Article citation info
Thajeel MM, Al-Bugharbee HR. Bearing condition monitoring: a review of feature extraction in temporal, spectral and joint temporal-spectral domains. Diagnostyka. 2026;27(1):2026103. https://doi.org/10.29354/diag/216964.

DIAGNOSTYKA, 2026, Vol. 27, No. 1

e-ISSN 2449-5220
DOI: 10.29354/diag/216964

BEARING CONDITION MONITORING: A REVIEW OF FEATURE EXTRACTION IN TEMPORAL, SPECTRAL, AND JOINT TEMPORAL-SPECTRAL DOMAINS

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Abstract

Rolling element bearings are critical components in rotating machinery. Their failure can lead to catastrophic consequences. Therefore, effective condition monitoring is very necessary to avoid the occurrence of such unexpected breakdowns and ensure safety. This review focuses on the recent advances in vibration-based feature extraction techniques for bearing fault diagnosis. More than 70 peer-reviewed journal articles published since 2019 are analysed. The analysis covers feature extraction techniques in the temporal domain, spectral domain, and joint temporal–spectral domain. Then, the reviewed features are critically assessed in terms of their diagnostic sensitivity, robustness to noise, and applicability under different operating conditions. The review aims to adopt a feature-centric and decision-oriented perspective and provides guidance for selecting suitable health indicators. It can serve as a useful reference for researchers and practitioners working in rolling element bearing fault diagnosis.

Keywords: Rotary machines, fault diagnosis, statistical features, machine learning

1. INTRODUCTION

The beating heart of any factory or manufacturing unit is the rotary machines [1]. Rolling element bearings (REBs) serve as crucial components for precise rotating equipment, allowing components to be relative one to another, and transmit load more easily [2]. In these components, failure can occur and develop over time for multiple reasons, such as design errors, usage circumstances, severe environments, lifespan constraints, and assembly concerns. Serious outcomes might result from such failure, including mechanical damage and production halts [3,4]. The failure in rolling element bearings is responsible for almost 30% of mechanical defects in various industrial sectors [5]. High load and running speed are common operation conditions in bearings. Furthermore, bearings are subject to defects due to contact of metal to metal. A survey in Europe demonstrated that 34% of bearings were able to maintain their life, and 66% have been changed prematurely due to various causes. These causes are as follows: 16% of bearing replacements were due to improper installation or dismounting, 14% were due to contamination or unfavorable operation conditions, and 34% were due to improper lubrication [6]. Consequently, bearing fault diagnosis was much required [7].

The research on condition monitoring focuses on numerous industrial components with rotary parts, such as rolling [8] and journal bearings [9], wind turbines [10], gearboxes [11], pumps [12], and induction motors [13]. The abnormality diagnosis approaches in a rotary system utilizing the data acquired via vibration [14], electric current [15], acoustic emissions [16], and temperature following up [17] have been extensively studied in the last few decades. Among them, vibration signal is the most suitable and prevalent condition utilized in the industry for rotating machines. Malla et al. [18] reported that monitoring vibration-based conditions enables the detection of 90% of failures or problems in machinery. This is because each machine component carries a specific dynamic signature that can be represented by vibration signal associated with the operating parameters of the machinery. A vibration-based condition monitoring approach in rotating machinery is utilized to detect various faults, including unbalance, eccentricity, looseness, misalignment, blade defects, defective bearings, cracked or bent shafts, and damaged gears.

Received 2025-06-22; Accepted 2026-01-14; Available online 2026-01-20

Utilizing information from data sources and several sensors has been proven beneficial in fault diagnosis to increase the degree of accuracy [19]. The processing of several source data according to their specific data types [20] was utilized to obtain usable features via transformation steps to improve the outcomes of fault diagnosis [21]. Features in machine learning represent independent data points from which the algorithms drive insights. These features were utilized with machine learning algorithms to perform predictions or tasks. Data preprocessing involves transforming the collected data into representation so the machine learning model can utilize it to learn. So, the features are the attributes that create the modified representation and contain valuable information derived from the data [22]

Vibration analysis techniques can be categories to three types: temporal, spectral, and joint temporal-spectral Domains [23], [24], [25]. Figure 1 illustrates some of the signal analysis and feature formation methods utilized in different domains. Numerous research have used various feature extraction methods to classify bearing abnormalities.

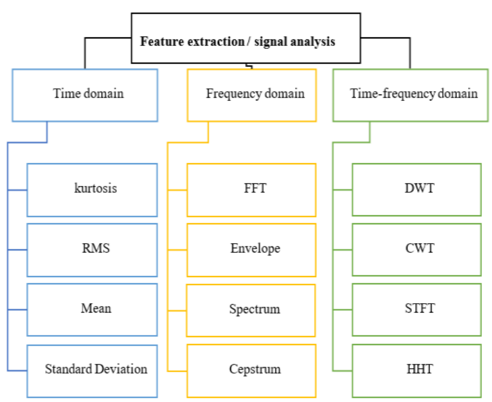

Fig 1. Signal analysis and Feature extraction techniques

Although enormous number of survey articles have been published on rolling element bearing fault diagnosis such as [3], [4], [18], [19], [22], [26], [27], [28], [29], [30], many of them focus primarily on the methods related to a specific signal domain or focus on the diagnostic algorithms. Contrarily, the current study introduces a feature-centric study that examines the feature extraction from the temporal, spectral, and joint temporal-spectral domains. Rather than listing surveyed methods, this study examines them to synthesise evidence to draw feature categories, their limitations and strengths under various challenging operating environments. The main goal is to provide a guideline, especially for early- stage researchers and practitioners to select the suitable features and adopting them as machine health indicators.

In this study, 104 peer-reviewed articles were surveyed to form the scope and context of the present work. More than 70 of them, which were published since 2019 and based on vibration signal analysis, were examined in depth in the temporal, spectral, and temporal-spectral domain features sections. They were analysed to form the basis of feature selection guidance per domain under various scenarios of diagnosis.

The main contributions of this study can be summarized as follows:

- It analyzes the feature extraction techniques in the temporal, spectral, and temporal–spectral domains and discussing their diagnostic importance, and limitations.
- A number of comparative tables is prepared to guide the early- researchers in choosing suitable features for fault diagnosis in REBs.
- More than 70 peer-reviewed articles published since 2019 are analysed in depth and categorised according to the signal domain. Popular features were compared under various diagnostic scenarios.

In addition to the summary and comparative analysis for features across different domain, the current study highlights the challenges scenarios in research such as the investigation of fault diagnosis under the presence of noise and variability of operating environment.

Notably, a quantitative overview of the reviewed prior work is presented in Section 2 to emphasize the publication trends and domain-wise research emphasis

The remaining outline of the present manuscript is organised as follows: Section 2 of this review presents a quantitative overview for the literature surveyed and focuses on existing approaches for extraction compact information (i.e. features) in the three common domains and evaluates different types of features applied for bearing fault diagnosis. Discussion in section 3 illustrates the advantages, limitation, and challenges of the current approaches in signal analysis and feature extraction. Finally, section 4 summarizes the review's main contribution and provides the conclusion.

2. SIGNAL ANALYSIS AND FEATURE EXTRACTION

The researchers follow a series of steps in bearing fault diagnosis utilizing vibration signals. The first step is the data acquisition from bearings during operation. Then, this data is well-processed which is followed by extraction of features and selecting the optimum set of them. Finally, the classification step is conducted by utilizing machine learning algorithms [1]. Data and signal processing techniques such as filtering, outlier removal, and data cleaning assist in processing the collected data by converting it into a comprehensible and coherent format while eliminating irregularities that might adversely impact a model's efficacy. The data processing stages involved in feature extraction approaches improve the visualization and analysis of the data.

The temporal domain analysis serves as a fundamental aspect of bearing fault detection. In this field, the signal resulting from vibrations or acoustic emission from damaged bearings is studied directly in its time form without complex transformations. The potential strength of temporal domain analysis excels in its simplicity and ability to provide a primary look into the behavior of the system, but it can be less accurate when dealing with complex or non-stationary signals. Many statistical features, such as Root mean square, Kurtosis, max, min, mean, can be extracted in the temporal domain and help in identifying bearing failures. The temporal domain provides a quick and simple analysis of the signal, and it can help in early detection of minor faults before they become more complicated [26].

The fault signal collected from the rotating machines is presented in the temporal domain and comprises intricate information from various system components. To overcome this, the signal amplitude was analyzed in the spectral domain and forming the signal spectrum. The predominant method to execute this transformation is to utilize the Fast Fourier Transformation (FFT) and envelope analysis[24] These approaches were utilized to convert the signal of the temporal domain, with a lot of information, to the succession of spectral domain signals, emphasizing frequency value and amplitude [24]. Traditional vibration analysis methods are primarily based on the characteristics in both domains cannot be simultaneously identified. Consequently, these approaches are unsatisfactory for examining the non-stationary signals. Such inadequacies necessitate the utilisation of more advanced methods such as Hilbert Huang transform (HHT) [31], short-time Fourier transforms (STFT) [32], Continuous Wavelet Transform (CWT) [33], Winger- Ville distribution (WVD) [34] that can handle with non-stationary signal and commonly utilized to demonstrate the fault location. Based on signal processing approaches, bearing fault detection research will be split into four categories for organised analysis. Studies on each topic will be evaluated and discussed to emphasize their significant contributions, methodologies, and conclusions. The categories are arranged as follows:

2.1. Scope of the Reviewed Literature

This review focuses on peer-reviewed journal articles published since 2019 that address rolling element bearing fault diagnosis using vibration-based signal analysis. More than 70 articles were analysed and clustered according to the domain where features were extracted. A quantitative overview showed that joint temporal–spectral approaches were the most dominant in the recent literature. In addition, the combining of multi domain features has recently received increasing interest.

2.2. Temporal Domain

This approach examines the vibration signal's form in relation to time. Metrics such as mean, maximum, and minimum value were employed to analyze the vibration signal. Table 1 illustrates popular temporal domain features and their mathematical equations. Kumbhar et al. [35] obtained a number of statistical features from temporal domain including crest factor, standard deviation, kurtosis, maximum, minimum, and root mean square. They uses these features in combination with the dimensional analysis (DA) technique and artificial neural network (ANN) to detect the bearing fault size. The findings showed a high prediction accuracy with very low rate error. The challenges include the loss of linearity with developing failure size, the effect of noise, and the necessity for adjustment of the simulation parameters. A key improvement of their model involves the use of RLS and LMS to suppress the noise and employing Kurtosis as a dominant diagnostic indicator. Shen et al. [36] employed the temporal domain to derive characteristics from vibration signals. The collected features contained four-dimensional features (peak value, effective value-RMS, standard deviation, and average value) and four dimensionless features (pulse factor, margin coefficient, kurtosis coefficient, and peak factor). The study showed that the parameters of dimensional features have significant sensitivity and low stability, while the parameters of dimensionless features have high stability and low sensitivity [37,38]. Ma et al. [39] utilized thirteen statistical features such as Kurtosis, average value, crest factor and use them as input of the back propagation artificial neural network for classification defects in bearings. The proposed method enhanced the signals by reducing the noise and achieving high classification accuracy.

Meltem et al. [23] extracted fifteen features in the temporal domain from the CWRU bearing's dataset including Skewness, Min, Var. To select the optimal features, the authors utilized five different feature selection algorithms such as Mutual Information (MI) and Random Forest Importance (FRI). The final stage was the classification utilizing using two kinds of machine learning classifiers. The RFI method was the most efficient in identifying the features most influencing the classification. AbsMax, P2P, and Complexity were the most selected features across different strategies, demonstrating their importance in bearing fault diagnosis.

Kaya et al. [40] presented a statistical approach utilizing a one-dimensional local binary pattern (1D-LBP) and one-dimensional grey level co-occurrence

Table 1. Popular temporal domain features.

Temporal domain features	Mathematical expression
Root Mean Square	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
Kurtosis	$Kurtosis = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}{(\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2)^2}$
Skewness	$Skewness = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^3}{(\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2)^{3/2}}$
Standard deviation	$Std = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$
Peak to peak	$Peak\ to\ Peak = x_{max} - x_{min}$
Crest factor	$CF = \frac{max\ \lvert x \rvert}{RMS}$
Mean absolute value	$MAV = \frac{1}{N}\sum_{i=1}^{N} \lvert x_i \rvert$
Impulse factor	$IM = \frac{max\ \lvert x \rvert}{MAV}$
Form factor	$Form\ factor = \frac{RMS}{MAV}$
Entropy	$Entropy = -\sum_{i=1}^{N} p_i . log(p_i)$
Mean	$Mean = \frac{1}{N}\sum_{i=1}^{N} x_i$
Variance	$Variance = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2$
Min	$Min = min\,(x_i)$
Max	$Max = max\,(x_i)$
Energy	$Energy = \sum_{i=1}^{N} x_i^2$
Impact factor	$Impact\ factor = \frac{Peak\ amplitude}{Energy}$

*Where N denotes the dimensionality of the vector x, μ is the athematic mean value, and x_i corresponds to the i^{th} component.

matrix (1D-GLCM) techniques, where the original vibration signals were re-scaled between 0 to 255, followed by the extraction of statistical features such as energy, correlation, contrast, and homogeneity. The model showed low computational cost and high diagnosis accuracy with the aim of effectively characterizing the vibration signals. However, the model experienced challenges such as sensitivity to settings, where increasing parameters such as P (neighbor value) increases the size of co-occurrence matrices and is time-consuming. Some of the extracted features, such as energy, showed less efficiency than the others. The outcomes demonstrated that correlation and homogeneity were the best characteristics.

Kuncan et al. [6] transformed the raw vibration signal into the 1D-LBP. After that, the effective features are extracted from the new signal. Twelve statistical features, Mean, Standard deviation, energy, etc., were utilized to detect the bearing fault. The sensitivity to slight variations in signal and calculation simplicity are the most significant benefits of 1D-LBP, which improved the accuracy of time signal analysis. The study showed that skewness was the best features for speed-variation datasets while entropy was the best for fault size discrimination. In addition, kurtosis was the most suitable for fault type classification. However, mean value was consistently the worst feature across all datasets.

Stepanic et al. [41] performed temporal domain digital processing to extract features from every recorded vibration signal. The developed ML-based algorithms utilized the nine retrieved characteristics including arithmetic mean, RMS, Modified square mean, Skewness index, Kurtosis index, and Shape factor as inputs and produce the categorization of bearings as either healthy or defective.

The latest progress in deep learning, especially convolutional neural networks (CNNs), have revolutionized the methodologies of fault diagnosis in REBs. These deep learning networks showed significant performance in automating the feature selection and powerful image processing [42],[43]. Some studies have represented the raw vibration signals into image formats suitable to with CNN to avoid traditional feature extraction problems such as the need for prior knowledge, experience, and the effect of human parameters [44].

Pinedo et al. [14] analysed the use of temporal domain statistical features for bearing wear assessment. It was found that RMS and kurtosis are identified as the most informative features as they behave in a monotonic trend with the degradation level. However, crest, impulse, and margin factors are neglected because of their poor sensitivity.

In their review, Jian et al. [27] found that Kurtosis performs better than crest factor as a fault indicator. Kurtosis grows with defect size at first but eventually decreases. RMS increased when defect size, load, and speed increased. Subsequently, when the speed was increased, the performance of fault diagnosis of RMS was increased. Compared to RMS and Kurtosis, Skewness was the poorest indicator. They also found that load and speed have no effect on Kurtosis and Skewness. These two parameters diagnose a tiny pit when driving at low speed.

Although the conventional temporal-domain analysis depend on manually extracted statistical features, recent studies have focused on investigation the use of deep learning models to automatically obtain diagnostic features from temporal-domain signals.
Zhang et al. [45] presented an efficient data preprocessing technique that transforms raw temporal domain signals into images without employing intricate processing techniques such as frequency transformation. The time signals were segmented into overlapping samples. Subsequently, these samples were mapped to grey image format scaled between 0 and 255 to correspond with pixel intensity. This approach intended to represent time signals as images to enhance the process of learning the representative features by the Convolutional neural network (CNN).
After that, the raw signal was converted to small images, each data point represented one pixel in the tiny square image to utilize the powerful classification techniques offered by CNN for processing the images. Han et al. [46] transformed the vibration signature into temporal domain images and fed them to the CNN. The proposed model combined CNN to obtain fault features from temporal domain signals and SVM for classification. Three cut-off conditions were applied to identify the appropriate time to stop training CNN and send the features to SVM. The improvements of the presented model were obtaining high classification accuracy, reducing time consumption to one-third of CNN, and high generalization ability. Gong et al. [47] combined SVM and a CNN. The raw signals were transformed into 2D representation through the data reconstruction approach [48] for analysis and feature extraction utilizing CNN, with the result classified by SVM to enhance the diagnosis accuracy. The performance was improved, and overfitting was mitigated by utilizing techniques such as global average pooling (GAP) and dropout. The model showed enhanced accuracy compared to traditional methods, but it depended upon the data quality and was computationally intensive. Kolar et al. [49] utilized the raw signals extracted from a three-axis accelerometer. These signals were directly fed into a multi-channel deep convolutional neural network (MC-DCNN) to analyze and classify faults without pre-processing requirements. The research showed that selecting optimal parameters like the number of kernels in the layers of the neural network was a significant challenge to enhance the performance. The recommendations included expanding the tests and utilizing additional data encompassing diverse fault types and operation conditions, emphasizing the necessity of integrating additional data such as electric current or acoustic signals to enhance the accuracy of diagnosis. The research indicated obstacles such as needing a long time for model training and utilizing a robust Graphic Processing Unit (GPU) to facilitate intensive computations. Kolar et al. [50] fed the triaxial raw vibration signals as high-resolution data into the CNN for fault diagnosis of rotary machinery. They optimized the hyperparameters utilizing the Bayesian technique. The proposed model obtained a high classification accuracy for two evaluation tests, eliminating the necessity of signal preprocessing. Nevertheless, training and evaluation data were acquired in laboratory conditions, which required further testing in real industrial environments and under simulated noisy conditions. Jin et al. [51] designed a model utilizing the raw signals without bypassing the necessity of manual feature selection or traditional noise removal techniques. The adaptive anti-noise neural network (AAnNet) model was based on CNN for feature extraction and the gated recurrent unit (GRU) for analyzing time dependencies with an attention mechanism to enhance feature classification accuracy generated by the CNN component. The challenges of high noise and various loads were

overcome by utilizing random sampling to simulate the noise during the training. The outcomes showed the model achieved high classification performance under fluctuating operation conditions and noise.

When fast outcomes are needed, the temporal domain approach is preferred. In this approach, it is possible to extract features from the same domain as data collection, and complex signal-processing techniques are rendered unnecessary. Therefore, the temporal domain analysis achieved a precise result with a wide range of intelligent algorithm techniques. In this domain, it is allowable to put some assumptions about the sorts of REB defects in the form of the vibration signal. However, the analysis approaches in the temporal domain lack accuracy and sensitivity compared to other approaches [26].

2.2.1 Comparative Analysis and Guidance for Temporal-Domain Features Selection

Features extracted from temporal-domain remain popular and be widely used for bearing fault diagnosis. This can be attributed to their simplicity and physical interpretability. Despite this, a comparative analysis of recent studies showed that their diagnostic importance is considerably dependent on noise severity, operating conditions, and fault severity. Statistical features like kurtosis, crest factor, and impulse factor showed great sensitivity to impulsive fault signatures. For this reason, they were considered effective for early fault detection, in particular at constant speed and noise level is low. In spite of that, several studies indicate that these indicators loss their effectiveness under the increase of background noise or fault size.

On the contrary, RMS and peak-to-peak values showed a more reliable correlation with damage progress that makes them useful for monitoring degradation trends. However, their sensitivity to the variation of bearing rotational speed and load, limits their robustness under variable operating environment.

The analysis of the literature also showed that there is no single feature in temporal- domain can perform accurate diagnosis over different operating scenarios. As a result, the combination of features and using features selection techniques will be suitable to increase the diagnosis reliability.

Temporal-domain features are suitable for real time applications; however, they lose this advantage when the machine works under noisy and none-stationary environment. A guidance for temporal features selection is summarised as in Table 2.

Table 2. A guidance for temporal-domain features selection

Diagnostic objective	Recommended temporal features	Key limitation
Early fault detection	Kurtosis, crest factor, impulse factor	Noise sensitivity
Fault severity tracking	RMS, peak-to-peak	Speed/load dependence
Real-time monitoring	RMS, mean, variance	Limited fault localization
Noisy environments	Selected features + FS	Reduced impulsiveness
Variable speed/load	Temporal features not recommended alone	Poor invariance

2.3. Spectral Domain

This approach involves converting the signal into discrete frequency parts, facilitating the analysis of the distinctive frequency components related to the failure. The modified signal is referred to as the signal spectrum. Table 3 provides a list of some of the popular spectral domain features. Alonso et al. [24] utilized the FFT and envelope analysis to analyze the vibration signals and detect failures in bearings. Furthermore, a kurtogram was employed to obtain the optimal bandwidth. The drawbacks of the proposed approach were difficulty in identifying ball fault by utilizing envelope analysis and computational cost of kurtogram. Combining the results from the envelope analysis with machine learning algorithms such as KNN and the Decision Tree achieved a high accuracy rate.Suhail et al. [52] build a model for automatically features formation utilizing the envelope analysis from the vibration signal in the spectral domain. Firstly, the Auto-Regressive (AR) approach was employed to filter the original signal, improve the residual signal for more analysis, and eliminate deterministic components. Secondly, the relevant frequency band was identified by Spectral Kurtosis (SK) analysis, which contains the characteristic frequencies of the bearings. Finally, the envelope analysis was utilized to isolate the signals, which interfaced with different forms of noise, and examine the frequency spectrum via Hilbert transform. FFT was utilized on the envelope signal to obtain the fault features. The developed method showed significant improvement in detection performance and its effectiveness in obtaining the features at resonance frequencies, and the features were independent of the fluctuation of speed. Khalil et al. [53] applied the spectral domain for vibration signals analysis and feature extraction via FFT, where the time signals were transformed into a frequency spectrum. This spectrum was divided into suitable bands called bins.

Then the cumulative energy of each bins was calculated to generate attributes representing the equipment's operational status. The attributes were employed to train the machine learning model, such as SVM and Ensemble Algorithms to precisely classify the bearing faults. The finding showed diagnosis

Table 3. List of spectral domain features [28].

Spectral domain features	Mathematical Equation
Frequency center	$Frequency\ center = \frac{\sum_{i=2}^{N}(x_i')^2}{4\pi^2 \sum_{i=1}^{N} x_i^2}$
Discrete Fourier Transform	$x(\omega) = \int_{-\infty}^{\infty} x(t)e^{-jwt}dt$
Root Variance frequency	$RVF = \sqrt{\frac{\sum_{i=2}^{N}(x_i')^2}{4\pi^2 \sum_{i=1}^{N} x_i^2} - (\frac{\sum_{i=2}^{N}(x_i')^2}{4\pi^2 \sum_{i=1}^{N} x_i^2})^2}$
RMS frequency	$RMSF = \sqrt{\frac{\sum_{i=2}^{N}(x_i')^2}{4\pi^2 \sum_{i=1}^{N} x_i^2}}$

*Where N represents the total number of elements in vector *x, j* denotes the imaginary unit, *w* signifies the angular frequency, and x_i signifies the *i*th element.

accuracy of over 90%, in addition to decreasing dependence on human interaction and simplifying application to analogous systems.

Envelope spectrum analysis was utilized in [54] to analyze vibration signals and detect the bearing defects. The signals were enhanced via a band pass filter, and the Hilbert function was applied to obtain the envelope spectrum and determine the fundamental frequencies related to the faults. The stochastic gradient descent with momentum (SGDM) algorithm was utilized to accelerate the process of learning, and techniques such as dropout and batch normalization were utilized to enhance the performance. The presented method reduced the interference and enhanced the signals, precisely determining the fault frequencies, achieved a significant diagnostic accuracy with 207,493 parameters by utilizing CNNs, and the average response time was 0.03 s. The characteristics of the motor states are frequently limited and singular due to limitations introduced by real-world operation conditions. To deal with these problems, Xu et al. [55] employed FFT to analyze vibration signals and extract impacted information related to bearing faults. For the purpose of reducing data dimensionality and securing data noise elimination, they utilized the singular value decomposition (SVD) technique. The extracted features were combined with the CNN and long short-term memory algorithm (LSTM) for further analysis and to improve diagnostic accuracy. Validation of the proposed model utilizing CWRU data showed a high accuracy. Walther et al. [56] proposed two approaches, hybrid and conventional, to classify bearing failure. The conventional approach employed the LSTM method to analyze raw data, obtaining excellent diagnostic accuracy utilizing all sensors. However, it exhibited inadequate accuracy with individual data or complicated microphone signals. The hybrid approach utilizing FFT to extract characteristic frequencies related to fault and LSTM as a classifier produced very high diagnostic accuracy with better result stability despite little data availability. The hybrid approach improved the performance by adding physical knowledge while reducing the need for large number of datasets. However, it requires prior knowledge of the system and provides complexity to the design by adding processing steps to transform data utilizing FFT and combining physical knowledge with the LSTM model.

The FFT demonstrates certain limits in performance, particularly with the hiding of unique frequencies by the source frequency and its inaccurate depiction of transitory events [29]. In addition to Fourier analysis,

Multiple techniques were employed to derive spectral spectrum characteristics from original vibration data. Shannon entropy [57], spectral Skewness, envelope spectrum analysis, and spectral Entropy were further strategies for feature extraction in the spectral domain [30]. Kannan et al. [58] automated the appropriate selection of bandpass filter settings for envelope analysis utilizing a real-coded genetic algorithm with a unique fitness function and cross-over choosing mechanism; this enabled differentiation for fault-related frequencies for rolling element bearings.

Under various bearing fault conditions, Chen et al. [59] employed the envelope spectrum characteristics peak intensity and frequency fluctuations as fault indicators. These attributes with a simple Naïve Bayes classifier simplify the algorithms utilized to obtain the features and diagnose the faults. Their suggested method also speeds up the time for diagnosing industrial bearing faults and minimizes the hardware setup and operation costs. Their classification method may fail on complex datasets with variable speed situations. In order to demodulate the signal, Chen et al. [60] utilized the simplified Box-Cox transform to build generalized envelopes (GEs) from the analytical signal. Then, they developed a family of spectra called generalized envelope spectra (GESs) to demonstrate cyclostationarity. A connection between logarithmic and exponentiation operations is established via the Box-Cox transformation. The findings from simulations reveal that GESs with varied values for transformation parameter (p) behave differently when subjected to varying levels of interference. To improve the cyclostationarity detection capabilities of individual GES, a new improved demodulation spectrum known as product envelope spectrum (PES) was created. This spectrum combines the performance benefits of many GESs.

2.3.1. Comparative Analysis and Guidance for Spectral-Domain Features Selection

Spectral-domain features are broadly utilised in bearing fault diagnosis because of their significant interpretability and straight correlation with the bearing fault characteristic frequencies. The examination of recent studies showed that these features are efficient for fault diagnosis particularly in the inner-, outer race, rolling elements and cage.

The conventional spectral spectrum – based features can be reliable for fault localisation when the operating conditions are steady; however, they lose their reliability under the non-stationarity of load and speed.

The comparative analysis also indicates that envelope spectrum-based features significantly improves the bearing fault characteristic frequencies through the demodulation of resonance frequency band. However, the selection of improper frequency band may lead to the deterioration of fault detection due to the induction of noise that my buried the fault signature. To cover this limitation, automatic resonance band-selection methods, such as spectral kurtosis, can be adopted. The use of these techniques enhance the isolation of high impulsiveness spectral bands and then subject them for further analysis.

In general, the diagnostic activeness of spectral-domain features relies on frequency band selection. A selection guidance for spectral domain features is summarized in Table 4.

Table 4. Selection guidelines for frequency-domain features

Diagnostic objective	Recommended frequency-domain features	Main limitation
Fault localization	FFT peaks at BPFO, BPFI, BSF, FTF	Speed dependence
Early fault detection	Envelope spectrum features	Sensitive to band selection
Noisy environments	SK-guided / optimized envelope features	Computational cost
Low SNR conditions	Log-envelope / product-envelope spectra	Parameter tuning
Real-time monitoring	FFT band-energy features	Limited incipient sensitivity
Variable speed/load	Frequency features not recommended alone	Frequency smearing

2.4. Temporal-spectral domain

The representation of vibration signals in temporal-spectral domain provides an effective scan for the non-stationary and transient components of the signal, which are commonly observed in rolling element bearings. The temporal-spectral feature extraction methods are useful in characterisation of the overtime evolving defect impulses or those buried in background noise.

Wavelet-based techniques, namely continuous wavelet transform (CWT), discrete wavelet transform (DWT), and wavelet packet decomposition (WPD), are among the most popular utilized temporal–spectral methods for bearing fault diagnosis. These techniques assist, by providing multi-resolution analysis, the accurate identification of transient components of a signal over different spectral bands.

Many studies indicate that wavelet-based features, such as entropy, wavelet energy, and statistical moments, perform accurate diagnosis when used with machine learning classification models. However, the surveyed literature report that their effectiveness is considerably reliable on comparative evidence indicates that their performance is largely influenced by a number of parameters such wavelet type and decomposition level. In addition, the computational burdens highly rises for high-resolution representations, in particular in real-time applications [61], [62], [63], [64], [65], [66], [67], [68].

Many signal decomposition techniques, such as variation mode decomposition (VMD), empirical mode decomposition (EMD), ensemble EMD have been widely also employed broadly for generating

Table 5. List of the temporal-spectral domain features [28].

Features	Mathematical Equation
STFT	$STFT_{x(t)}\,(t,\omega) = \int_{-\infty}^{\infty} x(t)\,\omega(t-\tau)\,e^{(-j\omega t)}dt$
Wavelet Packet Transform	$d_{j+1,2n} = \sum_m h(m-2k)d_{j,n}$
Continuous Wavelet Transform	$W_{x(t)}(s,\tau) = \frac{1}{\sqrt{2}}\int x(t)\varphi^*(\frac{t-\tau}{s})dt$
Discrete Wavelet Transform	$W_{x(t)}(s,\tau) = \frac{1}{\sqrt{2^j}}\int x(t)\varphi^*(\frac{t-k2^j}{2^j})dt$
Empirical Mode Decomposition	$x(t) = \sum_{j=1}^{n} c_j + r_n$

*Where τ is the time variable, $\omega\ (\tau)$ is the window function, φ^* is the complex conjugate of $\varphi\ (t)$, m is the number of coefficients, j and k are integers, $d_{j,n}$, $d_{j+1,2n}$ and $d_{j+1,2n+1}$ correspond to wavelet coefficients at sub-band n, $2n$, $2n+1$. Additionally, c_j refers to the j^{th} intrinsic mode function, r_n is the residual of the data $x(t)$ following the extraction of n intrinsic mode function.

temporal-spectral domain features. The main idea of these techniques includes decomposing of a vibration signal into a number of in intrinsic mode functions (IMFs). Then various features, including kurtosis, crest factor, and entropy, can be extracted from all or some of these components (i.e. IMFs). These features were reported as strong sensitivity indicators for fault severity. Nevertheless, the analyzed studies in this review indicate that signal decomposition-based techniques can usually lead to the generation of noise-dominated components. In addition, these techniques effectiveness is influenced by the suitable mode selection. Missing appropriate selection of useful mode, these methods might undergo from instability under varying operating conditions [69], [70], [71], [72], [73], [8], [74], [75], [76].

Recently, studies have increasingly investigated the use of temporal–spectral representations as 2D input for deep learning models. The 2D temporal-spectral representations can be obtained using wavelet scalograms, Hilbert-Huang spectrum and others. The subjection of these representation to deep learning model, such as convolutional neural network, enable them to automatically extract diagnostic defect features from complicated vibration signatures.

Although these techniques indicate considerably accurate classification, the studies reports that occasionally such superior performance is attributed to the quality of the temporal–spectral representation. Furthermore, there are several obstacles, including the high computational burdens and sensitivity to noise, limit the use of temporal-spectral features in real time applications [77], [78], [79], [31], [80], [81], [82], [83], [84], [85], [86].

2.4.1 Comparative Analysis and guidance for Temporal - spectral Features Selection

A comparative examination of recent studies showed that when defect impulses evolve over time or buried in background noise, the employment of the temporal-spectral features performed better than using temporal- or spectral-domain features alone.

Although short-time Fourier transform (STFT) provides features with straightforward interpretation, these features have limited capability for identification of short –time impulses. This is attributed to the fixed resolution of temporal-spectral spectrum.

In wavelet-based techniques, the limitation of fixed resolution is covered as these techniques offer the multi-resolution representation. Consequently, they enhance the identification of transient and nonstation defect signatures.

The comparative analysis of recent studies also indicates that despite the effectiveness of decomposition techniques such as EMD and EEMD for generating features, they usually produce redundant components. Additionally, their performance highly rely on the selection of useful modes. Selection of inappropriate modes can degrade the diagnosis accuracy.

In summary, temporal-spectral features are considered high health diagnostic indicators under the presence of non-stationary and complex operating conditions. However, they required high computational burdens. Table 6 offers a selection guidance for temporal-spectral features for different operating scenarios.

Table 6. Selection guidelines for temporal-spectral features

Diagnostic objective	Recommended temporal-spectral features	Main limitation
Non-stationary faults	CWT / WPD-based features	High computation
Transient fault detection	DWT / wavelet energy & entropy	Parameter sensitivity
Noisy environments	Optimized EEMD / VMD features	Mode selection required
Low SNR conditions	Median / entropy-based TF features	Requires optimization
Unknown fault frequencies	Decomposition-based TF features	Redundant modes
Deep learning input	TF images (STFT, CWT, WPD)	Memory & training cost
Real-time monitoring	Not recommended alone	Latency

2.5. Multi-domain analysis

Multi-domain integration approaches can be classified into three levels, namely, data-level integration, feature-level integration, and decision-level integration. The first category refers to the combination of data that obtained from multiple sources, such as vibration and acoustic emission [87], [88]. Raw signal concatenation is an example for the representative techniques in this category. Although data-level techniques preserve maximum information about the system condition, they may suffer from increased data dimensionality, incompatibility of sampling rate ,noise amplification and the sensitivity to domain shift under which signals were acquired [87], [88].

The second category, i.e. feature-level integration, includes approaches, such as deep fusion networks, that combine features from different domains, including temporal, spectral and temporal-spectral domains [21], [87], [89]. They typically require dimensionality-mitigation techniques; nevertheless, they improve diagnostic effectiveness. Additionally, these techniques can be configured to learn the variations of signals under domain shifts that consequently reduce the influence of operation non-stationarity [88], [89].

The third category contains the techniques, such as Bayesian inference, that aggregate the multiple classifiers outputs. The advantages of these techniques include the flexibility of training individual classifiers independently and the ability to make decisions even if one signal source fails. However, the techniques performance is limited by the availability of sufficient training labels and the risk of having similar failure mode across classifiers [12], [18].

In the current section, multi-domain techniques are analysed mainly from the perspective of feature-level integration.

Sharma et al. [90] utilized the temporal domain and spectral domain for signal analysis and feature extraction for fault diagnosis of electric motors. Features were extracted from the temporal domain (11 features), such as standard deviation, as well as from the spectral domain (2 features), including mean frequency and median frequency. The temporal domain analysis suffered from a variety of noise in the vibration signals, which made it difficult to accurately identify engine faults. While frequency analysis can be effective in identifying faults from vibration signals, manual methods such as visual inspection of frequency characteristics were often inadequate, requiring reliable and rapid automated systems to improve diagnosis. Overcoming these challenges required advanced feature selection and analysis methods such as principal component analysis (PCA) [91] and sequential floating forward selection (SFFS) [92] to reduce dimensionality and enhance performance. Saha et al. [93] analyzed the raw vibration signals obtained from bearings utilizing the FFT approach to transform time data into frequency spectrum. Statistical features such as RMS and standard deviation were extracted from the temporal domain. The SVM algorithm was employed as the primary approach to classify the bearing faults, and its performance was improved by utilizing the PSO algorithm to obtain the optimum value of the required the parameters. The proposed model showed high classification accuracy compared with conventional algorithms. The improvements engaged employing improved PSO to obtain optimal parameters and the introduction of various temporal features to improve model performance. Altaf et al. [94] extracted statistical features such as Kurtosis, RMS, Average, Skewness, and second derivative from the vibration signatures in the temporal domain, spectral domain, and power spectral domain to diagnose bearing fault. The features were obtained from the original signal and its second derivative. The authors integrated these features to create a comprehensive feature vector that improved the accuracy. The findings demonstrated that the presented approach obtained high accuracy of diagnosis up to 99.13% utilizing kernel linear discriminant analysis (KLDA) and 96.64% utilizing K-nearest neighbor (KNN), with high performance in decreasing the data size by 95%, which diminished the computational burden and time. In addition, the researchers present sufficient analysis of the obtained statistical features, and emphasise their physical relevance, and discriminative ability. For instance, features extracted from the second derivative and the PSD domain were shown to improve the fault.

Sahraoui et al. [95] analyzed the bearing vibration waveforms and the stator current to inspect the presence of bearing defects utilizing Adaptive time-varying morphological filtering (ATVMF) to obtain features in the temporal and spectral domain. Twenty statistical features from the temporal and spectral domain were extracted. They employed the ant colony optimization (ACO) algorithm to obtain the most significant features. The obtained features were classified utilizing the Random Forest (RF) algorithm. The outcomes showed high accuracy of up to 98.5% with strong stability for the two types of data. Song et al. [96] extracted 15 features in the temporal and spectral domains from vibration signals utilizing the Discrete Fourier Transform (DFT) technique, which addressed the problems of nonlinearity and non-stationarity of the signals. The obtained features included a unified representation of the temporal and frequency information. The proposed model fed the extracted features into a hybrid kernel SVM model optimized by the Bayesian Optimization (BO) algorithm. The outcomes demonstrated a high diagnostic accuracy in verification and experimental procedures. Xue et al. [97] utilized the first 256 data of the envelope spectrum, collected by the Hilbert transform (HT) as input to (DCNN) model that identifies the characteristics features of the signals in the temporal and spectral domains. The collected features were merged with two features extracted from the temporal domain (peak to peak and kurtosis index) to create a hybrid features set that was utilized to train the support vector machine (SVM). The findings revealed that the presented methods, which merged deep learning with the human experience, increased the diagnostic accuracy to 98.71% compared to 90.29% utilizing DCNN alone. Said et al. [98] utilized the time, frequency, and temporal-spectral domains for signal processing and feature extraction. The time signals were analyzed to extract features like RMS, peak, Kurtosis, etc., which represent the characteristics of the signal in time. Spectral descriptors such as characteristic frequencies of defects (outer race frequency, ball frequency, and inner race frequency) were utilized. Wavelet packet transformation (WPT) was utilized to segment the signal into several frequency bands, providing multi-resolution analysis that can identify small defects and more accurately represent the non-stationary signal. This approach combined temporal, spectral, and temporal-spectral analysis utilizing WPT and neural networks, which has significantly improved the accuracy of diagnosis and classification of bearing defects. Features analysis was performed to examine their sensitivity for fault presence across frequency sub-bands and then discarded those features whose sensitivity are low. Metwally et al. [99] initiated the analysis utilizing the temporal domain to analyze the raw signal and statistical features such as RMS, peak, and energy were extracted. After that, they convert the signal to the spectral domain with FFT. Finally, the researchers utilized an auto-regressive model to extract hidden features and reduce the noise. This process enhanced the classification accuracy. The results illustrate that the autoregressive model reported excellent classification accurace, which makes it the best choice in complicated faults and contaminated data. Sawaqed et al. [87] utilized multi domain to analyze the signals and identify the failure of the bearings in rotary machines. Eleven characteristics, such as variance, Skewness, and Kurtosis, were extracted in the temporal domain. In the spectral domain, two features were identified utilizing FFT. Wavelet Packet Decomposition was also utilized to decompose the signals into numerous levels and analyze energy across various time and spectral domains. The research showed that the temporal domain was effective for pulse signals, but the accuracy was low when the severity of the fault increased or when the bearings were overloaded. In such cases, it is appropriate to utilize the spectral domain to detect the faults. The spectral domain exhibits difficulties in identifying low-energy fault signals because of noise. Therefore, when the characteristics of the fault signal are non-stationary, the wavelet transformation is the best solution [100]. Cui et al. [101] obtained various statistical features from the temporal domain, spectral domain, and temporal-spectral domain to detect the bearing fault in wind turbines utilizing machine learning algorithms such as SVM, ANN, KNN, and Naive Bayes. The Neighborhood Components Analysis (NCA) technique was employed to obtain the optimal parameters and reduce dimensionality. The significance of numerous features could vary under various operation situations. The proposed model achieved the best classification accuracy of 89% with KNN and effectively obtained features from non-stationary vibration signals.

Abburi et al. [102] utilized the temporal domain, spectral domain, and temporal-spectral domain to analyze the vibration signal for the classification of bearing faults. Statistical features such as mean, crest factor, RMS, and Kurtosis were obtained. The authors also utilized advanced techniques such as the Real Fast Fourier Transform (RFFT) and STFT. Their method improved the accuracy and dealt with non-stationary signals with machine learning algorithms such as SVM and random Forest (RF). However, in their approach there is a chance for data leakage due to partitions and less performance due to imbalanced data. Chen et al. [103] introduced an MCNN-LSTM model that combined a multi-scale convolutional neural network and long short-term memory with direct feature extraction from the raw data without preprocessing for bearing fault diagnosis, which improved efficiency and conserved time. Ten comparative trials were conducted utilizing two groups of features, the first group extracted from the temporal domain and spectral domain, the other from the temporal domain and (EMD) and (HT). The proposed model obtained a classification accuracy of 98.46% with robust performance in high-noise situations and minimized computational complexity by decreasing the input data. Nevertheless, it faced challenges in significant noise environments and similar signals. The findings demonstrated that the model considerably improved the efficiency of bearing fault diagnosis compared to conventional approaches. Su et al. [104] presented knowledge-based features to detect rolling bearing defects. They proposed a deep convolutional neural network (CNN) technique called knowledge-informed deep network (KIDN) to extract and integrate features driven by knowledge and data. The features that are based on knowledge include temporal domain statistics associated to a fault, such as (RMS, kurtosis, Skewness, etc.) and spectral domain features, including the energy of the fault spectrum as calculated by the Hilbert transform and FFT. In order to classify faults, a feature fusion layer is created to combine knowledge-based features with data-driven features acquired from the CNN network's dense layer. The created feature vector is then utilized as a fused feature map. Theoretically, combining the two kinds of characteristics should increase accuracy and robustness by yielding more detailed information for system failure identification. In practical applications, multi-domain data representation captures more fault features under varied operation situations, improving model flexibility and resilience. Therefore, Sui et al. [88] presented a multi-domain strategy to identify bearing faults utilizing the envelope spectral transform for spectral domain converting and the Bessel transform for temporal-spectral domain converting. Their method provided a new path for fault identification, with ramifications for practice and theory. As demonstrated in many circumstances, features from multiple domains were more effective in extracting useful information than features from a single domain [89].

A comparative summary of multi-domain feature extraction and a guidance of selection is presented in Tables 7 and 8.

3. DISCUSSION

This section discusses, based on the comparative analysis in section 2, the advantages, limitations, and challenge of the surveyed feature extraction techniques.

Table 7. Comparison of Feature Extraction Domains for Bearing Fault Diagnosis

Domain	Typical Features	Main Advantages	Key Limitations	Recommended Applications
Temporal	RMS, Kurtosi, Skewness, Peak-to-Peak	Simple implementation, low computation cost, effective for early fault detection	Sensitive to noise, limited capability for non-stationary signals	Fast monitoring, low-cost systems, early fault screening
Spectral	Spectral energy, center frequency, envelope spectrum peaks	Accurate identification of fault characteristic frequencies	Loss of temporal information, noise sensitivity	Steady-state operation, frequency-specific fault diagnosis
Temporal–Spectral	Wavelet coefficients, IMF energy, entropy measures	Effective for non-stationary signals, rich fault representation	High computational cost, parameter sensitivity	Variable speed/load, complex industrial environments

Table 8. Guidance for Selecting Suitable Health Indicators

Operating Condition	Recommended Domain	Preferred Health Indicators	Rationale
Low noise, constant speed	Temporal	RMS, Kurtosis	Simple indicators sufficient to capture defect growth
High noise environment	Temporal–Spectral	Wavelet entropy, IMF energy	Enhanced noise robustness
Early fault detection	Temporal	Kurtosis, Impulse factor	Sensitive to impulsive behavior
Variable speed/load	Temporal–Spectral	CWT energy maps, EEMD-based features	Captures time-varying behavior
Real-time constraint	Temporal / Spectral	RMS, spectral energy	Low computational burden

The review highlights that feature extraction remain highly necessary step in the fault diagnosis of rolling element bearings process. Temporal-domain features provides low computational cost and interpretable health metrics. However, they suffer from poor robustness under noisy and non-stationary operating environment. Spectral features are helpful in localization of bearing defect characteristic frequencies, but their performance deteriorates with the presence of transient signal interference. Temporal–spectral approaches mostly overcome the limitations in temporal and spectral features, but they generate obstacles related to costly computation requirements and the need for parameters optimization.

Source of funding: *This research received no external funding.*

Authors contributions: *Research concept and design, M.O.; Collection and/or assembly of data, M.O.; Data analysis and interpretation, M.O., A.H.; Writing the article, M.O.; Critical revision of the article, R.R., A.H.; Final approval of the article, R.R.*

Declaration of competing interest: *The author declares no conflict of interest.*

4. CONCLUSIONS

Although this study does not propose a new taxonomy, it aims to provide a structured review of feature extraction and selection.

In this study, recent studies on bearing fault diagnosis techniques have been examined and more emphasis has been given to the advancements in feature extraction method in different signal domains.

It is reported that temporal features enable low computational cost and interpretation while spectral features offer accurate frequency-based classification. Additionally, temporal–spectral features show significant diagnostic performance for non-stationary signals.

In comparison to existing surveys, this study highlights feature-domain extraction and selection guidance under various operating challenges including noise robustness, non-stationary conditions and online application.

Despite the considerable progress, it is observed the increasing dependency on laboratory datasets obtained with unchanged speed and load conditions. This highlights the challenges of generalization to real world applications where noise and non-stationary operational conditions are common.

In addition, in spite of the automation of features learning by deep learning techniques, the explainability of obtained features remains in need for more research.

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