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Systematic Review

Vibration Signal Analysis for Intelligent Rotating Machinery Diagnosis and Prognosis: A Comprehensive Systematic Literature Review

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Abstract: Many industrial processes, from manufacturing to food processing, incorporate rotating elements as principal components in their production chain. Failure of these components often leads to costly downtime and potential safety risks, further emphasizing the importance of monitoring their health state. Vibration signal analysis is now a common approach for this purpose, as it provides useful information related to the dynamic behavior of machines. This research aimed to conduct a comprehensive examination of the current methodologies employed in the stages of vibration signal analysis, which encompass preprocessing, processing, and post-processing phases, ultimately leading to the application of Artificial Intelligence-based diagnostics and prognostics. An extensive search was conducted in various databases, including ScienceDirect, IEEE, MDPI, Springer, and Google Scholar, from 2020 to early 2024 following the PRISMA guidelines. Articles that aligned with at least one of the targeted topics cited above and provided unique methods and explicit results qualified for retention, while those that were redundant or did not meet the established inclusion criteria were excluded. Subsequently, 270 articles were selected from an initial pool of 338. The review results highlighted several deficiencies in the preprocessing step and the experimental validation, with implementation rates of 15.41% and 10.15%, respectively, in the selected prototype studies. Examination of the processing phase revealed that time scale decomposition methods have become essential for accurate analysis of vibration signals, as they facilitate the extraction of complex information that remains obscured in the original, undecomposed signals. Combining such methods with time–frequency analysis methods was shown to be an ideal combination for information extraction. In the context of fault detection, support vector machines (SVMs), convolutional neural networks (CNNs), Long Short-Term Memory (LSTM) networks, k-nearest neighbors (KNN), and random forests have been identified as the five most frequently employed algorithms. Meanwhile, transformer-based models are emerging as a promising venue for the prediction of RUL values, along with data transformation. Given the conclusions drawn, future researchers are urged to investigate the interpretability and integration of the diagnosis and prognosis models developed with the aim of applying them in real-time industrial contexts. Furthermore, there is a need for experimental studies to disclose the preprocessing details for datasets and the operational conditions of the machinery, thereby improving the data reproducibility. Another area that warrants further investigation is differentiation of the various types of fault information present in vibration signals obtained from bearings, as the defect information from the overall system is embedded within these signals.

Keywords: vibration signal analysis; rotating machinery; machine learning; signal processing; Maintenance 4.0

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1. Introduction

Numerous industries, including power generation, industrial manufacturing, and transportation systems, have come to depend on rotating machinery. These machines bring real value in an industrial setting; however, they are prone to breakdowns, which lead to downtimes and increasing maintenance costs. Consequently, the management of the health status of rotating machinery is crucial to sustainable productivity. This management involves both diagnosis and prognosis. On one hand, diagnosis entails detecting existing failures or abnormal functions in machinery to ensure a proactive approach and circumvent a reactive response to a catastrophic failure. On the other hand, prognosis forecasts the state of the equipment based on historical data and trends, allowing for accurate scheduling of maintenance operations, as well as replacement programs, to extend the life cycle of the equipment [1–16].

To maintain an accurate understanding of the critical component conditions within an industrial environment, the machinery is to be inspected while operational, and any harm to the equipment is to be avoided. On account of this, the monitoring of rotating machinery relies on non-destructive techniques (NDTs), namely Ultrasound Testing (UT), infrared (IR) images, Acoustic Sound-Based Condition Monitoring (ASCM), Electrical Signature Analysis (ESA), and vibration signal analysis (VSA). Figure 1 provides the concepts for each of the cited techniques.

Vibration signal analysis (VSA) is frequently employed for rotating machinery monitoring, as it visualizes vibration shocks and changes in movement patterns. Any imbalance, misalignment, bearing wear, or gear damage will cause the vibration signature to deviate from the baseline signature of a normal operating machine. As a consequence, a system response in the form of pulsations appears in the vibration signal, indicating particular types of faults [17–20]. Through a comprehensive analysis of the vibration signal, faults that are still obscure or have not fallen into the range of detection with other techniques are detected. Furthermore, with the advent of Artificial Intelligence (AI), mainly Machine Learning (ML), the analysis of vibration signals has been facilitated, allowing researchers and engineers to explore the information encapsulated in signals further [21].

Regardless of the specific non-intrusive testing method chosen, the fault detection process generally consists of similar steps, albeit with adjustments based on the type of data utilized (Figure 2).

Signal data and image data are differentiated in this context. The initial phase involves preprocessing the collected data and then converting raw data into numerical data for further analysis using signal processing or image processing techniques. This analysis yields a set of features derived from the processed numerical signal, which are then refined in the post-processing stage. Here, the most relevant features are chosen, potentially enhanced, and combined into a final feature vector suitable for classification via AI algorithms for diagnostic and/or prognostic purposes. Ultimately, these AI algorithms determine the machinery's current state and/or predict its future state.

In this review, a novel synthesis of the latest developments in the monitoring of rotating machinery using vibration signal analysis is presented. It distinguishes itself from prior reviews by concentrating on studies published in the last four years that have not been thoroughly examined elsewhere in the literature. By adopting an interdisciplinary approach, our review targets the comprehensive phases of the global monitoring process, from data retrieval to fault detection. Hence, the content provided offers an exhaustive understanding of the issue at hand, which has been insufficiently addressed in earlier works that tended to isolate specific components. In the retrieval process of studies to review, the selection is extended to Electroencephalograms (EEGs) given that they pertain to the same class of signals as vibration signals. Both are transient and non-linear and contain multi-scale information; thereby, the information extraction process of EEGs can be applied to vibration signals. This approach sheds light on a broader set of signal processing techniques that can potentially extract more intricate information from vibration signals. In addition, a comparative analysis of a range of emerging methodologies is conducted. It targets specific algorithms and frameworks, providing a critical assessment of their respective advantages, drawbacks, and potential avenues to assist researchers who are focused on this particular area of study. The review is concluded by drawing tangible conclusions from the substantial number of articles analyzed and providing specific directions for the implementation and of academic research work and its integration into Industry 4.0 systems.

In Section 1, the methodology of the review is explained, and a preliminary analysis of the selected studies is presented. Section 3 discusses the findings of the review in terms of the different phases of the monitoring process. Sections 4 and 5, respectively, contain the conclusions drawn and the future directions identified.

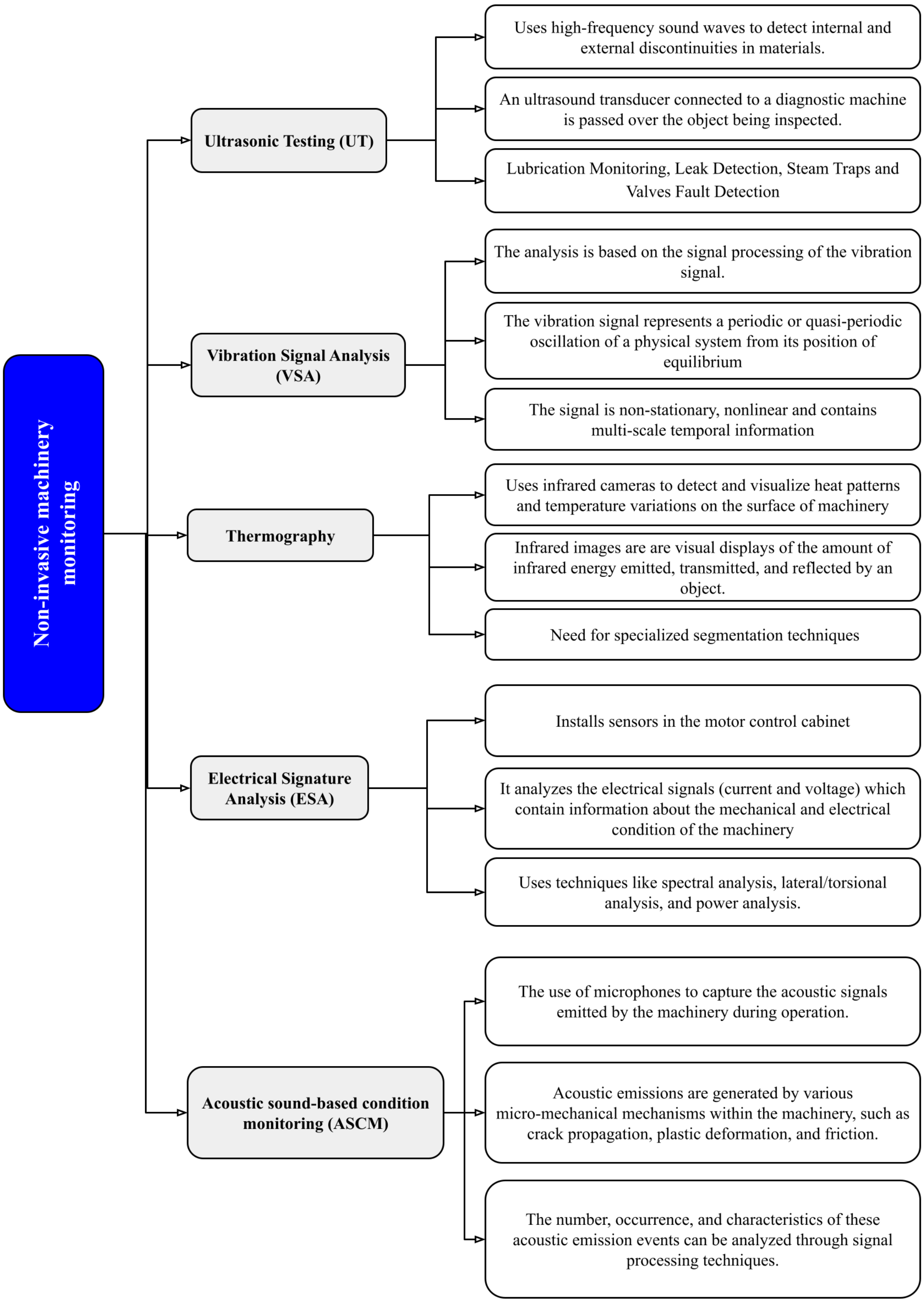

Figure 1. Non-intrusive monitoring approaches for rotating machinery.

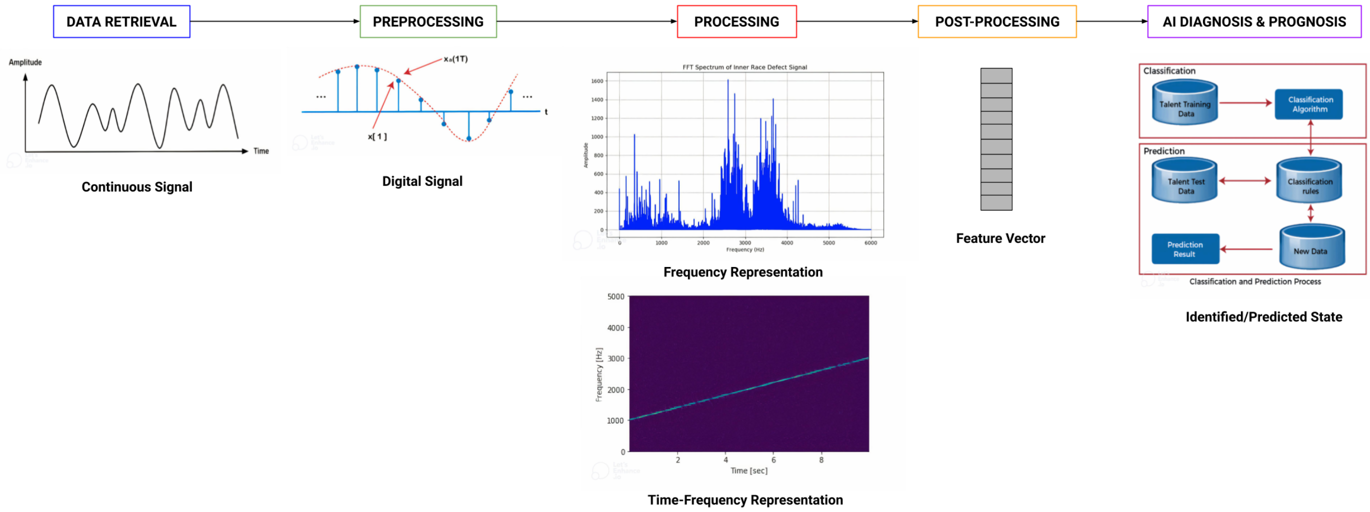

Figure 2. Global process of fault detection through NDTs.

2. Methods

The approach taken in this review was in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, as illustrated in Figure 3.

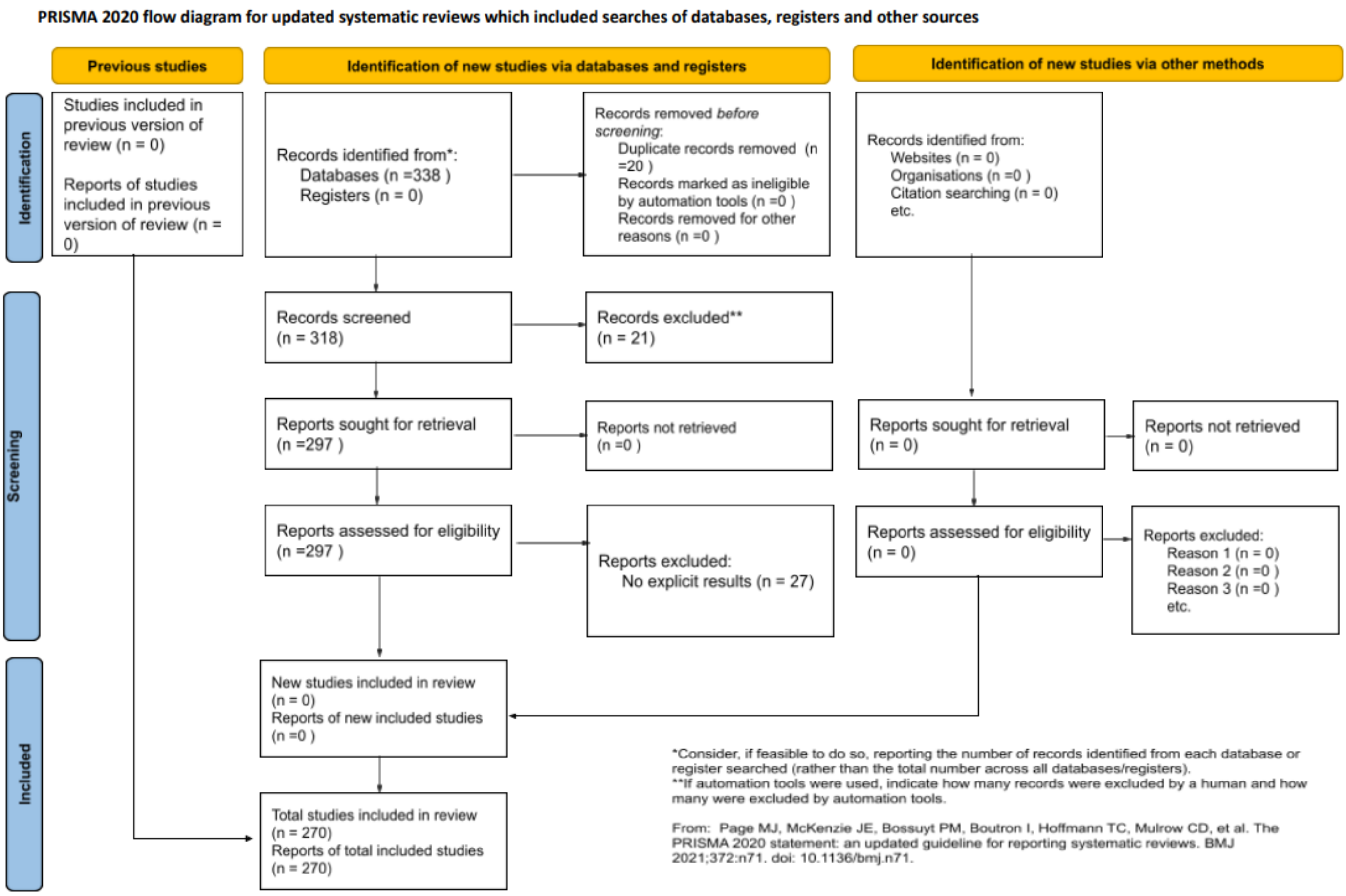

Figure 3. PRISMA flow diagram [22].

Figure 4 represents a flow diagram where each phase of the review process is detailed further.

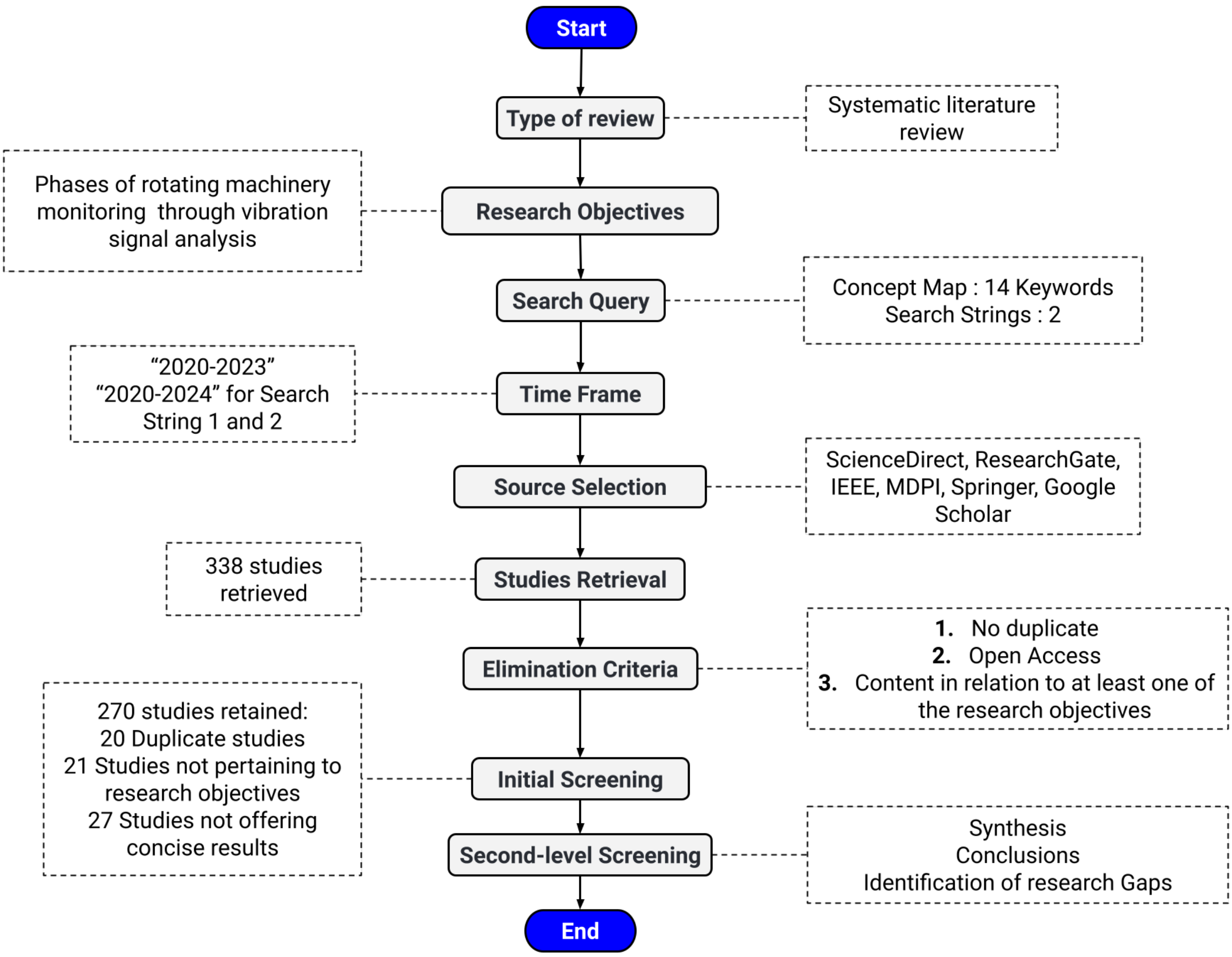

Figure 4. Overall flowchart of the methodology.

Studies eligible for inclusion were determined based on the accessibility of their full texts and their pertinence to at least one of the primary topics specified in Table 1.

Table 1. Scope of the review.

Main Objective	Preprocessing	Processing	Post-Processing	Diagnosis	Prognosis	Experimental Validation
Question asked	Were the data preprocessed?	How were the data processed?	How were the results of the processing optimized?	Which AI tools were used?	Which AI tools were used?	Were the results validated experimentally?

The primary data for this review were collected from a variety of databases, including ResearchGate, ScienceDirect, IEEE Xplore, MDPI, SpringerLink, and Google Scholar. The latter was particularly useful as a gateway to other databases owing to its extensive indexing capabilities and the significant impact factors of the sources it encompasses. The review specifically targeted studies published from 2020 to early 2024 to ensure the inclusion of the latest developments in the field. The studies conducted during this time frame are grounded in the research deficiencies recognized in previous years, suggesting that extending the review period would yield minimal information. In terms of the keywords researched, a total of 14 keywords were generated through collaborative brainstorming sessions, guided by the conceptual framework depicted in Figure 5.

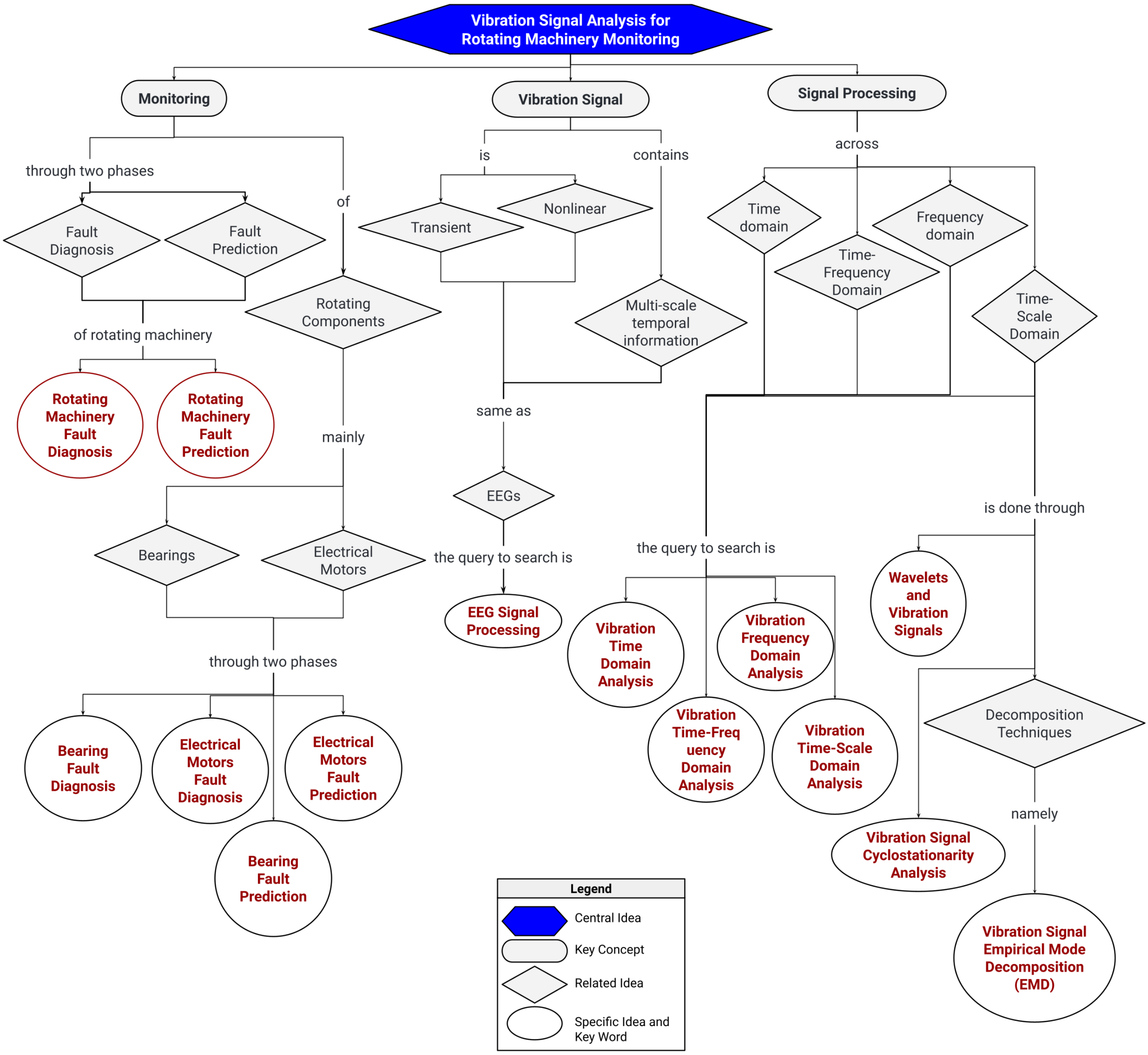

Figure 5. Concept map of the term concepts researched.

In addition, two search queries were generated through the PICO search strategy and synonym mapping, as detailed in Tables 2 and 3.

Table 2. First search string strategy.

PICO Element	Corresponding Element	Synonym 1	Synonym 2	Synonym 3	Synonym 4
P (Problem)	Rotating machinery	Rotating Equipment	Turbines	Motors	Generators
I (Intervention/Technology)	Vibration signal analysis	Vibration analysis	Vibration signal processing	Condition monitoring	
C (Comparison/Techniques)	Intelligent solutions	Artificial Intelligence	Deep learning	Intelligent algorithms	Machine learning
O (Outcome)	Diagnosis and prognosis of machinery conditions	Fault diagnosis	Failure prediction	Prognosis	Predictive maintenance

Table 3. Second search string strategy.

PICO Element	Corresponding Element	Synonym 1	Synonym 2
P (Population/Problem)	Rotating machinery	Rotating equipment	Bearing
I (Intervention/Technology)	Vibration signal processing		
C (Comparison/Techniques)	Intelligent solutions	Deep learning	Machine learning
O (Outcome/Goal)	Prognosis of machinery conditions	RUL prediction	Failure prediction

The resulting search strings are shown in Table 4.

Table 4. Search queries.

Search Query 1	Search Query 2
(“rotating machinery” OR “rotating equipment” OR “turbines” OR “motors” OR “generators”) AND (“vibration analysis” OR “vibration monitoring” OR “vibration signal processing”) AND (“fault diagnosis” OR “failure prediction” OR “prognosis” OR “predictive maintenance”) AND (“artificial intelligence” OR “machine learning” OR “intelligent algorithms” OR “deep learning”)	(“rotating machinery” OR “rotating equipment” OR “bearing”) AND (“vibration analysis” OR “vibration signal processing”) AND (“RUL Prediction” OR “failure prediction”) AND (“machine learning” OR “deep learning”)

The initial screening process was carried out independently by the reviewers, who evaluated the titles and abstracts of the studies retrieved to determine their relevance to the objectives of the review. Any discrepancies that arose were addressed through discussion, leading to a consensus on which articles warranted further investigation. During this stage, 20 studies were identified as duplicates, while 21 studies were excluded due to their lack of alignment with the research focus and 27 studies were excluded due to the absence of explicit results. Consequently, 266 studies advanced to a second-level screening, where the reviewers conducted a systematic analysis of each paper’s content, extracting pertinent data in accordance with the structured format presented in Table 5.

Table 5. Data extraction format.

Article Reference	Type of Study	Preprocessing	Processing Domain	Processing Method	Post-Processing	Diagnosis	Prognosis	Experimental Validation
[23]	Prototype	No	Time scale, time, and frequency domains	CEEMDAN decomposition, statistical features, and FFT	chi-square-RFE method	SVM, ELM, DBN, and DNN	No	No

In order to reduce bias, three independent reviewers utilized the CASP (Critical Appraisal Skills Programme) checklists, with any discrepancies addressed by a fourth reviewer. The results of the selection process are depicted in various figures, illustrating the distribution of the studies according to type (Figure 6) and keywords researched (Figure 7).

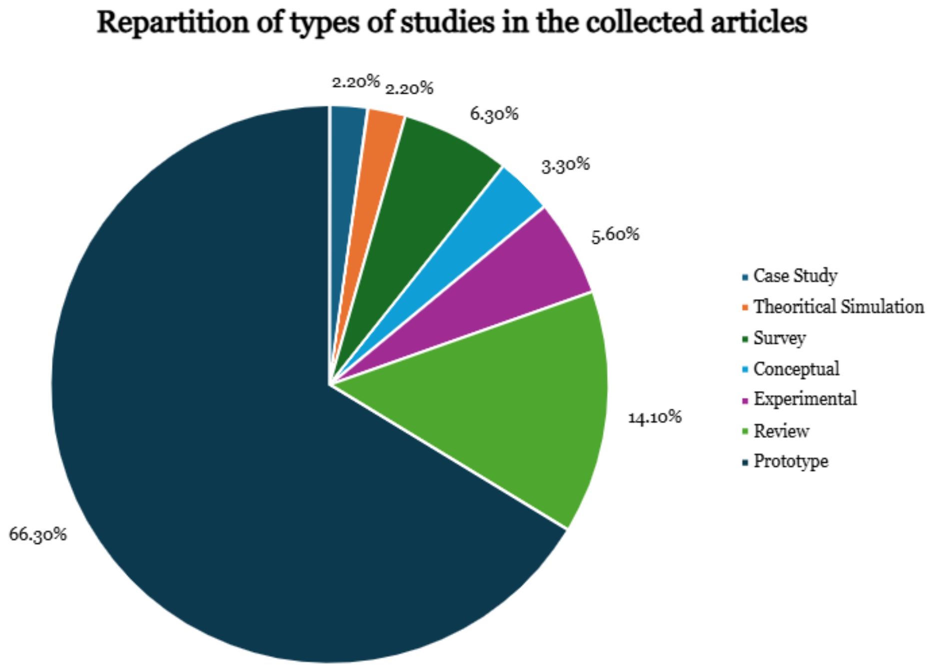

Figure 6. Types of studies retrieved.

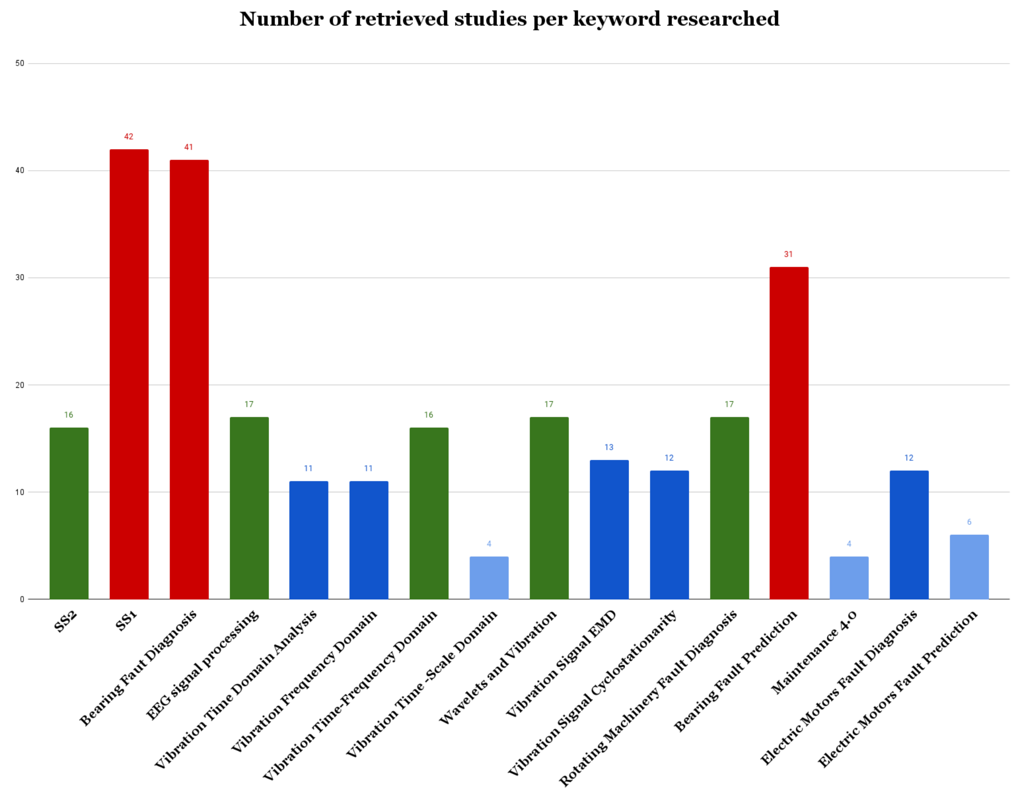

Figure 7. Studies retrieved per keyword.

Additionally, an UpSet plot was created to visualize the distribution of the data across the combinations of categories (Figure 8), complemented by a chronological chart that illustrates the progression of research relevant to the review's focus (Figure 9).

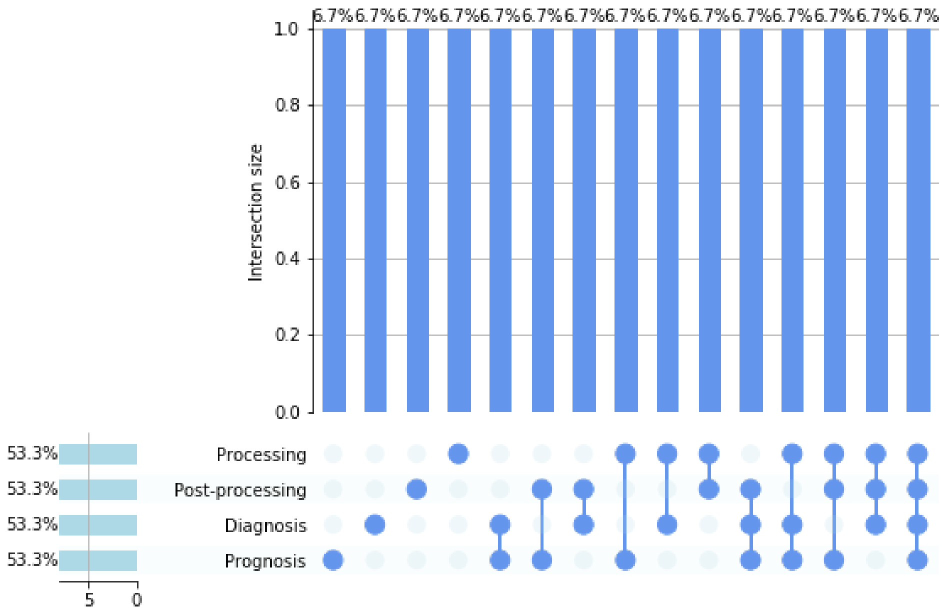

Figure 8. UpSet plot of the distribution of data across different categories.

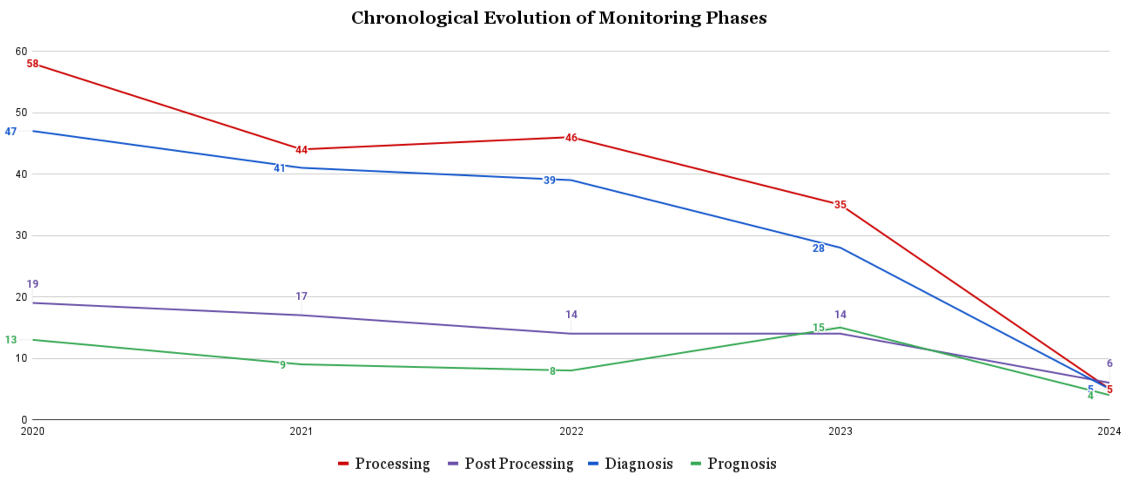

Figure 9. Evolution of the studies retrieved.

Ultimately, the studies chosen were organized into a table and categorized by the subjects they covered and their respective years of publication (Tables 6 and 7).

Table 6. Study characterization.

Research Objective	<2020	2020	2021	2022	2023	2024
Preprocessing	[24–26]	[27–41]	[42–55]	[56–67]	[20,68–86]	
Processing	[24,26,87–96]	[27–33,36–41,97–141]	[42–55,142–178]	[23,56–62,64–67,179–214]	[20,68–75,78,79,81–83,215–238]	[86,239–241]
Post-processing	[24,26,94]	[27–29,38,40,41,98,105,106,114,116,118,126,129,130,134,136,242,243]	[42–44,46,47,51,53,144,145,147,154,157,158,162,165,167,244]	[23,56,60,61,65,66,183–185,188,198,208,214,245]	[68,72,74,75,80–83,216,225,227,246,247]	[86,239–241,248]

Table 7. Study characterization of fault detection, fault prediction, and experimental validation.

Research Objective	<2020	2020	2021	2022	2023	2024
Diagnosis	[24–26,91,94,95]	[28–31,33,34,36–38,40,41,97–100,104,106–108,112,114–116,118–120,127,129,133–136,139–141,242,249–255]	[42–44,46,47,50–55,142,144–147,153,157,158,160–166,172–177,244,256–262]	[23,57,60–62,64–67,180,182,183,186–190,193,195,196,199–207,212–214,245,263–267]	[68,72,74–79,216,217,221–223,225,229–233,236,237,268–274]	[240,241,248,275]
Prognosis	[25,90,91]	[27,39,100,109–111,121,126,136,138,243,254,276,277]	[167,169–171,258,259,278,279]	[56,63,184,185,198,211,212,277]	[68,68,73,80,83–85,220,233,235,246,247]	[86,239,241]
expV	[26,89–91]	[29,30,36,39,40,99,101,112,113,116,128,129,131,140,141]	[42,45–48,51,55,145,148,155,162,166,172–174,177,261]	[58,61,64,66,67,199,200,202]	[78,80,215,217,222,223,234,236,237]	[240]

3. Results and Discussion

In the subsequent sections, the findings of the review pertaining to the main research objectives, established in Table 1, are presented.

3.1. Signal Preprocessing

Signal analysis essentially relies on signals that are collected during data collection. These are signals received in the acquisition phase in the form of a continuous time series that cannot be processed or analyzed directly by digital systems. These analog signals are discrete and show binary information that cannot be further processed numerically. On account of this, preprocessing techniques ensure the conversion of a signal from the analog continuous dimension into the discrete numerical dimension. The sampling technique retrieves samples of a continuous amplitude at regular intervals, generating a sequence of discrete time values. Through a low-pass filter and interpolation, the signal can be reconstructed. However, the sampled signal is often contaminated by noise, which causes distortion of the information content that was carried by the original signal. Techniques such as filtering, adaptive filtering, and sparse representation aid in denoising the sampled signal. This ensures the subsequent processes of signal interpretation and analysis are based on valid and reliable data [280–282].

In this context, we evaluated the proportion of studies that incorporated a preprocessing phase into their methodology. Our analysis revealed that among the 212 studies examined, only 47 of them integrated a preprocessing phase, accounting for 15.41% of the total studies. Although this percentage may not provide a comprehensive overview of the research practices in this domain, it is of significant importance, as the preprocessing phase is the basis upon which the evaluation of vibration signals from rotating machinery is built. The lack of signal processing results in information loss and erroneous diagnosis.

3.2. Signal Processing

Analysis of the data contained in a signal is conducted through signal processing techniques. These techniques examine the signal in four domains: time, frequency, time frequency, and time scale. Each domain offers different aspects of information (Figure 10).

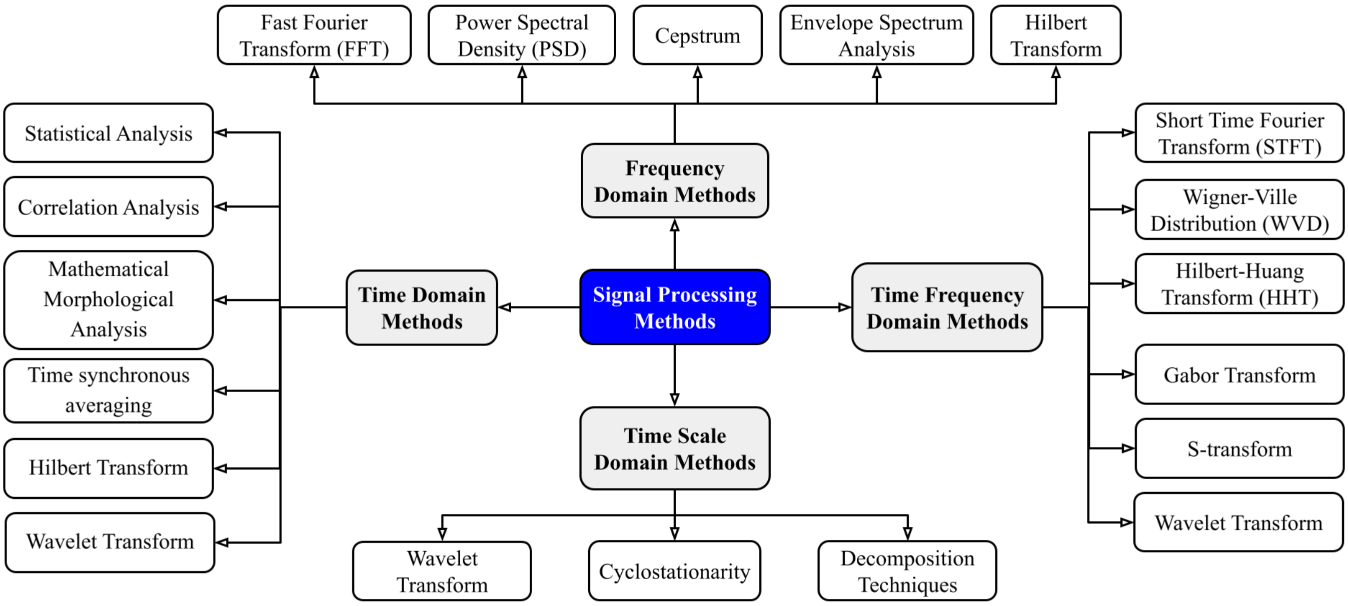

Figure 10. Signal processing methods.

In this part of the research, we review the techniques applied in signal processing for vibration signals and EEG signals. The heatmap in Figure 11 illustrates the distribution of the various signal processing techniques examined throughout the studied time period.

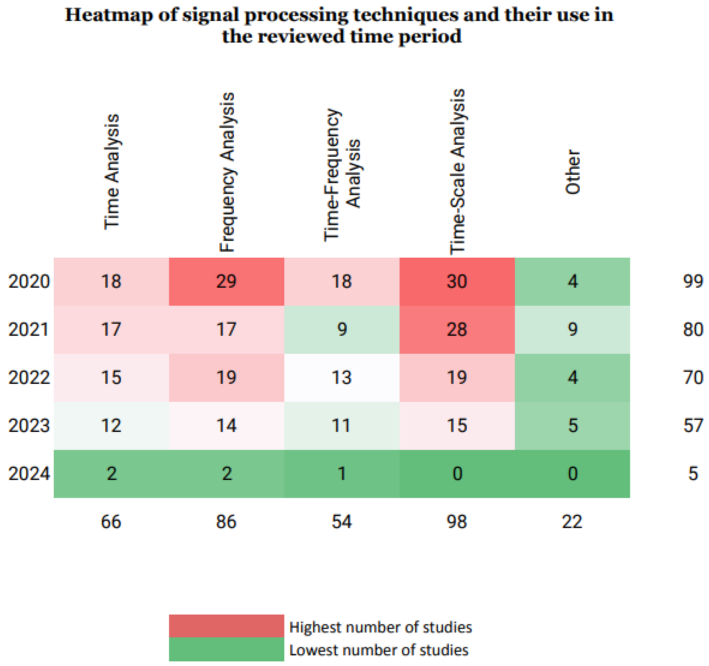

Figure 11. Heatmap of signal processing techniques and their use from 2020 to 2023 in the selected studies.

The reason we extended the research to the analysis of EEG signals is that they share many characteristics with vibration signals; for instance, both are transient and non-linear and contain multiscale temporal information. Consequently, research advances in EEG signal processing can benefit researchers in the field of vibration signals.

3.2.1. Time Domain Analysis

Time domain analysis revolves around the temporal characteristics of a signal, such as amplitude and phase. Statistical metrics such as the RMS, variance, standard deviation, peak-to-peak, crest factor, impulse factor, form factor, shape factor, clearance factor, kurtosis, skewness, and high-order statistics are frequently used to assess the temporal evolution of transient signals, mainly vibration signals [23,27–30,44,46,53,69,73,83,102,105,111,113,142,144,146,167,183,185,203,204,217,231,233].

In [20], the authors privileged filter-based methods and stochastic and advanced analytical techniques for feature extraction from vibration data, while the authors in [142] used Detrended Fluctuation Analysis (DFA).

The Hilbert transform, used in the studies referenced as [87,97–101,215], offered insights for the detection of rolling bearing faults, as well as wind turbine faults.

Several studies have employed different techniques, namely inter-channel correlation [102], time synchronous averaging [42], the time domain strain-life method [179], time-varying variance, time-varying kurtosis, the time-varying Kolmogorov–Smirnov test and autocorrelation [143], and the Higuchi fractal dimension (HFD) [43,216].

In [68], a combination of time domain features were extracted through an autoencoder neural network for fault classification in bearings and estimating their remaining useful life. In another work [180], periodic pulse information was extracted using the kurtosis of the unbiased autocorrelation of the squared envelope of a demodulated signal for the same purpose.

3.2.2. Frequency Domain Analysis

The inspection of a signal in the frequency domain involves examining its frequency components instead of its time-based characteristics. This approach allows us to analyze how fast the signal changes. In the following parts, the frequency domain techniques that were used in the studies reviewed are presented.

- The Fast Fourier Transform (FFT):
  The Fast Fourier Transform (FFT) is a mathematical tool and algorithm that decomposes a signal into a combination of sinusoidal functions possessing different frequencies. This method is a classical signal processing technique with prominence in identifying the generic frequency characteristics of signals. The studies referenced as [20,23,27–30,44–46,69,88,99,103–108,110–112,143–146,179–185,216–220] leveraged the advantages of the FFT for different applications, namely for rotating machinery diagnosis, predicting the remaining useful life (RUL) of bearings, and the maintenance of electrical machines.
  Nevertheless, the assumptions on which the FFT is founded give rise to several restrictions. First, it presumes that all the signals to be analyzed are continuous. The signals, however, are mostly discrete and sampled after undergoing a preprocessing phase. Another assumption in the Fourier transform is that the signal should be stationary. That is, its statistical properties remain constant with time. Again, these assumptions are often violated by real-life signals, which show non-stationary behavior. Furthermore, the FFT considers its input signal as periodic and linear. While this may be true for some signals, in most cases, it does not really explain the complexity of most real-world signals.
- Power spectral density (PSD):
  Power spectral density (PSD) refers to the representation of the amount of power that exists at each frequency band of a signal [283]. It is suitable for analyzing signals whose energy is spread over a range of frequencies rather than being concentrated within a few frequencies. The area under the PSD curve over a frequency range gives the total power of the signal in that range. In the papers cited as [88,113,142], PSD was useful for the analysis of transient signals such as EEG and speech.
- Cepstrum:

The cepstrum is a signal processing technique used when the frequency-based information of the signal, like the harmonics, needs to be examined separately. It is obtained by taking the inverse Fourier transform of the logarithm of the Fourier transform of a signal. On account of this, the signal is studied in the "quefrency" domain, where the quefrency denotes delays or periodicity in the original signal. This technique was used in the works of [100,142,147,148] to extract Mel frequency cepstral coefficients (MFCCs) as characteristics for the evaluation of signal health.

- Envelope spectrum analysis:
  Envelope spectrum analysis (ESA) is a highly effective method for detecting modulating patterns within a signal. By applying a Fourier transform to the envelope signal, a smoothed and time-variant version of the signal's amplitude is obtained. In practical applications, envelope spectrum analysis, including spectral kurtosis analysis, has been found to be more advantageous than traditional raw vibration analysis for early-stage fault detection and anomaly identification. This is because many types of machinery faults and defects manifest as fluctuations in amplitude in vibration signals. Several studies, as referenced in [47,56,89,90,97,98,149,221], have leveraged ESA for fault diagnosis and prediction in bearings.
- Other:
  In the study [57], Singular Spectrum Analysis (SSA) was used for decomposition of a signal into its fundamental parts to investigate trends, oscillations, and noise for the diagnosis of bearing faults while the study [106] used the Fractional Fourier Transform to extract the properties of vibration signals.
  Another study [27] used the Butterworth filter to refine the EEG signal by removing unwanted frequencies and thereby predicted epileptic seizures. Moreover, the implementation of modulation signal bispectrum analysis (MSB) in [91] yielded precise information regarding the modulation properties of the signal for gear monitoring.

3.2.3. Time–Frequency Analysis

Frequency domain analysis is certainly useful, but it has its limits. It can be susceptible to noise and interference, leading to inaccurate analysis. Furthermore, it is not well suited to transient signals since it analyzes the signal during a steady-state response of the system. Much of frequency domain theory assumes that the signal is stationary; in other words, its statistical properties do not change over time. However, this assumption will not hold for other signals that vary over time, such as vibration signals. Here, the use of time–frequency analysis techniques provides more insights into the varying metrics of a transient signal.

These methods are based on the concept of time–frequency distribution (TFD), where an estimate of the amount of energy in a signal is calculated from the signal under inspection and its complex conjugate. The TFD visualizes the evolution of the frequency content of a signal over time.

- The Short-Time Fourier Transform (STFT):
  The Short-Time Fourier Transform (STFT) is a mathematical technique that operates by dividing a longer time signal into shorter segments of an equal length and then computing the Fourier transform separately for each short segment, expressing the variation in the signal frequency in that segment over time [284]. This process captures both the temporal and frequency information, providing a three-dimensional representation of the signal. The STFT is recognized for its straightforwardness and clear physical explanation, which validates its application in the research works cited as [29,31,92,99,100,111,112,114,115,147,182,187,218,222,223].
- The S-transform:
  The S-transform, an extension of the Short-Time Fourier Transform (STFT), addresses certain limitations of the STFT, including the cross-term problem. It is obtained by convolving the FFT transformed signal with a Gaussian window function. Researchers used the S-transform in [106,189], respectively, for fault diagnosis in rotating machinery and for the classification of high-frequency oscillations in intracranial EEG signals.

Nevertheless, the S-transform may pose computational challenges, particularly with extensive datasets, and may exhibit redundancy by offering excessive information.

- Wavelets in the time–frequency domain:
  Signal transformation using wavelets is considered a versatile tool that can be adapted to each of the analysis domains. For adaptive time–frequency analysis of non-stationary signals, the wavelet transform (WT) decomposes the signal of interest into a set of basic localized waveforms called wavelets. A signal is analyzed by examining the coefficients of its wavelets [285]. In the time–frequency domain, wavelet analysis reveals the frequency components of signals, just like the Fourier transform, but it also identifies where a certain frequency exists in the temporal or spatial domain. Additionally, wavelet transforms have the capability to compress or denoise a signal with minimal loss in quality. Numerous studies [27,88,105,106,142,150,188,215,224,286] have utilized the wavelet transform as a valuable tool to characterize their signals and obtain high-quality representations in the time–frequency domain.
- The Wigner–Ville distribution (WVD):
  In contrast to linear representations, the Wigner–Ville distribution (WVD) is a quadratic time–frequency distribution with broad applications in signal processing and spectral analysis. It is defined as the expected value of the product of two versions of a signal that are shifted in time and frequency [287]. Belonging to the Cohen class of time–frequency distributions, the Wigner–Ville distribution offers advantageous properties, such as marginal distribution and localization in the time–frequency domain [288]. Although the WVD is functionally similar to a spectrogram, it outperforms it in terms of its temporal and frequency resolutions. This distinction resides in the principle of uncertainty in the time–frequency distribution that is not applicable to the bilinear Wigner–Ville transform, as it is not based on segmentation [289]. This method was used by the studies referenced as [32,100,225] for fault detection in wind turbine induction generators, as well as the classification of episodic memory and the prediction of heart disease in medical research.
- The Hilbert–Huang Transform (HHT):
  The Hilbert–Huang Transform (HHT) is a valuable signal processing method that leverages the advantages of Empirical Mode Decomposition (EMD), which will be discussed further in the time scale domain section, and Hilbert Spectral Analysis (HSA). The signal is decomposed into a limited set of intrinsic mode functions (IMFs), along with a trend component, through EMD. Hilbert Spectral Analysis (HSA) is applied to each IMF to determine the instantaneous frequency and amplitude [290]. Noteworthy studies that have utilized this method include references [88,101,151,218,226].
- The Gabor transform:
  The Gabor transform is a mathematical operation that examines the sinusoidal frequency and phase characteristics of a signal across time. By employing a Gaussian window function, it is able to analyze the signal in both the time and frequency domains concurrently, incorporating shifting, modulation, and power integration [291,292]. The studies referenced as [88,116,152], respectively, used this method for seizure detection, fault diagnosis in bearings, and distinguishing heart sounds. However, despite its numerous benefits, this method is not suitable for transient events, as it is specifically tailored to stationary signals.

3.2.4. Time Scale Analysis

In the time–frequency domain, signals are analyzed in terms of their frequency content over time, showing how the signal's energy is distributed across different frequencies. Traditional time–frequency methods suffer from a limitation in that the time–frequency resolution is restricted by the selection of the window or wavelet, which can impact the adaptivity of the analysis and the readability of the time–frequency representation. This constraint arises from the Heisenberg–Gabor uncertainty principle, where a small temporal window, associated with good time localization, leads to poor frequency resolution, and vice versa. Time scale techniques, such as those used for frequency super-resolution and intrinsic time scale decomposition, offer solutions to these limitations by providing enhanced adaptivity and resolution in the time–frequency domain, thereby allowing for more precise analysis of signals that are non-stationary and that contain multi-temporal scale information. They are significantly robust to noise and interference and provide an accurate representation of a signal's frequency content over time when coupled with time–frequency distribution (TFD) techniques.

- Wavelets and the time scale domain:
  Time scale analysis is commonly linked with the wavelet transform. Depending on the choice of the mother wavelet, the signal is viewed across different scales. The Continuous Wavelet Transform (CWT) and the Discrete Wavelet Transform (DWT) are two commonly used techniques in wavelet analysis. The CWT provides a continuous representation of a signal in the time scale domain, while the DWT offers a discrete representation that is often preferred in practice due to its computational efficiency. The studies referenced as [45,59,71,89,100,102,117–120,143,151–156,187,192,193,215,218,227] used these wavelet transforms to analyze wind turbine signals and diagnose faults in rolling bearings, as well as extract features from EEG signals.
  Advanced extensions of the wavelet transform provide a richer representation of signals by decomposing both their low-frequency (approximation) and high-frequency (detail) components at each level of the transform. In contrast, the standard wavelet transform only decomposes the approximation (low-frequency) part of the signal at each level.
  In contrast to the standard wavelet transform, the Wavelet Packet Transform (WPT) decomposes both low-frequency and high-frequency components at each level of the transform, thereby providing a richer representation of signals. This method was employed for fault diagnosis and prognosis in rolling bearings [121,157,238], as well as detecting drowsiness on the basis of EEG signals [43].
  On another hand, the Empirical Wavelet Transform (EWT) adaptively decomposes a signal into different frequency bands taking into account its specific spectral content. The Fourier spectrum of the signal is divided into multiple sub-bands depending on where significant transitions occur, thus defining the boundaries between the different frequency components. A corresponding wavelet filter is constructed for each segmented sub-band. Ultimately, the signal is decomposed using empirical wavelet filters, which results in a set of wavelet coefficients that represent the different frequency bands. This method demonstrated its effectiveness in the studies referenced as [60,148,159] for fault diagnosis in planetary gearboxes and for seizure detection from EEG signals.
  Additionally, other wavelet-based techniques, such as dyadic and binary-tree wavelet filters [92], the second-order synchroextracting wavelet transform [48], Modified Continuous Wavelet Decomposition (MCKD) [56], and Grossmann–Morlet time scale wavelets, have also shown promising results in extracting relevant time scale features.
- Cyclostationarity:
  Cyclostationarity is a fundamental concept in signal processing that pertains to periodic fluctuations in the statistical characteristics of a signal. Techniques for cyclostationarity analysis serve as robust methods for identifying and understanding cyclostationary signals, which display periodic statistical behaviors. They rely on the identification of frequency shifts to identify periodic patterns in signals that are referred to as cyclic frequencies. These methods are especially beneficial in scenarios like fault diagnosis in bearings, aiding in the detection and examination of cyclostationary patterns in signals associated with equipment malfunctions [49,112,114,122,123,143,149,181,194,226,228].
  Within cyclostationarity analysis, cyclic spectral coherence (CSCoh) is used as a statistical metric to assess the second-order cyclostationarity of signals. It measures the linear correlation between two signals in the frequency domain, enabling the detection of cycle frequencies in diverse datasets and the identification of significant

cycle frequencies in signals with cyclostationary attributes. Researchers delving into the realm of cyclostationarity have utilized CSCoh to pinpoint key cycle frequencies within signals, as noted in studies [42,106,124,195,196]. This analysis has led to a more profound comprehension of the cyclostationary nature of these signals.
The CSCoh function is closely connected to the cyclic spectral correlation function (CSC), which acts as a cross-correlation function. This metric reveals the similarity between a spectrum and its adjacent spectra, shedding light on how spectra vary across positions, a point highlighted in the study [124]. Furthermore, a separate study outlined in reference [72] introduced the Cyclic Spectral Covariance Matrix (CSCM) as a tool to glean insights into the cyclostationary characteristics of transient signals.

- Adaptive decomposition techniques in the time scale domain:
Adaptive decomposition techniques in signal processing are useful in complex environments with multiple sources operating on similar spectrum segments [293]. Their particularity resides in their ability to automatically adjust to the input signal's characteristics, offering a more flexible and effective approach compared to traditional decomposition methods. For instance, Empirical Mode Decomposition (EMD) identifies intrinsic modes, and Varional Mode Decomposition (VMD) separates modes variationally, with each having distinct advantages and limitations [293].
Empirical Mode Decomposition (EMD), being a data-driven method, decomposes a signal into a set of intrinsic mode functions (IMFs) based on its local characteristics. It is particularly suited to analyzing non-linear and non-stationary signals, such as vibration data, because it does not require a linear or stationary base as Fourier or wavelet transforms do. The flexibility of EMD in handling signals with time-varying frequencies and amplitudes has allowed researchers to effectively identify the different oscillatory modes of signals in various studies, namely vibration signals [30,56,59,73,74,87,93,94,101,125,126,142,160,188,192,197,198,215,225]. Moreover, EMD-based methods such as Ensemble Empirical Mode Decomposition (EEMD) [116], Complete Ensemble Empirical Mode Decomposition (CEEMD) [199], and Noise-Assisted MEMD (NAMEMD) [128] have been shown to improve the accuracy of fault diagnosis in mechanical systems by isolating and localizing faults better. However, EMD is an empirical method that lacks a solid mathematical background.
Variational mode decomposition (VMD) is commonly applied in the analysis of vibration signals due to its ability to adaptively and non-recursively segregate non-stationary signals into their fundamental modes [294] and mitigate mode mixing [295], a prevalent challenge encountered in other decomposition methodologies such as Empirical Mode Decomposition (EMD). Furthermore, VMD formulates the decomposition problem as a variational optimization problem. It extracts band-limited intrinsic mode functions (IMFs) adaptively by optimizing the objective functions related to the signal's frequency content [296].
The studies referenced as [61,129,130] used this method to perform a time scale analysis of vibration signals and ultimately assess the health of rotating machinery. Other studies have used other VMD-based methods, such as adaptive variational mode decomposition in [131] and Recursive Variational Mode Extraction (RVME) [200], to diagnose faults in rolling bearings.
In another study [132], VMD was coupled with other decomposition techniques, including EMD, local mean decomposition, local characteristic scale decomposition, Hilbert vibration decomposition, the EWT, and adaptive local iterative filtering, to analyze non-stationary signals from rotating machinery. Consequently, time–frequency representations (TFRs) with no interference of the cross-terms and auto-terms and a fine resolution were obtained.
In the same context of decomposition techniques, the authors in [50] proposed a novel feature adaptive extraction method for time scale analysis consisting of a slope and threshold adaptive activation function with the tanh function (STAC-tanh) for

diagnosing bearing faults. Additionally, in [178], the authors used Adaptive Periodic Mode Decomposition for the same purpose.
Finally, multivariate variational mode decomposition (MVMD) was used in [297] to recognize human emotions in EEG signals, and enhanced symplectic geometry mode decomposition (ESGMD) was used in [186] to diagnose faults in rotating machinery under variable speed conditions.

3.2.5. Other Approaches to Signal Processing

While signal processing methods are frequently used for feature extraction, other studies have leveraged AI algorithms to this end. These AI algorithms include a kernel extreme-learning-based multi-layer perceptron (KExL MLP) [201], convolutional neural networks (CNNs) [51,75,161,162,229], deep neural network (DNNs) [163], and fault-oriented support vector machines (FO-SVMs) [52]. In [95], a hybrid genetic algorithm (GA) and a deep belief network (DBN) coupled with Particle Swarm Optimization (PSO) were employed to diagnose bearing faults and their severity. Additionally, some studies have opted to use image processing and texture analysis to process signals. For instance, one study [164] considered the initial signal as a two-dimensional image instead of a one-dimensional time series, while another study [33] converted it into a gray-scale image. Local Binary Patterns (LBPs) were used in another study [133] for texture-based feature extraction. In another study [202], snowflake-like symmetric images were generated from the signals using the Symmetrical Dot Pattern (SDP) technique, which served as feature patterns for diagnosing bearing faults. Locally stationary processes (LSPs) were employed in the study [32] to assess the time-varying characteristics of non-stationary signals. Sparse Regularity Tensor Train (SR-TT) decomposition was utilized in another study [230] to analyze high-dimensional EEG data. Finally, geometrical features, as well as chaotic and fractal dimensions, were extracted in [165,203] to detect health anomalies.

3.3. Signal Post-Processing

The concept of signal post-processing refers to the process of refining the data that are intended to be utilized by machine learning algorithms for classification purposes. To effectively carry out this process, signal post-processing techniques can be classified into three distinct categories—feature selection techniques, feature fusion techniques, and data augmentation techniques—as shown in Figure 12. Feature selection techniques specifically aim to identify the most informative features from a set of features that have been extracted during the processing phase, while feature fusion techniques focus on structuring and combining the selected set of features into the optimal format that can be easily analyzed by the machine learning algorithm. On the other hand, data augmentation techniques are employed to expand and diversify the learning process when the original dataset is limited in size. These post-processing steps facilitate the transition from signal processing to machine learning, as they not only contribute to a reduction in computational costs but also enhance the predictive accuracy.

3.3.1. Feature Selection

Feature selection aims to eliminate unnecessary or repetitive attributes, which can decrease overfitting and improve generalization. A variety of techniques can be implemented for this purpose, ranging from machine learning algorithms and correlation analysis to dimensionality reduction methods. The feature selection algorithms used in the studies selected in our review are presented in Table 8. The correlation analysis methods and dimensionality reduction methods are shown in Table 9 and Table 10, respectively.

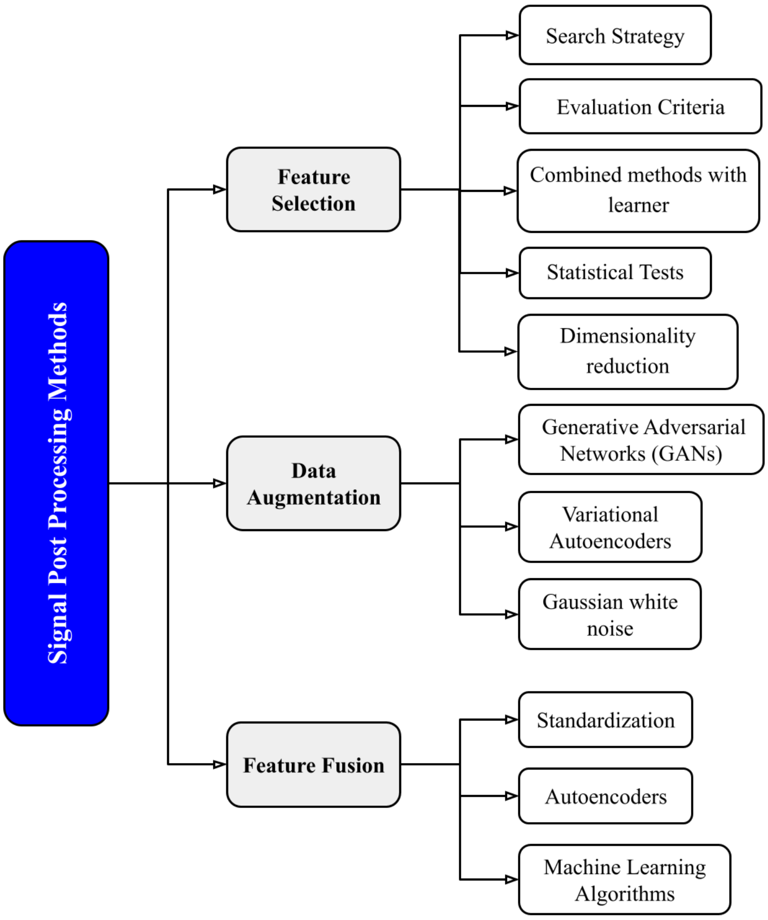

Figure 12. Signal post-processing methods.

Table 8. Feature selection algorithms.

Feature Selection Approach	Algorithm	Studies
Fuzzy-Logic- and Kernel-Based	Fuzzy Logic Embedded RBF-Kernel-Based ELM (FRBFELM)	[60]
Neural-Network- and CNN-Based	Convolutional Neural Networks (CNNs)	[29,51,116]
Heuristic Search Methods	Gray Wolf Optimizer Cuckoo Search (CS) Monotony Evaluation	[147] [56] [86,167]
Adaptive Multiscale Convolutions	Stacked Residual Adaptive Multiscale Convolution (Res AM) Blocks Multiscale Convolutional Strategy	[75] [162]
Genetic Algorithms	Genetic Algorithms (GAs)	[41,94,134]
Sequential and Recursive Selection	Sequential Forward Floating Selection (SFFS) Recursive Feature Elimination (RFE) Sequential Backward Feature Selection (SBFS)	[27] [23,188,225] [44]
Optimization-Based Approaches	Expectation Selection Maximization (ESM) Correlation-Based Feature Selection (CFS) Discriminant Regularizer with Gradient Descent	[286] [157] [145]

Table 9. Correlation analysis methods for feature selection.

Feature Selection Approach	Method	Studies
Statistical Correlation Analysis	Statistical Correlation Pearson's Correlation	[42,53,68,80] [198,246]
Connection Weights and Fisher's Criterion	Connection Weights Fisher's Criterion	[43,245] [129]
Correlation Coefficients	Correlation Coefficients Calculated for Intrinsic Mode Functions (IMFs) Correlation Metrics	[126] [65,86]
Advanced Correlation Techniques	Gray Relation Analysis (GRA) Differential Evolution Discriminating Capability Frequency Spectrum Averaging Acceleration Responses and Wavelet Scalograms	[185] [118] [165] [47] [227]
Novel Techniques	Frequency Band Entropy (FBE) and Envelope Power Spectrum Analysis for Selecting the Optimal Intrinsic Mode Functions (IMFs)	[130]

Table 10. Dimensionality reduction methods for feature selection.

Feature Selection Approach	Method	Studies
PCA Variants	Principal Component Analysis (PCA) K-Principal Component Analysis (K-PCA) Weighted Principal Component Analysis (WPCA)	[24,28,40,74,86,214,216] [28,60,136] [286]
Singular Value Decomposition	Multi-Weight Singular Value Decomposition (MWSVD) Singular Value Decomposition (SVD)	[157] [68,136]
Neighborhood Component Analysis	Neighborhood Component Analysis (NCA)	[183]
Non-Linear Dimensionality Reduction	T-Distributed Stochastic Neighbor Embedding (t-SNE)	[105]

3.3.2. Data Augmentation

When the data availability is limited, data augmentation techniques enable the extension of the size and diversity of the dataset. Such techniques involve creating more data from existing data by applying different transformations. The significance of data augmentation is particularly evident for signal data, which are typically high-dimensional and scarce, posing challenges for training accurate classification models.

Our research indicates that data augmentation is carried out using various methods, including Gaussian white noise [106], one-dimensional deep convolutional generative adversarial networks (1D-DCGANs) [244], cubic B-spline interpolation algorithms [167], and variational autoencoders [243]. Furthermore, a study referenced as [242] combined sample-based and dataset-based approaches, incorporating techniques such as using additional Gaussian noise, masking noise, signal translation, amplitude shifting, and time stretching to improve the enhancement process.

3.3.3. Feature Fusion

Feature fusion techniques improve the discriminative power of the classification models in signal data classification by combining information from different feature extraction methods. This integration of diverse features allows the model to create more robust representations that can accurately distinguish between various classes or categories in the dataset. In [46], the researchers explored different combinations of fused features to identify the most appropriate set, while the studies [184,246] focused on standardizing the features prior to classification. For the same purpose, the authors in [167] used an SAE (stacked autoencoder).

In contrast to the methodology in [46], ref. [82] performed feature fusion before feature reduction by merging the time–frequency content from individual channels with deep features extracted separately using a convolutional neural network (CNN). Furthermore, in [81], a multi-feature fusion network (MFFNet) was introduced after feature extraction to enhance the effectiveness of the model training.

3.4. Diagnosis

Recent advancements in Artificial Intelligence (AI) have enabled the development of a wide variety of classification algorithms, thereby facilitating the detection of component defects in rotating machinery. They are broadly classified into four categories based on their learning approach: classical learning, ensemble learning, reinforcement learning, and deep learning [298]. Classical learning techniques are categorized into supervised or unsupervised learning algorithms. Through supervised learning, the input data are mapped to the output data with labels, while unsupervised learning infers hidden patterns or structures in the data without labeling the output [299]. The ensemble learning approach is built upon meta-learning and aims to combine the strengths of certain base learners in deriving a more robust, accurate predictive model by aggregating their predictions. Meanwhile, the reinforcement learning (RL) approach aims to train software to make decisions that provide the maximum reward signal possible from a specific environment [299]. Finally, deep learning (DL) algorithms are developed using artificial neural networks, which are designed to imitate the composition and operations of the human brain. The standard forms of such models are multiple layers. Every layer in the neural network transforms the input inside it non-linearly with the purpose of understanding the complicated patterns or relationships in the data [298]. The different algorithms in each category are shown in Figure 13.

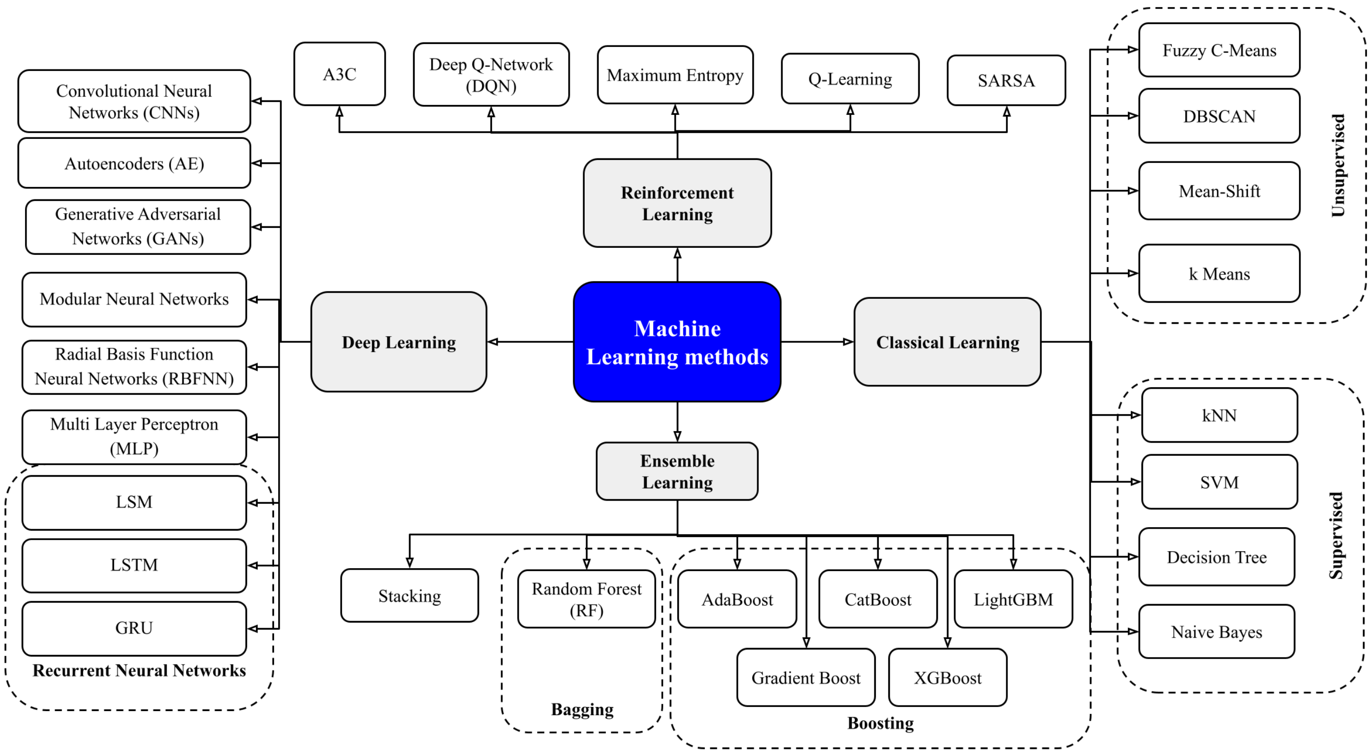

Figure 13. Machine learning methods.

The analysis of the studies we collected in this review shows that certain algorithms are privileged for the detection of industrial anomalies through vibration signals, as shown in Figure 14.

Support vector machines (SVMs), convolutional neural networks (CNNs), Long-Short Term Memory (LSTM), k-nearest neighbors (kNN), and deep belief networks (DBNs), respectively, outrank other machine learning algorithms in terms of their use for intelligent diagnoses in rotating machinery. In the subsequent sections, the most relevant studies that used these algorithms are discussed.

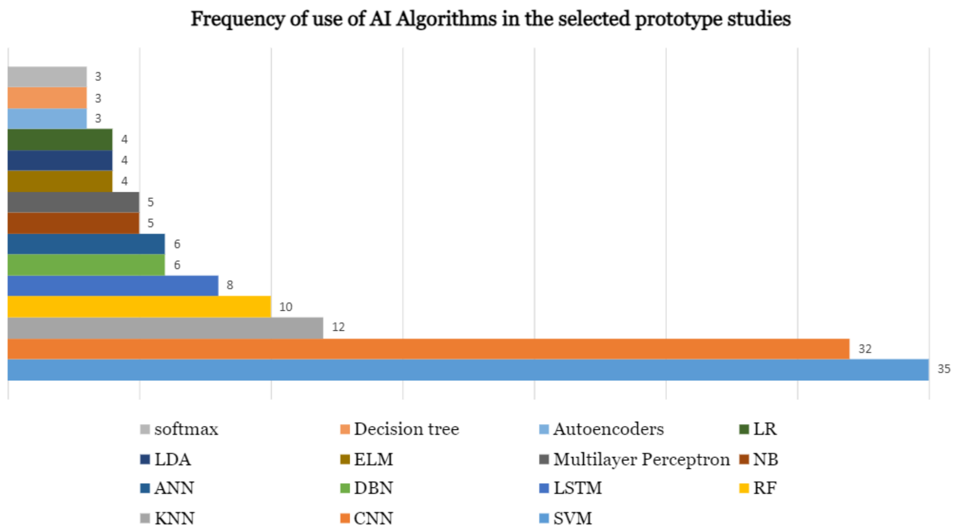

Figure 14. Frequency of use of machine learning algorithms in the studies reviewed.

3.4.1. Support Vector Machines

A support vector machine (SVM) is a supervised learning algorithm used for classification and regression tasks. It aims to find the optimal hyperplane in an N-dimensional space to separate different classes and maximize the margin between the closest points in different classes [300].

In [23], a comparison of the performance of different fault identification models (an SVM, an ELM, a DBN, and a DNN) was performed for the diagnosis of faults in wind turbine bearings. The SVM model was composed of two layers; features with large chi-square value were the inputs to the algorithm, and their labels were the output. The weights of the features were calculated, and the features with the least weight were removed. The SVM classifier achieved an 99.5% accuracy with the time domain features that exceeded that of the ELM and DBN classifiers; however, the DNN classifier ranked first. Using the frequency domain features, the SVM and DNN algorithms ranked first in terms of their accuracy.

The survey in [257] shows that SVMs are quite useful for analyzing failures in bearings, as they provide accurate results and can handle complex data distributions. However, they may have shortcomings in terms of probabilistic findings.

The study in [157] used a support vector machine (SVM) with a Gaussian kernel function to convert inseparable data points from a low-dimensional space into a high-dimensional space. A genetic algorithm determined the optimal parameters for the SVM within the training set following a five-fold cross-validation process. The SVM model conducted fault identification on the basis of a feature matrix extracted through the Wavelet Packet Transform (WPT) and Multi-Weight Singular Value Decomposition (MWSVD). WPT-MWSVD+SVM outperformed the other methods with a penalty parameter of 25.15 and a kernel parameter of 212.47. This study concluded that an SVM coupled with the proposed feature extraction methods was proficient in diagnosing inner race and outer race faults.

In [183], the inputs to the SVM algorithm were feature vectors comprising various statistical features. Instead of a conventional hidden layer, the algorithm employed a radial basis function (RBF) as a kernel function to convert the input data into a higher-dimensional space. The output data were represented by a single neuron that generated a binary classification (0 or 1) based on whether the input data belonged to a specific class of either faulty or non-faulty bearings. Comparisons were made with KNN, ANN, and Naive Bayes classifiers, resulting in an average accuracy rate of 86.11% for the SVM algorithm. In contrast, the KNN, ANN, and NB classifiers achieved accuracy rates of 95.37%, 92.59%, and 83.33%, respectively.

In the study [253], a comparison was made between an SVM and other models, such as a CNN, a CNN + MMD (Maximum Mean Discrepancy), a CNN + CMMD (Conditional Maximum Mean Discrepancy), an MDDAN (Multi-Scale Deep Domain Adaptive Network), a DIAN (Deep Intra-class Adaptation Network), and an MDIAN (Multi-Scale Deep Intra-Class Adaptive Network), for diagnosing bearing faults. This study revealed that the SVM, as a traditional machine learning method, struggles to effectively handle the difference in the distribution between the source and target domains, which is crucial in transfer learning tasks. The SVM assumes that the source and target domains share the same distribution, resulting in its inferior performance compared to that of more advanced models like the MDIAN, which outperformed all the other methods in this study.

3.4.2. Convolutional Neural Networks (CNNs)

Convolutional neural networks (CNNs) in signal processing are specialized neural network architectures designed to process and analyze signals such as audio, speech, and time series data. In this context, CNNs apply convolutional operations to extract features from signals, enabling tasks like classification, denoising, and pattern recognition. By leveraging filters and pooling layers, CNNs can capture the temporal dependencies and spatial patterns within signals, making them effective tools for various signal processing applications. The hierarchical feature enhancement methods employed in CNNs allow for the effective conversion of feature signals into two-dimensional spaces, enhancing these networks' ability to process transient signals efficiently. This justifies their wide use in diagnosing faults in rotating machinery [301].

In [242], two-dimensional spectrograms served as the input data for the CNN developed. To simulate practical noise levels, white Gaussian noise was introduced into the raw signals at SNRs of 4 dB and 0 dB. The integrated CNN approach demonstrated an impressive average accuracy of 99.02%, surpassing the performance of other time–frequency analysis methods such as the STFT and WT across different working conditions. The model was compared with a basic neural network (NN), a recurrent neural network (RNN), and an SVM. The NN algorithm was less efficient in capturing the data information compared with the CNN and the RNN, while the testing accuracies achieved by the SVM method were not very promising either.

In [268], a review of the application of deep learning to intelligent fault diagnosis for rotating machinery affirmed that CNNs have strong data compatibility, a strong feature extraction ability, fewer model parameters than fully connected networks, and flexible and changeable structures. However, there is a problem of information loss, and the quality of the extracted features is affected, along with a significantly long training time.

The research in [244] explored the utilization of a one-dimensional convolutional neural network (1D-CNN) for diagnosing faults in rotating machinery. The 1D-CNN architecture in this study was composed of an input layer, a feature extraction layer, and a classification layer. The feature extraction layer was made up of three convolutional layers and three pooling layers, which extracted features from the original vibration signal and reduced the dimensionality of the feature vector. The classification layer consisted of two fully connected layers, with the second fully connected layer having the same number of neurons as the fault labels for classification. This study utilized a Softmax regression classifier for output classification. By comparing the performance of the proposed method with that of two other methods (Markov chain and a variational autoencoder (VAE)), the results demonstrated that the method proposed surpassed the two other methods, achieving a higher accuracy rate in fault identification.

The authors in [256] proposed the use of ensemble adaptive convolutional neural networks (ECNNs) composed of ten individual CNNs with different properties. Each CNN consisted of convolutional layers for feature extraction; Batch Normalization (BN) layers to normalize the activations of the convolutional layers; pooling layers to downsample the output of the convolutional layers through max pooling and average pooling layers; and fully connected layers for classification. This research employed a range of optimization algorithms, such as stochastic gradient descent (SGD), RMSProp, Adgrad, Adadelta, and Adam. To excel in diagnostic tasks, deep neural networks (DNNs) with multiple hidden layers are used. However, it should be noted that incorporating more hidden layers may result in decreased computational efficiency. In order to enhance the stability during the later stages of training, an adaptive learning rate algorithm called EDLR was employed, which gradually decreased the learning rate as the iteration progressed. Additionally, parameter transfer was employed in this study to minimize the training time. This technique involved pre-training one model and then exploiting its parameters as the initial parameters for the other models. A comparison with other existing methods, such as AdaBoost, random forest (RF), and Ensemble Deep Autoencoders (EDAEs), concluded that the ECNNs and EDAEs achieved a 100% precision rate and 94% and 98% F-1 scores, respectively.

In [33], the Deep Fully Convolutional Neural Network (DFCNN) designed contained several layers, with each one fulfilling specific functions. The convolutional layers executed convolution operations on the local regions of the input signals through the use of convolution kernels and extracted the signal characteristics. The convolution window weights were the same and were not modified when sliding over the entire image; therefore, overfitting was eliminated and the memory requirements were minimized in training. The activation layers non-linearly remapped each value of the output of the convolution to help the CNN converge. The implementation used the activation function Leaky ReLU. The additional Batch Normalization (BN) layers helped decrease the internal covariance shift, which expedited the training process, enhanced the network efficiency, and further increased the generalization ability. Finally, the pooling layers performed downsampling operations to reduce the parameters of the neural network. A 6×6 input feature window was considered in this study and pooled to the largest layer, 3×3 in size, of output features using a pooling operation of 2×2 with a step of 2. To benchmark the DFCNN, the performance of the method was compared with that of various other methods: among others, a support vector machine (SVM), a multi-layer perceptron (MLP), and a deep belief network (DBN). The results showcased that the SVM, MLP, and DBN had very little adaptability, with average accuracies of 66.6%, 75.9%, and 75.7% across the six cases. In the meantime, the DFCNN method portrayed the best accuracy among all methods, with an average accuracy of 90.5%.

As discussed in the SVM section, the study in [253] developed a transfer learning model for bearing fault diagnosis based on a Multi-Scale Deep Intra-Class Transfer Learning (MDIAN) approach and compared it to different machine learning algorithms. This study used a CNN model that included a modified ResNet-50, a multiple-scale feature extractor, and a classifier. Originally intended for low-level feature extraction, ResNet-50 was adjusted by eliminating its last two layers and replacing them with the multiple-scale feature extractor. The extractor captured high-level features from the low-level features provided by ResNet-50. The classifier based its fault diagnosis on the high-level features. The proposed CNN algorithm surpassed traditional machine learning approaches such as an SVM and basic CNN models, demonstrating enhanced accuracy and efficiency in reducing the distribution gap between the source and target domains. However, the proposed CNN network was still outranked by an MDIAN, which is particularly effective in identifying faults in rollers and outer rings.

A review conducted in [260] covered four traditional types of deep learning models, deep belief networks (DBNs), autoencoders (AEs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs), and their use in the detection of motor faults. It highlighted that CNNs offer tremendous mass data processing capabilities, as well as local perception, shared weights, and spatial or temporal downsampling, all of which help to lower the number of network parameters and avoid network overfitting.

3.4.3. Long Short-Term Memory (LSTM)

LSTM is a type of recurrent neural network (RNN) designed to handle the challenges in processing sequential data in signal processing. LSTM is particularly effective in capturing the long-term dependencies and temporal relationships within signals. It is designed to address the vanishing gradient problem present in traditional RNNs. It offers robust classification capabilities, especially when combined with time–frequency and time–space properties.

The study conducted in [107] used an LSTM model based on instance transfer learning to study failures in bearings. The LSTM model incorporated memory cells and three gates (an inputting gate, a forgetting gate, and an outputting gate) within its network structure. The model used data from the frequency spectra obtained through the fast Fourier transform (FFT) to enhance the clarity of the information on bearing faults. To train the LSTM model, datasets from different probability distributions (Dsrc-I and Dtar-I) were used to learn the mapping relationship between the source domain (Dsrc) and the target domain (Dtar). The model structure also included peephole connections, which allowed the cell state at the last moment to influence the three gates, thereby enhancing the control and information processing. In a comparative analysis with a CNN, a DBN, and an SAE, LSTM ranked third, with the CNN and the DBN achieving higher accuracies.

In a study [30] conducted on diagnosing bearing faults, a novel approach was proposed using a multi-scale CNN and an LSTM model consisting of two modules. The first module involved two one-dimensional CNNs with varying kernel sizes and depths, which were simultaneously applied to raw signals to extract features from different frequency domains. The feature vectors obtained from the CNNs were then fused using element-wise products. The second module, known as the classifier, comprised a hierarchical LSTM and a fully connected layer. The hidden states of LSTM1 served as the input for LSTM2, and the outputs of LSTM2 were fed into the fully connected layer. This study's results demonstrated that the combined model achieved an average accuracy rate of 98.46%, while the LSTM network alone achieved a comparatively lower accuracy rate of 66.39%.

The authors in [147] employed a modified transformer architecture incorporating a Bidirectional LSTM (BiLSTM) network for the classification of vibration signals. In contrast to the traditional LSTM, the BiLSTM used an update gate to handle long-term dependency information. Within the modified transformer network, the BiLSTM served as a branch layer coupled with Global MaxPooling for extracting high-level non-sequential features from various perspectives. To confirm its efficacy, experiments revealed that this particular BiLSTM branch bolstered the performance of the modified transformer by approximately 2 percentage points compared to relying solely on the attention mechanism. During the experiments, the BiLSTM was equipped with 128 hidden units. The model underwent testing with a CNN in place of an LSTM, demonstrating that the LSTM-based model attained a superior accuracy rate and a reduced standard deviation when compared to that with the CNN.

3.4.4. KNN

K-nearest neighbors (KNN) is a non-parametric lazy learning algorithm used in signal processing to classify data points based on the 'k' closest training examples in the feature space. It leverages the proximity of the data points to make predictions or classifications. KNN is particularly effective for tasks like classifying transient disturbances to power quality based on the signal features extracted from the data.

In [160], an EMD-KNN method was applied to analyzing wind power rolling bearings. It incorporated the KNN algorithm to identify the frequency characteristics of various states using complex signal data. To gauge the similarity between the data points, the algorithm used the Euclidean distance as the distance measurement method. Prior to inputting data into the KNN algorithm, data normalization was carried out to standardize them. Weighted voting based on K-nearest neighbors was employed to make classification decisions regarding the data points. This study showcased that the KNN classifier's accuracy in fault diagnosis was 100% with a significantly shorter processing time of 0.449198 s in comparison to that of random forest (RF), Naive Bayes (NB), and a Discriminant Analysis Classifier (DAC).

In the KNN algorithm employed in [134], the positions of the training samples remain fixed, and when a new data point is introduced, the distances between this data point and all the training samples are computed. Subsequently, K samples with the shortest distances are pinpointed within the training set. By examining these distances, the algorithm selects the neighbors closest to the new data sample. The KNN algorithm achieved an accuracy score of 99.2%, outperforming a decision tree classifier with 98.5% accuracy, while a random forest (RF) model achieved 99.5% as its accuracy rate.

3.4.5. Random Forest

Random forest is an ensemble learning method that combines multiple decision trees to improve the accuracy and robustness of the predictions. A set of decision trees classify signals, extract features, and make predictions based on the input data. By aggregating the predictions of individual trees, random forest provides the final classification outputs.

The study referenced in [134] explored the optimization parameters for a genetic algorithm (GA) and three distinct classifiers—k-nearest neighbors (KNN), decision trees (DTs), and random forest (RF)—in order to enhance the performance in diagnosing bearing faults in induction motors. In this study, each tree in the architecture of the random forest (RF) algorithm was trained on a random subset of features and samples from the training data. The class predicted by the individual trees was based on the mode of the class labels, while the mean value was predicted for regression tasks. This collaborative learning method aimed to address the issue of overfitting that can arise with single decision trees. The random forest model achieved an accuracy of 99.5%, the decision tree model reported 98.5%, and the k-nearest neighbors algorithm achieved an accuracy of 99.2%.

In [129], a diagnosis model was proposed for a centrifugal multi-level impeller blower. This model utilized VMD, MSDIs, Fisher's criterion, and RF. This approach involved decomposing the vibration signals using VMD and constructing six types of MSDIs from the decomposed signals. The top-ranked MSDIs were then selected as the fault features using Fisher's criterion. The RF classification process included bootstrap-sampling the training set to reduce overfitting and random feature selection for each node to enhance the model's performance. Additionally, tree construction was based on the best features selected from a random subset, with node splitting conducted until a stopping criterion was reached. The aggregation of the classification outputs was built upon a majority voting strategy. Notably, the model achieved a classification accuracy of 95.58%.

3.4.6. Deep Belief Networks (DBNs)

DBNs are types of generative neural networks that combine unsupervised learning principles and neural networks. Deep belief networks (DBNs) are deep neural network architectures composed of multiple layers of restricted Boltzmann machines (RBMs) [302]. In signal processing, DBNs are used to learn hierarchical representations of the input signals [303].

The study in [23] combined 10,000 samples into a feature set to train and test four classification models (an ELM, SVM, DBN, and DNN) following a 7:3 ratio. Interestingly, the DBN exhibited superior performance when frequency domain features were used in conjunction with a second FFT. However, despite this advantage, the DBN was slightly outperformed by the other classifiers in the study.

In another study referenced as [145], a DBN algorithm with five hidden layers was used for bearing fault diagnosis. The first two layers consisted of 512 neurons, the third layer of 128 neurons, the fourth layer of 64 neurons, and the final output layer of 9 neurons. Remarkably, this approach achieved an accuracy rate of 94.07%. The DBN algorithm outperformed a CNN, an SVM, and RF in the proposed framework, which incorporated a novel deep autoencoder method with discriminative information fusion in the model.

In their research, the authors in [95] employed adaptive deep belief networks in conjunction with Dempster–Shafer theory to develop a technique for diagnosing the severity of bearing faults. The DBN employed a stacked architecture comprising multiple restricted

Boltzmann machines (RBM). Each hidden layer from the previous RBM served as the visible layer for the subsequent RBM. The RBMs in the DBN were structured so that the visible layer (V) and the first hidden layer (H1) constituted the first RBM, while H1 and the second hidden layer (H2) constituted the second RBM, and so on. The neurons in the visible layer were interconnected with the neurons in the hidden layer in each RBM through a weight matrix. The DBN training process involved two main steps: a pre-training process that sequentially trained the weights in each stacked RBM and a fine-tuning process that optimized the entire network after pre-training. Furthermore, a classifier was implemented on the topmost layer of the DBN network to generate probabilistic outputs and enable multi-class classification. A Softmax regression model in the final layer of the DBN structure mapped the non-normalized output to the probability distribution of the predicted output classes and facilitated multi-class classification and probabilistic output for subsequent D-S evidence fusion. This study demonstrated that the combined approach of using an adaptive parameter-optimized DBN and a D-S-based information fusion scheme significantly improved the accuracy of the results in diagnosing bearing faults.

The study in [260] evaluated deep learning algorithms and their performance in fault detection in electric motors. The review emphasized that DBNs (deep belief networks) are able to learn the data features adaptively, without the need for a formal mathematical model. One of the key advantages of the DBN is its hidden multi-layer structure, which effectively tackles the issue of dimensionality problems. Additionally, the DBN's semi-supervised training method proves to be highly effective in addressing the limitations of the standard neural network training methods when dealing with problems in multi-layer networks.

3.4.7. Other Machine Learning Algorithms

In terms of the other classifiers that have been employed for the purpose of making diagnoses in rotating machinery, Table 11 presents the additional classifiers used in the studies reviewed.

Table 11. Other classifiers used for rotating machinery diagnoses.

Category of Classifiers	Algorithm	Studies
Neural-Network-Based Classifiers	Graph Neural Network (GNNs)	[229]
	Deep Neural Networks (DNNs)	[23]
	Recurrent Neural Networks (RNNs)	[260,268]
	Generative Adversarial Networks (GANs)	[268]
	Spiking Neural Networks (SNNs)	[57]
	A Stacked Inverted Residual Convolution Neural Network (SIRCNN)	[108]
	Class-Level Matching Transfer Learning Network	[273]
Statistical- and Clustering-Based Classifiers	Fuzzy-Logic-Based Confidence Decision	[78]
	K-Means Clustering	[153]
	Discriminant Analysis Classifier (DAC)	[160]
	Gaussian Mixture Model (GMM)	[286]
	Local Binary Pattern (LBP)	[133]

In the medical field, the classifiers in Table 12 achieved significant results in pattern recognition in EEGs and similar signals. An alternative viewpoint would be to investigate these classifiers considering the similarities between these signals and vibration signals.

Table 12. Classifiers for EEG and ECG signal classification.

Category of Classifiers	Algorithm	Studies
Neural-Network- and Attention-Based	Bayesian Quadratic Discriminant Transfer Neural Network (BQDTNN)	[201]
	Multi-Head-Attention-Based Long Short-Term Memory (MHA-LSTM)	[263]
Fuzzy Logic and Statistical Methods	Fuzzy RBF-ELM Classifier	[60]
	Gaussian Discriminant Analysis (GDA)	[28]
Ensemble Methods	EBT Classifiers	[190]
	Ensemble Classifier Algorithms	[44,203]

3.4.8. Comparative Research

To draw conclusions, a comparative analysis of the frequently used machine learning algorithms discussed was performed. This analysis included an evaluation that compared the strengths and weaknesses of each algorithm, taking into account factors such as data size, overfitting, accuracy, and computational demands. Table 13 provides a consolidated overview of the principal advantages and disadvantages, along with the scalability, of the algorithms evaluated.

Table 13. Comparison between the most used AI algorithms.

Classifier	Advantages	Disadvantages	Scalability
SVM	Effective in high-dimensional cases Non-linear separation Efficient memory usage Generalization (robust even with biased training samples)	Complex kernel selection Long training time Difficult to interpret the model Hyperparameter tuning	Small datasets [a few hundred to a few thousand training samples]
CNN	Excellent feature extraction Temporal and spatial analysis Efficient learning	Data requirements (large labeled datasets) Difficult to interpret	Large datasets [thousands to millions of training samples]
LSTM	Handling long-term dependencies Well suited to time series analysis Robust to noise	Training challenges (need to balance the learning of short-term and long-term dependencies in signals)	Large datasets [few thousand to millions of training samples]
KNN	Simplicity Non-parametric Transparent decision-making process	Sensitive to outliers Need for optimal k Memory-intensive	Small datasets [a few hundred to a few thousand training samples]
RF	Robustness Feature importance	Long training time Hyperparameter tuning required Memory-intensive	Wide range of dataset sizes [a few hundred to millions of training samples]
DBN	Unsupervised feature learning Handling complex patterns Robustness to noise Versatility	Challenging to interpret Sensitivity to hyperparameters (number of layers, number of units, learning rate)	Large datasets [a few thousand to millions of training samples]

Figure 15 offers a comparative analysis of these algorithms with respect to their complexity and accuracy and a ranking of their computational costs.

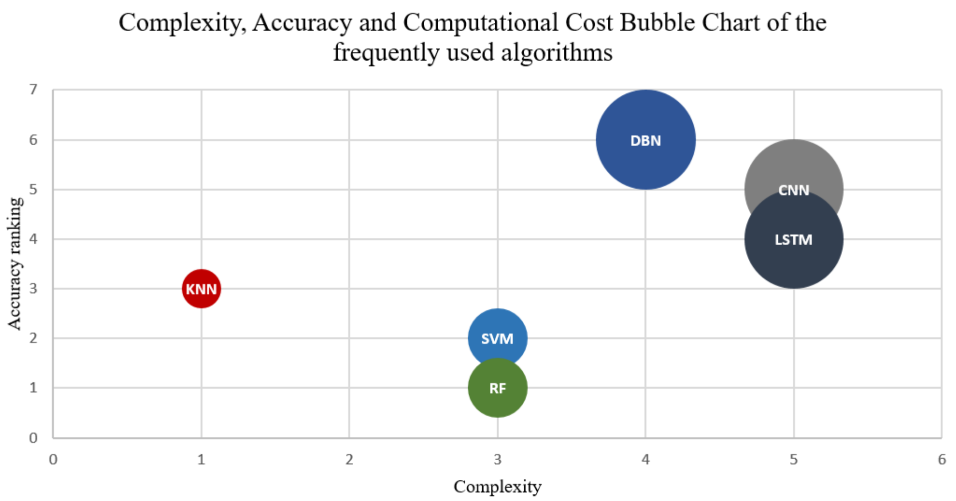

Figure 15. Bubble chart depicting the relationship between the complexity and accuracy of the algorithms discussed regarding their computational cost (bubble size).

Table 14 displays the data utilized to construct the bubble chart depicted in Figure 15. These data were derived from the conclusions of the various studies reviewed in the preceding sections.

Table 14. Algorithm ranking in terms of complexity, accuracy, and computational cost on the basis of the reviewed studies' findings.

Algorithm	Complexity Ranking	Accuracy Ranking	Computational Cost
SVM	3	2	3
CNN	5	5	5
LSTM	5	4	5
KNN	1	3	2
RF	3	1	3
DBN	4	6	5

In terms of overfitting, it is worth noting that SVMs, RF, and KNN are less prone to overfitting compared to CNN, LSTM, and DBN models. The maximization of the decision boundaries from the training data points included in the SVM and the ensemble learning approach of Random Forest reduce the variance in the models, thus rendering them less prone to overfitting [304]. However, CNN and DBN models tend to overfit, the former when working with small datasets for training and the latter when the complexity of the network architecture is too high for the available data [305,306]. Similarly to CNNs, limited training data cause LSTM algorithms to overfit [307]. Given these findings, the implementation of regularization techniques and hyperparameter tuning in CNN, LSTM, and DBN models is necessary [308].

3.5. Prognosis

Recent research has significantly advanced the use of machine learning techniques to construct health indicators (HIs) and predict remaining useful life (RUL). Each method brings distinct advantages to the table, particularly in dealing with feature extraction and degradation modeling. In this section, we summarized and examined the methods used for wear modelization and prediction in the studies collected pertaining to this subject.

On one hand, Table 15 lists the prevalent machine learning algorithms utilized in this field.

Table 15. Machine learning algorithms used for rotating machinery prognosis.

Category of Classifiers	Algorithm	Studies
Common Machine Learning Algorithms	K-Nearest Neighbors (KNN)	[184]
	Random Forest Along with Linear Regression and Gradient Boosting Model	[276]
	Long Short-Term Memory (LSTM)	
	Artificial Neural Networks (ANNs)	[100,136]
Advanced and Hybrid Machine Learning	Wavelet Neural Network (WNN)	[73]
	Stacking Ensemble Model	[84]
	Quantum Particle Swarm Optimization (QPSO) with Backpropagation (BP) Neural Network	[309]
	Dempster–Shafer Evidence Theory	[309]
	Stacked Layer Deep Neural Network (DNN) with Gaussian Window	[90]
	Stacked Autoencoder and Recurrent Neural Network (RNN)	[167,220]
	Adaptive Neuro-Fuzzy Inference System (ANFIS)	[39,111]
	Neuro-Fuzzy Network (NFN)	[111]
	Gate Recurrent Unit (GRU)	[246]
	Hybrid Autoencoder	[243]
	Auto Deep Neural Network (AutoDNN)	[83]

Several other research efforts have focused on simulating the degradation processes for rotating machinery components. Among these models are theoretical simulations combined with finite element analysis [258] and the Gray Markov model used to estimate the trends in degradation [126]. Moreover, the authors in [110] adopted a Bayesian method paired with a normal–uniform–triangular (NUT) distribution to represent uncertainty.

The review conducted in [86] underscored the crucial role of distance-based methodologies, using metrics such as Mahalanobis and Euclidean distances, in evaluating the similarity between healthy and faulty signals. These approaches were further enhanced by the application of clustering algorithms, which facilitated the identification of healthy sample centers. Importantly, degradation functions, encompassing linear, quadratic, and exponential forms, offered a systematic framework for delineating the anticipated progression of machinery health over time. This study emphasized that while attention mechanisms and graph networks improve the feature extraction in intricate environments, their efficacy may be compromised by limited datasets and inherent biases. Furthermore, the authors presented transfer learning as a viable solution for alleviating these challenges by enhancing the model performance in scenarios with scarce data. The incorporation of temporal dependencies and varying operational conditions remains a vital area for ongoing research and development.

Conversely, the investigation in [39] concentrated on predicting the RUL of wind turbine bearings by employing a Particle Swarm Optimization (PSO)-augmented Adaptive Neuro-Fuzzy Inference System (ANFIS). This hybrid approach, which integrated both data-driven and physics-based methodologies, effectively captured the non-linear degradation patterns in the health indicators. The incorporation of PSO led to a notable enhancement in the model performance, as evidenced by a reduction in the Root Mean Square Error (RMSE) from 6.616 to 4.2975.

On the other hand, new approaches have been introduced by researchers in recent years that combine existing methods with new emerging technologies. In the following subsections, we discuss the most notable of these approaches.

3.5.1. Convolutional-Network-Based Models

In [239], the deployment of a Convolutional Neural Network Autoencoder (CNN-AE) to detect deviations, alongside a CNN to characterize fault modes, yielded encouraging outcomes for predictive maintenance applications. The use of Bayesian Neural Networks (BNNs) to estimate remaining useful life (RUL) resulted in precise, probabilistic predictions, utilizing the Weibull distribution to effectively model the lifespan of bearings. Furthermore, the implementation of Relative Root Mean Square (RRMS) health indices provided a more detailed insight into the progression of degradation, ensuring that the predicted RUL values were closely aligned with the actual results. Methodical optimization of the hyperparameters also enhanced the performance across various tasks, leading to a significant decrease in the unexpected failure rate of the components from 10% to 0% and an extension of the maintenance intervals by 8.92 years.

Using convolutional networks in a different approach, the authors in [171] introduced a Temporal Convolutional Network (TCN) with Residual Self-Attention mechanisms (RSA) for feature extraction in RUL prediction models. The TCN-RSA architecture included multiple temporal convolution blocks with causal dilated convolution layers, which optimized the extraction of temporal features while preserving past information. By tuning the hyperparameters, including the time-moving window size and the number of basic blocks, the model successfully achieved an optimal trade-off between its computational efficiency and predictive accuracy, significantly advancing the predictive capabilities of deep learning models in time-sensitive environments.

Similarly, the studies referenced as [25,185,233] leveraged the strengths of CNNs for estimation of the RUL of induction motors and rotating bearings, respectively.

3.5.2. Spatiotemporal Feature Extraction

Advanced methods for extracting spatiotemporal features, including the spatiotemporal non-negative projected convolutional network (SNPCN) and Bidirectional Non-Negative Matrix Factorization (BiNMF), were employed in [169] to enhance the trend consistency and mitigate volatility in degradation modeling. Notably, the SNPCN model demonstrated more rapid stabilization throughout the training process and exhibited strong alignment between the predicted health indicators and the actual measurements, resulting in reduced prediction errors in the later operational phases.

3.5.3. ResNet and Attention Mechanisms

The researchers in [170] developed a Residual Neural Network (ResNet) architecture that incorporated both channel attention and time attention mechanisms for the extraction of features from bearing vibration signals. By employing a multiscale pooling technique for adaptive feature recognition and integrating a parametric sigmoid (PSigmoid) function, they achieved a 14% improvement in the prediction accuracy compared to earlier approaches. This methodology also demonstrated superior performance relative to other leading algorithms, with enhancements ranging from 3% to 6%.

3.5.4. Adversarial Out-Domain Augmentation

The adversarial out-domain augmentation (AOA) framework, as presented in [247], leveraged historical data from multiple operational and degradation-related fields to create pseudo-domains that significantly enhanced the source domains. Visualization methods such as t-distributed stochastic neighbor embedding (t-SNE) illustrated that this approach surpassed conventional domain adaptation and deep learning methodologies for predicting remaining useful life (RUL) while showcasing exceptional efficacy in managing previously unencountered target domains.

3.5.5. Change Point Detection

The research presented in [68] focused on identifying the change points within time series data, which represent pivotal transitions in machinery from optimal to deteriorating conditions in the context of bearings. This study employed an autoencoder architecture, comprising an encoder, a decoder, and latent space, to effectively reduce reconstruction errors, facilitating timely detection of these change points. Through Pearson's correlation analysis, significant features were identified while a Gated Recurrent Unit (GRU) model with an attention mechanism focused on the most relevant elements in the time series data to boost the prediction accuracy.

3.5.6. LSTM-Based Models

The research presented in [85] introduced an Automated Model Pruning (AMP) algorithm with the aim of creating a more efficient Bidirectional Long Short-Term Memory (Bi-LSTM) model. A Deep Deterministic Policy Gradient (DDPG) was implemented for adaptive pruning control to facilitate dynamic modifications to the pruning rates across various layers. The model proposed achieved a notable pruning rate of 36% and a 3% enhancement in the prediction accuracy compared to the original Bi-LSTM framework. The streamlined model demonstrated reduced Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics, indicating its superior performance. However, the sensitivity analysis indicated that while an increase in the pruning rate can enhance the model's compression and inference speed, excessive pruning may lead to a decline in the overall performance.

A Multi-Scale Long Short-Term Memory (MS-LSTM) framework was introduced in [63] for predicting remaining useful life (RUL) through a three-dimensional input layer. The framework adeptly handles time series data by varying the sequence lengths, thereby improving the training efficiency and mitigating the risk of overfitting. The incorporation of two hidden LSTM layers, complemented by dropout techniques, further refined the process of feature extraction, while a fully connected output layer ensured precise RUL predictions. Additionally, the sequence-to-one model, bolstered by a sliding window technique, enabled the model to effectively assimilate insights from historical monitoring data.

The studies referenced as [198,278] used Maximum Correlation Kurtosis Deconvolution (MCKD) and a statistical process analysis, respectively, to improve their LSTM models' prediction accuracy for the RUL of bearings.

3.5.7. Domain Feature Disentanglement

To effectively forecast Remaining Useful Life (RUL) values across diverse operational scenarios, the study in [211] proposed a Domain Feature Disentanglement Transfer Learning Network (DFDTLN) that extracted domain-invariant features. This neural network model, leveraging Rectified Linear Unit (ReLU) activation, accelerated the convergence. Domain adaptation techniques and Maximum Mean Discrepancy (MMD) were employed to reduce discrepancies between the source and target domains and facilitate effective domain adaptation, respectively, ensuring that the model captured relevant features across varying conditions. Additionally, within the model, joint-learning autoencoders separated domain-invariant features from domain-specific ones to address the challenge of the degradation of bearings under different working environments. The efficiency of this feature separation was corroborated through t-distributed stochastic neighbor embedding (t-SNE) visualizations, while quantitative assessments such as Proxy A-distance and MMD further affirmed the model's resilience in adapting to different domains.

3.5.8. Data Transformation

The review conducted in [212] emphasized that data-driven models simplify the computation of RUL predictions, particularly in systems where complex calculations may be unnecessary or resource-intensive. By focusing on simplifying the prediction process, these models were shown to enable faster and more efficient decision-making in industrial applications.

The research presented in [138] utilized a data transformation methodology that involved the application of a K-means algorithm to categorize features derived from time domain characteristics and Shannon entropy, effectively converting one-dimensional vibration signals into two-dimensional images. This innovative transformation facilitated the implementation of a convolutional neural network (CNN) structured on the AlexNet framework for classification purposes. Achieving an accuracy rate of over 98%, this study underscored the potential of integrating clustering methods with image-based deep learning approaches for the task of remaining useful life (RUL) estimation, as well as fault classification.

3.5.9. Transformer Models

In [41], the authors introduced a new methodology that begins with the application of separable convolutions to capturing local features from input vibration signals. These extracted features are then processed through a Vision Transformer framework, which is specifically designed to develop global feature representations essential for comprehending the overall health trends in machinery.

To enhance performance, an advanced MobileViT model is utilized, incorporating an optimized loss function and a novel training strategy. The refined features are subsequently directed through global average pooling layers and fully connected layers to facilitate RUL estimation. This architectural design effectively merged the advantages of convolutional networks, which excel in local feature extraction, with the capabilities of transformers, which are adept at global representation learning, ultimately resulting in improved RUL predictions.

In the research paper cited as [248], a Time Domain Convolutional Network (TCN) is presented, incorporating a residual framework within the transformer architecture. The TCN was designed to capture the temporal dependencies present in vibration data effectively, while the residual framework mitigated the risk of learning degradation throughout the training of deep models. This approach ensured that both the short-term and long-term features were precisely identified and processed in predicting the RUL of bearings.

The research in [310] presented a Transformer Autoencoder designed to generate two-dimensional input samples from multi-point vibration monitoring signals and enhance the quality of the input data and the model's capacity to identify significant features. By merging a Denoising Convolutional Autoencoder (DCAE) with the transformer architecture, the model proficiently captured both spatial and temporal characteristics and developed health indicators (HIs) efficiently. The model's capability to continuously assess the condition of machinery was thus significantly improved. This study also introduced an innovative application of an exponential function derived from the root mean square (RMS) of the data, which regulated the DCAE's output to produce a smooth and interpretable degradation curve. A novel loss term was proposed to enforce a shape constraint on the HIs, ensuring adherence to the anticipated degradation pattern. The integration of these components resulted in enhanced HI performance and more accurate predictions of RUL.

In the study referenced as [311], a Patch Positional Transformer Recurrent Neural Network (PPTRNN) was proposed for enhancing the prediction of the lifespan of bearings with two new methodologies. A patch mask mechanism was implemented alongside a transformer architecture to facilitate the visualization of attention maps and aid in the comprehension of the attention dynamics in deep learning models, especially in contexts dominated by periodic signals, such as those encountered in vibration-based monitoring. Additionally, the integration of periodic positional encoding bolstered the model's capacity for expression, particularly in relation to periodic offsets in the signal position. By embedding positional information, the model was better equipped to identify and interpret periodic patterns, which are vital for accurate remaining useful life (RUL) predictions in systems characterized by cyclic operations. This enhancement enabled the transformer network to more adeptly model long-range dependencies and temporal fluctuations within the vibration data, ultimately resulting in heightened prediction accuracy.

3.6. Experimental Validation

Experimental validation in research work on rotating machinery monitoring, especially when accompanied by machine learning (ML), is crucial to establish the reliability and trustworthiness of the developed models. It serves as a means of ensuring that the systems perform as expected in practical settings and that their results are reproducible under varying conditions. Validation methods, such as real-time trials and simulation, are essential for assessing the dependability of AI systems and form the foundation for continuous validation strategies post-deployment. The aforementioned research works constructed their models by utilizing data extracted from various databases (Table 16).

Table 16. Databases used in the selected studies.

Database	Studies
CWRU [312]	[34,53,57,75,83,114,144,164,229,233,243,271,286]
IMS [313]	[41,68,198,235,239,314]
MFPT bearing dataset [315]	[57,182,268]
SEU gearbox dataset [316]	[268]
PU bearing dataset [317]	[182]
PRONOSTIA dataset [318]	[169,171,198,211,247,252]
XJTU-SY dataset [319]	[170,171,235,247]
Paderborn University dataset [317]	[57,75,273]

These databases are useful for launching the learning and training processes for AI algorithms. However, it is imperative to perform experimental validation using real-time data to ensure the accuracy and reliability of the proposed models. Surprisingly, only a small percentage of the studies reviewed, at 10.15%, actually validated their models using real-time experimental data. This stems from the reproducibility challenges encountered in the field, as the former serves as a fundamental element in scientific inquiry, guaranteeing that experimental findings can be consistently replicated by other investigators operating under comparable conditions. Nevertheless, within the domain of rotating machinery monitoring, the pursuit of reproducibility during the experimental validation stage encounters numerous difficulties.

3.6.1. Reproducibility Challenges in Experimental Validation

The principle of reproducibility serves as a fundamental element in scientific inquiry, guaranteeing that experimental findings can be consistently replicated by other investigators operating under comparable conditions. Within the domain of rotating machinery monitoring, the pursuit of reproducibility during the experimental validation stage encounters numerous difficulties. In the following sections, we examine several challenges that present considerable barriers to the reproducibility of vibration datasets.

- Machinery complexity and variability:
  Turbines, pumps, motors, and other rotating systems are characterized by considerable mechanical intricacy. Factors such as material degradation, fluctuations in load, misalignments, and design discrepancies can result in differing test conditions, even when the same equipment is employed. This variability poses challenges for experimental replication, as minor differences in configurations can significantly affect the vibration patterns, signal responses, and the overall efficacy of monitoring systems. The intrinsic variability in machinery operations indicates that even minor variations in the operating conditions, such as temperature, can produce divergent results.
- Operational factors and environment:
  The inherent variability in the dynamic settings (with temperature, humidity, vibration, and power supply fluctuations) of industrial environments often prevents researchers from achieving uniformity in their experimental setups, complicating the pursuit of reliable results. Additionally, operational parameters such as rotational speed, load, and the procedures for starting and stopping the machinery frequently vary, further complicating the design and implementation of experiments.
- Sensor parameterization:
  The efficacy of monitoring systems is largely influenced by the sensors employed for data acquisition, as well as the parameters for signal sampling, which are often set in the acquisition devices. Variations in the positioning, calibration, and sensitivity of sensors can produce notable discrepancies in the data gathered, even when observing the same equipment. Furthermore, the signal sampling parameters, which are often set in the acquisition devices, can lead to divergent interpretations of identical datasets. Consequently, reproducibility is further hindered if intricate parameters are not fully disclosed or comprehended by external researchers.
- Data availability and transparency:
  Another important aspect of experimental validation, which is data sharing, is frequently obstructed by the proprietary characteristics of industrial data and inadequate documentation of experimental parameters. Numerous researchers and companies exhibit hesitance in revealing comprehensive information regarding their equipment, primarily due to confidentiality issues. As a result, this reluctance can lead to a significant gap in access to essential experimental information or raw data, which are necessary for other researchers to accurately validate their work.

3.6.2. Reproducibility Enhancements

On the basis of the discussion above, we identified potential solutions for enhancing the reproductibility of experimental validation data.

- Standardization of experimental protocols:
  Standardization of protocols related to machinery monitoring can simplify supervising and guiding experimental activities. By clearly defining the types of sensors to use, the guidelines for their placement, the methods for signal preprocessing, and the specific

operating conditions, researchers can minimize discrepancies in their experimental setups. The implementation of international standards, such as ISO13373 [320], which pertains to condition monitoring and diagnostics for machinery, offers a structured approach to ensuring that experiments are conducted in a consistent manner across various laboratories and sectors. Following these established standards can lead to the improved reliability and reproducibility of experimental outcomes.

- Improved data documentation and sharing:
  To facilitate the replication of experiments, it is essential to meticulously document the conditions under which they are conducted and to promote open sharing of data. Researchers are encouraged to provide comprehensive details regarding the specifications of the equipment utilized, the environmental variables present, the calibration of sensors, and the particular algorithms employed in data analysis. The adoption of open access platforms and data repositories would significantly enhance the dissemination of experimental findings, allowing other researchers to replicate and expand upon previous studies. Furthermore, advocating for the implementation of FAIR (Findable, Accessible, Interoperable, and Reusable) data principles can greatly improve the transparency and accessibility of research endeavors.
- Digital twins and simulation models:
  The implementation of digital twins, which are virtual representations of physical equipment, offers researchers the capability to model diverse operational scenarios in a regulated environment. By merging real-time data from existing machinery with simulation frameworks, digital twins facilitate the evaluation of monitoring strategies across a broad spectrum of conditions, eliminating the necessity for physical trials. This approach can greatly improve the consistency of findings, as the virtual setting ensures a controlled and repeatable context that reduces the impact of external factors.

3.7. Practical Industrial Implementation

The development of AI-based diagnosis and prognosis models based on vibration signal analysis is a significant step in the automation of maintenance in the context of Industry 4.0. However, these models need to be tailored to meet the needs of an industrial setting. A key prerequisite for obtaining sufficiently accurate forecasts and assessments is access to high-quality data. Incorrect positioning of sensors results in incorrect data collection, which affects the monitoring system. Specifically, the use of Internet of Things (IoT) sensors is beneficial in this situation, provided that their initial configuration is adjusted for this purpose. Their use greatly reduces the amount of manual interference, thus reducing the error margins. Following their collection, data have to undergo a solid preprocessing phase to reduce noise resulting from the industrial environment. Furthermore, in the acquisition chain, the horizontal integration approach of Industry 4.0 ensures a continuous real-time flow of information. This approach establishes seamless communication between machines and systems that operate at the same level of the production process. For real-time integration of AI-driven maintenance models, a vertical integration approach is mandatory to connect the models to existing information systems, such as Enterprise Resource Planning (ERP) systems and Manufacturing Execution Systems (MESs). Consequently, adjustments are needed to bypass compatibility issues.

From an internal model design point of view, the scalability of the data influences the performance of the models. In industrial settings, numerous machines produce significant amounts of vibration data that require real-time processing. The AI model must be flexible enough to accommodate various types of machinery and operational environments while also featuring an architecture that can effectively manage extensive datasets.

Ultimately, the transparency of AI models influences their marketing. Stakeholders tend to adopt models that offer clear, logical insights. This emphasizes the need for a transparent and easily interpreted industrial solution.

4. Conclusions

In our comprehensive review, we have thoroughly examined the evolving landscape of vibration signal analysis for diagnosing and predicting the health of rotating machinery. The key findings of the research are as follows.

1. Despite being the foundation of vibration signal analysis, the preprocessing phase was found to be significantly lacking in the datasets used in the studies we reviewed. Primarily, this issue arises because the databases already encompass the preprocessing phase yet they do not specify all parameters, including the overlap percentage, the window size, and the type of sampling window.
2. Signal processing techniques in the time domain, the frequency domain, and the time–frequency domain are widely utilized in vibration signal analysis. However, time scale domain techniques can extract non-linear information about a machinery's health state, thereby expanding the detection results. The optimal approach to analyzing vibration signals would involve a combination of time scaling methods and time–frequency representations.
3. An emerging trend involves the representation of vibration signals as 2D images instead of traditional 1D time series signals. This innovative technique offers a new perspective on signal analysis and enables the use of image classification algorithms for fault diagnosis.
4. Incorporating a post-processing step into the construction of a diagnosis or/and prognosis model significantly improves the performance of AI algorithms. This step can rely on feature selection and dimensionality reduction, as well as data augmentation if needed.
5. In this review, SVMs, CNNs, LSTM, KNN, and random forest were found to be the top five most solicited algorithms for diagnosis. Each algorithm offers good results depending on the scalability of the data, the available resources, and the conception of its architecture.
6. Studies on the estimation of the remaining useful life (RUL) and health indexes (HIs) of rotating components generally employ traditional AI algorithms; however, the implementation of transformer-based models is being explored for this purpose.
7. The lack of experimental validation in most of these studies is notable, as they have typically tested their models' efficiency on public databases that do not accurately represent all industrial scenarios.
8. The primary emphasis of the research in this domain lies in identifying faults in rolling bearings, with less attention given to detecting other mechanical defects, such as imbalances, misalignments, gear defects, and belt pulley defects.

5. Future Directions

Our investigation of the analysis of vibration signals for the diagnosis and prognosis of rotating machinery provided a thorough examination of the existing methodologies while also shedding light on potential avenues for future research. Although significant progress has been made in areas such as signal processing techniques and intelligent fault detection, there are still areas that require further exploration to improve effectiveness, reliability, and practicality.

The identified future directions are as follows:

1. Experimental studies that provide vibration datasets should prioritize the inclusion of preprocessing information such as sampling rates, overlap percentages, and window types and sizes. The omission of such crucial data may cause researchers to derive inaccurate results in feature extraction given that most signal processing techniques rely on these parameters.
2. The limited real-time validation and scarcity of standardized datasets also present substantial hurdles to generalizing these approaches across different machinery and

conditions, advocating for an increase in collaborative efforts to create accessible and high-quality datasets.

3. Experimentation with newer machine learning architectures, such as transformers and generative adversarial networks, alongside efforts to incorporate domain knowledge directly into algorithm designs, could bolster diagnosing and prognosing capabilities further.
4. Future research efforts that investigate the feasibility and integration of these algorithms into modern industrial management systems, either by employing cutting-edge machine learning methods for real-time fault detection or by examining the potential of transfer learning for broader implementation in diverse operational contexts, are regarded as promising pathways for new academic contributions. Additionally, the explainability and interpretability of AI systems remain vital areas of focus to foster trust and broader acceptance of these technologies in real-world applications.
5. By considering the synergy between different techniques, such as combining CNNs and LSTMs, researchers can potentially address the limitations of individual methods and create more robust and effective solutions. This integrative approach not only showcases the potential for innovation in the field but also underscores the significance of collaboration and cross-pollination between diverse methodologies to advancing the accuracy of fault diagnosis.
6. The utilization of cutting-edge machine learning approaches, such as deep reinforcement learning, should be explored for prognosis modeling.
7. Utilizing EEG and ECG signal processing techniques and classification methods can yield substantial outcomes due to the shared characteristics these signals have with vibration signals.
8. It is worth noting that the vibration signals captured in bearings encapsulate information on bearing defects as well as information on other defects present in the global system. This calls for future research on the distinctions between each class of information.

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Abbreviations

The following abbreviations are used in this manuscript:

1D-DCGAN	One-Dimensional Deep Convolution Generative Adversarial Network
AdaBoost	Adaptive Boosting
Adam	Adaptive Moment Estimation
Adgrad	Adaptive Gradient Algorithm
AE	Acoustic Emissions
AE	Autoencoder
ANN	Artificial Neural Network
ANFIS	Adaptive Neuro-Fuzzy Inference System
ASCM	Acoustic-Sound-Based Condition Monitoring
BiLSTM	Bidirectional LSTM
BN	Batch Normalization
BP	Backpropagation

BQDTNN	Bayesian Quadratic Discriminant Transfer Neural Network
CFS	Correlation-Based Feature Selection
CNN	Convolutional Neural Network
CSC	Cyclic Spectral Correlation
CSCM	Cyclic Spectral Covariance Matrix
CSCoh	Cyclic Spectral Coherence
CS	Cuckoo Search
CWT	Continuous Wavelet Transform
DAC	Discriminant Analysis Classifier
DBN	Deep Belief Network
DFA	Detrended Fluctuation Analysis
DFCNN	Deep Fully Convolutional Neural Network
DNN	Deep Neural Network
Dsrc	Source Domain
DT	Decision Tree
Dtar	Target Domain
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
ECNN	Ensemble Convolution Neural Network
EDAE	Ensemble Deep Autoencoder
EDLR	Extreme Deep Learning Regression
EEG	Electroencephalogram
EEMD	Ensemble Empirical Mode Decomposition
ESGMD	Enhanced Symplectic Geometry Mode Decomposition
ELM	Extreme Learning Machine
EMD	Empirical Mode Decomposition
ESA	Electrical Signature Analysis
ESM	Expectation Selection Maximization
EVT	Empirical Wavelet Transform
FFT	Fast Fourier Transform
FO-SVM	Fault-Oriented Support Vector Machine
FBE	Frequency Band Entropy
FRBFELM	Fuzzy Logic Embedded RBF-Kernel-Based ELM
GAMD	Generalized Adaptive Mode Decomposition
GAN	Generative Adversarial Network
GDA	Gaussian Discriminant Analysis
GMM	Gaussian Mixture Model
GNN	Graph Neural Network
GRA	Gray Relation Analysis
GRN	Gate Recurrent Network
GRU	Gate Recurrent Unit
HFD	Higuchi Fractal Dimension
HHT	Hilbert–Huang Transform
HI	Health Index
HSA	Hilbert Spectral Analysis
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
KExMLP	Kernel Extreme-Learning-Based Multi-Layer Perceptron
KNN	K-Nearest Neighbors
K-PCA	K-Principal Component Analysis
LBP	Local Binary Pattern
LSP	Locally Stationary Process
LSTM	Long Short-Term Memory
MCWD	Modified Continuous Wavelet Decomposition
MDPI	Multidisciplinary Digital Publishing Institute
MFCCs	Mel Frequency Cepstral Coefficients
MFFNet	Multi-Feature Fusion Network
MHA-LSTM	Multi-Head-Attention-Based Long Short-Term Memory

ML	Machine Learning
MLP	Multi-Layer Perceptron
MRA	Multi-Resolution Analysis
MSB	Modulation Signal Bispectrum
MSDI	Mode Shape Damage Index
MWSVD	Multi-Weight Singular Value Decomposition
MVMD	Multivariate Variational Mode Decomposition
NAMEMD	Noise-Assisted Multivariate Empirical Mode Decomposition
NCA	Neighborhood Component Analysis
NDT	Non-Destructive Technique
NFN	Neuro-Fuzzy Network
NN	Neural Network
NUT	Normal–Uniform–Triangular
PCA	Principal Component Analysis
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSO	Particle Swarm Optimization
PSD	Power Spectral Density
RBF	Radial Basis Function
RBM	Restricted Boltzmann Machine
RFE	Recursive Feature Elimination
RF	Random Forest
RMLCT	Refined Matching Liner Chirplet Transform
RMS	Root Mean Square
RMSProp	Root Mean Squared Propagation
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RUL	Remaining Useful Life
RVME	Recursive Variational Mode Extraction
RVM	Relevance Vector Machine
SAE	Stacked Autoencoder
SBFS	Sequential Backward Feature Selection
SFFS	Sequential Forward Floating Selection
SGD	Stochastic Gradient Descent
SIRCNN	Stacked Inverted Residual Convolution Neural Network
SNN	Spiking Neural Network
SR-TT	Sparse Regularity Tensor Train
SSA	Singular Spectrum Analysis
STAC-tanh	Slope and Threshold Adaptive Activation Function with Tanh Function
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
SVR	Support Vector Regression
TFD	Time–Frequency Distribution
TFR	Time–Frequency Representation
t-SNE	T-Distributed Stochastic Neighbor Embedding
UT	Ultrasonic Testing
VMD	Variational Mode Decomposition
VSA	Vibration Signal Analysis
VS	Vibration Signal
WNN	Wavelet Neural Network
WPT	Wavelet Packet Transform
WT	Wavelet Transform
WVD	Wigner–Ville Distribution

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