



MACHINE LEARNING FOR TOOL CONDITION MONITORING AND PREDICTIVE MAINTENANCE IN CNC MACHINING: A SYSTEMATIC REVIEW

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ABSTRACT

Computer Numerical Control (CNC) machining is the backbone of precision manufacturing, but the productivity, part quality and machine uptime of CNC machining are dependent on the condition of the cutting tool. Conventional fixed-interval tool replacement either discards valuable tool life or permits the tool to be used past safe bounds of dimension, and progressive flank wear, chipping and breakage also affect surface finish and dimensional accuracy. This systematic review follows the reporting guidelines outlined in the PRISMA 2020 statement, and summarizes the existing research literature between January 2016 and September 2026 addressing the application of machine learning (ML) for CNC tool condition monitoring (TCM) and predictive maintenance (PdM). Studies were classified along four dimensions: machining operation, sensing modality, learning method and maintenance objective. It has been revealed that cutting force, vibration, acoustic emission and spindle current/power are the most important indirect measurement signals; that feature quality has significant influence on the performance of traditional classifiers; and that the deep sequence model, including convolutional and long short-term memory models, is now the most popular model for wear estimation and remaining useful life prediction. The reported accuracy is generally in the range of 85% to 99%, but is rarely comparable because the datasets, tools, materials, and validation procedures vary. The research gaps identified were: lack of or costly labelled data, poor cross-machine generalisation, real-time deployment latency, class imbalance and data quality, limited interpretability, under-used ensemble and hybrid methods, under-representation of small firms and developing economies, and incompleteness in integrating with digital twins and CAD/CAM data. The review suggests a research agenda, in which transferable and explainable models are coupled with design-of-experiments process knowledge, low-cost edge sensing and human-centred implementation, particularly relevant for manufacturers operating in resource constrained industrial environments.

Keywords: CNC machining; Machine Learning; Tool Condition Monitoring; Tool Wear; Predictive Maintenance; Remaining Useful Life; Industry 4.0; Systematic Review

1 INTRODUCTION

The geometric flexibility and high accuracy, repeatability and productivity of Computer Numerical Control (CNC) machining make it one of the most common methods of creating precision components in the aerospace, automotive,

tooling, energy and general engineering industries. The performance, however, will be closely dependent on the condition of the cutting tool. Cutting edge gradually deteriorates as it suffers high mechanical and thermal loads, abrasion, adhesion and diffusion during cutting. This wear can lead to poor surface finish, dimensional inaccuracies, increased cutting forces, higher energy usage, and ultimately to unexpected tool failure, causing damage to the workpiece or spindle (Mohanraj et al., 2020; Munaro, Attanasio and Del Prete, 2023).

Tool wear and tool failure are therefore one of the most common reasons for unplanned stoppages on machining centres (Kasiviswanathan et al., 2024). The traditional approach in industrial practice has been fixed-interval tool replacement, and operator experience and manual inspection on a periodic basis. This is inefficient since tools do not wear at a uniform rate – early replacement wastes unused tool life, late replacement generates scrap and downtime. There is also a set of related work that aimed at reducing tool wear and enhancing product quality through optimization of cutting parameters off-line, using the Taguchi method, analysis of variance (ANOVA) and grey relational analysis.

In CNC milling of mild steel, for instance, spindle speed contributed 63.40% of the total variance in flank wear, while surface roughness had 82.81% of the total variance due to feed rate (Mapindu et al., 2026b). Similar design of experiments (DOE) analyses have been performed to optimise honing parameters in terms of surface finish and energy consumption (Tayisepe et al., 2024) and wood-machining parameters for surface quality and energy efficiency (Tayisepe et al., 2023) and weld parameter optimization (Mapindu et al., 2026d). Off-line optimisation ensures good operating windows, but cannot monitor the condition of a specific tool as it wears. To overcome this drawback, Tool Condition Monitoring (TCM) has been developed to infer the tool condition from process signals during the cutting operation and enable condition-based and predictive tool replacement decisions (Tran et al., 2023). Data-driven TCM has become more of a reality thanks to the use of Industry 4.0 technologies such as sensors, the Industrial Internet of Things (IIoT), Cloud and Edge Computing, and Artificial Intelligence (AI) (Çınar et al., 2020; Zonta et al., 2020). Support vector machines (SVMs), random forests (RFs), artificial neural networks (ANNs) and deep learning architectures can be used to learn the relationship between cutting-force, vibration, acoustic emission (AE), spindle current and spindle temperature signals and the tool wear state (Munaro, Attanasio and Del Prete, 2023; Yedurkar, Schlech and Sause, 2025). Advances in the above enable replacement of tools to be planned based on condition not on time.

Adoption is however, not widespread. A study of the Zimbabwean manufacturers revealed a high level of availability of sensors, programmable logic controllers (PLCs) and networked computers, but that the lack of an Industry 4.0 strategy and high cost of the solutions as well as low level of policy support limit their implementation on intelligent systems (Muhla et al., 2025a). In such contexts, companies must also be flexible in the face of changing markets (Muhla et al., 2023), and acquire digital competencies to develop intelligent systems, which are competencies that learning factories can develop (Ndiyamba et al., 2026). A few reviews have explored the application of ML in predictive maintenance applications in general (Carvalho et al., 2019; Zonta et al., 2020; Phan et al., 2022; Surucu, Gadsden and Yawney, 2023; Guidotti, Pandolfo and Pulina, 2025) and specifically in TCM (Mohanraj et al., 2020; Colantonio et al., 2021; Patil et al., 2021; Mohamed et al., 2022).

This review is different in three ways. First, it provides a single taxonomy for CNC machining which combines sensing, feature engineering and learning method and maintenance objective. Second, it critically compares conventional ML approach with deep and hybrid approaches for wear estimation and remaining useful life (RUL) prediction. Third, it discusses implementation aspects that are less well-appreciated such as low cost sensing and installation in resource-limited industrial environments, and integration of process knowledge based on DOE.

The review is guided by four research questions (RQs):

- RQ1: Which machine learning techniques are used in CNC tool condition monitoring and predictive maintenance?
- RQ2: Which sensing technologies and machining data are commonly used to monitor cutting-tool condition?
- RQ3: How is machine learning applied to tool-wear detection, classification, prediction and RUL estimation?
- RQ4: Which limitations and research gaps constrain the practical implementation of ML-based TCM and predictive maintenance?

2 BACKGROUND AND THEORETICAL FOUNDATION

2.1 Tool wear mechanisms and their consequences

CNC Machining process exists in the cutting tool-workpiece interface and cutting tool-chip interface where the material is removed by both shearing and friction. Abrasion, adhesion, diffusion, oxidation under continuous cutting and thermo-mechanical fatigue and chipping under intermittent cutting are the mechanisms behind the development of wear. The most commonly used wear criterion is flank wear (VB), which is defined as the width of worn flank as measured on the

clearance face and is standardised for tool-life testing (Mohanraj et al., 2020). The high spindle speed dependence on flank wear reported in the Taguchi based milling experiments (Mapindu et al., 2026b) is attributed to a thermally activated wear mechanism, due to the fact that the cutting-edge temperature increases with cutting speed. As wear takes place, cutting forces, amplitude of vibration, spindle power and heat generation will change, surface roughness will get worse, and dimension errors will increase. If it is not being detected in time, the tool can break, stopping the machine and causing a bottleneck with a high cost impact.

2.2 Direct and indirect tool condition monitoring

The process of determining the health of a cutting tool while it is in use, thus allowing the state and remaining life to be judged without interrupting production to assess the tool physically is called Tool Condition Monitoring (TCM). Direct methods measure the wear geometry directly (optical, vision or laser) – accurate, but limited in-process by coolant, chips, lighting and access. Indirect methods involve inferring tool state from process signals which vary as the tool deteriorates, such as cutting force, vibration, AE, spindle current/power, and temperature (Mohanraj et al., 2020; Tran et al., 2023). Shamim and Ruddro (2025) suggest that the sources of information in an AI-based maintenance system are mainly vibration, acoustic, thermal and ultrasonic sensing. The idea is simple: if a tool creates a unique signal "fingerprint," then as it wears, that fingerprint changes, but a trained model can identify the change.

2.3 From reactive to predictive maintenance

The maintenance strategies that can be used span from reactive (run-to-failure) to time-based preventive maintenance to condition-based maintenance (CBM) or predictive maintenance (PdM), which relies on measured condition and forecast degradation to schedule intervention (Zonta et al., 2020; Yedurkar, Schlech and Sause, 2025). There's no denying the price of staying on the reactive end of the spectrum. In a coal fired power station in Zimbabwe, corrective maintenance made up approximately 72% of the maintenance mix and a reliability optimum, with reduced failures and reduced maintenance cost, was identified using a RF model trained on the operating data from the previous 13 years (Senda et al., 2026).

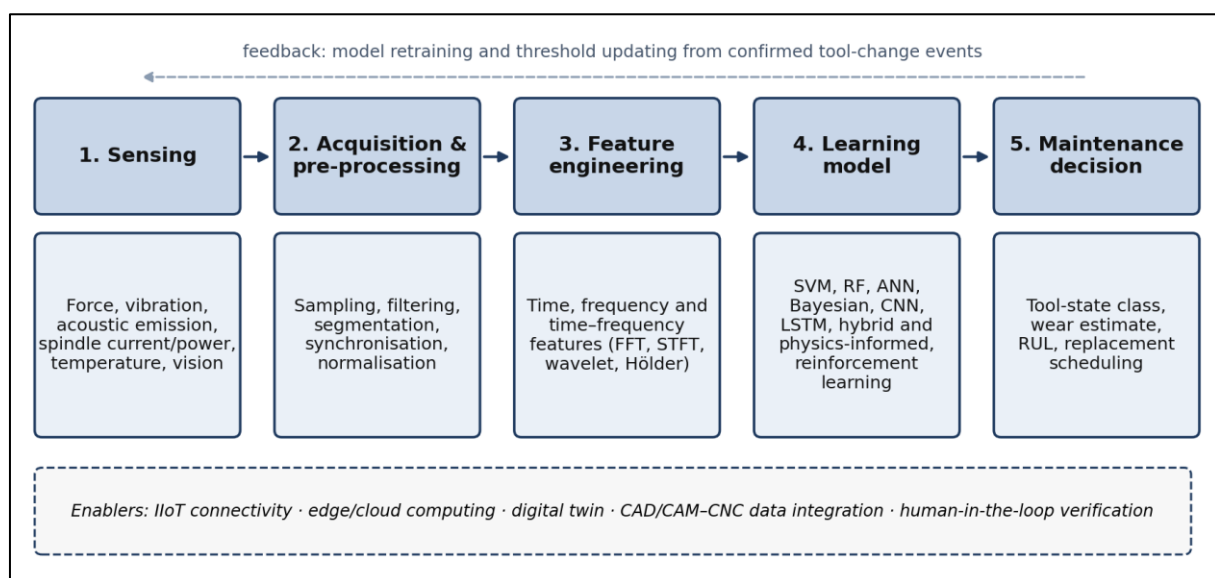


Figure 1: Conceptual framework of machine-learning-based tool condition monitoring and predictive maintenance in CNC machining (developed by the authors from the reviewed literature).

A multi-agent CBM system consisting of infrared, flow and conductivity sensors, PLC, OPC server and rule-based diagnostic agents was installed in a copper-cable manufacturing plant to detect all the injected furnace fault conditions without false alarms, with a payback period of 3 months (Mashava et al., 2026). Similar AI-based, digital-twin-based asset management is discussed in Rojas, Peña and García (2025) for mining machines. Even though the problem area of these cases is not cutting tools as such, but boilers and furnaces, the same sensing to decision chain can be realised economically with commercially available components in developing industrial economies. In the context of CNC machining, the equivalent chain is sensing, signal acquisition and pre-processing, feature engineering, learning model and maintenance decision, which is enabled by connectivity and computing (Figure 1).

2.4 Position of TCM within the CAD/CAM-CNC digital chain

The TCM is also part of the larger digital chain of the CAD/CAM-CNC system. The development of intelligent toolpath generation and integration of CAD/CAM with data on the shop floor are key topics in Industry 4.0 and 5.0 for machining

research (Simonič, Palčič and Klančnik, 2025). If the estimation of the tool condition is fed back to computer-aided manufacturing (CAM) and to the controller, cutting parameters, toolpaths and tool-change points can be adjusted to the actual tool condition. This convergence of virtual process models and measured signals is demonstrated in several examples, such as digital-twin driven monitoring of milling cutter wear (Zi, Gao and Xie, 2024) and digital-twin approaches to TCM in turning (Rawal et al., 2025).

3 REVIEW METHODOLOGY

This review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement (Page et al., 2021) to ensure that the identification, screening, eligibility assessment and inclusion of studies were transparent and reproducible.

3.1 Information sources and search strategy

Scopus, Web of Science, IEEE Xplore, ScienceDirect and SpringerLink were searched as the primary databases. To capture the relevant work that was not indexed in the primary databases, Google Scholar and backward and forward citation searching were also employed. The search string was generated by the research questions and included three concept blocks, “CNC” OR “machining” OR “milling” OR “turning” OR “drilling”, “tool condition monitoring” OR “tool wear” OR “tool life” OR “remaining useful life” OR “predictive maintenance”, and “machine learning” OR “deep learning” OR “artificial intelligence” OR “neural network”. The string was modified to suit the syntax of each database and used for titles, abstracts and keywords.

3.2 Search period and eligibility criteria

The search spanned from January 2016 to 22 September 2026. This period reflects the emergence of Industry 4.0, industrial ML, sensor-based monitoring and data-driven predictive maintenance, with the majority of the studies relevant to this period published from 2018, coinciding with the quick growth of deep learning. A few earlier publications were kept that had laid the groundwork in tool wear measurement or monitoring. The inclusion and exclusion criteria are briefly summarised in Table 1.

Table 1: Inclusion and exclusion criteria

Criterion	Inclusion	Exclusion
Topic	Machine learning or data-driven methods applied to tool condition monitoring, tool wear, tool life or RUL in CNC or conventional machining	Studies without a machining context or without an ML/data-driven element
Study type	Peer-reviewed journal articles, conference papers, systematic reviews and theses with sufficient methodological detail	Editorials, patents, product brochures, non-scholarly web content
Period	January 2016 – September 2026; earlier foundational works where essential	Superseded or redundant earlier versions of the same study
Language	English	Other languages
Quality	Clear objective, described set-up and dataset, stated validation method and reported metrics	Insufficient methodological or validation detail

3.3 Study selection and quality assessment

Identification, screening and eligibility/inclusion were the four PRISMA phases of the selection process. All records were combined and any duplicate records were eliminated. Titles and abstracts were then scanned for the criteria listed in Table 1 and the full text of any potentially relevant records was then checked. Each full-text report was reviewed for clarity of the research objective, description of the experimental setup, the description of the experimental dataset, transparency of pre-processing, transparency of feature extraction, the validity of the model (hold-out, cross-validation or cross-condition testing) and reporting of performance metrics. Reports which failed to meet these requirements were not included. Any disagreements among reviewers were resolved by discussion. The movement of records in the review is outlined in Figure 2.

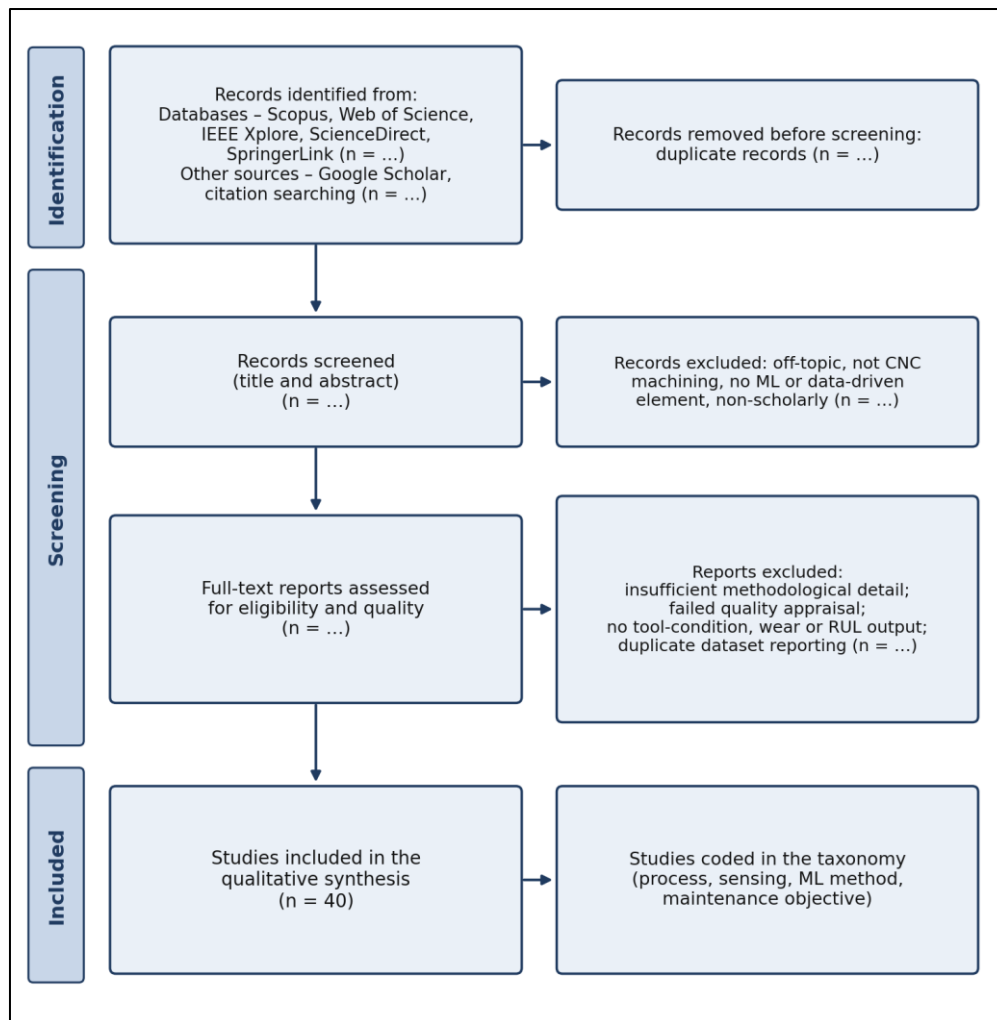


Figure 2: PRISMA flow diagram of study identification, screening and inclusion (adapted from Page et al., 2021).

3.4 Data extraction and synthesis

The machining operation, workpiece material, tool type, sensor(s) and signals, data source, pre-processing and features, learning algorithm, scheme of validation, performance metrics and maintenance objective were extracted from each included study and presented in a structured matrix. As the studies were diverse in their settings and metrics, a quantitative meta-analysis was inappropriate and a narrative and thematic synthesis was performed in the following manner: by the four dimensions of classification described in Section 4.

4 CLASSIFICATION AND TAXONOMY

The included literature can be organised along four dimensions: machining operation, sensing technology, machine-learning method and predictive-maintenance objective. Feature engineering, which links sensing to learning, is treated as a separate subsection because of its decisive influence on model performance.

4.1 Classification by machining process

Milling dominates the literature, followed by turning, reflecting both industrial importance and the availability of public milling datasets. Table 2 summarises the typical monitoring targets and ML applications for each process.

Table 2: Classification of the literature by machining process

Machining process	Typical monitoring target	Examples of ML applications	Representative studies
Turning	Flank wear, tool faults, insert condition	ANN, SVM, RF, Bayesian classifiers, CNN	Thangarasu et al. (2020); Colantonio et al. (2021); Patange et al. (2022)
Milling (general)	Flank wear, tool breakage, insert condition	Decision tree, RF, SVM, CNN, LSTM	Patange and Jegadeeshwaran (2020); Huang et al. (2021); Traini et al. (2019)
End milling	Flank wear	Wavelet features + SVM/DT/MLP; audible sound + SVM	Kothuru, Nooka and Liu (2018); Mohanraj et al. (2021)
Face milling	Insert health	Tree-based and Bayesian classifiers	Patange and Jegadeeshwaran (2020)
Titanium-alloy milling	Online wear state	Wear-law-informed Siamese LSTM	Qin et al. (2023)
High-speed CNC milling	Wear and RUL	LSTM, CNN, autoencoder, hybrid deep learning	Sayyad et al. (2023); Elminir et al. (2024); Chen et al. (2025)
Multi-operation CNC	Tool wear and failure	SVC with random-forest feature selection; multi-stage deep learning	Abubakr et al. (2021); Hassan, Mohamed and Attia (2024)

4.2 Classification by sensing technology

Table 3: Comparison of sensing modalities used in CNC tool condition monitoring

Sensing modality	Information captured	Advantages	Limitations
Cutting force (dynamometer)	Force components and their fluctuation	High sensitivity to wear; physically interpretable	Expensive; intrusive mounting; limits workpiece size
Vibration (accelerometer)	Dynamic response of tool-spindle system	Low cost; easy mounting; widely used with DL	Affected by machine structure and other vibration sources
Acoustic emission / sound	High-frequency stress waves; audible noise	Sensitive to micro-fracture and chipping	Noise contamination; sensor placement critical
Spindle current / power	Motor load and cutting energy	Often available from controller; non-intrusive; low cost	Lower sensitivity for light cuts and small tools
Temperature	Thermal state of cutting zone	Relates directly to wear mechanisms	Difficult to measure in-process; slow response
Vision / optical	Wear land geometry	Direct measurement; high accuracy	Needs interruption or clean access; coolant and chips

The signal is one of the most common signals, and tool degradation changes the dynamic behaviour of the cutting process. Patange et al. (2022) used a micro-electro-mechanical systems (MEMS) accelerometer to capture vibration signals during turning and divided the vibration signals into six tool conditions; Huang et al. (2021) transformed the vibration signals into time-frequency images for a deep convolutional neural network (CNN). The use of cutting-force signals is also popular, since the cutting force varies as wear occurs; Thangarasu et al. (2020) used cutting force and surface roughness to forecast flank wear in hard turning of EN8 steel using an ANN. Acoustic emission sensors are used to capture elastic waves at high frequency levels, which are produced in the cutting area, and which are also caused by micro-fracture and friction; machine noise and coolant can also interfere with the signal. Low cost microphones have also been used with SVMs to detect wear in end milling without regard to microphone placement (Kothuru, Nooka and Liu, 2018). The spindle current and spindle power are good industrial outputs that can be considered as attractive indicators because CNC controller can provide them, which also eliminates the need for extra sensors. The process independent classification approach that involves only current sensors is capable of achieving 0.911 accuracy, which is

improved to 0.958 when the approach is customized for a particular material, making the use of lower cost TCM possible for small and medium size enterprises (SMEs) (Abubakr et al., 2021). Other factors such as temperature and vision are also explored, but in-process usage is not possible due to accessibility, coolant, chips, lighting, and dust (Mohanraj et al., 2020; Mohamed et al., 2022).

The information content is enhanced with multi-sensor fusion, but at the cost of increased cost and complexity. The main sensing options are compared in Table 3. Where money is limited, low cost embedded sensing is an important enabler. Arduino class microcontroller based obstacle detection systems have been successfully used in assistive systems with ultrasonic sensors with a response time lower than 100ms at an affordable cost compared to commercial systems (Munotyaani et al., 2026), and similar architectures are becoming more common in vibration and current acquisition systems for machine tools. Distributed sensor nodes can also be made to be energy autonomous by designing renewable energy harvesting locally; for instance, vertical axis wind turbines (VAWT) harvesting energy from the slipstream of a vehicle (Muyambo et al., 2025).

4.3 Signal processing and feature engineering

Most often, the raw signals are not directly fed to the conventional classifiers. Typical features extracted include time domain measures like root mean square, kurtosis, skewness and peak, frequency domain through fast Fourier transform and time–frequency measures derived with short-time Fourier transform (STFT), wavelet packet decomposition, and empirical mode decomposition (Kasiviswanathan et al., 2024). Mohanraj et al. (2021) used wavelet features and Hölder exponents to represent the regularity of the signals in end milling and demonstrated that not only the choice of the signal regularity feature, but also the choice of the classifier affects the classification accuracy. Sayyad et al. (2023) used time–frequency features with deep learning models to predict the RUL of milling cutters. Selection techniques like random-forest importance ranking (Abubakr et al., 2021) and automated pipelines for feature selection (Rahman, 2025; Gougam et al., 2024) are applied to reduce dimensionality, enhance generalisation and reduce computation. This means features can be extracted directly from raw signals or signals that are only lightly processed, making deep networks less reliant on the features being engineered by experts and making them more data-intensive.

4.4 Classification by machine-learning method

The machine learning techniques adopted in CNC TCM can be classified as: Tree based ensemble methods, Support vector machines, Artificial neural network, Bayesian classifiers, Deep learning and Hybrid / Reinforcement learning. Tree-based classifiers like decision trees and RFs are interpretable classification models that have been found to be accurate in experimental studies (Patange et al., 2022). They proved to be robust as well as to non-linear relationships, and their feature-importance measures are crucial in their choice for the plant where they were applied as the basis of a preventive maintenance decision model for utility boilers (Senda et al., 2026).

Even though SVMs are very effective in classification of tool conditions in small-scale datasets with complex relationships, the quality of the features affects the performance of the SVM (Mohanraj et al., 2021; Abubakr et al., 2021). ANN models are used to learn the non-linear relationship between machining parameters, process signals and wear (Thangarasu et al., 2020) and Bayesian classifiers provide a probabilistic approach to the tool health states (Patange and Jegadeeshwaran, 2020). Since 2020, deep learning has emerged as the main paradigm for wear estimation and RUL prediction. CNNs are used to learn spatial patterns from spectrogram or original signals (Huang et al., 2021), and there is a proposal for the RUL of the milling tool using a pyramid CNN with group convolution and channel attention (Hu, 2023).

Temporal evolution of wear is modeled with recurrent architectures, such as long short-term memory (LSTM) networks. An LSTM–autoencoder model achieved 98% accuracy on the PHM 2010 milling dataset (Elminir et al., 2024) while an LSTM–fully convolutional network with attention demonstrated higher accuracy than five competing RUL models on a complete lifecycle of cutters from the PHM 2010 dataset (Chen et al., 2025). Some proposed methods have been suggested to improve generalisation of the wear level across operations for multi-stage deep frameworks, which first classify the wear levels and then regress them (Hassan, Mohamed and Attia, 2024). Hybrid and physics-informed methods: Incorporate process information into data-driven models. In online use for milling machines, Yang et al. (2022) first introduced data-driven learning (DDL) and then introduced model-informed wear detection (MIWD), which obtained an average test accuracy of 96.6%, and Qin et al. (2023) introduced the tool wear law to a Siamese LSTM network, which achieved an average test accuracy of 98.2% in the milling of Titanium alloy.

Reinforcement learning is emerging: In milling TCM study, the accuracy for the classification was 98.66% using the SARSA algorithm, and it was higher than that of LSTM (94.85%) and feed-forward networks (98.16%) (Kaliyannan et al., 2024). Even in the presence of limited failure data with labels and explainability is required, rule-based expert systems in multi-agent architectures continue to be valuable (Mashava et al., 2026). In general, the performance of monitoring and prediction will be affected by the choice of algorithms, data quality, feature extraction, and the features of the machining process.

4.5 Classification by predictive-maintenance objective

The literature can be separated according to the level of prediction expected from the system:

- Tool-state classification determines whether the tool is sharp, worn, chipped, broken or in another defined state.
- Tool-wear estimation quantifies the amount of wear, typically flank wear VB, as a continuous variable.
- Tool-life prediction estimates the useful cutting time before a specified wear limit is reached.
- Remaining useful life prediction estimates how long the tool can continue operating from its current state before replacement or failure, often with uncertainty bounds.

Classification studies are the most numerous, but the balance has shifted towards regression and RUL prediction, which support scheduling rather than only alarm generation (Traini et al., 2019; Kamat, Kumar and Kotecha, 2024; Al-Refaie, Al-Atrash and Lepkova, 2025). Table 4 summarises representative studies across these objectives.

Table 4: Representative studies on ML-based tool condition monitoring, wear estimation and RUL prediction

Study	Process / data	Method	Objective and key outcome
Kothuru, Nooka and Liu (2018)	End milling; audible sound	Frequency features + SVM	Wear classification; position-independent detection across cutting conditions
Traini et al. (2019)	Milling; real machine data	ML framework for PdM	Cutting-tool wear prediction to support maintenance scheduling
Abubakr et al. (2021)	Machining; current, vibration, AE	RF feature ranking + SVC	Tool failure detection; 0.911 accuracy with current sensors only
Huang et al. (2021)	Milling; vibration	STFT + deep CNN	Wear monitoring from time-frequency images
Yang et al. (2022)	Milling; online signals	Hybrid data-driven and model-informed	Online wear detection with physical consistency
Qin et al. (2023)	Titanium-alloy milling; spindle vibration	Wear-law-informed Siamese LSTM	Online TCM; 98.2% average test accuracy
Sayyad et al. (2023)	Milling; multi-sensor	Time-frequency features + deep learning	RUL prediction of milling cutters
Gougam et al. (2024)	CNC milling; machining signals	Feature extraction, automatic selection, optimised regression	Wear prediction; RMSE of 8.7–10.4 μm
Elminir et al. (2024)	High-speed milling; PHM 2010	LSTM–autoencoder	RUL estimation; 98% accuracy
Kaliyannan et al. (2024)	Milling; vibration	LSTM, FFNN, SARSA reinforcement learning	Tool-state classification; SARSA 98.66%
Kamat, Kumar and Kotecha (2024)	Milling	DeepTool deep learning framework	Wear-onset detection and RUL prediction
Chen et al. (2025)	Milling; full-lifecycle multi-sensor	Parallel fully convolutional network with attention	RUL; outperformed five competing models
Mapindu et al. (2026b)	CNC milling of mild steel; Ra and VB	Taguchi L9 + ANOVA + GRA	Parameter optimisation; spindle speed 63.40% of VB variance

5 CRITICAL ANALYSIS AND SYNTHESIS

5.1 Areas of agreement

Five points of agreement can be drawn. First, the indirect signals like vibration, cutting force, AE, spindle power and temperature contain enough information to monitor in order to ensure reliability (Mohanraj et al., 2020; Mohamed et al., 2022; Tran et al., 2023). The second is that these signals can be analysed automatically using the power of ML and detect changes in the tool condition without needing to rely on manual inspection and operator judgement. Third, feature engineering is important: statistical, wavelet and Hölder based features, in addition to feature selection, have significant improvements in classification (Mohanraj et al., 2021; Patange et al., 2022; Abubakr et al., 2021). Fourth, the use of ML-based TCM provides the flexibility of predictive maintenance, providing indications that the tool needs to be replaced based on a predictive analysis rather than a scheduled change. Fifth, the quality of the sensor data and their disciplined use in data processing must be reliable to ensure effective monitoring and prediction (Surucu, Gadsden and Yawney, 2023).

5.2 Areas of disagreement and divergence

There is conflicting literature on a few issues. No single algorithm is consistently the best in all cases: SVM, RF, ANN, and deep models all have been reported to be the best on different datasets, processes, and validation protocols. Comparing reported accuracies directly is not possible as there are differences in machines, tools, materials, sensors, datasets, and validation methods used (Colantonio et al., 2021). While conventional ML features ground-truthed features and works effectively on small datasets, deep ML learns the features from the data but requires more data and computational resources. Single-sensor designs are more cost-effective and robust (Abubakr et al., 2021), while multi-sensor fusion delivers higher information, but also comes with higher cost and complexity. The accuracy of the models that are developed under controlled lab conditions may be lost on the shop floor since cutting conditions, materials and tools are frequently changing (Patange et al., 2022; Tran et al., 2023). Last but not least, conventional models are easier to explain to the maintenance personnel while deep models are difficult to explain to the maintenance personnel, thus impacting trust and adoption.

5.3 Linking design-of-experiments process knowledge with machine learning

There is a common lack of linking the off-line process optimisation to online monitoring in the TCM literature. DOE studies measure the quality and degradation responses as a function of process parameters. In CNC milling, a Taguchi L9 design and ANOVA were used to identify the optimum values of cutting speed, depth of cut, and feed rate, which were found to be 1000 rpm, 0.10 mm/rev and 0.5 mm depth of cut, respectively, and were confirmed by the grey relational analysis within the 95% confidence interval (Mapindu et al., 2026b). A similar Taguchi-ANOVA-grey relational framework has been used to tackle conflicting quality objectives in injection moulding (Mapindu et al., 2026a) and fused deposition modelling (Mapindu et al., 2026c), and regression models based on orthogonal arrays have been applied as tools to guide process design in edible oil vacuum bleaching (Jansen et al., 2025) and honing and wood machining (Tayisepe et al., 2024; Tayisepe et al., 2023). The following three complementarities to ML-based TCM are highlighted. First, main effects derived from DOE experiments show which parameters (and, consequently, which operating regimes) should be included in the training data for a monitoring model to generalise. Secondly, the results of replicated DOE trials are well labelled wear and quality data at low cost that can be used to initialize ML models or can be used to benefit from transfer learning. Third, the percentages from ANOVA give physically motivated priors for hybrid models, akin to the wear-law informed networks proposed by Qin et al. (2023) and Yang et al. (2022). This is a relatively unexplored area of coupling DOE and ML.

5.4 Implementation in resource-constrained industrial settings

The majority of studies are conducted in properly funded laboratories, and there is little evidence from SMEs and developing countries (Carvalho et al., 2019; Elkateb et al., 2024). The barriers are not just technical, but organisational, as well, according to research in Zimbabwe. Manufacturers already have sensors, PLCs and networked computers but need an integration strategy, solutions are expensive and there is little policy support (Muhla et al., 2025a). Commercially available hardware, open-source software, and the ability to explain the results and notify technicians automatically when needed have been crucial to the successful implementation of data-driven maintenance at local levels (Mashava et al., 2026; Senda et al., 2026). Human factors are also significant: ergonomic design and a good safety culture are crucial in minimising workplace accidents in Zimbabwean manufacturing (Muhla et al., 2025b); passively designed exoskeletons with ergonomic design can reduce the strain of operators in complicated tasks that involve handwork (Tandi et al., 2025). In the case of TCM, it is a need to focus on the operator's needs in alarms, dashboards and tool change procedures, in line with the human-centred focus of Industry 5.0. Learning factories, which provide an opportunity for students and practitioners to create and test monitoring systems on actual equipment, are a practical way to close the skills gap (Ndiyamba et al., 2026), and agile organizational practices enable firms to absorb technologies without negatively impacting production (Muhla et al., 2023).

5.5 Datasets, validation and reporting practice

Many recent deep-learning studies are based on a few public data sets, such as the data sets from the PHM 2010 milling challenge and NASA milling. These datasets have allowed for benchmarking but have the disadvantage of promoting over-fitting to the specific machines and conditions. Random splits over windows (from the same tool) are common forms of validation, which overestimate accuracy due to high correlation of windows from the same tool; less common, but more realistic, are leave-one-tool-out and cross-condition validations. The computational latency, memory demands, and uncertainty estimates are crucial for on-machine deployment, but they are rarely reported in few studies (Tran et al., 2023; Guidotti, Pandolfo and Pulina, 2025). Standardized reporting of the provenance, validation protocol and deployment metrics of datasets would significantly increase comparability.

6 RESEARCH GAPS AND FUTURE DIRECTIONS

Table 5 presents the eight research gaps identified in the review, the evidence supporting each gap and the recommended direction for future research.

Table 5: Research gaps and future directions

Gap	Evidence from the review	Future direction
1. Limited data and labelling cost	Data availability is a major problem and data augmentation is strongly recommended (Surucu, Gadsden and Yawney, 2023). New datasets and improved sensing are also needed (Carvalho et al., 2019).	Public CNC tool-wear datasets, synthetic-to-real augmentation, DOE-based labelled data generation (Mapindu et al., 2026b) and efficient labelling.
2. Limited model generalisation	Models may give inconsistent results when operating conditions change and are often designed for specific equipment (Tran et al., 2023; Carvalho et al., 2019).	Transfer learning, domain adaptation and validation across machines, tools and materials.
3. Real-time deployment and latency	Real-time PdM remains a major challenge; cloud latency and low-latency communication are unresolved (Zonta et al., 2020; Tran et al., 2023).	Lightweight edge and on-machine models; low-latency IIoT networks; reporting of inference time.
4. Data quality and class imbalance	Sensor drift, degradation and missing values affect data quality (Surucu, Gadsden and Yawney, 2023). Minority classes can perform poorly, such as a needle-stop class with an F1-score of 0.4 (Elkateb et al., 2024). PdM depends on failure histories (Carvalho et al., 2019).	Methods for imbalanced and censored data and rare faults; systematic capture of failure histories.
5. Model interpretability	ANN and SVM outputs are difficult to explain and justify (Carvalho et al., 2019); rule-based agents remain valued where explainability is mandatory (Mashava et al., 2026).	Explainable AI, uncertainty quantification and studies of operator trust.
6. Under-used methodologies	Ensemble methods are not applied systematically; hyperparameter tuning and data augmentation are often absent (Carvalho et al., 2019; Surucu, Gadsden and Yawney, 2023). Physics- and DOE-informed hybrids are rare (Qin et al., 2023).	Ensemble and hybrid models, formal hyperparameter optimisation, coupling of DOE process knowledge with ML.
7. Under-researched industries and regions	Research concentrates on high-income settings; SMEs and developing regions are under-represented (Carvalho et al., 2019; Elkateb et al., 2024). Integration strategy, cost and policy support are key barriers in Zimbabwe (Muhla et al., 2025a).	Affordable IIoT and current-based TCM for SMEs; local case studies; skills development through learning factories (Ndiyamba et al., 2026).
8. Emerging technologies not fully integrated	Virtual machining, sensor fusion, cloud migration and shared knowledge bases are proposed but not fully implemented (Tran et al., 2023); integration across system layers is still developing (Zonta et al., 2020).	Integration of digital twins, CAD/CAM data, edge AI and secure IIoT with ML-based TCM (Zi, Gao and Xie, 2024; Simonič, Palčič and Klančnik, 2025).

6.1 Limitations of the review

This review has limitations. Although five major databases and supplementary sources were searched, relevant studies published in other languages or in grey literature may have been missed. The heterogeneity of experimental conditions and metrics precluded meta-analysis, so conclusions on relative algorithm performance are qualitative. Publication bias towards positive results may overstate the accuracy achievable in practice. Finally, the fast pace of research on deep and physics-informed learning means that some very recent developments may not be captured.

7 CONCLUSION

This systematic review aimed at exploring the use of machine learning for CNC tool condition monitoring and predictive maintenance. For RQ1, the primary approaches are RFs, SVMs, ANNs, Bayesian classifiers and more recently hybrid physics-informed models and RL models (Carvalho et al., 2019; Surucu, Gadsden and Yawney, 2023; Qin et al., 2023; Kaliyannan et al., 2024). In response to RQ2, the most prominent signals are vibration, cutting force, AE, and spindle current/power and current-only monitoring is a practical low cost solution (Abubakr et al., 2021; Tran et al., 2023). When applied to the classification of tool states, estimation of wear, prediction of tool life, and estimation of remaining useful life (RUL), the accuracy of ML is typically in the range of 85-99% when compared to RQ3, with the difficulty in comparison arising from the limited number of standard datasets and standard validation procedures (Carvalho et al., 2019; Colantonio et al., 2021).

For RQ4, the following gaps were identified: data availability and labelling, generalisation, real-time deployment, data quality and class imbalance, interpretability, under-used methods, under-represented industries and regions, and incomplete integration of emerging technologies (Surucu, Gadsden and Yawney, 2023; Tran et al., 2023; Zonta et al., 2020; Elkateb et al., 2024). The results contribute to engineering practice and to industrial policy. The model created on one machine or material should not be expected to be applicable to another. Implementations should therefore be flexible to accommodate asset-specific calibration and enable real-time data collection and lightweight edge deployment as well as using pre-built models (Tran et al., 2023; Carvalho et al., 2019).

The knowledge gained from designed experiments (Mapindu et al., 2026b) can be used for data collection and model design, while the use of interpretable and low-cost architectures that have been proven in local industrial settings (Mashava et al., 2026; Senda et al., 2026) can be a realistic option for SMEs. Transferable and explainable models, data augmentation for rare and imbalanced faults, real-time edge-based system, and combining digital twins, CAD/CAM data and human-centred design with ML-based TCM (Surucu, Gadsden and Yawney, 2023; Zi, Gao and Xie, 2024; Zonta et al., 2020) are recommended for future studies.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

The authors declare no conflict of interest.

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