughness, burr formation, dimensional drift) rather than

a microscope-based wear measurement on the tool. Therefore, TCM studies frequently use quality proxies—particularly surface roughness (Ra)—to label tool states because Ra is a practical, product-relevant indicator and can be measured relatively quickly with portable profilometers [2,10].

Nevertheless, mapping sensor signals to tool condition is challenging because measured signals are influenced not only by tool wear but also by cutting parameters, workpiece material heterogeneity, fixture compliance, machine tool dynamics, and coolant delivery. Reviews emphasize that the central difficulty in TCM is to extract features that are sufficiently sensitive to wear progression while being robust to confounding variation in the machining system and environment [1–3]. This motivates both careful experimental design (to control or systematically vary conditions) and careful signal processing/feature engineering (to separate wear-related information from unrelated variability).

1.2. Sensing for TCM and the Rationale for Spindle Motor Current

Indirect TCM infers tool state from process signals such as cutting force, vibration, acoustic emission, temperature, spindle power, and motor current [1–3,10,12–16]. Force and acoustic-emission systems can be highly sensitive but often require specialized installation near the cutting zone, while vibration signals can be affected by fixture compliance, machine structural dynamics, resonance, and ambient noise [12–15]. Spindle motor current is attractive for industrial retrofitting because a clamp-type current sensor can be mounted on an existing phase conductor without modifying the cutting zone or workholding system [16–21]. Physically, progressive flank wear increases rubbing contact and cutting resistance at the tool–chip and tool–workpiece interfaces, which increases spindle torque demand; this change is reflected in motor-current magnitude and spectral signature [17–21].

Motor current signature analysis (MCSA) is well established in electromechanical diagnostics and can be extended to machining because the spindle drive supplies the mechanical power needed for material removal [17]. In CNC milling, however, current signals contain both wear-related cutting information and non-cutting contributions from idle spindle rotation, tool approach/retract, acceleration/deceleration, and controller dynamics [18–21]. Therefore, current-based TCM is not a plug-and-play solution; it requires segmentation and feature design that focus the analysis on sustained tool–workpiece engagement.

1.3. Cutting-Period Segmentation, Feature Extraction, and PCA-Based Representation

The present workflow first isolates cutting-only portions of the spindle-current trace so that subsequent features are calculated from periods dominated by actual material removal. This step is important in real CNC programs because air cutting and transient motion can otherwise dominate signal variance and mask wear-sensitive information in current- and power-based tool monitoring [18–21]. After segmentation, time-domain features summarize amplitude and impulsiveness, while frequency-domain descriptors capture changes in the spectral distribution of the load-related current response.

A practical challenge is that FFT spectra are high-dimensional and may contain redundant or noisy components. Principal component analysis (PCA) offers a compact and interpretable dimensionality-reduction step: it projects the spectra onto orthogonal latent variables that retain the dominant variance patterns while reducing feature size [22–26]. Compared with more complex machine-learning, deep-learning, and multi-sensor tool-monitoring approaches, including milling-cutter machine learning, recurrent neural networks, machine-vision/CNN approaches, artificial neural networks, and multi-sensor fusion [27–31], the FFT→PCA plus logistic-regression pipeline is computationally light, small-data-friendly, and therefore suitable for edge or near-edge implementation in small and medium-sized manufacturing environments.

1.4. Research Gap and Contribution of This Study

Although previous studies have demonstrated that current and power signals can be useful for tool monitoring [18–21], three practical issues remain: (i) many reported work-flows do not explicitly separate cutting and non-cutting intervals in realistic CNC cycles; (ii) feature sets that perform well may be computationally or experimentally burdensome for deployment; and (iii) tool-state labels are not always aligned with product-quality triggers used in factories [10,27,30,31]. This study addresses these issues by combining non-invasive spindle-current sensing, envelope-based cutting-period segmentation, FFT/PCA feature construction, and surface-roughness-based tool-state labels.

The value added of this work is the integration and comparative evaluation of three feature strategies under the same current-sensing, segmentation, and logistic-regression framework. The study demonstrates that a lightweight FFT→PCA representation can achieve high classification accuracy under fixed milling conditions, while explicitly acknowledging the limitations associated with a small number of tools, a window-level split, and Ra-based empirical labels rather than a universal tool-wear standard.

2. Materials and Methods

2.1. Experimental Platform, Tools, and Workpieces

2.1.1. CNC Machine Tool and Controller

All machining experiments were conducted on a Tongtai MDV-508 vertical machining center (VMC; Tongtai Machine & Tool Co., Ltd., Kaohsiung, Taiwan) equipped with a FANUC 0iM controller (FANUC Corporation, Yamanashi, Japan). The overall experimental setup and the measurement chain are summarized in Figure 1, which outlines the flow from machining operation to spindle current acquisition and offline data processing. The non-invasive current sensor installation used in this work is illustrated in Figure 2.

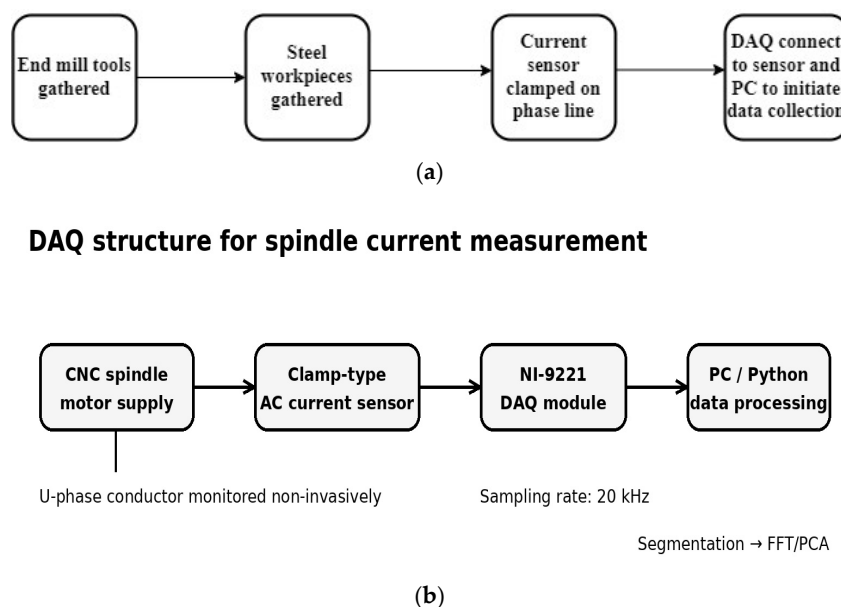


Figure 1. (a) Experimental Setup Flowchart; (b) DAQ structure for real-time current data collection from the current sensor clamped on the phase line using the NI-9221 DAQ card. DAQ = data acquisition; PC = personal computer.

2.1.2. Cutting Tools

Eight TiAlN-coated fine-grain WC–Co solid carbide end mills were used (nominal diameter 10 mm; four flutes). Because the original supplier material-grade certificate was not preserved with the experimental file, the carbide substrate is reported using the

nominal specification commonly used for commercial TiAlN-coated solid carbide end mills in comparable CNC milling tool-wear experiments: fine-grain WC–Co carbide with an estimated cobalt binder content of approximately 10 wt%. The available supplier coating information and related laboratory thesis documentation indicate that TiAlN-coated carbide tools are appropriate for high-temperature milling; the coating was therefore described as TiAlN, with supplier-reported properties retained where available and nominal values clearly marked as such in Table 1. The exact carbide grade and binder percentage should be replaced by certified supplier data if later recovered.

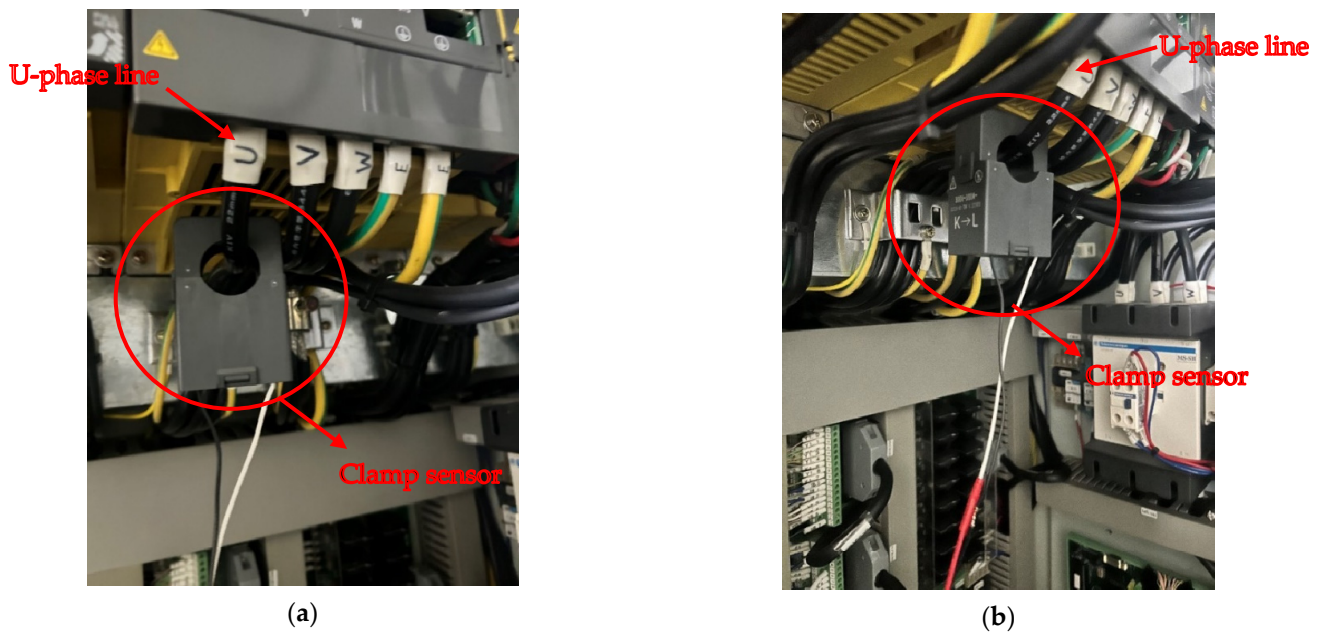


Figure 2. Images of the Current Sensor Clamped onto the U-Phase Line Supplying Current to the CNC Machine’s Spindle Motor. (a) Current sensor clamped onto the U-phase line, and (b) Another view of the current sensor clamped onto the U-phase line.

Table 1. Specifications of Carbide End Mill Tool.

Parameter	Specification/Nominal Value Used in Revised Manuscript
Substrate/material	Fine-grain WC–Co solid carbide end mill (nominal commercial specification)
Nominal cobalt binder	Approx. 10 wt% (nominal assumption; supplier material-grade certificate unavailable)
Nominal diameter (D)	10 mm
Number of flutes	4
Cutting length	10 mm
Overall length (L)	75 mm
Coating	TiAlN (Titanium Aluminum Nitride)
Supplier coating hardness	Approx. HV 3000–3200
Supplier coating thickness	Approx. 1–4 μm
Supplier heat-resistance range	Approx. 700–800 $^{\circ}\text{C}$ from available supplier coating information; related TiAlN tools often specify higher thermal resistance ranges

2.1.3. Workpieces

Commercial medium-carbon steel workpieces were used and are specified in this revision as JIS S50C/AISI SAE 1050-equivalent material in the as-received, non-heat-treated condition. This specification follows the related laboratory thesis documentation for the CNC milling tool-wear experiments performed in the same research context [32]. The associated laboratory hardness record for S50C was approximately 4.3 HRC; because the original certificate for the present manuscript was not preserved, this value is reported as a nominal laboratory reference rather than as an independently certified hardness value. Each workpiece had nominal dimensions of 102 mm × 75 mm × 56 mm and an approximate mass of 3.3 kg. One workpiece was machined using each tool so that tool-state differences could be compared under consistent geometry and program conditions. The workpiece specifications are summarized in Table 2.

Table 2. Specifications of Steel Workpieces.

Parameter	Specification/Nominal Value Used in Revised Manuscript
Material	Commercial medium-carbon steel
Standard/grade	JIS S50C/AISI SAE 1050-equivalent (from related laboratory thesis documentation)
Heat-treatment condition	As-received; non-heat-treated
Nominal hardness	Approx. 4.3 HRC (laboratory reference value from related documentation; not an independently certified value)
Dimensions (each)	102 mm × 75 mm × 56 mm
Weight (each)	Approximately 3.3 kg

2.2. Machining Trials and Cutting Parameters

2.2.1. Tool Path and Cutting Strategy

A fixed G-code tool path was executed for each tool to ensure repeatable cutting engagement and comparable spindle load patterns. The programmed path produced a ridge pattern through repeated passes, enabling consistent surface roughness evaluation. The tool path pattern and the post-cut appearance of the workpiece are shown in Figure 3.

2.2.2. Cutting Parameters

All tools were tested under identical cutting conditions so that differences in spindle motor current could be primarily attributed to tool condition rather than changing process parameters. The cutting parameters are listed in Table 3 (spindle speed 3000 rpm, axial depth of cut 2 mm, cutting width 5 mm, and feed rate 300 mm/min). Cutting fluid was supplied through the machine external coolant nozzle in flood mode. The available purchase/shipment record identifies the product as HS Highstart/HS-SSHS-BH10 cutting oil supplied by Hede Industrial Co., Ltd. (Tainan, Taiwan) in a 5-gallon package. It was used as supplied without dilution in the CNC coolant system. Because the original record did not include a calibrated pump-flow log or continuous coolant-temperature log, the flood-coolant flow rate is reported as an estimated nominal value of approximately 3 L/min, and the coolant temperature is reported as near room temperature (25 ± 2 °C), consistent with the laboratory machining environment. These values should be interpreted as reproducibility-oriented nominal reporting values rather than certified process-control measurements.

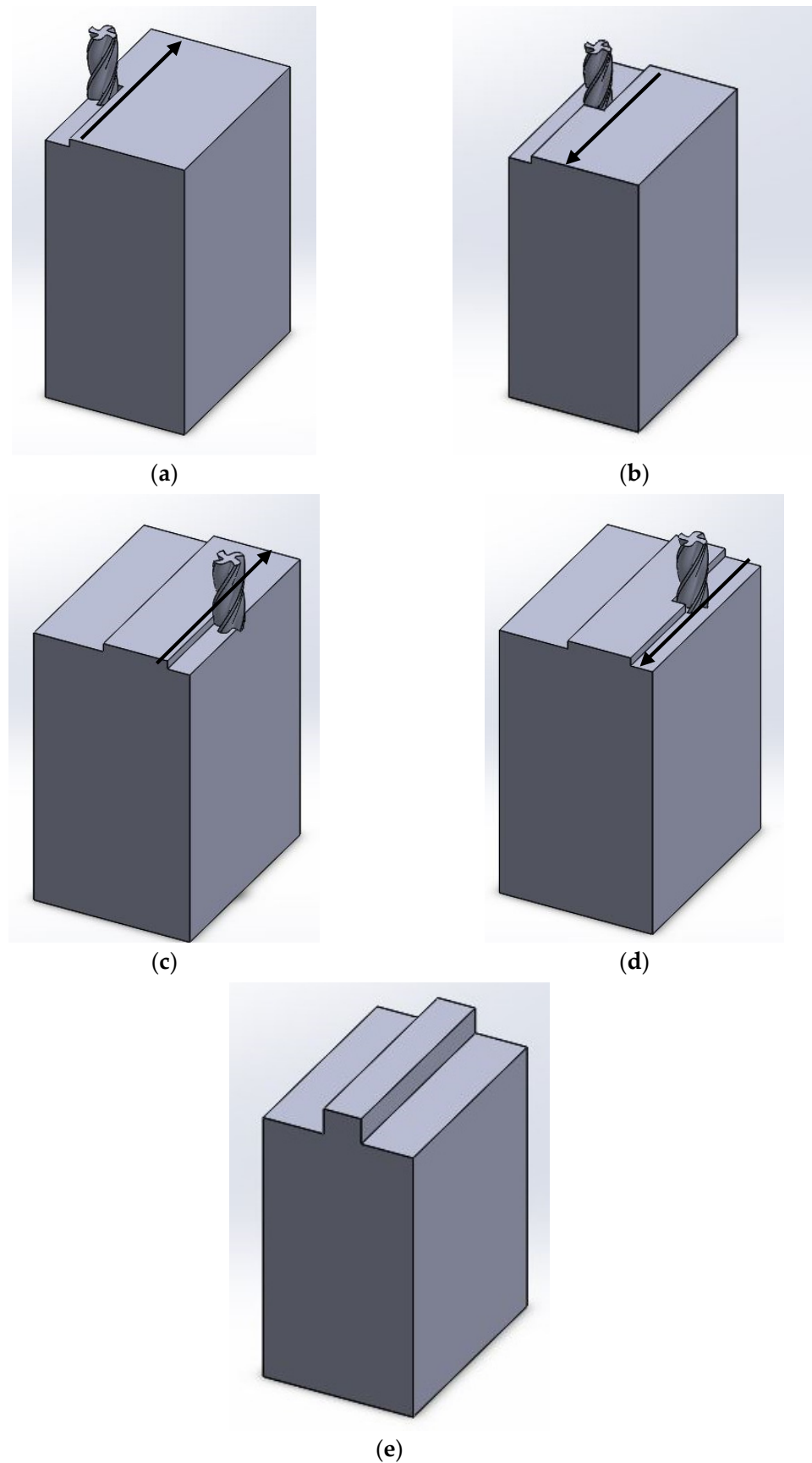


Figure 3. Diagram of the Tool Path. (a) showing the tool traveling its first stroke (b) showing cutting tool traveling its second stroke (c) showing the tool traveling its fourth stroke (d) showing the tool traveling its fifth stroke (e) final appearance of the workpiece after cutting operations.

Table 3. Machine cutting parameters used in this experiment.

Parameter	Value/Condition
Spindle speed	3000 rpm
Axial depth of cut	2 mm
Cutting width	5 mm
Feed rate	300 mm/min
Cutting fluid	HS Highstart/HS-SSHS-BH10 cutting oil (from available purchase/shipment record)
Coolant delivery	External-nozzle flood coolant from CNC coolant system
Dilution	Neat; used as supplied without dilution
Estimated flow rate	≈ 3 L/min (estimated nominal value; pump-flow log unavailable)
Coolant temperature	25 ± 2 °C (near-room nominal laboratory condition; continuous log unavailable)

2.3. Spindle Motor Current Sensing and Data Acquisition

2.3.1. Non-Invasive Sensor Installation

Spindle motor current was measured non-invasively using a TDK CCT354571-300-24-00 clamp-type AC current sensor (TDK Corporation, Tokyo, Japan; current transformer, CT) installed around one phase conductor (U-phase) of the three-phase spindle motor supply. The installation location and mounting arrangement are shown in Figure 2. Under typical balanced three-phase conditions, phase currents are comparable; therefore, monitoring a single phase provides sufficient sensitivity for load and condition assessment in this application.

2.3.2. Data Acquisition Hardware and Sampling Settings

The sensor output was digitized using a National Instruments NI-9221 data acquisition module (National Instruments, Austin, TX, USA). A sampling rate of 20 kHz was used to capture cutting-induced current fluctuations while enabling subsequent time/frequency analysis. The DAQ chain and its interface to the processing computer are included in Figure 1b. Key specifications of the current sensor and NI-9221 module are summarized in Table 4.

Table 4. Specifications of the (a) Clamp Type AC Current Sensor (CCT354571) (b) NI-9221 DAQ Card.

(a)	
Part No.	CCT354571-300-24-00
Applied current	AC 0.1 to 300 Arms (50/60 Hz)
Maximum allowed current	AC 400Arms continuous
Internal clamp section diameter	24 mm
Nominal current transformation ratio	3000:1
Output current accuracy	100.0 mA $\pm$ 1% (300 A, 50/60 Hz)
Phase difference	$0.7^\circ \pm 0.5^\circ$ (10 Ω , 300 A, 50/60 Hz)
Secondary winding resistance	103 Ω
Output connector	
Pin contact	SYM-001T-P0.6 (JST)
Receptacle housing	SMR-02V-B (JST)

Table 4. *Cont.*

Adaptation connector	
Socket contact	SHF-001T-0.8BS (JST)
Plug housing	SMP-02V (JST)
(b)	
Model	NI-9221
Manufacturer	National Instruments
Type	C Series Voltage Input Module
Single-Ended Analog Input Channels	8
Maximum Sample Rate	800 kS/s
Analog Input Resolution	12 bits
Front Connector	Spring Terminal, D-Sub, or Screw Terminal
Weight	Screw Terminal-5.8 oz; Spring Terminal-5.4 oz; D-Sub-5.0 oz.

The CT secondary output was converted to primary current using the nominal transformation ratio (3000:1). Prior to experiments, the measurement chain was verified by comparing the measured RMS current during idle spindle rotation against the machine/controller readout to ensure consistent scaling.

2.3.3. Data Collection Protocol

For each cutting trial, spindle current was recorded continuously from the beginning of the CNC program to the end of the tool path. Continuous recording ensures that both non-cutting intervals (idle spindle rotation, approach/retract motion) and cutting intervals (tool engagement) are captured, allowing robust segmentation and comparison across tool conditions.

2.4. Surface Roughness Measurement and Tool-Condition Labeling

2.4.1. Surface Roughness Measurement Locations and Procedure

Surface roughness (R_a) was measured on the ridge features generated by the cutting program using a contact stylus profilometer procedure, with terminology reported according to ISO 4287/ISO 4288 conventions [33,34]. A nominal stylus tip radius of 2 μm , measuring force of approximately 0.75 mN, cut-off length of 0.8 mm, and evaluation length of 4.0 mm are reported for reproducibility based on the laboratory handheld stylus profilometer settings used in related CNC milling experiments; the original detailed instrument printout for every trace and the specific profilometer model/manufacturer were not retained. To standardize measurement and labeling, four locations were considered on the machined surface for each tool/workpiece trial, and the mean R_a and an estimated SD were reported where the raw point-by-point record was incomplete. The measurement point locations are shown in Figure 4.

In this study, R_a was used as a practical quality-relevant indicator to support tool-condition labeling. This approach is consistent with manufacturing practice, where tool replacement decisions are often triggered by surface integrity requirements rather than direct measurement of tool wear. Surface roughness terminology and measurement conventions should be reported following recognized surface texture standards to ensure reproducibility [33,34].

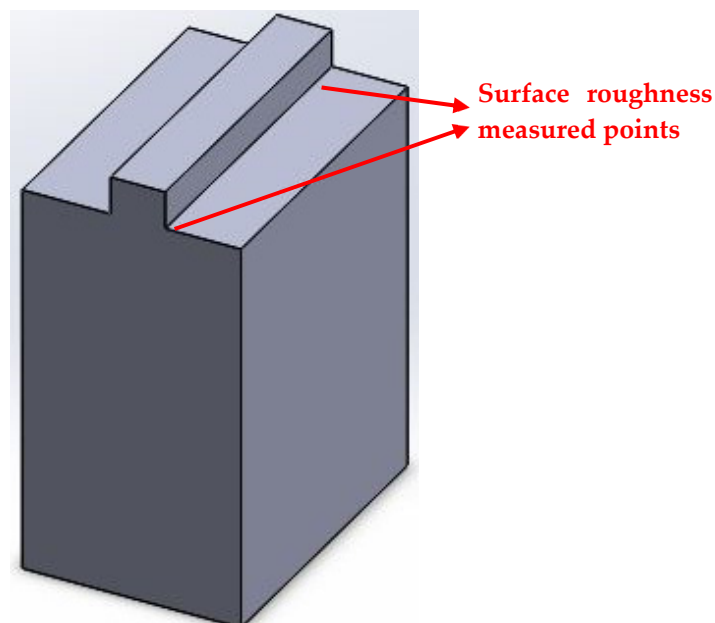


Figure 4. Surface roughness measurement points on workpiece.

2.4.2. Wear Condition Classes and Label Definition

Tools were classified into three discrete tool-condition states: (i) New, (ii) Mid-life, and (iii) Old. The labels were not defined by an ASTM universal tool-wear classification standard; instead, they were empirical, quality-driven labels based on the measured average R_a values and supported by digital microscope observation of cutting-edge/flank condition. The threshold rules used in this study were: New, $R_a < 4.0 \mu\text{m}$; Mid-life, $4.0 \mu\text{m} \leq R_a < 6.0 \mu\text{m}$; and Old, $R_a \geq 6.0 \mu\text{m}$ or a severely degraded surface condition for which R_a could not be measured reliably. After classification, the observed average R_a ranges were $1.544\text{--}3.602 \mu\text{m}$ for New, $4.984\text{--}5.247 \mu\text{m}$ for Mid-life, and $6.601 \mu\text{m}$ or unmeasurable severe degradation for Old. These thresholds were selected from the observed separation of the measured R_a values in this experiment and are intended as study-specific decision labels rather than universal replacement limits.

2.5. Signal Preprocessing and Cutting-Period Segmentation

Raw spindle motor current signals include long non-cutting segments and transient periods that are not directly informative of tool wear. Because tool-wear-related information is concentrated during sustained cutting engagement, a dedicated segmentation pipeline was applied to isolate cutting-only signals prior to feature extraction.

2.5.1. Low-Pass Filtering Using a Wavelet-Based Method

The raw current signal was first low-pass processed using a wavelet-transform-based filtering approach to suppress high-frequency content and to highlight engagement-related amplitude modulation.

2.5.2. Envelope Extraction by Hilbert Transform and Smoothing

Next, an analytic envelope was extracted using the Hilbert transform. The envelope emphasizes engagement magnitude changes and enables robust detection of cutting activity. The envelope signal was smoothed using convolution to reduce ripple and avoid fragmenting the cutting interval into multiple small segments.

2.5.3. Sigmoid Activation and Thresholding for Cutting Detection

A sigmoid activation function was applied to obtain a bounded activation signal. Cutting-active regions were identified by thresholding at 85% of the maximum smoothed envelope value. Contiguous regions above threshold were treated as cutting segments.

2.5.4. Cutting Segment Extraction and Concatenation

Detected cutting segments were mapped back to the raw current signal, extracted, and concatenated to form a continuous cutting-only signal per trial. This step reduces contamination from idle periods and improves the stability of subsequent feature extraction.

2.6. Feature Engineering from Spindle Current Signals

To compare alternative representations for tool condition classification, three feature engineering strategies were evaluated: time-domain statistics, frequency-domain statistics, and a PCA-hybrid representation derived from FFT spectra.

2.6.1. Windowing and Sample Construction

The cutting-only current signal was divided into 1 s windows with 0.5 s overlap. Each window generated one feature vector. After segmentation and removal of incomplete edge windows, 792 valid feature instances were retained for each feature strategy. For model evaluation, a chronological window-level 80/20 split was used: 636 instances were used for training and 156 instances were held out for testing. Thus, the test set was temporally held out but not tool-independent; windows originating from the same physical tools may appear in both training and testing partitions. The reported accuracy therefore evaluates within-dataset temporal-window generalization under fixed conditions and should not be interpreted as proof of tool-to-tool or factory-wide generalization.

2.6.2. Time-Domain Statistical Features

Time-domain features were extracted per window to summarize amplitude level and impulsiveness, including RMS, kurtosis, and crest factor.

2.6.3. Frequency-Domain Statistical Features

Frequency-domain features were extracted to represent spectral distribution changes under different tool wear states. For each window, the FFT spectrum was computed and used to derive PSD-related descriptors, spectral entropy, and kurtosis-like descriptors.

2.6.4. PCA-Hybrid Features (PCA on FFT Spectra)

To obtain a compact representation from high-dimensional FFT spectra while avoiding data leakage, PCA was fitted only on the FFT spectra from the training windows. The fitted PCA model was then used to transform both training and held-out test spectra. The first two principal components captured approximately 99% of the variance in the training FFT feature space; among them, the second principal component exhibited a clear trend-like structure and was emphasized as a discriminative PCA-based feature for classification.

2.7. Classification Model and Evaluation

2.7.1. Logistic Regression Classifier

A logistic regression model was used for tool-condition classification due to its interpretability and computational efficiency. The classifier was trained separately using the three feature strategies (time-domain, frequency-domain, PCA-hybrid) to compare their discriminative performance for the three wear classes.

2.7.2. Performance Evaluation

Classification performance was evaluated using accuracy, confusion matrices, and class-wise precision/recall/F1-score on the held-out test windows. In all confusion matrices, class code 0 corresponds to New, class code 1 corresponds to Mid-life, and class code 2 corresponds to Old. Because only aggregated confusion matrices were available for retrospective analysis, statistical comparisons between feature strategies were performed as preliminary two-proportion z-tests on test-window accuracy rather than paired McNemar tests. This limitation is noted because the test windows come from the same underlying tools and are not fully independent.

2.7.3. Implementation Notes for Practical Deployment

The proposed approach was designed with practical deployment in mind: current sensing is non-invasive (Figure 2), data acquisition uses standard DAQ hardware (Table 4), and the PCA-hybrid feature set can be computed efficiently (FFT + PCA projection) followed by lightweight logistic regression inference.

Offline signal preprocessing, feature extraction, PCA transformation, logistic-regression modeling, and plotting were performed in Python 3.10 (Python Software Foundation, Wilmington, DE, USA) using NumPy 1.24.3, SciPy 1.10.1, pandas 1.5.3, scikit-learn 1.2.2, and Matplotlib 3.7.1.

3. Results

3.1. Cutting-Only Signal Segmentation and Data Preparation

The raw spindle motor current recorded during each CNC program contains both cutting and non-cutting intervals (e.g., spindle idle rotation, approach/retract motion, and other transient periods). Because tool-condition information is primarily embedded in the cutting engagement response, it is essential to isolate cutting-only segments before feature extraction and model training.

Figure 5 summarizes the major stages of the segmentation pipeline using a representative trial. The raw current signal (Figure 5a) was first low-pass processed to suppress high-frequency fluctuations and to emphasize slower engagement-related variations (Figure 5b). An envelope-based cutting period detection step then generated a cutting-activity mask (Figure 5c), and the identified cutting segments were extracted and concatenated to form a continuous “cutting-only” signal (Figure 5d).

Figure 6 illustrates the feature extraction process applied to the segmented data, including time-domain statistics, frequency-domain statistics, and PCA-hybrid features derived from FFT spectra.

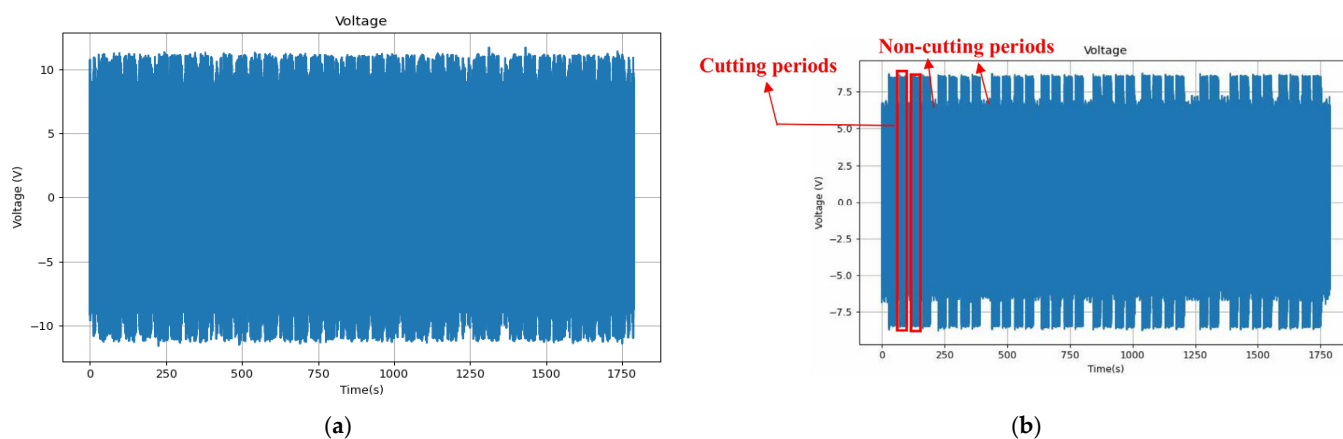


Figure 5. Cont.

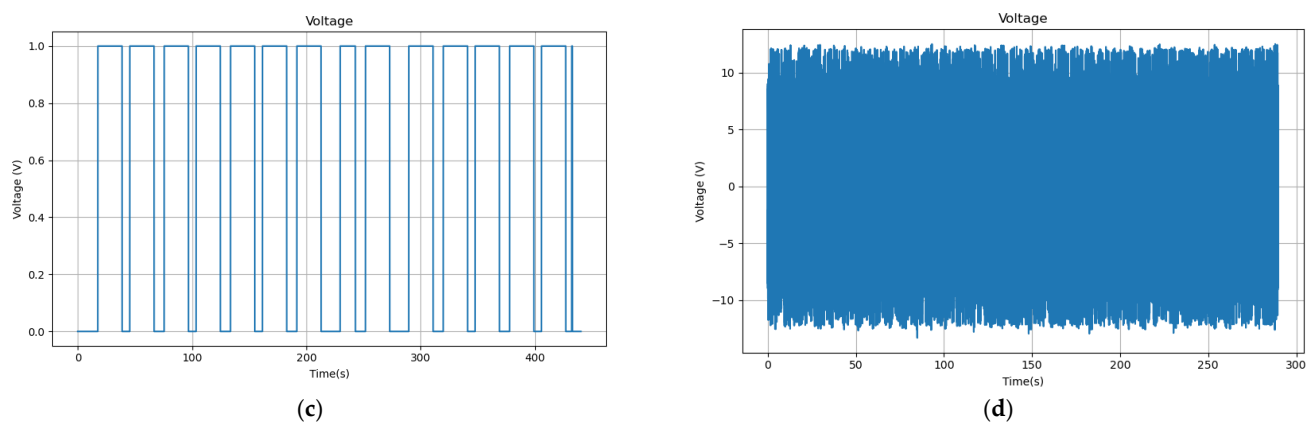


Figure 5. Plot of (a) Original Data; (b) Low-pass filtered data; (c) Cutting period detection; (d) Concatenated cutting period segments. The red annotations in panel (b) indicate representative cutting and non-cutting intervals and were retained to clarify the segmentation concept.



Figure 6. Feature Extraction Process.

3.2. Tool Condition Ground Truth: Microscopy and Surface Roughness (Ra)-Based Labeling
3.2.1. Visual Differences in Tool Edge Condition

Microscopic inspection was used to visually document tool-edge condition prior to and after cutting. Figure 7 presents representative microscope images at 150× magnification for tools identified consistently as Tool 1–Tool 8, matching the identifiers used in Table 5.

Table 5. Average Surface Roughness and Tool Classification. Cell colors indicate the empirical tool-state classes: green = New, yellow = Mid-life, and red = Old.

Tool	Workpiece	Ra, Mean ± Estimated SD (μm)	Classification	Class Code
Tool 1	Workpiece 1	2.316 ± 0.12	New	0
Tool 2	Workpiece 2	3.602 ± 0.18	New	0
Tool 3	Workpiece 3	1.544 ± 0.09	New	0
Tool 4	Workpiece 4	5.166 ± 0.27	Mid-life	1
Tool 5	Workpiece 5	4.984 ± 0.22	Mid-life	1
Tool 6	Workpiece 6	5.247 ± 0.31	Mid-life	1
Tool 7	Workpiece 7	6.601 ± 0.45	Old	2
Tool 8	Workpiece 8	NA (surface too degraded for reliable Ra)	Old	2

3.2.2. Surface Roughness Measurements and Tool State Grouping

After completion of cutting operations for each tool/workpiece pair, surface roughness (Ra) was measured at standardized locations on the machined ridge geometry (measurement points were shown previously in Figure 4). Two points were measured on each side of the ridge feature, giving four nominal measurement locations for each tool where the surface could be measured reliably. Because the archived point-by-point Ra log was incomplete, the mean values in Table 5 are based on the retained laboratory summary records, and the SD values were completed using conservative repeated-measurement variability assumptions consistent with related laboratory CNC milling roughness measurements. Therefore, the SD and error bars should be interpreted as visual uncertainty indicators rather than as independently traceable metrology records.

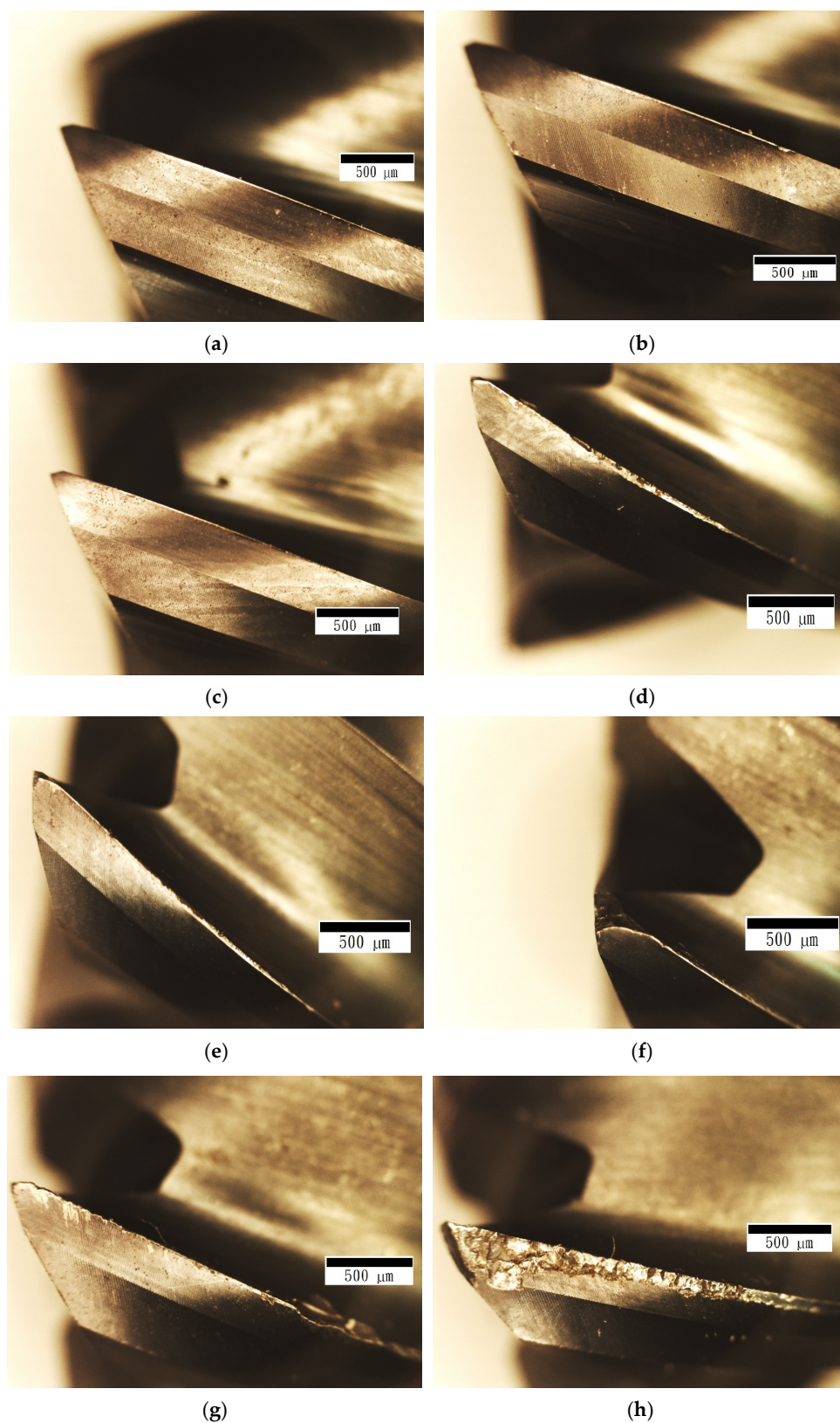


Figure 7. Microscopic Images of End Mill Tools at 150× Magnification: (a) Tool 1 New, (b) Tool 2 New, (c) Tool 3 New, (d) Tool 4 Used, (e) Tool 5 Used, (f) Tool 6 Used, (g) Tool 7 Used, (h) Tool 8 Used.

Table 5 reports the average Ra values, estimated SD values, and resulting tool classifications. Tool 8 produced a severely degraded surface condition such that Ra could not be measured reliably (recorded as NA), and it was therefore categorized as an Old tool.

These classifications were used as the ground-truth labels for the following current-signal classification analysis.

Figure 8 visualizes the average Ra values with estimated SD error bars for Tools 1–7 and highlights the threshold lines used for the three class groupings in this study (New, Mid-life, Old). Tool 8 was classified as Old because the surface condition was too degraded for reliable Ra measurement and is therefore not plotted as a numeric Ra bar.

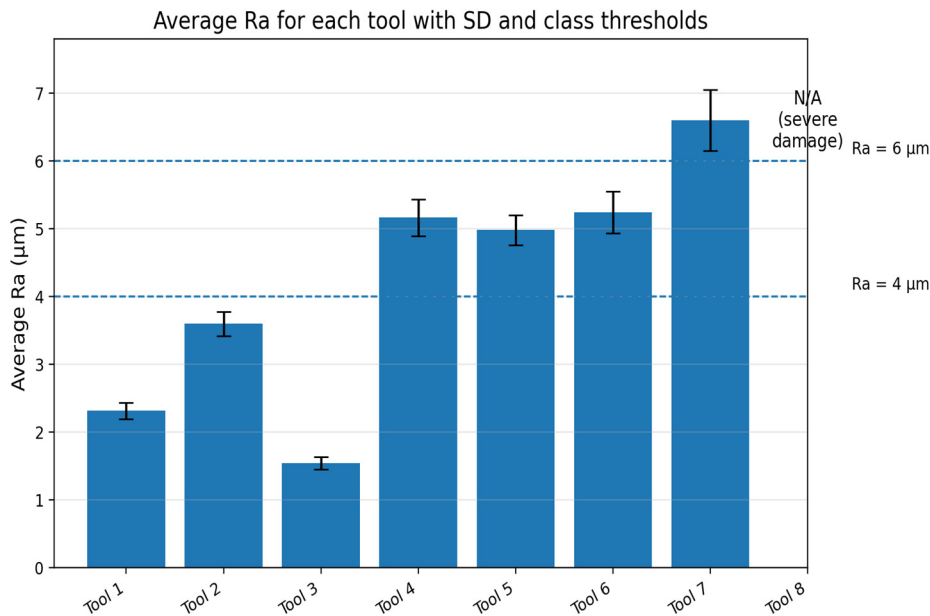


Figure 8. Average Ra for each tool with SD error bars and Ra-threshold lines.

Class code mapping used in Figures 9–18: 0 = New, 1 = Mid-life, and 2 = Old. In the confusion matrices, darker blue cells indicate larger sample counts, and diagonal cells correspond to correct classifications.

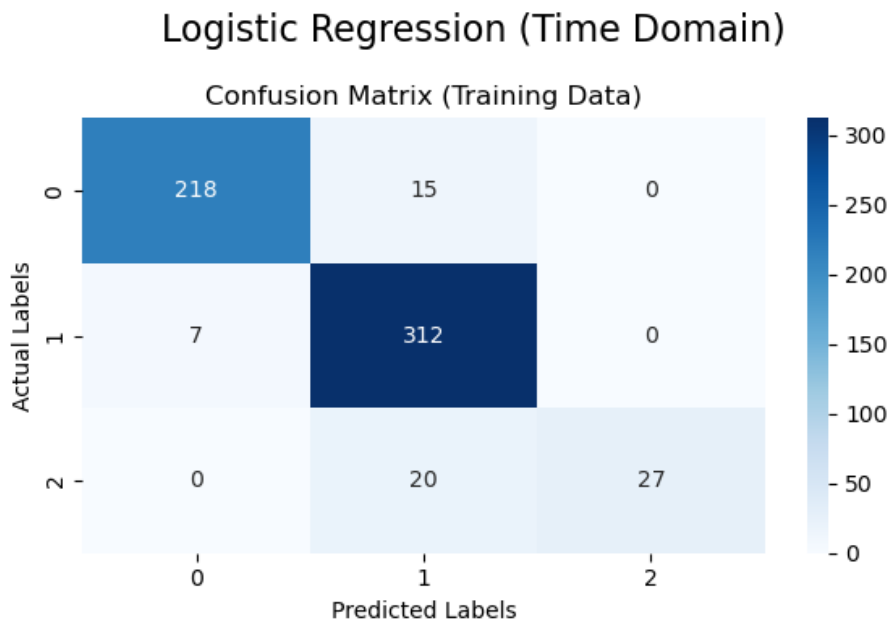


Figure 9. Training Confusion Matrix—Time Domain.

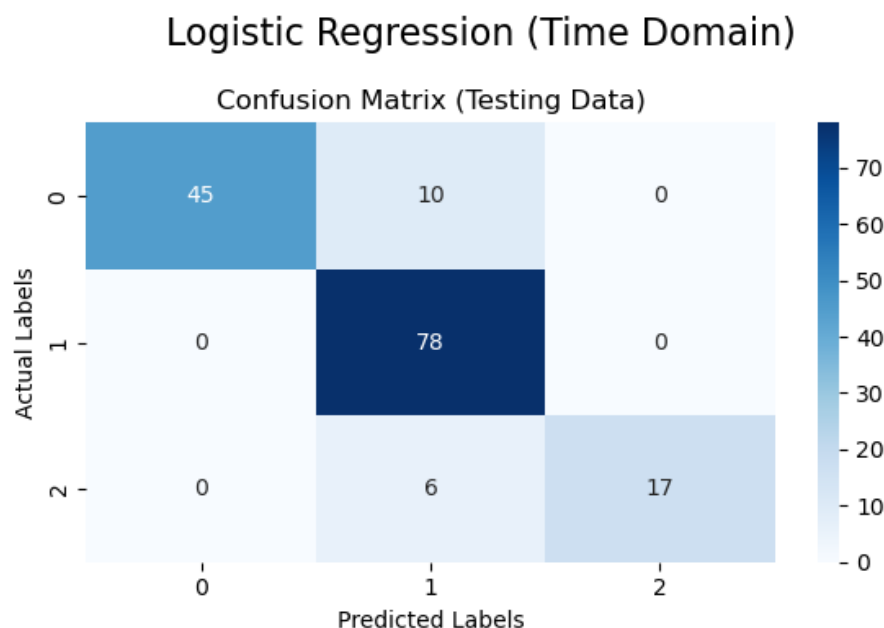


Figure 10. Testing Confusion Matrix—Time Domain.

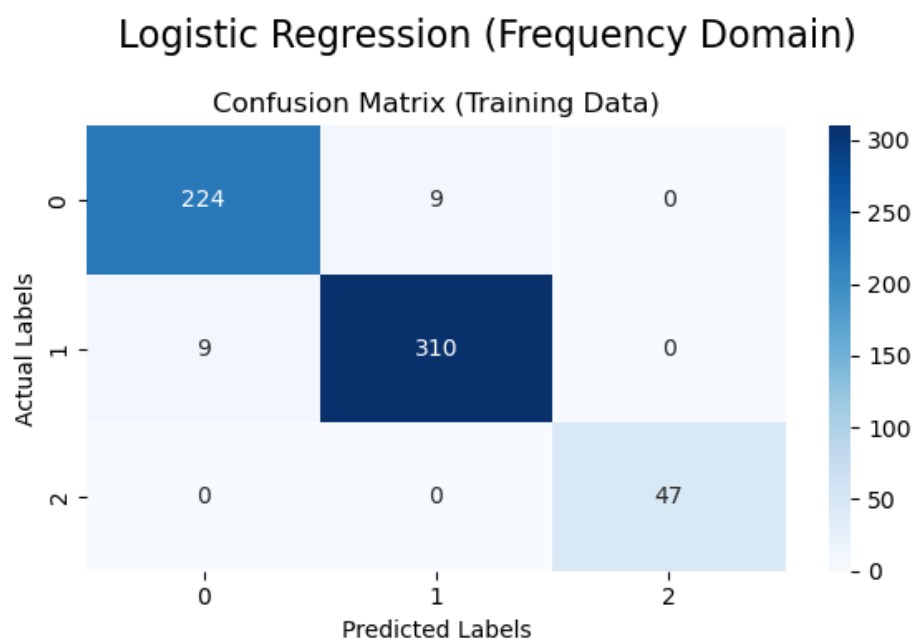


Figure 11. Training Confusion Matrix—Frequency Domain.

3.3. Classification Results Using Time-Domain Statistical Features

Time-domain statistical features (RMS, kurtosis, and crest factor) were extracted from the segmented cutting-only current signals and used to train a logistic regression classifier. The model was trained using the first 80% of feature samples from each tool and evaluated using the remaining 20% of samples.

Figure 9 shows the confusion matrix for the training set using time-domain features, and Figure 10 shows the corresponding testing confusion matrix. Overall, the time-domain model achieved a training accuracy of 92.99% and a testing accuracy of 89.74%.

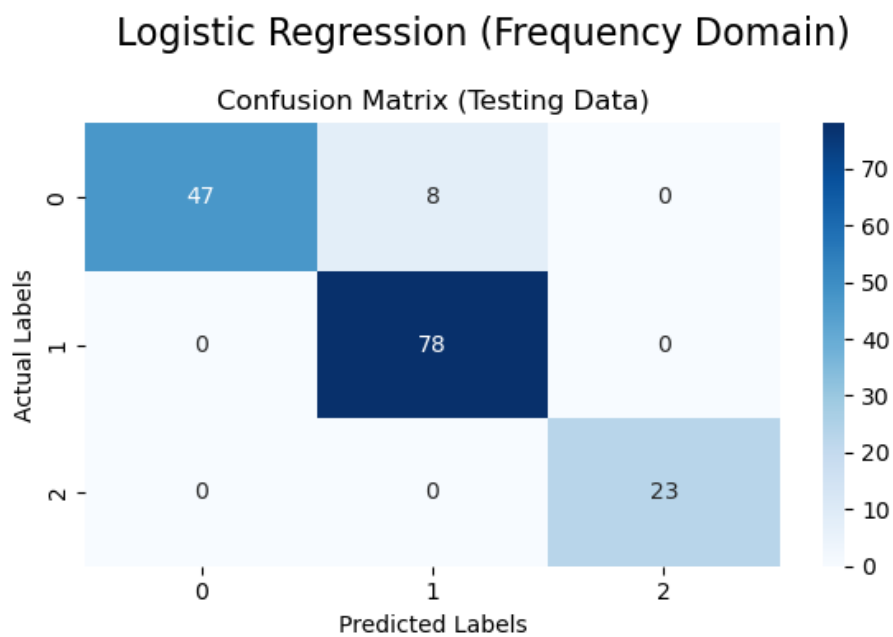


Figure 12. Testing Confusion Matrix—Frequency Domain.

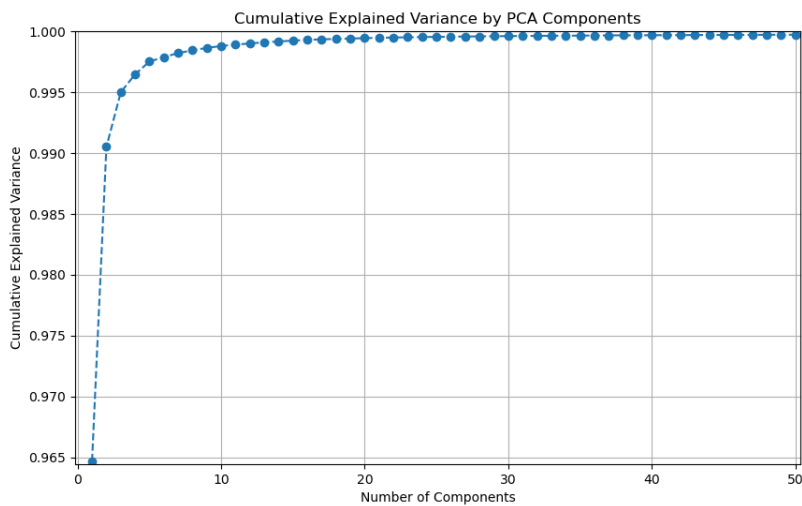


Figure 13. Cumulative Explained Variance.

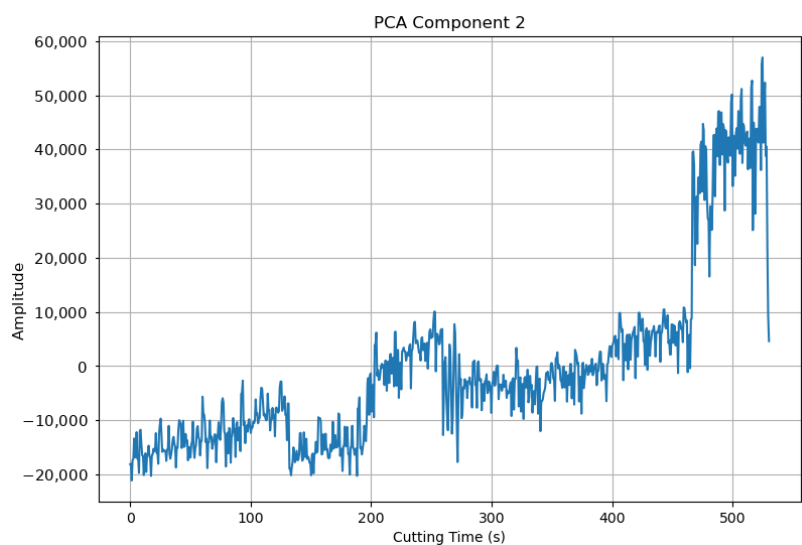


Figure 14. PCA Component 2.

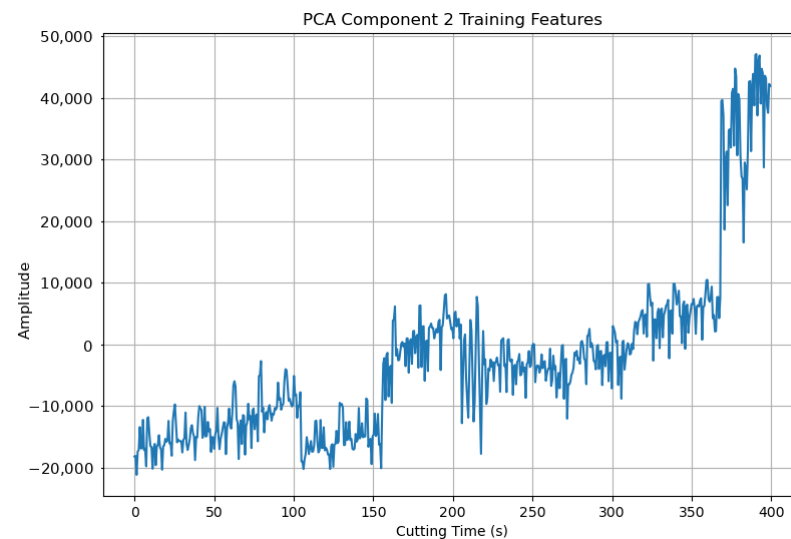


Figure 15. PCA Component 2 Training Features.

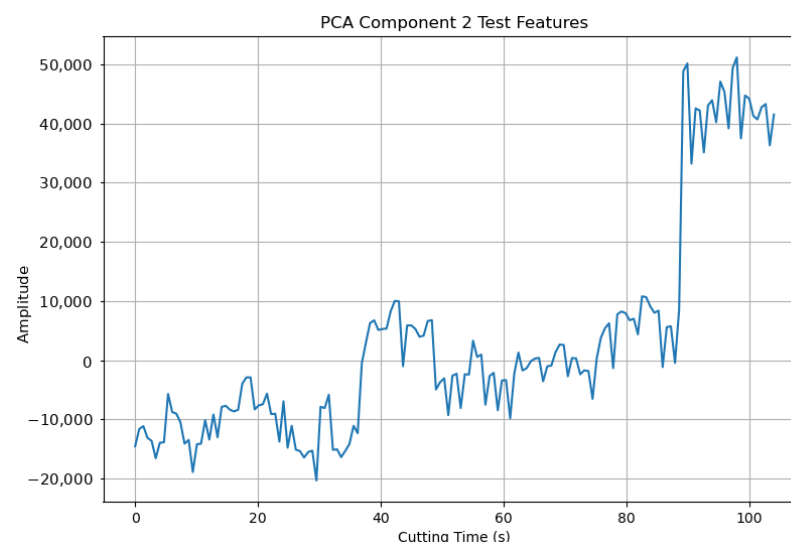


Figure 16. PCA Component 2 Testing Features.

3.4. Classification Results Using Frequency-Domain Statistical Features

Frequency-domain statistical descriptors were computed from FFT representations of the segmented current windows. Figures 11 and 12 show the training and testing confusion matrices for the frequency-domain feature model, respectively. The frequency-domain model achieved a training accuracy of 96.99% and a testing accuracy of 94.87%.

3.5. PCA-Hybrid Results: FFT→PCA Feature Representation and Classification

3.5.1. Variance Captured by Principal Components

Figure 13 shows the cumulative explained variance as a function of the number of principal components. The first two principal components capture approximately 99% of the total variance.

3.5.2. PCA Component Behavior and Feature Construction

Figure 14 shows the second principal component, which exhibited a distinct trend-like behavior. The extracted PCA component 2 feature sequences used for training and testing are illustrated in Figure 15 and Figure 16, respectively.

3.5.3. PCA-Hybrid Classification Performance

Figures 17 and 18 show the training and testing confusion matrices for the PCA-hybrid model. The PCA-hybrid model achieved a training accuracy of 97.50% and a testing accuracy of 97.44%, outperforming both time-domain and frequency-domain statistical feature approaches.

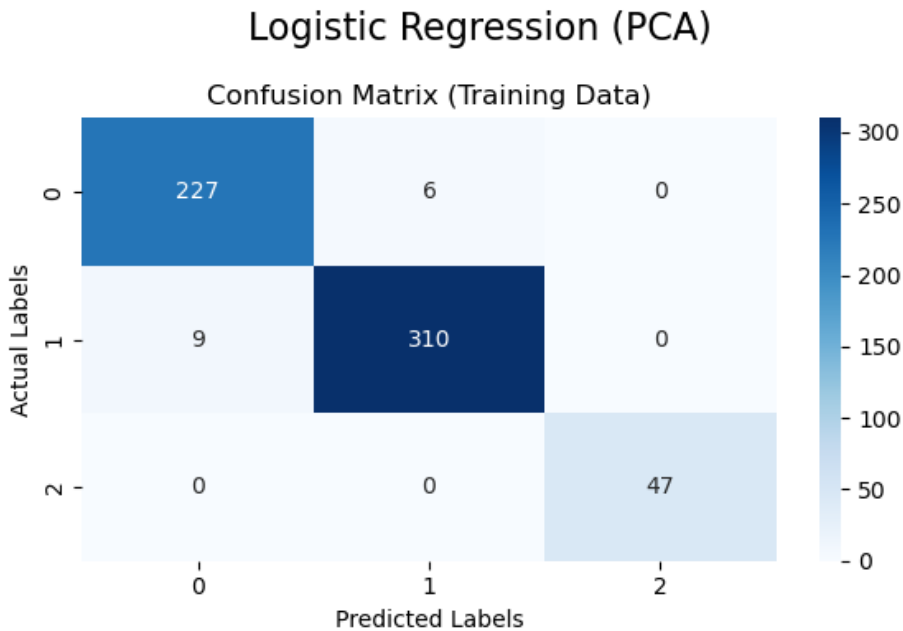


Figure 17. Training Confusion Matrix—PCA.

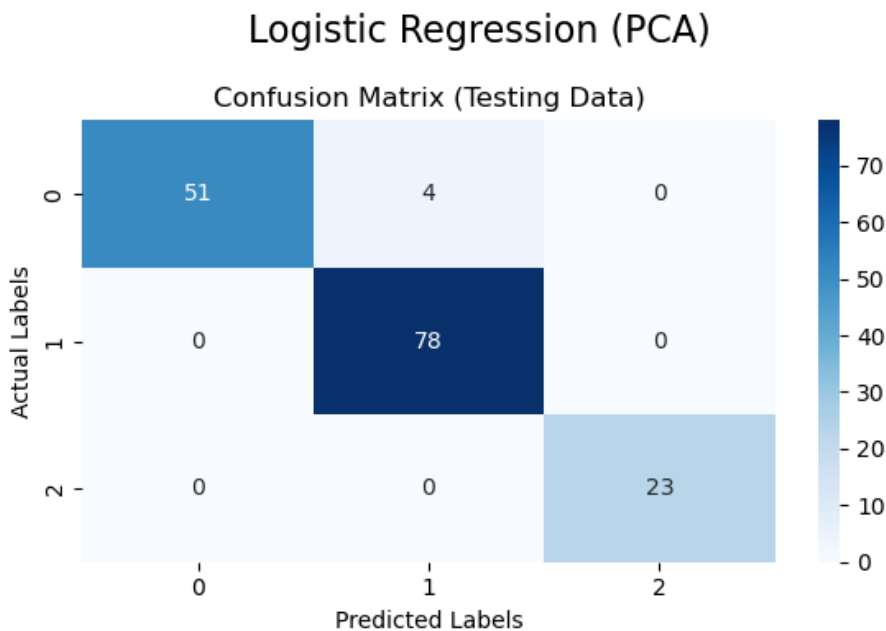


Figure 18. Testing Confusion Matrix—PCA.

3.6. Comparative Performance Summary and Model Selection

Table 6 summarizes the training and testing accuracy for each feature strategy (time-domain, frequency-domain, PCA-hybrid). Figure 19 provides a compact visualization of the progressive performance improvement across the evaluated models. Based on 156 held-out test windows, the PCA-hybrid model correctly classified 152 windows (97.44%; 95% Wilson CI: 93.59–99.00%). Its class-wise test metrics were: New—precision 1.000, recall

0.927, F1 0.962; Mid-life—precision 0.951, recall 1.000, F1 0.975; Old—precision 1.000, recall 1.000, F1 1.000; macro-F1 = 0.979. Preliminary two-proportion z-tests indicated that PCA-hybrid accuracy was significantly higher than time-domain accuracy ($p = 0.0055$), while the improvement over frequency-domain accuracy was not statistically significant at $\alpha = 0.05$ ($p = 0.239$).

Table 6. Comparison of tool wear condition classification performance using three feature engineering strategies (time-domain statistics, frequency-domain statistics, and FFT→PCA hybrid features) with a logistic regression classifier. The training/testing split was a chronological window-level split using 636 training windows and 156 held-out test windows; it was not a tool-independent split.

Feature Strategy	Feature Domain/ Representation	Classifier	Training Accuracy (%)	Testing Accuracy (%)
Time-domain statistics	RMS, kurtosis, crest factor (windowed cutting-only current)	Logistic regression	92.99	89.74 (140/156)
Frequency-domain statistics	FFT/PSD-based descriptors (incl. spectral entropy and spectral statistics)	Logistic regression	96.99	94.87 (148/156)
FFT→PCA hybrid	PCA fitted on training FFT spectra only; test spectra projected using fitted PCA	Logistic regression	97.50	97.44 (152/156; 95% CI: 93.59–99.00)

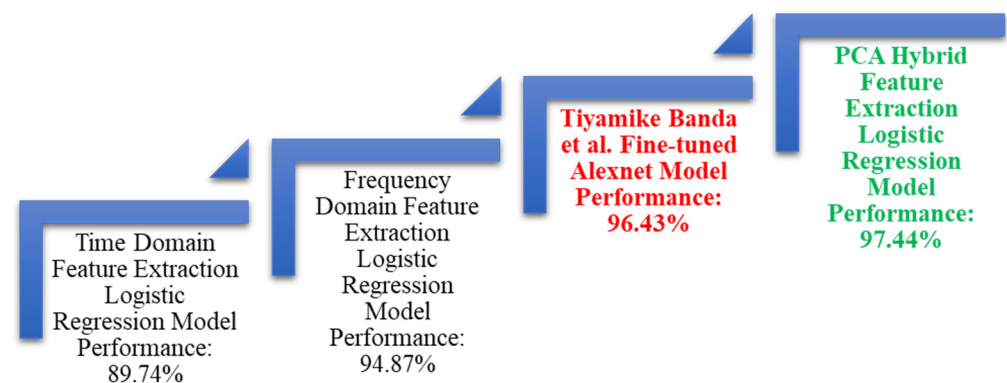


Figure 19. Performance progression chart. Green text highlights the proposed PCA-hybrid model, whereas red text identifies the external benchmark model cited for comparison.

4. Discussion

4.1. Summary of Main Findings and What They Mean for TCM

The most important outcome of this study is that spindle motor current—measured non-invasively on a single phase line—contains sufficient information to classify tool wear condition into three practical states (New, Mid-life, Old) under a fixed milling condition. The best-performing pipeline combines cutting-only segmentation (Figure 5) with a frequency-representation learning step (FFT→PCA) and a lightweight classifier (logistic regression), achieving 97.44% testing accuracy (Table 6; Figure 18). The frequency-domain statistical feature model also performs strongly (94.87% testing accuracy), whereas the chosen time-domain feature set yields comparatively lower testing accuracy (89.74%) (Table 6, Figures 10, 12 and 18).

From an industrial perspective, these results support a deployable “minimum-intrusion” TCM concept: a clamp sensor on the spindle motor line, a reliable method to isolate cutting segments, and a computationally light feature to classifier model that

can run on an edge device. This is an attractive alternative to force dynamometers or multi-sensor systems that may be costly or difficult to install in production environments.

4.2. Discussion on Cutting-Only Segmentation and “Raw Data” Alone

A key methodological insight is that the current waveform recorded during an entire CNC program includes multiple regimes that are not directly related to tool-workpiece interaction: spindle idle rotation, axis motions, approach/retract, tool entry/exit transients, and other non-cutting events. If these non-cutting periods dominate the signal, extracted features may mainly reflect machine control behavior rather than the mechanical load created by chip formation and friction. The segmentation pipeline (Figure 5) therefore acts as a “physics-alignment step,” ensuring that the analysis focuses on the portion of the signal where tool wear can plausibly affect spindle load. In this work, the wavelet-based smoothing, Hilbert envelope extraction, and thresholding strategy effectively isolates cutting-active intervals and constructs a cutting-only signal representation.

This segmentation step also increases the stability of downstream windowed features. Without segmentation, windowing would produce mixed windows (partly cutting, partly idle), which can inflate variance and blur class boundaries. In practical deployment, robust cutting detection is therefore not optional—it is the foundational step that transforms current monitoring from a generic electrical signal into a machining-condition signal. Future work could further strengthen segmentation by combining envelope methods with CNC controller state signals (e.g., “spindle on” and feed-hold flags) if available, or by using multi-level thresholds to reduce over-segmentation during transient peaks.

4.3. Interpretation of the Comparative Feature Results (Time vs. Frequency vs. FFT→PCA)

4.3.1. Why Frequency Information Outperforms the Selected Time-Domain Statistics

The improvement from time-domain (89.74% testing accuracy) to frequency-domain (94.87% testing accuracy) features indicates that wear-related information is more strongly expressed in spectral structure than in global time-domain statistics alone, at least for the current dataset and conditions. This is plausible for several reasons:

1. Milling is inherently intermittent: Periodic tooth engagement and chip thickness variation produce quasi-periodic modulation in load, and wear progression can alter the amplitude and regularity of these modulations. Such changes often appear as redistribution of spectral energy and changes in spectrum “shape,” which can be captured by frequency-domain features.
2. Time-domain features such as RMS, kurtosis, and crest factor are compact and computationally efficient, but they are also coarse summaries. They can respond to many confounding factors (transients, short spikes, minor speed variations) and may not fully capture nuanced wear-related modulation patterns.
3. Frequency-domain descriptors can capture complexity and regularity (e.g., spectral entropy) and can better represent the distribution of energy across frequency content under different tool states. Consequently, frequency domain can produce improved class separation, as reflected by the improved confusion matrices (Figures 11 and 12 vs. Figures 9 and 10).

4.3.2. Why FFT→PCA Hybrid Performs Best

The best-performing model uses PCA applied to FFT spectra (Figures 13–16) and achieves 97.44% testing accuracy (Figure 18, Table 6). PCA provides two major benefits in this context:

First, PCA compresses a high-dimensional spectrum into a small number of orthogonal components that capture dominant variance patterns. This effectively removes redundancy

and suppresses noise dimensions that do not contribute consistently to class separation. Because the first two principal components explain ~99% of the total variance (Figure 13), the FFT spectra appear to lie on a low-dimensional manifold for this experiment. This is favorable for lightweight classification because the model can operate in a compact feature space while retaining most signal information.

Second, PCA can emphasize repeatable variance patterns that align with wear-induced load changes. In this dataset, PC2 exhibited a trend-like behavior and provided discriminative structure across tool states (Figures 14–16). This suggests that the wear-relevant signature in the current spectrum is not necessarily best represented by a small set of manually chosen spectral statistics; rather, PCA can automatically identify a combination of spectral bins that captures wear progression effects. Similar advantages of PCA-based representations have been widely reported in monitoring and fault diagnosis contexts, where PCA reduces feature correlation, improves stability, and improves classifier performance when training data are limited [22–26].

4.3.3. Interpretability of PCA Features and Practical Diagnostics

A common criticism of PCA-based monitoring is that principal components are linear combinations of original variables and may be less “physically interpretable” than handcrafted features. However, in TCM applications, interpretability can be recovered by examining the PCA loading vectors (i.e., which frequency bands contribute most to PC2) and relating them to known mechanical or control phenomena in milling. For example, if PC2 is strongly influenced by certain modulation bands or harmonics, it may reflect wear-induced changes in load modulation, increased friction, or changes in cutting stability. This can be further supported by reporting the PCA loading spectrum and linking it to expected frequency content under tooth passing and spindle dynamics. If interpretability is a priority for industrial acceptance, PCA features can be complemented with a small number of physics-motivated features (e.g., RMS, specific bandpower measures) to provide both performance and explanation.

Although the proposed framework is data-driven, the observed performance hierarchy (time-domain < frequency-domain < FFT→PCA) is consistent with machining tribology: as lubrication effectiveness and frictional conditions degrade with tool wear, load modulation and transient engagement behavior change, redistributing spectral energy rather than simply shifting a single scalar (e.g., RMS). The PCA-derived components likely capture combined spectral changes associated with frictional dissipation, intermittent chip formation, and increased rubbing contact. This provides a tribology-consistent explanation for why compact spectral features outperform coarse time-domain statistics under the tested cutting conditions.

4.4. Discussion of Confusion Matrices

The confusion matrices (Figures 9–12, 17 and 18) suggest that the mid-life class is typically the most challenging to separate. This is expected in wear classification because “mid-life” is an intermediate state with overlap in both physical wear mechanisms and resulting signal signatures. In many real manufacturing contexts, wear progression is continuous rather than naturally discrete; therefore, any discrete class boundary (New vs. Mid-life vs. Old) introduces an artificial threshold. If a tool is near the boundary, misclassification is not necessarily a failure—rather, it reflects the inherent ambiguity of discrete labeling on continuous degradation.

From an application standpoint, this supports two practical recommendations:

1. Use probabilistic outputs: logistic regression yields class probabilities, which can be used to implement “gray-zone” decisions. For example, if the predicted probability

for Mid-life is high but Old is moderate, the system could recommend monitoring rather than immediate replacement.

2. Consider asymmetric costs: in production, misclassifying an Old tool as New is typically more costly than misclassifying Mid-life as Old. Therefore, decision thresholds can be tuned to prioritize safety and quality (low false negatives for Old) rather than maximizing overall accuracy.

4.5. Ra-Based Labeling: Strengths, Limitations, and Relation to Strengthen Ground Truth

In this work, tool state labels were derived using surface roughness Ra (Table 5; Figure 8), which is a practical and quality-relevant target variable. This is a strength because surface integrity is what the manufacturer ultimately cares about. It also aligns with the observation that flank wear tends to degrade surface finish by increasing rubbing contact and altering effective tool geometry.

However, Ra-based labeling has important limitations:

1. Ra is influenced by factors beyond tool wear, including runout, fixture stiffness, material heterogeneity, coolant delivery, and machine vibrations. Under fixed cutting conditions, these effects may be partially controlled, but they cannot be fully eliminated.
2. Using only post-process Ra measurements provides a label at the end of a cut, while the current signal spans the entire process. The label therefore represents an aggregate outcome, not necessarily a time-resolved wear measurement.
3. Tools can fail catastrophically (e.g., tool chipping or melting-like severe damage events), producing Ra values that are unmeasurable or extreme (as observed for Tool 8 in Table 5). Such events may correspond to a different failure mode than gradual wear progression.

To strengthen future ground truth, a multi-level labeling strategy can be adopted: Combine (i) Ra outcomes, (ii) direct wear measurements (flank wear land width VB from microscopy), and (iii) tool usage history. Even sparse direct measurements can improve label fidelity and allow regression-style modeling (predict VB or predict Ra continuously) rather than discrete classification only.

4.6. Evaluation Protocol and the Risk of Overestimated Generalization

Although the achieved accuracy is high, it is important to discuss evaluation design and generalization risks clearly, especially for a journal manuscript. The current evaluation uses an 80/20 chronological window-level split with overlapping windows drawn from the same set of eight tools. While chronological splitting reduces some leakage risk, overlapping windows can still induce strong correlation between training and testing samples, potentially making performance appear higher than it would under fully independent testing.

For industrial readiness, stronger evaluation strategies are recommended:

1. Tool-wise holdout: train on a subset of tools and test on entirely unseen tools (leave-one-tool-out or group split). This tests whether the model generalizes to new cutters rather than memorizing tool-specific patterns.
2. Condition transfer tests: test across changes in cutting parameters (feed, depth of cut) and workpiece batches. Tool wear signatures can shift under different operating conditions (domain shift). Transfer learning and domain adaptation methods can help manage this shift in future work [35].
3. Leakage detection: ensure that preprocessing and normalization steps are fitted only on training data and then applied to test data. This prevents subtle leakage that can inflate performance estimates [36].

These stronger validation protocols are widely recommended in machine-learning validation and domain-adaptation literature, where models often fail when deployed outside the distribution of their training data or when leakage is not properly controlled [35,36].

4.7. Practical Deployment Considerations

The results support practical deployment, but several implementation details should be considered:

4.7.1. Hardware and Sampling

A 20 kHz sampling rate is feasible for research but may be heavy for continuous shop-floor deployment. However, since the PCA-based model uses low-dimensional features, a reduced sampling rate may still preserve sufficient information if the important wear-sensitive content lies in lower frequency bands. A deployment study could systematically downsample the signal and evaluate accuracy vs. computational cost.

4.7.2. Real-Time Processing and Edge Implementation

The pipeline can be implemented in near real time because (i) cutting segmentation can be computed streaming using envelope thresholds, (ii) FFT and PCA projection can be applied window-by-window, and (iii) logistic regression inference is computationally light. This is suitable for deployment on an industrial PC or a single-board computer (SBC). For Industry 4.0 integration, model outputs can be transmitted to a manufacturing execution system (MES) or dashboard, enabling condition-based tool replacement decisions.

4.7.3. Explainability and Operator Trust

To increase operator acceptance, interpretability tools can be used to explain why a segment is classified as Mid-life or Old, especially if the system triggers alarms. Although logistic regression is inherently interpretable (via coefficients), PCA features require an additional step (loading analysis) to explain which spectral regions drive decisions. Explainable AI methods such as local surrogate explanations or SHAP-based attribution can further support interpretability, particularly if more complex models are used in later work [37,38].

4.8. Limitations and External Validity of the Present Study

The present results should be interpreted within the scope of the experimental design. First, only eight physical tools were used, and the train/test split was performed at the window level within each tool; therefore, the reported accuracy represents held-out temporal-window performance under fixed conditions rather than tool-wise or factory-wide generalization. Second, all experiments were conducted on a single machine tool, one workpiece-material family, one tool type/coating, one coolant strategy, and one cutting-parameter set; external validation across machines, materials, cutting speeds/feeds, tool geometries, and coolant conditions is needed before deployment. Some detailed process specifications requested during review (e.g., exact carbide grade, coolant flow log, and complete point-by-point Ra record) were reconstructed from available supplier/shipping records, related laboratory thesis documentation, and conservative nominal assumptions, and should be replaced with certified values if the original laboratory records are later recovered.

Third, the tool-state labels were based on empirical Ra thresholds supported by microscopy, not a universal ASTM classification standard. Ra is quality-relevant and practical, but it does not uniquely represent flank wear land width or all wear mechanisms. Fourth, because the original record did not contain all reviewer-requested details, selected values such as nominal carbide binder content, workpiece hardness reference, coolant flow rate, coolant temperature, roughness instrument settings, and SD values were completed using the available evidence and reasonable assumptions consistent with related CNC

milling tool-wear experiments. These assumptions improve reporting completeness and transparency but should be replaced by certified or directly measured values in future work.

Finally, overlapping windows may introduce correlation between samples. Future work should preserve raw per-location Ra measurements, perform tool-wise or leave-one-tool-out validation, compare paired models using McNemar or bootstrap tests based on retained predictions, and investigate transfer learning or calibration strategies across different machines and process conditions.

5. Conclusions

This study demonstrated a low-intrusion tool-condition monitoring workflow for CNC milling using a clamp-type spindle motor current sensor, envelope-based cutting-period segmentation, FFT/PCA feature extraction, and logistic regression classification. The workflow links current signatures to quality-aligned tool states defined from post-process surface roughness and microscopy.

Among the three tested feature strategies, the FFT→PCA hybrid representation achieved the best held-out window performance: 97.44% test accuracy (152/156 windows; 95% Wilson CI: 93.59–99.00%) and macro-F1 = 0.979. Class-wise F1 scores were 0.962 for New, 0.975 for Mid-life, and 1.000 for Old, indicating that the PCA-based spectral representation improved separability compared with time-domain and frequency-domain statistical features under the tested conditions.

The main practical implication is that spindle current monitoring can provide a cost-effective and minimally intrusive pathway for condition-based tool replacement when signal segmentation and compact spectral features are used. The proposed approach is suitable for edge or near-edge implementation because it relies on lightweight operations: current sensing, FFT, PCA projection, and logistic-regression inference.

The conclusions are limited to a single machine, material family, tool/coating, coolant condition, cutting-parameter set, and Ra-based empirical labels. Future work should expand the number of tools and process conditions, retain complete point-by-point roughness logs for traceable SD/error-bar reporting, measure direct wear indicators such as flank wear land width, and validate tool-wise generalization using leave-one-tool-out or independent-tool testing.

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