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Research paper

Deep Learning for Vibration Signature Analysis in CNC Turning: A Review of Modern Techniques and Future Directions

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Abstract

The digital transformation of manufacturing, driven by Industry 4.0, demands unprecedented levels of autonomy, quality, and operational efficiency. At the heart of these smart production systems lies Computer Numerical Control (CNC) turning, a critical subtractive manufacturing process known for its versatility, repeatability, and ability to achieve sub-micron precision. As the backbone of modern machining, CNC turning plays a vital role in sectors such as aerospace, automotive, and medical device manufacturing. Realizing its full potential requires robust, real-time in-process monitoring to ensure zero-defect output and stable performance. Vibration Signature Analysis (VSA) is a critical, non-invasive diagnostic tool for characterizing the dynamic behavior of machining operations. However, conventional VSA methods rely heavily on manual feature extraction and linear modeling, which are limited in handling the nonlinear, high-dimensional nature of machining dynamics. Deep learning (DL) has introduced a transformative shift, enabling automated, end-to-end learning from raw sensor data to deliver precise diagnostics and prognostics. This review provides a comprehensive overview of DL-based approaches applied to VSA in CNC turning. It critically evaluates dominant architectures, highlights the persistent challenge of model generalizability, and proposes-es concrete solutions. Furthermore, it highlights promising future directions such as domain adaptation, transfer learning, and physics-informed neural networks, aiming to guide researchers and practitioners toward the development of intelligent, adaptive, and self-optimizing manufacturing systems.

Keywords: *Vibration Signature analysis; CNC turning; Deep learning; Feature extraction; Convolutional Neural Networks (CNNs).*

1. Introduction

Industry 4.0 and smart manufacturing have fundamentally reshaped the modern industrial landscape, demanding production systems that are not only automated but also intelligent, adaptive, and self-aware [1]. This transformation is driven by the need to minimize operational costs, reduce unplanned downtime, and maximize productivity, which are all directly impacted by the health of manufacturing equipment [2]. A core element of this paradigm is the Computer Numerical Control (CNC) machine tool, a cornerstone of precision manufacturing [3]. The reliability and efficiency of CNC operations, particularly turning, are essential for maintaining production quality and economic viability. As a foundation machining process, turning fabricates a vast range of essential cylindrical components, from simple fasteners to complex shafts. These parts are fundamental to nearly every industrial sector, including automotive, aerospace, and energy production. However, these processes are susceptible to inherent dynamic instabilities, most notably tool wear and chatter vibrations, which can degrade surface finish, compromise workpiece accuracy, and lead to catastrophic tool failure [4], [5]. Consequently, the development of robust and intelligent monitoring systems has become a critical necessity for competitive manufacturing [6].

To achieve this, Condition Monitoring (CM) has emerged as a key enabling field. While various signals such as motor current, acoustic emissions, and cutting forces can be used, Vibration Signature Analysis(VSA) remains one of the most powerful, non-intrusive, and widely adopted modalities [6], [7]. Vibration signals, captured from the machine structure or tool holder, serve as a rich, information-dense medium that encapsulates the complex dynamics of the tool-workpiece interaction [8], [9]. These signatures serve as a direct indicator of the cutting process's health, facilitating on-site identification of irregularities and the prediction of component health [4] [10]. The effectiveness of such a system, however, hinges on a sophisticated data acquisition and processing framework, capable of capturing high-fidelity data from multiple sensors in real-time and extracting meaningful information from it [11 - 14].

Historically, vibration analysis has relied on signal processing techniques that decompose the signal into time-domain statistical features or frequency-domain spectral components[15], [16]. While foundational, these methods often require significant domain expertise to manually engineer features that correlate with specific physical phenomena, a process that demands significant time and often lacks adaptability across different operating conditions [9], [17]. The advent of machine learning offered a more automated approach, yet conventional models still depended on this handcrafted feature extraction as a preliminary step [18 - 20]. This dependence on manual feature engineering represents a significant bottleneck, limiting the adaptability and performance of traditional monitoring systems.

Deep Learning (DL), a subfield of machine learning that enables end-to-end learning directly from raw or minimally processed data[21], [22], [23]. The core advantage of DL is its ability to perform automatic feature extraction, where the model itself learns the most salient features from the data, thus overcoming the primary limitation of traditional approaches [17]. DL architectures, particularly Convolutional Neural Networks (CNNs), have demonstrated an exceptional ability to autonomously learn hierarchical feature representations from complex signals [24], [25]. By treating the 1D vibration time-series [26] or their 2D time-frequency representations (e.g., spectrograms) as inputs[27]These models can bypass manual feature engineering and uncover intricate patterns that are often imperceptible to traditional analysis [28], [29]Other than CNNs, architectures like Recurrent Neural Networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM), have been effectively used to model the temporal dependencies in sequential sensor data for tool wear prediction [30]. This capability has catalyzed a new generation of highly accurate monitoring systems for detecting faults in rotating machinery[24], predicting tool wear from the force or vibration signal [31], [32], [33], and estimating surface roughness [34], [35].

Despite these significant advancements, a critical research gap persists. The performance of DL models is often evaluated under a specific, limited set of experimental conditions. However, in a real-world industrial setting, CNC turning operations are performed on a wide variety of workpiece materials such as steels, aluminum alloys, and composites under a diverse range of machining parameters like feed rate, depth of cut, and cutting speed [36 - 38].The dynamic signatures of vibration are known to change significantly with these variations [39], [40], [41]. Therefore, the central challenge is no longer just to build a predictive model, but to build one that is robust and generalizable across this operational spectrum. A crucial question for practical industrial deployment is whether a DL model can accurately monitor tool wear across different materials and cutting parameters [17], [33].

This review paper aims to address this context by providing a comprehensive survey of the current state of VSA in CNC turning, with a particular focus on the integration of DL techniques. It explores the progression from traditional signal processing and feature engineering methods to contemporary DL-based models capable of learning directly from raw sensor data. Key elements such as data collection strategies, sensor selection, and signal transformation techniques are thoroughly discussed for both classical and DL driven approaches. By analyzing research contributions over the past decade, this review aims to establish a clear understanding of the field's evolution and provide a structured framework for future work. By synthesizing a decade of research, this review seeks to provide a foundational understanding and a methodological roadmap for tackling the specific challenge of developing robust DL based monitoring systems that can effectively operate across different materials and machining parameters.

2. Methodology

This review was conducted through a systematic search of academic databases, including IEEE Xplore, Scopus, and Google Scholar, using keywords such as "CNC turning," "vibration signature analysis," "condition monitoring," "deep learning," "signal processing," and "feature extraction". Fig. **1** shows a word cloud showing the central themes of this review. The search was primarily limited to journal articles and conference papers published from 1980 to the present to ensure relevance to the current state of the art. The initial pool of articles was filtered based on their direct relevance to vibration-based monitoring in machining, with a strong preference for studies involving CNC turning and DL applications. The reviewed reference papers formed the core of this review, supplemented by reputed and recent publications identified during the search process to ensure comprehensive coverage of all related concepts. The synthesized information is structured to provide a logical progression from fundamental concepts to advanced techniques and future trends.

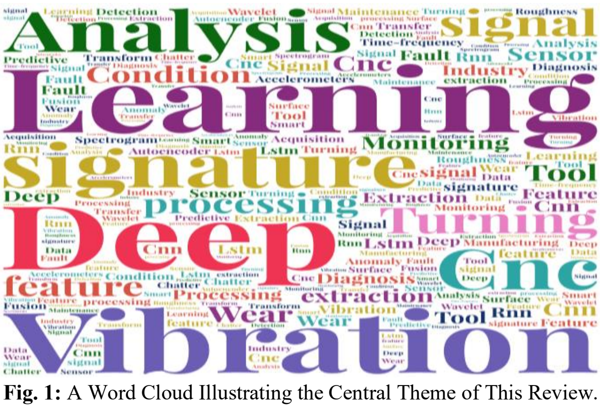

Fig. 1: A Word Cloud Illustrating the Central Theme of This Review.

3. Literature review

The contemporary research landscape in CNC turning monitoring is characterized by a definitive shift away from traditional analytical methods towards data-driven, intelligent systems powered by DL. This evolution is driven by the capacity of DL models to autonomously interpret the complex, non-linear dynamics captured in vibration signals, thereby overcoming the limitations of previous approaches. This section synthesizes the state of the art by examining the dominant DL architectures, their principal applications, and the emerging trends poised to shape the future of intelligent machining.

Vibrations in CNC turning are an unavoidable byproduct of the material removal process. As highlighted by[40], these vibrations emanate from various sources, including the cutting forces, tool-workpiece interaction, and the machine's structural response. The characteristics of the vibration signal, such as amplitude, frequency, and temporal evolution, are intrinsically linked to the state of the machining operation. For instance, the onset of chatter, a detrimental self-excited vibration, manifests as a distinct high-amplitude frequency component in the vibration spectrum, a phenomenon extensively reviewed by [5]. Similarly, the progression of tool wear, a critical factor influencing surface finish and dimensional accuracy, subtly alters the vibration signature over time. [38]have demonstrated a clear correlation between the frequency components of vibration signals and the extent of tool wear in milling processes, a principle that is equally applicable to turning. They also highlighted that the challenge lies in effectively capturing and interpreting this vibrational language to monitor and control the turning process in real-time.

The foundation of any successful DL application in vibration analysis is a robust data acquisition and signal processing pipeline. As detailed by [14]A variety of sensors can be employed for Condition Monitoring(CM), with accelerometers being the most common for capturing vibration data due to their sensitivity and ease of installation. They also explored the use of multi-sensor fusion to create a more comprehensive picture of the machining process. [42] demonstrated a sophisticated sensor fusion framework that integrates force and vibration signals for accurate tool fault prediction.

Research shows a clear shift towards DL methods and multi-sensor data fusion, accompanied by increasing use of automatic feature extraction and interest in transfer learning, few-shot learning, and unsupervised approaches[43]. M. Soori et al.[23] reviewed the applications of Machine Learning(ML) and Artificial Intelligence (AI) systems in CNC machine tools, investigating recent achievements to enhance productivity and value in manufacturing processes. They identified areas such as reducing machine downtime, optimizing CNC machine tools, cutting tool wear prediction, and surface quality prediction as key applications. V. Nasir et al. provided a critical review of DL for intelligent machining and tool monitoring, focusing on its opportunities and challenges[17].

J.L. Wilk-Jakubowski et al.[43] conducted a comprehensive decade-spanning analysis (2015–2024) on ML applications in vibration and acoustics, highlighting its growing impact across diverse engineering systems like civil infrastructure, transportation systems, energy installations, and rotating machinery. Their review specifically covered CNNs, RNNs, LSTMs, autoencoders, Nearest Neighbour Search (NNS), Support Vector Machine (SVM), decision trees, K-means clustering, and random forests, Ghazali et al.[7] conducted a systematic review emphasizing the importance of data acquisition, feature extraction, and fault recognition techniques using artificial intelligence in vibration analysis for machine monitoring and diagnosis.

4. Machine health to intelligent monitoring

The evolution of manufacturing from manual craftsmanship to the highly automated environments of Industry 4.0 has been paralleled by an evolution in how we ensure machine reliability. The practice of CM did not emerge in a vacuum but evolved as a direct response to the increasing costs of production downtime and the demand for higher quality and efficiency [1], [6]. This section traces the history of CM, focusing on the rise of VSA as a cornerstone technique and mapping its progression from traditional signal processing to modern, data-driven intelligent systems.

4.1. Condition monitoring

Historically, maintenance strategies have progressed through several stages, as illustrated in Fig. 2. The earliest approach was Reactive Maintenance, or "run-to-failure," where repairs were performed only after a component had broken down. This strategy is costly and unpredictable, leading to significant unplanned downtime [44]. The next logical step was Preventive Maintenance, where components are replaced on a fixed schedule based on their average expected lifetime. While an improvement, this approach is often inefficient, as it can lead to the premature replacement of healthy components or fail to prevent unexpected early failures [2], [45].

The current state of the art, driven by the principles of "smart manufacturing," is predictive maintenance [1], [44]. Predictive maintenance aims to predict failures before they happen by continuously monitoring the health of the machine in real-time. This is the central goal of CM. In the context of CNC machining, effective CM translates directly to tangible benefits: preventing catastrophic tool failure, minimizing scrap rates, ensuring consistent part quality, and optimizing tool life, thereby maximizing economic efficiency [4], [6].

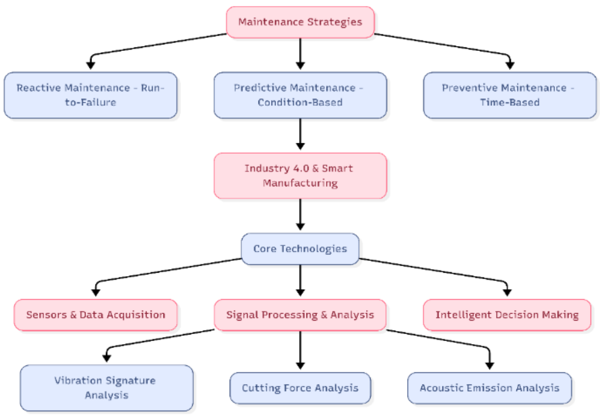

Fig. 2: A Tree of Evolution in Maintenance Strategies.

4.2. Vibration signature analysis

Among the various signals available for CM in machining, for example, force, temperature, acoustic emission, and vibration are among the most widely used and information-rich modalities [2], [7], [8]. The dynamic forces generated during the cutting process, as the tool shears material from the workpiece, propagate through the machine structure as mechanical vibrations [40], [46]. These vibrations are a direct reflection of the physical events occurring at the tool-workpiece interface. Consequently, any change in the process, such as the progressive wear of the cutting tool, a change in material properties, or the onset of regenerative chatter, will modulate the characteristics of the vibration signal [5], [38], [39].

An effective VSA system relies fundamentally on a robust Data Acquisition (DAQ) pipeline. This involves carefully selected sensors, typically tri-axial accelerometers mounted close to the cutting zone [13], [47], coupled with a DAQ device capable of sampling the signal at a high frequency to capture the full spectrum of the machining dynamics [12], [48], [49], [50]. The captured "vibration signature" is a complex, non-stationary time series signal that contains a wealth of information. The primary challenge, and the focus of decades of research, has been to develop methods to effectively decode this information to make an accurate assessment of the machine's health [17], [22].

4.3. The evolution of analysis techniques

The methods used to interpret vibration signatures have evolved dramatically, moving from manual, expert-driven analysis to fully automated, intelligent systems. As illustrated in Figure 3, the traditional pipeline is a multi-step, human-in-the-loop process requiring deep domain expertise at the feature engineering stage. In contrast, the modern DL pipeline automates this critical step, allowing the model to learn optimal features directly from the data, thereby creating a more streamlined and adaptable workflow.

4.4. Traditional signal processing

The initial approaches to VSA were rooted in classical digital signal processing, which can be categorized into three domains:

Time-Domain Analysis: This involves calculating statistical metrics directly from the raw signal. Features like Root Mean Square (RMS), Kurtosis, and Skewness provide a general characterization of the signal's energy and distribution [9], [15]. While simple to compute, these features often lack the sensitivity to detect the early onset of faults [2].

Frequency-Domain Analysis: This approach uses the Fast Fourier Transform (FFT) to convert the time-series signal into a frequency spectrum, revealing the dominant frequencies present in the vibration [58], [60]. Changes in the amplitude of specific frequency bands can be correlated with phenomena like tool wear or chatter [5], [38]. However, the FFT assumes the signal is stationary, a condition rarely met in machining where the process dynamics are constantly evolving[51].

Time-Frequency Analysis: To overcome the limitations of FFT, time-frequency techniques were developed to analyze non-stationary signals. Methods like the Short-Time Fourier Transform (STFT) and, more powerfully, the Wavelet Transform, provide a 2D representation showing how the signal's frequency content changes over time [16], [51], [52]. This allows for the localization of transient events and provides a much richer basis for analysis than time or frequency domain methods alone.

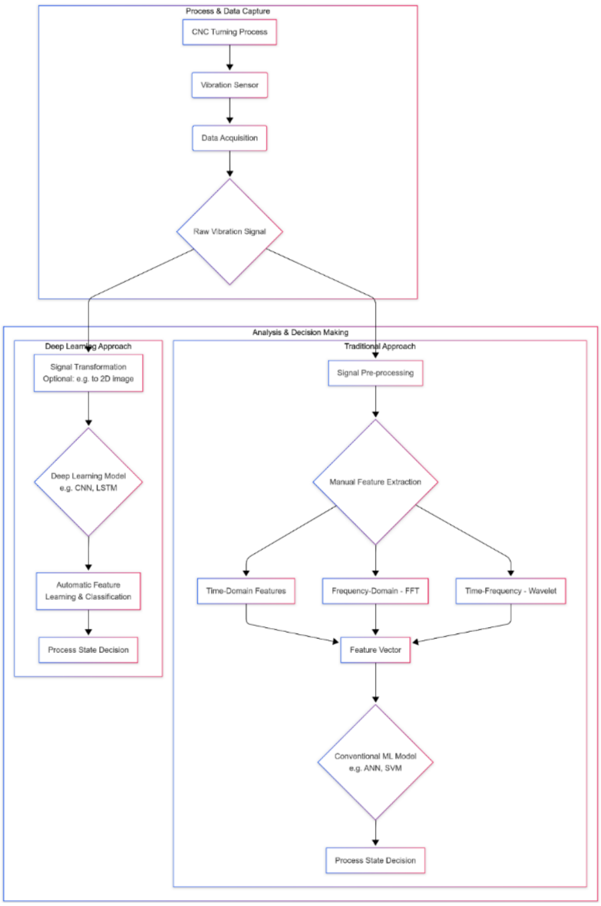

Fig. 3: Flowchart Comparing the Traditional VSA with the Modern DL Approach.

4.5. The machine learning era

The features extracted using the techniques above were then used as inputs for conventional ("shallow") machine learning algorithms. Models such as Artificial Neural Networks (ANNs) [53], [54], SVMs, and k-Nearest Neighbors were trained to map the handcrafted feature vectors to specific process states (e.g., 'fresh tool', 'worn tool') [18], [20]. This two-step process—manual feature extraction followed by classification—was the dominant paradigm for over a decade [43]. However, its effectiveness is fundamentally constrained by its reliance on domain expertise. The process of selecting and engineering the right features is critical, non-trivial, and often results in a model that fails to generalize to different machining conditions, materials, or machines [17], [22].

4.6. The deep learning revolution

The past decade has been characterized by the rise of DL, which fundamentally changes the analysis pipeline [21], [22]. DL models, particularly CNNs and RNNs, are capable of end-to-end learning. As shown in Fig. **4**They can take raw or minimally processed data, like 1D time-series or 2D time-frequency images, as input and automatically learn a hierarchy of increasingly complex features relevant for the classification task [24], [28].
This automated feature learning is the most significant advantage of the DL approach [17]. CNNs have proven highly effective for classifying vibration signals represented as 2D images [27], while 1D CNNs can operate directly on the raw signal [25], [26]. RNNs and their variants like LSTMs are particularly well-suited for modeling the temporal evolution of signals, making them excellent for anomaly detection and prediction tasks [30], [55], [56]. This ability to learn directly from complex data has led to a new generation of monitoring systems with unprecedented accuracy and robustness [24], [57], [58], setting a new standard for intelligent CM in modern manufacturing.

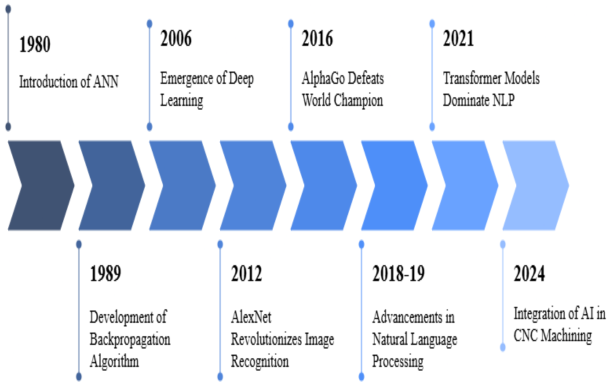

Fig. 4: A Timeline Illustrating Deep Learning Advancements with Their Subsequent Application in Vibration Analysis for CNC Machining.

Phase 1: The foundational era — The birth of core concepts (1980s-2006)
This period was characterized by fundamental breakthroughs in machine learning that laid the theoretical groundwork for the DL revolution, long before these techniques were applied to industrial machinery.
1980 — The Architectural Blueprint of the CNN: The "Neocognitron," developed by Kunihiko Fukushima, introduced the seminal concepts of hierarchical layers, convolutional filters, and feature pooling. This architecture, inspired by the human visual cortex, was the first to demonstrate robustness to shifts in pattern position and became the direct intellectual ancestor of all modern CNNs.[59]
1989 — The First Trainable CNN: The critical breakthrough came when Yann LeCun and colleagues successfully applied the backpropagation algorithm to train a CNN. Their model, which could recognize handwritten zip codes with remarkable accuracy, proved that the CNN architecture was not just a theoretical model but a practical and effective tool for real-world pattern recognition[60].
2006 — The Deep Learning "Ignition Point": For years, training very deep networks was plagued by the vanishing gradient problem. Geoffrey Hinton et al. provided a solution with their "fast learning algorithm for deep belief nets." This work effectively solved the training problem for deep architectures and is widely credited with launching the modern DL era[61].
Phase 2: The translation era — Adapting deep learning for vibration analysis (2012-2017)
Following the validation of DL in computer vision, researchers began exploring its potential for other data types, with time-series signals from machinery being a prime candidate.
2012 — The Catalyst for Cross-Disciplinary Adoption: The decisive victory of AlexNet, a deep CNN, in the ImageNet competition was a watershed moment. Its unprecedented performance showcased the immense power of DL to the entire scientific community, inspiring researchers in fields like mechanical engineering and signal processing to adapt these models for their data[62].
2016 — The Proof of Concept for Vibration-Based Diagnosis: A highly influential paper by O. Janssens et al. marked one of the first and most convincing applications of CNNs to machine health monitoring. They pioneered the approach of converting 1D time-series vibration data into 2D image-like representations (spectrograms) and feeding them into a CNN for fault detection. This elegantly bridged the gap between advanced image recognition techniques and the domain of industrial signal processing[24].
Phase 3: The Specialization Era — Deep Learning for CNC Machining (2018-Present)
In recent years, the focus has shifted from general machinery to specific, high-value applications like CNC machining. The research has matured from simple fault detection to nuanced tasks like tool wear monitoring and surface roughness prediction in real-time.
2018-2019 — End-to-End Learning Becomes the Norm: Researchers began leveraging 1D CNNs to work directly on raw vibration signals, eliminating the need for manual feature engineering or conversion to 2D representations. Comprehensive review papers started appearing, solidifying DL's role in machine health and documenting the shift towards these more sophisticated, end-to-end models[22].
2021 — Maturation of Methods for CNC Turning: Research specifically addressing tool CM in turning operations using DL gained significant traction. Authoritative reviews summarized the state-of-the-art, covering the use of various sensors (vibration, force, acoustic emission) and decision-making methods, confirming DL as a key enabling technology for intelligent machining[2].
2024 and Beyond — The Frontier: Advanced Architectures and Real-World Integration: Current research focuses on deploying these models in real industrial environments. Recent studies demonstrate the use of CNNs on raw sensor data from CNC lathes to achieve highly accurate real-time process monitoring. The frontier is expanding to include more complex architectures like LSTMs for time-series prediction, autoencoders for anomaly detection, and physics-informed neural networks (PINNs) to create more robust and generalizable models for the smart factories of the future[26].

5. Data acquisition systems

Data Acquisition (DAQ) is a method for transferring data from the physical world into a digital device. This process involves capturing real-world signals through sensors and routing them through a connected data acquisition (DAQ) controller. This controller digitizes the signals, allowing them to be processed by a computer. Software on the computer then performs calculations and scales the data, presenting it in a graphical user interface. This enables the user to visualize and control real-world hardware and systems with a connected computer[49].

Data acquisition (DAQ) systems are essential for capturing real-time vibration data. Subramaniam et al. [48]present an overview of DAQ system design, highlighting the evolution from traditional signal logging to modern real-time, distributed, and trigger-less acquisition methods. Modern DAQ setups integrate sensor networks with high-speed analog-to-digital converters, supporting time-stamped data and real-time correlation of multi-channel input. These features enable effective identification of fault conditions during turning operations.

Farooq et al. [49]developed a low-cost, 16-channel DAQ system suitable for industrial monitoring applications. By using microcontrollers, GSM/Wi-Fi modules, and LabVIEW-based interfaces, the system allows for remote access, alert generation, and graphical display of sensor data. Though initially applied to plant systems, its architecture is adaptable to CNC machine vibration monitoring.

Real-time data acquisition has been further advanced through embedded multi-node systems, as discussed by Kumar et al.[63]. Their design integrates sensor nodes connected to a master controller that handles data aggregation and transmission. Such systems provide modularity, making them well-suited for applications requiring distributed sensor placement, such as monitoring spindle vibrations, tool wear, or workpiece chatter in CNC turning.

In their study, Del Conte et al.[50]emphasize the use of open-architecture CNC controllers to acquire internal machine parameters (such as feed rate and axis positions) without the need for additional sensors. Their validation experiments show that synchronized DAQ using commercial CNC variables provides sufficient resolution and repeatability for process diagnostics. This approach reduces system complexity and cost, making real-time VSA implementation more feasible on shop floors.

Data acquisition systems generally include analog signal conditioning, A/D converters, and software platforms for visualization and storage. Sampling frequencies range from kHz to MHz, depending on the vibration bandwidth of interest. Signal synchronization with spindle rotation is often used to extract features tied to tool passes or chatter frequencies [46], [64].

6. Sensor technologies for machining dynamics interpretation

The foundation of any data-driven model for interpreting machining dynamics lies in the fidelity and relevance of the signals captured from the process. The choice of sensor technology is therefore a critical first step that determines the type, quality, and richness of the data available for subsequent analysis by DL algorithms. While vibration signals, captured by accelerometers, are the primary focus of this review, a comprehensive understanding of alternative and complementary sensors is essential. The trend towards multi-sensor fusion, where data from different types of sensors are combined, has been shown to yield more robust and accurate monitoring systems [35], [65].

6.1. Classification of sensor technologies for CNC turning

Vibration Sensors: As the primary focus of this review, vibration sensors—predominantly accelerometers—are the most widely used for monitoring machining operations[7], [9]. Their popularity stems from their excellent frequency response, robustness, and ability to be mounted non-intrusively on the machine structure [14]. Tri-axial accelerometers are particularly valuable as they capture the directional nature of cutting forces and vibrations, providing a more complete dynamic signature[66]. The choice between a high-sensitivity piezoelectric accelerometer and a compact MEMS-based sensor often depends on the application's specific frequency range and environmental constraints [13]. The location of the accelerometer is a critical decision; mounting it on the tool holder provides signals highly correlated with the tool-workpiece interaction, including chatter [5], tool wear [38], and surface roughness [67], while mounting on the spindle housing can provide a more general overview of the machine's health [46].

Force Sensors: Cutting force is a direct indicator of the state of the machining process. Dynamometers provide highly accurate, multi-axis force measurements (Fx, Fy, Fz) that are strongly correlated with tool wear, chip formation, and cutting stability[31], [41]. However, they are typically expensive, intrusive, and less robust for industrial environments compared to accelerometers[2]. DL models often use force signals as a benchmark or for sensor fusion applications [65].

Acoustic Emission (AE) Sensors: AE sensors detect high-frequency stress waves generated by material deformation, friction, and fracture events at the cutting zone [6], [18]. They are extremely sensitive to the onset of tool chipping or breakage, but can be susceptible to background noise.

Sensor Fusion: While vibration is a powerful signal source, no single sensor can capture all aspects of the complex turning process. A growing trend is sensor fusion, where data from multiple, heterogeneous sensors (e.g., vibration, force, and temperature) are combined[35], [42]. This approach creates a richer, more robust dataset that allows DL models to learn more comprehensive patterns, improving the accuracy and reliability of predictions for phenomena like tool wear and surface roughness [33], [65].

To provide a clear and comparative overview, Table 1 summarizes the primary sensor technologies employed for indirect CM in machines. The table details each Sensor, Sensor Type(s), Sensor Location, Placement Method, and Application Focus with direct citations from the provided literature.

Table 1: Comparative Analysis of Sensor Technologies for CNC Turning Monitoring

Author/Year	Sensor	Sensor Type(s)	Sensor Location	Placement Method	Application Focus
Janssens, O. et al. (2016)[24]	Vibration	Accelerometer	Bearing housing	Not Specified	Fault detection in rotating machinery.
Jauregui, J.C. et al. (2018)[41]	Kistler 9121, Cutting Force, Vibration	Dynamometer, Accelerometer	Tool Holder	Bolted/Clamped	Tool condition monitoring (wear).
Nastac, S. (2018)[51]	Kistler 8763B, Vibration	Accelerometer	CNC milling machine table and spindle	Not Specified	Tool trajectory conformity estimation.
Lin, W.J. et al. (2019)[34]	Vibration	Accelerometer	Spindle	Magnet	Surface roughness prediction.

Wszołek, G. et al. (2020)[13]	MPU-6050, ADXL345, LIS3DSH, LIS3DH, Vibration	MEMS Accelerometers	Spindle housing, machine body	Glued with cyanoacrylate adhesive	Vibration monitoring of CNC machinery.
Çetinkaya, M.B. et al. (2021)[54]	Not specified	Accelerometer	Sensor mounted on the tool holder.	Placement method not specified.	Analyzing vibration characteristics and predicting cutting parameters.
Miao, H. et al. (2021)[46]	Not specified	Displacement Sensors	Spindle housing and workbench.	Not Specified	Analyzing the vibration of a CNC milling machine spindle system.
Pacheco-Chérrez, J. et al. (22)[18]	Vibration, Acoustic	Accelerometer, Microphone	Bearing housing	Not Specified	Bearing fault detection.
Brito, L.C. et al. (2023)[64]	Vibration	Accelerometer	Workpiece Holder	Screwed/Clamped	Indirect monitoring of end micro milling.
Do, J.S., Kareem, A.B. and Hur, J.W. (2023)[55]	Vibration	Accelerometer	Vertical Carousel Storage and Retrieval System (VCSRS) frame	Not Specified	Vibration anomaly detection.
Kounta, C.A.K.A. et al. (2023)[27]	Vibration	Accelerometer	Spindle housing	Magnetically mounted	Detection of machining vibration chatter.
Apostolou, G. et al. (2024)[11]	Vibration	Accelerometer	CNC Machine tool	Not Specified	Quality control framework for vibration monitoring.
Chen, J. et al. (2024)[67]	PCB 352C33 Vibration	Accelerometer	Near the cutting tool	Not Specified	Predicting surface roughness.
Kaliyannan, D. et al. (2024)[58]	Vibration	Accelerometer	Spindle housing	Magnet	Tool condition monitoring in milling.
Hassan, I.U. et al. (2024)[14]	Kistler 8763B & Kistler 8704B500	Piezoelectric and MEMS Accelerometers	Sensors mounted on a bearing test rig	Magnetic base.	Comparing different vibration sensors for condition monitoring.
Stathatos, E. et al. (2024)[26]	Vibration	Accelerometer	Tool-post	Bolted	Raw signal classification for process monitoring.
Tambake, N. et al. (2024)[66]	Vibration	Accelerometer	Workpiece fixture	Not Specified	Monitoring hobbing tool health.
Çekik, R. and Turan, A. (2025)[56]	Vibration	Accelerometer	Not specified.	Not Specified	Anomaly detection in CNC vibration data.

7. Signal processing and feature extraction

Raw vibration data are typically nonlinear and nonstationary, so signal processing is needed to extract informative features[4]. Common approaches fall into three domains, as shown in Fig 5 it categorizes the key signal processing methods used in traditional VSA, breaking them down into time-domain, frequency-domain, and time-frequency domain techniques, each designed to extract different types of information from the raw signal.

Time-domain features: Simple statistics (RMS, peak-to-peak, variance, skewness, kurtosis, etc.) or time-series coefficients (AR, MA, ARMA) are easily computed and often used. For instance, root-mean-square amplitude and crest factor can indicate overall vibration energy or impulsiveness. However, purely time-domain features can be sensitive to noise and may miss frequency details.

Frequency-domain features: Fourier-based transforms (FFT/DFT/DCT) reveal dominant spectral components. Typical features include peak frequencies, spectral amplitudes, power spectral moments, and crest factors. Jauregui et al. (2018) showed that bearing the dominant frequency shifts in FFT spectra correlates with tool wear, and combining FFT features from both cutting forces and vibration improves wear detection bandwidth[41]. Nonetheless, the fixed resolution of the FFT can struggle with the transient nature of turning vibrations.

Time–frequency features: Wavelet and short-time Fourier (STFT) analyses capture how frequencies evolve during cutting. Methods like discrete/continuous wavelet transforms (DWT, CWT) and STFT are widely used. For example, Thomazella et al. employed STFT and a ratio-of-power metric to detect chatter in grinding[52], a technique similarly applicable to turning chatter analysis. Empirical mode decomposition (EMD) variants (EEMD, CEEMD, etc.) are also used to decompose vibration signals into intrinsic mode functions. These time-frequency features (wavelet energy, envelope spectra, IMFs) often reveal subtle changes due to cutting dynamics or incipient faults. By constructing these features, the data becomes more compact and informative for ML models.

Advanced signal processing can also mitigate noise. For example, envelope analysis and Hilbert transforms isolate bearing fault frequencies, and adaptive filtering can remove machine-specific resonance. In summary, literature emphasizes combining multiple features across domains. Mohamed et al. (2022) note that fusing time-, frequency-, and time-frequency features often yields better fault signatures. Accordingly, many CNC turning studies extract statistical features along with spectral-energy features to characterize tool wear or chatter.

Table **2** focuses on the techniques and methods used in signal processing and feature extraction from the provided literature.

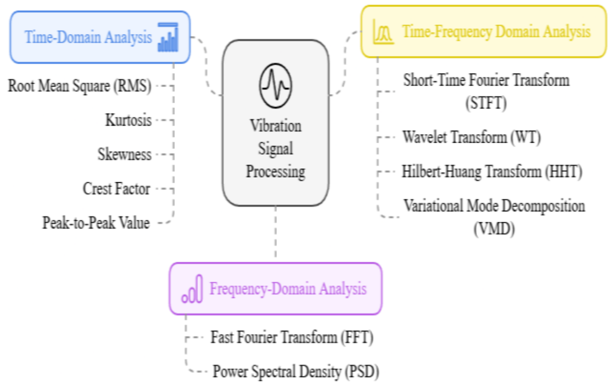

Fig 5: Traditional Feature Extraction Techniques for Vibration Signal Analysis, Categorized by the Time, Frequency, and Time-Frequency Domains.

Table 2: Comparative Analysis of Sensor Technologies for CNC Turning Monitoring

Authors/Year	Application/Focus	Signal Processing Technique	Feature Extraction Method
Fukushima (1980)[59]	Foundational Pattern Recognition	Not Applicable (Theoretical Model)	Hierarchical feature extraction layers
Teti, et al. (2010)[6]	Review of Machining Operations Monitoring	Multi-sensor signal processing	Statistical features, frequency domain features
Janssens, et al. (2016)[24]	Fault Detection in Rotating Machinery	Raw vibration signal analysis	Learned features via convolution
Jauregui, et al. (2018)[41]	Tool Condition Monitoring	Time-frequency analysis (Continuous Wavelet Transform - CWT)	Not specified (Analysis of plots)
Nastac (2018)[51]	CNC Milling Machine Tool Trajectory Conformity	Joint Time-Frequency Analysis	Analysis of spectrograms
Lin, et al. (2019)[34]	Surface Roughness Prediction (Milling)	Fast Fourier Transform (FFT)	Frequency-domain features
Wszołek, et al. (2020)[13]	Vibration Monitoring of CNC Machinery	Spectral analysis (FFT)	Amplitude of specific frequency components
Çetinkaya, et al. (2021)[54]	Vibration Analysis of a Turning Lathe	Time and frequency domain analysis	Statistical features
Huang & Lee (2021)[35]	Tool Wear and Surface Roughness Estimation	Sensor fusion (vibration, acoustic emission, current)	Raw data as input
Chuya-Sumba, et al. (2022)[25]	Fault Diagnosis of Rotating Machines	Raw vibration signal	Learned features via convolution
Brito, et al. (2023)[64]	Indirect Monitoring of End Micro milling	Time-domain and frequency-domain analysis	Statistical and spectral features
Do, et al. (2023)[55]	Vibration Anomaly Detection	Raw vibration data	Learned features via autoencoder
Kounta, et al. (2023)[27]	Detection of Machining Vibration Chatter	Short-Time Fourier Transform (STFT)	Spectrogram images
Zhang, et al. (2023)[31]	Tool Wear Condition Monitoring	Raw force signals (applicable concept to vibration)	Learned features via convolution
Apostolou, et al. (2024)[11]	Quality Control in Vibration Monitoring	Time and frequency domain analysis	Not specified (Framework)
Chen, et al. (2024)[67]	Surface Roughness Prediction in Turning	Vibration signal analysis	Not specified in title/abstract
Cooper, et al. (2024)[65]	Process Signature Prediction in Machining	Multi-sensor fusion	Learned features
Kaliyannan, et al. (2024)[58]	Tool Condition Monitoring in Milling	Not specified in title/abstract	Not specified in title/abstract
Stathatos, et al. (2024)[26]	CNC Turning Process Monitoring	Raw signal classification	Learned features via convolution
Çekik & Turan (2025)[56]	Anomaly Detection in CNC Machine Vibration	Raw vibration data	Learned features via LSTM
Kotha Amarnath, et al. (2025)[42]	Tool Wear Prediction During Machining	Sensor Fusion	Not specified in title/abstract
Li, et al. (2025)[68]	Tool Wear State Identification	Raw cutting force signal	Learned features via DL

8. Deep learning techniques

The deep convolutional layers are adept at extracting salient features directly from raw data. They retain the benefits of parallel computing found in shallower networks while also possessing self-learning capabilities to uncover more intrinsic patterns within complex data [34]. CNNs are popular for both 1D signal and 2D image inputs. In 1D-CNNs, raw time-series or envelopes are directly fed into convolutional layers to learn hierarchical features [56]. For example, Chuya-Sumba et al. applied a 1D-CNN to raw spindle vibration and reached 99% accuracy in bearing fault detection, with only ~8 ms per inference (suitable for real-time)[25]. When time-frequency images (STFT spectrograms or wavelet maps) are used, 2D-CNNs can exploit spatial patterns [31] [32].

RNNs, particularly LSTM and GRU architectures, are used to capture temporal dependencies. For instance, Qin et al. combined CNN and LSTM into a hybrid network for milling force prediction, and similar CNN–LSTM hybrids are used in turning to fuse spatial (spectral) and temporal features [65]. Critically, the choice between these architectures involves a trade-off. While CNNs are computationally efficient and excel at learning hierarchical features from spatially represented data like spectrograms, LSTMs are inherently designed to model sequential data, making them theoretically superior for capturing long-range dependencies in raw time-series for tasks like remaining useful life prediction. However, this sequential processing often leads to higher training times and computational costs compared to CNNs[69].

LSTM-based autoencoders have also been applied for unsupervised anomaly detection. Do et al. trained an LSTM-autoencoder on normal vibration sequences and achieved 97.7% accuracy in detecting abnormal events (e.g., a misfeed) [57]. Such autoencoders learn to reconstruct normal signals, so a high reconstruction error flags an anomaly [57].
Transformer-based models are emerging. Si et al. proposed a CNN + Vision Transformer (ViT) hybrid (called PSD-CVT) for tool wear prediction: they first converted vibration signals to power spectral density (PSD) images, then fed them through a CNN and a ViT in parallel l [32]. The ViT's attention mechanism captures global dependencies in the image, while the CNN handles local texture features [32]. Similarly, MobileViT (a lightweight CNN+ViT) has been used on spectrograms for wear classification[66].

8.1. Beyond CNNs and LSTMs: emerging architectures

While CNNs and LSTMs dominate the current literature, other advanced DL architectures are emerging with significant potential for VSA:
Generative Adversarial Networks (GANs): A primary challenge in fault diagnosis is the scarcity of data for faulty conditions. GANs can address this by learning the distribution of training data and generating synthetic yet realistic vibration signals corresponding to specific faults. This data augmentation approach can help create more balanced datasets, improving the robustness of classifiers trained on them [70].
Graph Neural Networks (GNNs): In a multi-sensor setup, GNNs can model the CNC machine as a graph, where sensors are nodes and the physical or spatial relationships between them are edges. This allows the model to learn not just from individual sensor streams but also from the complex inter-relationships between them, offering a more holistic view of the machine's dynamics [71].
In summary, the deep-learning toolkit includes plain CNNs, RNNs (LSTM/GRU), autoencoders, and hybrid networks. Studies often report that hybrid architectures outperform single-type models [53]. For example, Turan et al. proposed a multi-channel RoughLSTM network by combining CNN features with LSTM and showed it beat standalone CNN–LSTM hybrids in detecting spindle anomalies[53].
Table **3** listed representative models: e.g., 1D-CNN, CNN–LSTM, etc., citing pertinent literature like[25], [32], [57]. And the new Table 4 provides a quantitative comparison of their performance.

Table 3: Deep Learning Methods in CNC Monitoring: A Chronological Overview

Author/ Year	CNN	RNN / LSTM	General DL / DNN	Reinforcement Learning	Process Name & Part Monitored
Çekik & Turan (2025)[56]		✓			Anomaly detection in CNC vibration
Li et al. (2025)[68]			✓		Tool wear state identification
Stathatos et al. (2024)[26]	✓				CNC turning process monitoring
Kaliyannan et al. (2024)[58]			✓	✓	Tool condition monitoring
Ong et al. (2024)[57]			✓		Health monitoring of rotating machinery
Si et al. (2024)[32]			✓		Intelligent tool wear prediction
Kounta et al. (2023)[27]	✓				Detection of machining chatter
Zhang et al. (2023)[31]			✓		Tool wear condition monitoring
Do et al. (2023)[55]		✓			Vibration anomaly detection
Chuya-Sumba et al. (2022)[25]	✓				Intelligent fault diagnosis
Huang & Lee (2021)[35]			✓		Tool wear and surface roughness estimation
Li et al. (2020)[28]			✓		Gear fault diagnosis
Lin et al. (2019)[34]			✓		Surface roughness estimation
Janssens et al. (2016)[24]	✓				Fault detection in bearings

Table 4: Comparative Performance of Key DL Models in CNC Turning Monitoring

Author/Year	Application	DL Model	Input Data	Key Performance Metric	Comments/Cost
Janssens et al. (2016)[24]	Bearing Fault Detection	2D-CNN	Spectrograms	98.79% Accuracy	Proof-of-concept for converting 1D signals to 2D images for CNNs.
Zegarra et al. (2021)[69]	Tool Wear Estimation	CNN vs. CNN-LSTM	Force & Vibration	CNN-LSTM > CNN	The hybrid model better captured spatio-temporal features.
Chuya-Sumba et al. (2022)[25]	Bearing Fault Diagnosis	1D-CNN	Raw Vibration Signal	99% Accuracy	Fast inference time (~8 ms), suitable for real-time monitoring.
Zhang et al. (2023)[31]	Tool Wear Monitoring	1D-CNN	Raw Force Signals	~98% Accuracy	Demonstrates end-to-end learning directly from raw sensor data.
Do et al. (2023)[55]	Anomaly Detection	LSTM-Autoencoder	Raw Vibration Signal	97.7% F1-Score	Unsupervised method, valuable when fault data is unavailable.
Si et al. (2024)[32]	Tool Wear Prediction	CNN + Vision Transformer (ViT)	PSD Images	99.4% Accuracy	The attention mechanism in ViT helps capture global spectral features.
Stathatos et al. (2024)[26]	Process Monitoring	1D-CNN	Raw Vibration Signal	98.2% Accuracy	Focus on real-time classification of cutting vs. non-cutting states.

9. Emerging trends

The progression of research from simple fault detection to robust, intelligent monitoring reveals several key trends that will define the future of VSA in manufacturing. These trends address the primary limitations of current models and aim to bridge the gap between laboratory research and industrial deployment.

9.1. The generalizability challenge: from lab to shop floor

A primary hurdle for industrial adoption is model generalizability. A model trained under a specific set of conditions often fails when deployed in a production environment with different machines, tools, or workpiece materials. For example, a model trained exclusively on data from turning AISI 1045 steel may fail to accurately predict tool wear when the workpiece material is changed to a nickel-based superalloy like Inconel 718. The superalloy's higher thermal conductivity and work-hardening characteristics produce fundamentally different vibration signatures that the original model has not been trained to interpret. This necessitates a move towards more robust solutions. A key research question here is: How can we develop models that maintain high accuracy across a wide range of operational conditions without requiring complete retraining for each new scenario? Domain adaptation, a subfield of transfer learning, offers a promising solution by enabling a model trained on a "source" domain (e.g., one material) to be adapted to a "target" domain (e.g., a new material) with minimal labeled data [72].

9.2. Sensor fusion for robustness

A key trend is the fusion of multiple sensor modalities with transfer learning, explainable AI (XAI), digital twins, and cloud-based monitoring. As noted, fusing multiple sensor modalities like vibration + force + AE yields more robust signatures. Downey et al. pioneered an automated multi-sensor acquisition for vibration, AE, force, and imaging on a live lathe[12]. Recent works systematically fuse these streams: for example, Amarnath et al. concatenated synchronized force and vibration features and fed them to an ML classifier, achieving over 98% accuracy in multi-condition diagnosis [42]. Sensor-fusion frameworks (even using ensemble learning) are cited as “superior” to single-sensor approaches in tool wear prediction [12] [42].

9.3. Transfer learning and data scarcity

Transfer learning is increasingly is used to cope with scarce data; e.g., using ImageNet-based CNNs on tool wear images[56]. Transfer learning is emerging to reduce data requirements. In anomaly detection, Turan et al. used a transfer-learning CNN pretrained on simulated or related vibration data, then fine-tuned on limited real CNC data; their model could “detect vibration without requiring real data during training”[53]. In tool wear, one study used a CNN pretrained on a source tool set and successfully transferred it to a new tool condition, with minimal retraining. Such approaches allow leveraging large “generic” datasets (perhaps from milling machines) to bootstrap models for turning. For example, a model pre-trained on vibration data from a milling machine could be fine-tuned to monitor a turning operation, significantly reducing the data collection and training burden [72].

9.4. Explainable AI (XAI) for trust and interpretability

For operators and engineers to trust and adopt DL-based monitoring systems, they cannot be complete "black boxes." XAI is being investigated to enhance the trustworthiness and interpretability of these models [73]. Techniques like class activation maps or LRP have been applied to vibration spectrograms to highlight which frequency bands or time segments influenced the decision. For example, Chen et al. (2023) used an XAI method to identify globally important time–frequency bands for predicting surface roughness from vibration [14]. Integrating interpretability is crucial for certification of monitoring systems, though it is still nascent in CNC monitoring. Integrating interpretability is crucial for the certification and deployment of safety-critical monitoring systems. A key challenge is to develop XAI methods that provide explanations that are not only faithful to the model's logic but also easily understandable to a human operator on the shop floor [73].

9.5. The need for standardized benchmarks

A significant barrier to progress in the field is the lack of public, large-scale, and well-annotated benchmark datasets for CNC turning. Most researchers collect their data under unique conditions, making it nearly impossible to perform a fair, apples-to-apples comparison of different DL models and signal processing techniques. The creation of standardized open-source datasets, covering a wide range of materials, cutting parameters, and tool wear stages, would be a major catalyst for the field. It would enable reproducible research and accelerate the development of more generalizable models [74].

9.6. Barriers to industrial adoption and integration pathways

Beyond technical challenges, several practical barriers hinder the widespread adoption of DL in manufacturing [74]:

Integration with Legacy Systems: Many factories operate with older CNC machines that lack modern data connectivity interfaces. Integrating new sensor and DAQ systems can be costly and complex.

Computational Cost: Training deep models can be computationally expensive, and deploying them for real-time inference on the edge may require specialized hardware.

Operator Training: The shift to data-driven monitoring requires upskilling the workforce. Operators and maintenance staff must be trained to understand and trust the outputs of AI systems.

Overcoming these barriers requires a focus on developing lightweight models suitable for edge deployment, creating modular and cost-effective integration solutions, and aligning with the Industry 5.0 vision of human-AI collaboration. The economic incentive is clear: a successful DL-driven CM system can translate to significant gains by reducing unplanned downtime, minimizing scrap rates, and optimizing tool replacement schedules, leading to a quantifiable return on investment [75].

9.7. Digital twins and cyber-physical systems

The concept of a digital twin, a virtual replica of the CNC and tool/workpiece, is a prominent emerging trend. By combining real-time sensor data with a physics-based or hybrid model of the CNC machine, a digital twin can simulate the current state, predict future faults, and optimize parameters. For instance, a twin of a lathe spindle could accept real-time vibration input to predict the onset of chatter and suggest adjustments to the cutting speed to avoid it. This aligns with the broader vision of Cyber-Physical Systems in Industry 4.0, where intelligent algorithms and blockchain-enabled data integrity can create secure and autonomous manufacturing environments[76].

Aligning with Industry 5.0's emphasis on human and AI collaboration, the focus is shifting towards intelligent systems that provide operators with interpretable suggestions rather than enabling fully autonomous control [21], [42]. Complementing this vision, cloud-based and distributed monitoring systems are emerging. In such setups, multiple CNCs stream data to a centralized cloud platform that runs big-data analytics and batch learning. This enables benchmarking across machines, fleet-level tool life prediction, and centralized model updates.

The MDPI review notes that "wireless sensor networks" and smart infrastructure let shops collect sensor data remotely and provide proactive alerts [11]. Cloud integration can relieve individual machines from heavy computation, at the cost of requiring connectivity.
In summary, cutting-edge trends include combining multiple sensors (e.g., AE+vibration+force), using transfer learning to adapt models across machines, applying XAI to understand deep models, constructing digital twins for virtual testing, and leveraging cloud/IoT platforms for large-scale monitoring. These trends all point toward fully automated, low-latency, and transparent CM systems in Industry 4.0/5.0 environments.

10. Conclusion

This review has systematically charted the transformative evolution of VSA for CNC turning, culminating in the current state-of-the-art dominated by DL methodologies. The central finding is a definitive paradigm shift from traditional, expert-driven monitoring systems reliant on manual feature engineering to modern, end-to-end learning frameworks. DL models, particularly CNNs and RNNs, have demonstrated an unparalleled ability to autonomously extract salient features from complex vibration signals. This has led to remarkable advancements in critical applications, including high-accuracy tool wear prediction, real-time chatter detection, and in-process surface roughness estimation, thereby laying the groundwork for the next generation of intelligent manufacturing systems.
Despite these significant achievements, our analysis reveals that the most pressing challenge hindering the widespread industrial adoption of these technologies is model generalizability. The performance of most DL models is validated under controlled laboratory conditions, and their robustness often degrades significantly when faced with variations in workpiece materials, cutting parameters, and machine dynamics inherent to real-world production environments. This gap between laboratory success and shop-floor robustness represents a critical bottleneck. The future of this research field is therefore not merely in the pursuit of higher accuracy on benchmark datasets, but in the development of models that are fundamentally more robust, adaptable, and trustworthy across a diverse operational spectrum.
To address this challenge, this review has identified several promising future research directions that are already gaining traction. The path forward lies in a synergistic approach that combines multiple advanced techniques. Multi-sensor fusion promises to create richer, more resilient input data streams. Domain adaptation and Transfer learning stand out as a powerful strategy to mitigate data scarcity and efficiently adapt models to new tasks and conditions with minimal retraining. Furthermore, the integration of Explainable AI (XAI) is essential for building operator trust and moving beyond "black box" models, while the development of digital twins provides an overarching framework to merge data-driven insights with physics-based models for truly predictive and holistic process control.
Ultimately, the successful integration of robust and interpretable DL models for VSA is not merely an incremental improvement but a critical enabler for the fully autonomous, self-aware, and resilient manufacturing ecosystems envisioned by Industry 4.0 and beyond. This review provides a comprehensive foundation and a methodological roadmap for the research community to tackle the remaining challenges and unlock the full potential of intelligent machining dynamics.

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