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State-of-the-art review into signal processing and artificial intelligence-based approaches applied in gearbox defect diagnosis

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HIGHLIGHTS

- This paper provides a review of signal processing methods
- Artificial intelligence-based approaches are applied for gearbox defect diagnosis
- Vibration instrumentation tools are utilized in signal processing analysis of mechanical systems

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ABSTRACT

Various industrial applications, including rotating and reciprocating machinery, depend on gears. Therefore, a sudden breakdown of the gears could result in substantial financial losses. Due to this, extensive studies have focused on defect diagnosis. Both machinery maintenance decisions and preventive maintenance techniques have been aided by vibration analysis. An increased vibration is a warning sign that a machine is about to malfunction or break down. Observing and evaluating the machine's vibration pulses can identify the nature and extent of the issue and, as a result, predict when the machine will fail. The vibration signal may identify gearbox defects early on and diagnose its problems. Hence, this research highlights the main crucial steps that can be followed for defect detection and identification, mainly based on vibration analysis methodologies. It provides an application methodology for various signal-processing techniques used successfully in rotating machinery. The study briefly explains the applied methods to diagnose problems that depend on hybrid artificial intelligence approaches, such as fuzzy sets, expert systems, and neural networks. The key aspect of the present paper is the parametric comparison of the performance of various artificial Intelligence systems used in rotary machines. As such, the paper reports a comprehensive study of the gearbox defect diagnosis and provides useful analysis, which would be helpful for the usage of such techniques in the engineering industry.

1. Introduction

Modern businesses use machines extensively, which are essential for running factories. The machinery must be carefully monitored as it will suffer enormous losses if it suddenly breaks down. This may be avoided by performing a machine diagnostic to identify the problem or prospective issues, such as friction whirl, wear, damaged bearing, misalignment, imbalance, and cracked gear teeth [1]. Over the years, several diagnostic techniques, such as vibration signal analysis, corrosion monitoring, oil analysis, particle analysis, wear debris analysis, and acoustic signal analysis, have been widely used [2]. By implementing these strategies, the accuracy and effectiveness of fault diagnosis analysis can be improved, leading to better operational efficiency and decreased downtime in rotating equipment.

Vibration signal analysis is one of these studies that is often used since it allows for identifying various issues without shutting down or disassembling the equipment. These signals" variations often reveal the existence of a defect. Analysis of vibration signals also offers specific benefits and drawbacks. Vibration analysis may be applied to monitor machines in real time, and numerous sophisticated signal-processing methods can be used. Noise contamination and good vibration sensor installation location are the limits of vibration analysis [3]. Over 82 percent of fault diagnostic techniques use vibration analysis [4]. Moving parts in most machines produce undesirable vibration, so vibration analysis may be used to determine whether a machine can be kept running or needs to be shut down and fixed [2]. The frequency and vibration amplitude may all show the severity and origin of the machine issue and can be used to assess the machine's condition [5]. Without vibration equipment, a rained person's intellect, touch, and hearing senses may first function as a vibration analyzer to assess machine faults. However, human perception is relatively restricted, making it hard to identify problems not detectable by touch or hearing alone. Vibration analysis is divided into three categories according to a real-time spectrum analyzer: time domain (TD), frequency domain (FD), and time-frequency domain (TFD) [6]. Data

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time series are analyzed using TD and FD analysis. TFD analysis simultaneously uses TD and FD [2]. Use condition monitoring systems that continuously monitor key parameters and signals of the equipment. These systems can provide real-time data and alerts for timely fault diagnosis and preventive actions.

Many researchers recently studied the intelligent fault diagnosis of worm gearboxes based on different adaptive fault analysis techniques and optimization processes [7-11]. Collecting comprehensive data can ensure that all relevant data is collected and recorded accurately. This includes data from sensors, monitoring systems, and other sources. High-quality and comprehensive data will provide a solid foundation for fault diagnosis analysis. Furthermore, many studies examined extensive artificial intelligence techniques as part of a comprehensive survey of fault diagnosis developments in industrial rotating equipment. They summarized the fundamental ideas, methodologies, solving algorithms, and fault diagnosis applications [12-15]. Subsequently, Santos et al., [16] investigated diagnosing faults in electric motors using a Convolutional Neural Network (CNN) technique. A method for monitoring rotary machines' condition and identifying faults was developed by Zhang [17]. Incorporate domain expertise, such as combining domain experts' knowledge and expertise with the analysis process. Domain experts can provide valuable insights and context to aid in accurate fault diagnosis. Their input can guide the analysis process and help interpret the results.

Consequently, a review of failure modes, condition monitoring, and fault diagnosis methods for large-scale wind turbine bearings was presented to design a maintenance plan to minimize damage levels and failure modes. Accordingly, Sanz et al. [18] systematically reviewed semi-supervised learning for industrial fault detection and diagnosis. In addition, some of the most common errors are avoided by implementing a set of best practices in the conclusions of this work. The authors of [19-22] present a comprehensive review of fault diagnosis based on artificial intelligence for rotary machines. As the rotary parts industry has become more data-driven for operations and maintenance, data-driven decision-making techniques have become increasingly prevalent. In a study involving multiview and multilayer patent analysis, Wang et al., [23] examined the relationship between artificial intelligence and wind power regarding tracking and predicting its technology knowledge interactions. Fault diagnosis techniques fall into two categories: data-driven and model-based. Unlike model-based methods, data-driven approaches do not need assumptions that call for an analytical system model. Advanced signal processing techniques are used in data-driven strategies. Data-driven techniques are frequently used in machine diagnosis and monitoring instead of model-based approaches since it is difficult to simulate a malfunctioning system. Generally, vibration analysis for machine monitoring and diagnostics consists of 3 stages: data acquisition, signal processing\ features extraction, and classification of faults (see Figure 1).

Many techniques and instruments have been used; choosing the right ones might be challenging. Each technique and tool has its properties, benefits, and drawbacks. From the literature, one can see that the early detection of faults (fault diagnosis) analysis helps detect faults in rotary machines early. By identifying and addressing issues at an early stage, potential breakdowns and costly repairs can be avoided. This increases the reliability and availability of the machines.

Prevention of catastrophic failures: Rotary machines, such as turbines and compressors, can experience catastrophic failures if faults are not detected and addressed promptly. Fault diagnosis analysis helps identify potential failures and take preventative measures to avoid catastrophic incidents. The present work differs from all previously published research in that it provides a strategy for all modern devices and technologies used in analyzing sources of errors in rotating equipment, as well as the modern methods used in signal analysis. Bu utilizes advanced analytics techniques, such as machine learning algorithms and ANN, to analyze the collected data. These techniques can help identify patterns, anomalies, and potential faults that may not be easily detectable through traditional analysis methods.

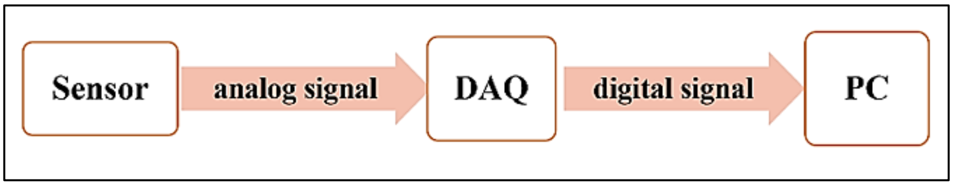

Figure 1: Data collection and signal conversion from analog to digital

Consequently, this work will contribute to helping workers in this field choose the appropriate tools and practices with the machine's operating conditions to be monitored by giving them an idea of the advantages, disadvantages, and differences between the techniques used in each of the above stages.This article is structured as follows. Section 2 will adhere to the vibration analysis processes depicted in Figure 1. First, Subsection A discusses the data collecting phase, which entails the types of vibration sensors and data acquisition process utilized to collect vibration data. In addition, many sensor attachment strategies are covered in this section. Based on the TD, FD, and TFD, Section B highlights signal processing and feature extraction techniques that researchers have recently used. The defect recognition step, the last level of vibration analysis, is covered in Section C. This section covers a variety of AI-based defect identification methods, including fuzzy logic, support vector machines (SVM), artificial neural networks (ANN), and genetic algorithms (GA). Section 3 describes the research's comments and findings, while Section 4 summarizes the study.

2. Materials and methods

2.1 Data acquisition system

Data acquisition systems acquire information from numerous devices and measure, store, display, and analyze it. A transducer or sensor that transforms a measurably physical quantity into an electrical signal is necessary for most measurements. Examples include heat, strain, speed, pressure, vibration, and sound. Signal conditioners receive sensor output signals and transform them so the data collecting system can use them. These signals are amplified, filtered, isolated, and linearized by signal conditioners, which convert current to voltage and voltage to frequency. The data acquisition system's inbuilt analog-to-digital converter (ADC) receives input from the signal conditioner's output. After conditioning the analog signal, the ADC transforms it into a digital signal that can be transferred from the data collection system to a computer for processing, graphing, and storing [24]; see Figure 2. The following sub-section discusses the main components of data acquisition systems. The opposed end is similar, while the (right half) was used to move and change the inner cylinder position.

The estimated error for calibrating the NTC thermistors is 0.18°C. The NTC junctions were embedded into holes and drilled on the back surface of cylinders; 7 holes are made of (2mm) diameter of the crest and concave along the outer cylinder wall. After that, the NTC, which can withstand high temperatures, gets inserted, and a high-temperature treatment of epoxy steel glue secures the measurement junctions entirely in the hole. After removing any extra glue, fine-grinding paper is used to polish the outside cylinder surfaces properly. The heater terminals and every NTC thermistor wire have been removed from the test area. The output signal out of an NTC thermistor is sent to an electronic card with capacitors, which transforms the resisting value into voltage. The movement is then transmitted to a data-gathering device, which records and displays it for the control program using Lab VIEW software before being attached to a personal computer to ensure that all relevant data is collected and recorded accurately. This includes data from sensors, monitoring systems, and other sources. High-quality and comprehensive data will provide a solid foundation for fault diagnosis analysis.

2.1.1 Data acquisition card (DAQ)

Data acquisition cards (DAQ) are made to transform physical analog signals into digital form and scale those signals into physical amounts following the sensitivities of the sensors/transducers they are used with. A computer with control software and data storage capacity is constantly attached to a DAQ card. The DAQ card features analog input and output channels for its analog-to-digital converter (ADC) [25].

2.1.2 Sensor

The sensor, whose types are illustrated in Figure 2, is a piece of hardware necessary for data collecting. There are several types of vibration sensors, such as a laser Doppler vibrometer (LDV), displacement sensor, velocity transducer, and accelerometer. Piezoelectric and micro-electromechanical system (MEMS) accelerometers are different categories of accelerometers. A sensor or transducer may transform mechanical signals into electrical signals [26]. The frequency range, sensitivity, design, and operating constraints determine the sensors employed. No matter what kind of sensor is used, a firmer mounting will increase a sensor's frequency range and reading accuracy. Table 1 displays the advantages and disadvantages of each vibration sensor.

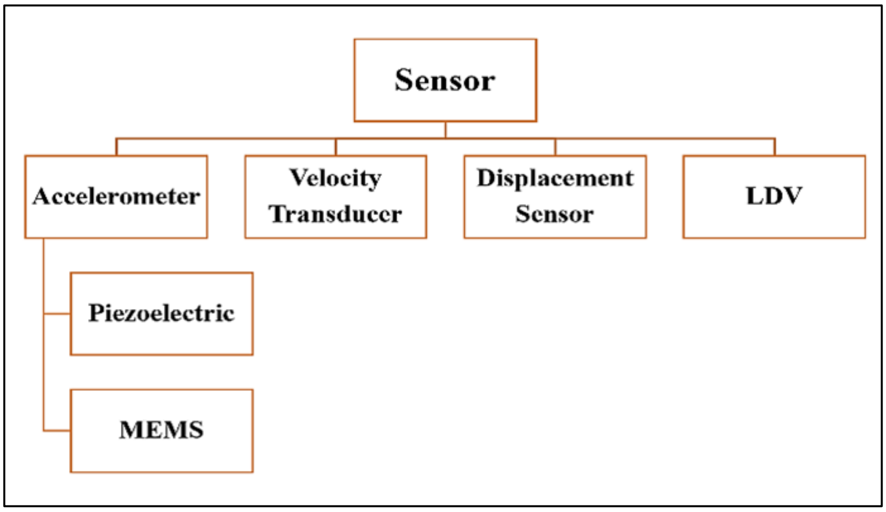

Figure 2: The typical types of vibration sensors

2.1.2.1 Accelerometer

The accelerometer is a tool to measure a structure's vibration or acceleration in terms of g (m/s), the SI unit of measurement. The accelerometer's piezoelectric material generates a charge in direct proportion to the force exerted, which is how it functions. Any change in this component will result in a difference in the control generated, which is then magnified. This is because of the relationship between force and acceleration. Unlike a triaxial accelerometer, a uniaxial accelerometer could only detect vibration in one direction. However, triaxial accelerometers are more expensive than uniaxial accelerometers, but their memory capacity is greater [27]. Due to its dependability, simplicity, and resilience, an accelerometer is an extensively used sensor. The technology may be classified as a piezoelectric and MEMS accelerometer based on the technology employed.

- A piezoelectric accelerometer utilizes quartz or ceramic crystals" piezoelectric properties to provide an electrical output corresponding to the applied acceleration. These crystals are often preloaded. Depending on this acceleration, the charge generated might change [28]. Piezoelectric accelerometers have several benefits, including higher sensitivity, less weight, and improved frequency and dynamic range. The outside world can, however, interfere with it.

- Furthermore, due to the AC coupling, electronic integration is necessary to get velocity and displacement data [29]. In their work, Salami et al. [30] employed a piezoelectric accelerometer and showed how LabVIEW could monitor and analyze vibration data .The piezoelectric accelerometer for measuring vibrations is shown in Figure 3a.
- MEMS accelerometer typically comprises a proof mass that can be moved and plates suspended mechanically from the frame. The spring is stretched or compressed because the proof mass resists accelerated motion. The applied acceleration produces a force that is equivalent to that. The DC coupling of MEMS accelerometers makes them perfect for detecting low-frequency vibration and acceleration. While using less computing power provides good sensitivity [31]. Data quality reaching 10kHz, modern MEMS accelerometers are pretty good. The low ratio of signal to noise is a disadvantage. Contreras - Medina et al. [32] employed a cheap MEMS accelerometer to detect failures in a machine.

2.1.2.2 Velocity transducer

When an item moves relative to another, a velocity transducer detects the voltage produced, often in units of cm/s or m/s. It operates without an external device and relies on the theory of electromagnetic induction [33]. The magnet in the coil will move as the sensor's surface is placed, producing a voltage proportionate to the vibration's speed. A meter or analyzer receives this voltage signal, which indicates the vibration created. Velocity sensors are not advised to diagnose machinery at high speed since their operating frequency range is limited to 10Hz to 2000Hz. At working temperatures exceeding 121°C, nearly all velocity transducers are susceptible to reliability problems. As a velocity transducer is typically less expensive than other sensors and is easier to install, using one to monitor vibration in spinning equipment makes sense. Rossi [34], used a velocity transducer to capture the vibration of the compressor's frame, which typically has frequencies under 10Hz. In ,Figure 3b, a velocity transducer was used to depict the vibration measurement.

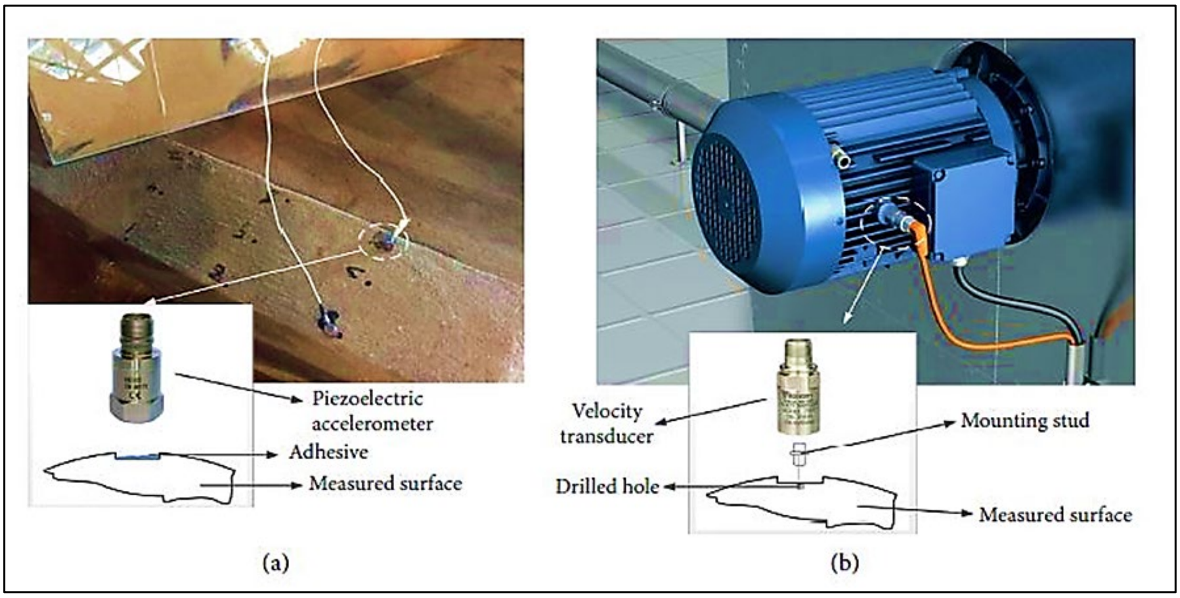

Figure 3: Vibration measurement utilizing (a) a piezoelectric accelerometer with adhesive mounting and (b) a velocity transducer with a surface-mounted stud [35]

2.1.2.3 Displacement sensor

The vibration is measured using a displacement sensor, often called an eddy current or proximity sensor. It is possible to represent displacement in m, cm, or mm. While it can capture low-frequency vibrations of less than 10Hz, it is frequently used to monitor ibrations up to 300Hz. At vibration frequencies above 1kHz, the amplitude is often lost in the noise [36]. It has a good dynamic range within a specific frequency range, a good sensitivity, and an easy postprocessing circuit. Unfortunately, certain traditional displacement sensors are difficult to install and susceptible to shocks, and they are not calibrated for unidentified metal kinds. Sarhan et al. [37] employed displacement sensors to track the machining center's cutting forces under various circumstances. Saimon et al. [38] developed a fiber-optic displacement sensor (FODS) for industrial applications.

2.1.2.4 Laser doppler vibrometer (LDV)

A non-contact optical instrument that can measure the velocities of any vibrations occurring in any location on the surface of a particular machine. The LDV reflects a coherent, frequency-modulated laser beam from a vibrating surface. The Doppler shift of the reflected beam is then compared to that of the reference beam. The He-Ne laser is no longer as typical in LDV as a stronger infrared (invisible) fiber laser. With the development of this technology, the goal of doing long-distance measurements without compromising signal quality was attained [39]. Numerous points in the measurement have been accelerated using the continuous-scan laser Doppler vibrometer (CSLDV). The laser beam will sweep continuously across a structure along a predetermined path by the required scan frequencies. Changing the measuring point is simple with LDV; diverting the laser beam is required. Despite this, the cost and mobility issues prevent the widespread use of LDV in machine monitoring and diagnostics. Table 1 summarizes the advantages and disadvantages of the above-discussed vibration measurement/sensing technologies.

Table 1: Sensor properties

Sensors	Advantages	Disadvantages
Piezoelectric accelerometer	Dynamic range, strong frequency response, and high-sensitivity	Electronic integration is necessary to get displacement data and velocity, yet it is susceptible to influence from the surroundings.
MEMS accelerometer	More affordable than a piezoelectric sensor, requiring less computing power, and having a higher sensitivity	Has a low ratio of signal to noise.
Velocity Transducer	Operates independently of any other device and is often less expensive than other sensors.	Operating frequency range limitations and reliability issues with most velocity transducers at operating frequencies of greater than 121°C
Displacement Sensor	Excellent little maintenance, simple postprocessing Circuit, and sensitivity	It is not easy to install and shock-prone
LDV	Ability to perform extended measurements without sacrificing signal quality and ease of changing measurement locations	Very expensive and not portable.

2.1.3 Install the sensor

Data collection depends on the installation technique of sensors. To monitor machine parameters in real-time, sensors are frequently permanently attached at predetermined locations in the machine. Four different installation techniques can be distinguished—stud mounting, adhesive mounting, magnet mounting, and unmounting. Usually, stud mounting is recommended for permanent installation needs. The sensor is screwed into a stud to secure it to the device. This mounting method provides the broadest frequency response compared to other techniques and is highly dependable and secure. Ensure the area is clear of paint and clean before installing the sensor. Any flaws in the surface might lead to false readings or sensor damage [40]. No substantial machining is necessary since epoxy, wax, or glue will be applied during adhesive attachment. The best option in most cases is adhesive installation if drilling the machine for stud attachment is impossible. Despite being simple to use, this mounting method suffers from damping in the glue, which decreases measurement accuracy [40].

The sensor must also be removed more carefully than with other attachment techniques. The magnetic connection strategy is often only acceptable for short-term applications with a portable analyzer since high-frequency signals may be interfered with. There is often no extraneous mechanism between the target surface and the transducer when using the non-mounting approach, commonly applied via a probe tip. It is frequently used in challenging-to-reach locations. Nevertheless, the probe's length will influence the measurement, with longer probes resulting in more incorrect readings.

2.2 Features extraction

The steps of signal processing and feature extraction for this investigation are depicted in Figure 4. It may be classified into TD, FD, and TFD analysis. A root-mean-square (RMS), kurtosis, crest factor, and peak-to-peak are statistical aspects of the TD analysis. Envelope Analysis, Cepstrum Analysis, Spectrum Analysis, and Fast Fourier Transform (FFT) are components of FD analysis. In contrast, Power Spectral Density (PSD), wavelet transform (WT), Short-Time Fourier Transform (STFT), Wigner-Ville Distribution (WVD), and Hilbert-Huang Transforms (HHT) are components of TFD analysis.

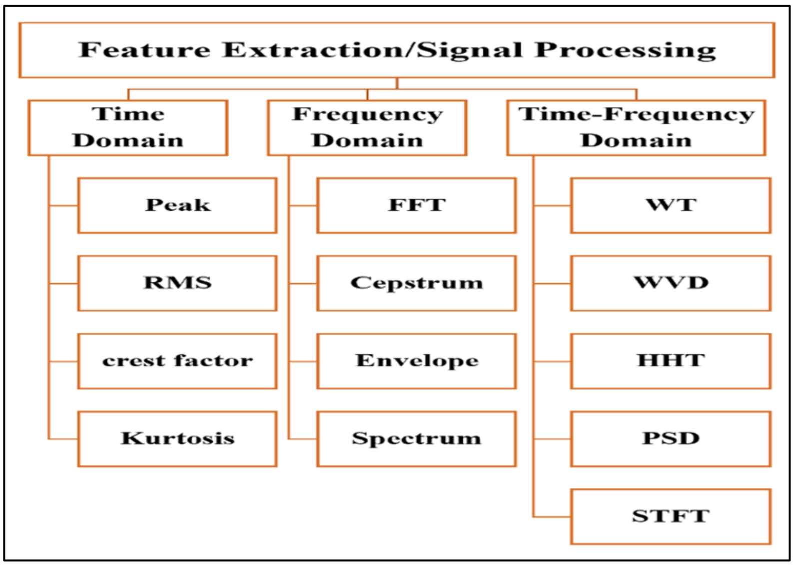

Figure 4: The commonly applied feature extraction /signal processing approaches

2.2.1 Time domain (TD) analysis

The recorded vibration signal in the TD is analyzed using the most basic vibration analysis for machine diagnostics. A plot of the signal's amplitude against time is used in TD analysis to determine the vibration signals" proximity, velocity, and acceleration values. Although more advanced TD approaches have been utilized, the visual analysis of the time waveform should not be discounted since it gives users access to data. Amplification modulation, shaft imbalance, transients, and higher-frequency daring are the details included in this information [41]. Variations in vibration signals for various machine failures cannot be distinguished by simple visual inspection due to the noisy nature of the data, particularly at the beginning of failure. Because of this, a signal processing technique is needed to extract the crucial information from the TD signals by transforming the raw signals into the proper statistical characteristics, such as peak, RMS, crest factor, and kurtosis. Many statistical factors are typically derived from the TD signal to choose the statistical parameter that best distinguishes between faulty and healthy machine vibration signals [42]. The peak, RMS, crest factor, and kurtosis statistical factors are described in this article. Table 2 lists the benefits and drawbacks of each parameter.

Table 2: Advantages and disadvantages of time-domain methods

Time-domain methods	Advantages	Disadvantages
Peak	A quick and straightforward method	Sensitive to noise
RMS	A quick and uncomplicated procedure that is directly tied to the vibration profile's energy composition	Only high-amplitude components are susceptible to changes in RMS vibrations.
Crest factor	Crest factor meter, easily accessible and reasonably priced	Only trustworthy when strong impulsivity is present.
Kurtosis	Great sensitivity to shock, high effectiveness in detecting periodic impulse force, and shape factor assimilation that is independent of signal amplitude	Expensive kurtosis meters might be inaccurate.

2.2.1.1 Peak-to-peak

The peak is the signal's greatest value, *v(t)*, across the monitored period; it can be mathematically defined as As shown in Equation 1:

$$peak \ = |v(t)| \max \tag{1}$$

The vibration signal's peak values will change if impacts are present. The peak value rises when there is a defect. Based on the amplitudes of the associated peaks, the fault's kind and severity may be determined. Lahdelma [43] investigated the peak value characteristic to identify machine bearing and gear failures.

2.2.1.2 Root-mean-square (RMS)

The Value of RMS displays the vibration's power content and helps identify imbalances in the spinning gear. This is the most straightforward and efficient method for finding defects, particularly imbalances in spinning equipment, according to [44]. This methodology is only suitable for analyzing a single sinusoid waveform, and it still has issues with spotting errors at an early stage. RMS is highly appropriate for steady-state applications and studying a single sinusoid waveform. Because peak value is more susceptible to noise, RMS is chosen. The region underneath the half-wave, which is 0.707, is equivalent to the RMS validating a pure sinusoid. RMS value is characterized by the Equation 2:

$$\mathrm{RM} = \sqrt{\frac{1}{T}\int_{T_1}^{T_2} v(t)\mathrm{d}t} \tag{2}$$

T denotes the time passage, and *v(t)* is the measured vibration signal. Bartelmus et al. [45] used RMS as a diagnostic feature to detect gearbox faults, where the transmission error function and load variation correlation behavior models for gearboxes are provided.

2.2.1.3 Crest factor

The Equation 3 is a representation of a crest factor, which is the ratio of peak to its RMS:

$$\text{Cres Factor} \ = \frac{\text{peak}}{\text{RMS}} \tag{3}$$

The crest factor will be $\sqrt{2}$=1.414 for a pure sine wave and about 3 for typically distributed random noise. The crest factor, independent of speed compared to peak and RMS, is frequently employed when measurements are made at various rotating rates. Crest factors are only trustworthy when there is strong impulsivity present. Jiang et al. [46] used SVM and crest factor information to identify gear problems. The most sensitive characteristic for gear failure was discovered to be the crest factor, and this feature attained 93.33 percent diagnostic accuracy.

2.2.1.4 Kurtosis

In distribution and vibration analysis, kurtosis, a non-dimensional statistical measure of the number of outliers, measures the number of transitory peaks. A high value of kurtosis and many transient peaks may indicate wear. Running speed or load has little influence on kurtosis, and the signal must be very impulsive to be effective. Kurtosis characteristics reveal details about the impulsiveness or non-Gaussianity of the vibration signals. Kurtosis is typically preferred over crest factor in applications for machine condition monitoring, yet the latter is more well-liked. Crest factor meters are more readily available and less costly than kurtosis meters. Kurtosis was one of the five characteristics used by Fu et al. [47] to diagnose rolling bearings using an unsupervised AI technique. Based on the findings, the proposed technique was shown to have a sensitive reflection on defect identifications, even a minor fault.

2.2.2 Frequency domain (FD) analysis

Most signals in the actual world may be reduced to a mixture of individual sine waves. Every sine wave will display as a vertical line in the FD, with the height and location of the bar denoting the amplitude and frequency, respectively. When the amplitude is displayed versus frequency in an FD study, it is simpler to identify the resonant frequency component than in a TD analysis. This is one of the explanations for why FD techniques are effective in finding machine defects. The FD analysis allows for the observation of several signal properties that are hidden from view from a TD perspective. However, signals whose frequencies fluctuate over time are unsuitable for frequency analysis. Table 3 lists the benefits and drawbacks of each FD strategy.

Table 3: Frequency-domain techniques (advantages and disadvantages)

Frequency domain methods	Advantages	Disadvantages
FFT	a quick and simple method	unable to quickly and effectively assess transitorily features
Cepstrum Analysis	Simple to use and helpful for sidebandanalysis	can only be used with harmonics separated from one another, and filtering averages out the variations in the spectrum's curve.
Envelope analysis	Excellent bearing system application; performs well even when a minor random fluctuation occurs.	This May result in a severe diagnostic Mistake inappropriate for gear systems.
Spectrum analysis	Higher spectrum estimating performance compared to the FFT, helps identify signals that change Considerably over a short time	owing to its intricacy calls for specialized knowledge.

2.2.2.1 Fast fourier transform (FFT)

The Fourier transform (FT) creates the spectrum F(t) by shifting a TD signal f(t) into the FD. FT is provided by:

$$F(\omega) = Ff(t) = \int_{-\infty}^{\infty} f(t)e^{-i\omega t}\mathrm{d}t \tag{4}$$

where (ω) is the frequency and (t) is time. The inverse Fourier transform (IFT) can be used to return it to the TD from the FD. You may get this as:

$$f(t) = F^{-1}\big(F(\omega)\big)\frac{1}{2\pi}\int_{-\infty}^{\infty} F(\omega)e^{i\omega t}d\omega \tag{5}$$

The FFT approach is practical and popular for extracting discretized time signals through FT. A peak on the faultless industrial machinery's FFT plot represents the operational device's inherent frequency. Thus, a flaw in the device can be found when the natural frequency peak is not the only peak on the plot. However, Goyal and Pabl (2015) asserted that a small amount of temporal information is lost during the domain transfer [29]. Additionally, FFT cannot quickly and timely explore transitory characteristics, forecast faults, and assess the severity of flaws. Isolate the signal frequencies for the diagnosis procedure; it is, nevertheless, the quickest method. TD signal analysis and FFT are

typically combined to diagnose the low-speed machine and provide more detailed findings. However, the main issue depends on how much the defect affects carrier frequency. Saucedo-Dorantes et al. [4] employed the FFT and PSD approach to identify bearing issues in the motor and diagnose the spot in a gearbox. They discovered that the suggested process works well at low operating frequencies but is unsuitable for detecting wear at high operating frequencies.

2.2.2.2 Cepstrum analysis

Cepstrum analysis, created in the 1960s, is known as the power spectrum's logarithm power spectrum. Any periodic structure in the range, including echoes, sidebands, and harmonics, may be found using cepstrum analysis. This enables the detection of faults that generate low-level harmonically related frequencies, such as the bearing and tooth faults. Power cepstrum is the form of cepstrum that is most frequently used in machine diagnosis and monitoring. Four different conditions of cepstrum exist.: complex cepstrum, phase spectrum, power spectrum, and real cepstrum. Cepstrum analysis is crucial for diagnosing gearboxes, according to Goyal and Pabla [33].

2.2.2.3 Envelope analysis

Demodulated resonance analysis or amplitude demodulation are other names for envelope analysis, which Mechanical Technology Inc. developed. With this method, the low-frequency signal and background noise are separated. In the bandpass filtering and demodulation stage of envelope analysis, the signal envelope is extracted, and its spectrum may include the needed diagnostic data. It is used for diagnosing low-speed machines and rolling element bearings and has the benefit of spotting bearing issues before they become serious. Induction motor bearing faults were also detected using envelope analysis by Leite et al. [48], and the suggested approach can effectively do so even without model-specific information.

2.2.2.4 Spectrum analysis

FFT and spectrum analysis are connected in that the signal is frequently transformed from the TD to the FD using the FFT in spectrum analysis. A logarithmic amplitude scale (dB) should be used for spectrum comparison since variations on this scale might indicate the vibration's status. However, one must deal with the slight variations in the machine's rotational speed. This approach can identify a defect that can rapidly modify the vibration signature. Even with the wealth of material available, spectrum analysis is a complicated analysis requiring professional skills to utilize its diagnostic potential fully. In contrast to cepstrum analysis, spectrum analysis provides no information on the temporal localization of the frequency component. Salami et al. [30] used the spectrum analysis technique for machine condition monitoring. Compared to the FFT method, this method could offer smoothed, high-resolution spectrum estimations of the vibration signals.

2.2.3 Time-frequency domain (TFD) analysis

TD and FD are combined in the TFD analysis. This implies that the time-variant properties of the signal and its frequency component may be determined concurrently in this analysis. The previous techniques for vibration analysis (TD and FD methods) principally rely on the stationary assumption that local characteristics in the TD and FD cannot be detected concurrently. As a result, such techniques are ineffective for non-stationary signal analysis. WT, HHT, WVD, STFT, and PSD are among the TFD analytic techniques included in this work. Table 4 lists each TFD technique's advantages and disadvantages.

Table 4: Time-frequency domain techniques (advantages and disadvantages)

Time-Frequency Domain Methods	Advantages	Disadvantages
WT	Provide greater flexibility than STFT, better temporal localization at high frequencies, and access to various wavelet algorithms.	It is not easy to pick the mother wavelet type due to the convolution of a priori basis functions with the original signal.
WVD	It has a high time and frequency resolution, and its use does not need a window function's help.	Interference-prone, slower than STFT
HHT	It has vital time and frequency resolution and does not call for primary basis functions.	Misinterpretation of the results brought on by IMFs produced in the low-frequency area
STFT	low computational complexity, straightforward approach, and suggested for newcomers to time-frequency analysis	Finding a quick and efficient method to compute STFT with constant frequency resolution for the whole signal is challenging.
PSD	FFT may be used to calculate this directly, with relatively little computing power	the window size affects frequency resolution

2.2.3.1 Wavelet transform (WT)

Morlet adopted the WT approach in Wei et al., [49]. A linear transformation creates wavelets, which are local functions of time with predetermined frequency content, from a temporal input. Wavelets are employed as the foundation rather than sinusoidal functions. An appropriate wavelet basis must be selected to prevent inaccurate diagnosis findings based on the signal structure. Compared to STFT, WT offers better time localization at high frequencies. When assessing the transient signal of the recorded vibration signal and working with non-stationary signs, WT is recommended. Compared to WVD, the WT method is more vulnerable to stiffness fluctuation, according to Zou and chen [50]. Wavelet transform (WT) may be divided into discrete and continuous types (DWT and CWT). A pair of low-pass and high-pass filter wavelets are commonly used to apply the scaling factor known as the power of two in DWT. For the CWT, the scaling element is chosen randomly or using convolution. Standard WT algorithms like DWT and CWT, which cannot generate a sparse representation, are inefficient in extracting features from specific types of signals. It has weak frequency resolution for high-frequency elements, and for low-frequency components, it has low temporal localization. The wavelet packet transform (WPT) method is born as a result. It is a more sophisticated version of CWT that can analyze various non-stationary signals since it enhances frequency resolution and further decomposesthesignal's high-frequency detail information. WT can identify the changes in vibration frequency content within the machine cycle, according to Dalpiaz and Rivola [51], who used it to monitor the status of an automatic packaging machine. DWT is more computationally efficient than CWT, although CWT has the advantage of having a more sensitive scale parameter. The CWT and WPT were used by Al-Badour et al., [52] to find defects in rotating machinery. The WPT method develops the DWT approach with a higher tolerable frequency resolution. Regarding the speed and spectrum characterization of the vibration signal, they discovered that the WPT approach is superior to the CWT method.

2.2.3.2 Wigner-ville distribution (WVD)

Ville processed the signal using Wigner's WVD approach, which is how the Wigner-Ville distribution became known. The signal is correlated with a time and frequency translation to produce a time-frequency energy density, a particular instance of the Cohen class distributions. Where x* is the conjugate of x and is the delay variable, the WVD of a signal x(t) is. WVD provides several benefits, including superior accuracy, less dependence on the window function, and more excellent resolution than STFT. Because of the cross-term interference issue, researchers do not directly employ WVD to ascertain the time-frequency structures of signals. WVDto ascertain the time-frequency structures of signals.

$$W_X(t,\omega) = \frac{1}{2\pi}\int_{-\infty}^{th\infty} x\left(tth\frac{\tau}{2}\right)\cdot x^*\left(t-\frac{\tau}{2}\right)\cdot e^{-j\tau\omega}d\tau \tag{6}$$

Staszewski et al., [53] used the weighted version of the original WVD approach to conduct the gearbox's defect detection investigation [53]. They asserted that the weighted form of the original WVD might minimize interference in the TFD at the expense of a loss in frequency resolution. Climente-Alarcon et al. [54] Gave an example of using the WVD approach to diagnose induction devices. When harmonics tracing is challenging, the proposed method could help produce more accurate diagnosis findings.

2.2.3.3 Hilbert-huang transforms (HHT)

David Hilbert originally described the Hilbert transform. The HHT was subsequently introduced in Huang et al., [55] to distinguish between the features of stationary, non-stationary, and transient signals. The Hilbert transform (HHT) comprises motions of empirical mode decomposition (EMD). Combining these two approaches will provide a Hilbert spectrum, which may be used to identify flaws in an operational machine. Any publications relating to the EMD approach thus belong to this manuscript's HHT portion. A complex multicomponent signal may be decomposed using this technique into many intrinsic mode functions (IMFs).

2.2.3.4 Short-time fourier transform (STFT)

Gabor invented STFT in communication in 1946. It can overcome FFT's limitations and is mainly used to extract narrowband frequency information from noisy or non-stationary data. The original vibration signal is divided into time segments by windowing in the STFT approach, and Then FT is applied to every time interval. Given is the mathematical formula for STFT.

$$STF\,T(f,\tau) = \int_{-\infty}^{\infty} x(t)\omega(t-\tau)e^{-j2\pi ft}dt \tag{7}$$

where x(t) is the interpreted signal, and ω(t) is the window function cantered at time T. STFT depends on the width of the window. A high window width is preferred to increase frequency accuracy, whereas a small one is desired to increase time accuracy. The primary flaw with this method is that it can not simultaneously attain excellent resolution in the TD and FD. Safizadeh et al. [56], advocated using STFT for diagnosing machinery and demonstrated its superiority to traditional machine diagnostic techniques, although STFT offers only approximate time-frequency information.

2.2.3.5 Power spectral density (PSD)

To estimate the energy intensity of frequencies and assess the timeseriesdata's oscillatory signal amplitude, PSD can be employed. The one-sided PSD from the complex spectrum may be calculated in (m /s^2)^2/Hz as:

$$PS\,D(f) = \frac{2|X(f)|^2}{(t_2-t_1)} \tag{8}$$

where t_2 and t_1 are the time, and $X(f)$ is the complex spectrum of the vibration *x(t)* in a period. It may be measured in (m/s^2/Hz) units. If the FFT of a vibration signal is utilized, the following formula may also be used to compute PSD directly in the FD:

$$PSD = \frac{(G_{\ rms})^2}{f} \tag{9}$$

where (G_{rms}) is the root-mean-square of acceleration in a specific frequency (*f*). *PSD* may examine the problematic frequency ranges without encountering a slip variation problem and is not bound to concentrate on a single harmonic. It may be calculated directly using FFT or converting the autocorrelation function, which requires minimal computing resources. The suggested approach can successfully identify defects for every working point of the induction motor. The PSD technique has been used with WT to diagnose errors in induction machines. To increase the accuracy of the diagnosis, an adequate understanding of the appropriate mother wavelet and sample frequencies is still necessary.

2.3 Gear fault classification

Recently, machine learning techniques have been used to monitor the machine's state and diagnose faults in rotating machines, especially gearbox faults. Common faults in the gearbox are simulated, such as faults in the teeth, including broken, wear, pitting, etc., and bearings. Vibration data for these faults are recorded, and statistical features are extracted from them. Then, artificial intelligence algorithms are used to design an artificial intelligence model to train the machine that those data are features of faults that occur in the gearbox. The features of the vibration signals are entered into the artificial intelligence model, and the model separates the features and distinguishes the signal of each malfunction from the other, where the outputs are classifications of the faults that occur in the gearbox. Therefore, when vibration signals similar to the signs of one of the faults that have been trained appear, it is predicted that the machine will malfunction. Artificial intelligence techniques monitor the state of the machine in two ways. The first method is when maintaining the machine or when an abnormal behavior appears for the machine, so the vibration signals of that machine are recorded, and the statistical features of those signals are extracted and then entered into the artificial intelligence model to identify the presence of faults and this method is called (offline). The second method is to link the artificial intelligence model directly with the vibration signals from the machine. When there is any malfunction, it is indicated immediately. This method is called (online). Figure 5 shows how, according to Ghazali and Rahiman [35], AI-based approaches contribute to around 57% of the total vibration analysis methodology in machine diagnosis and monitoring. This is because most of the previously described techniques need a high level of skill for implementation to be effective, making them unsuitable for general users.

Additionally, the expert is not always accessible. This is where AI-based methods may be helpful since they let non-expert users draw reliable conclusions without the assistance of a machine diagnostic expert. Any job carried out by a computer or machine challenging enough to require intelligence can be called artificial intelligence (AI). SVM, ANN, fuzzy logic, and GA are AI-based vibration analyzing techniques for machine monitoring and diagnostics.

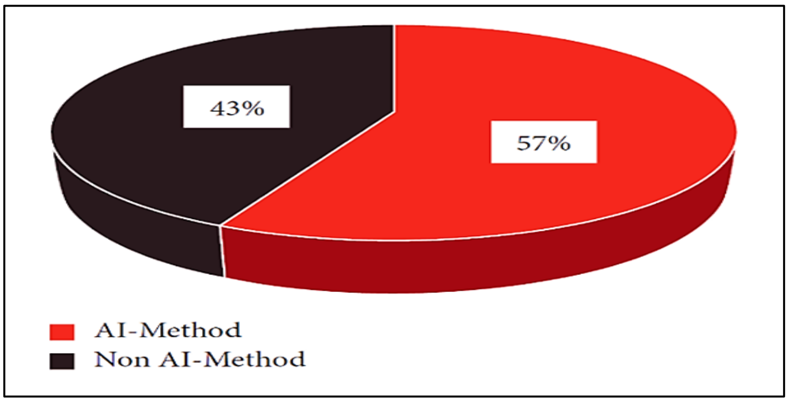

Figure 5: The percentage of vibration analysis for machine diagnosis and monitoring that uses AI vs. non-AI technologies [35]

2.3.1 Support vectors machine (SVM)

Vapnik introduced SVM as the most used classification algorithm. The optimum hyperplane is then selected after nonlinearly transforming the data set or sample space into a high-dimensional, kernel-induced feature space. According to Figure 6, the optimal hyperplane has the most significant difference between classes 1 and 2.Support vectors are data points from both classes located closer to the hyperplane and affect the orientation of the hyperplane. The features extraction method yields the SVM's learning and test data; when the SVM algorithm has been trained, the SVM matrix is generated. To improve outcomes, SVM is frequently used with optimization techniques like GA and particle swarm optimization (PSO). SVM is commonly used in vibration analysis for machine diagnostics for some reasons, including its compatibility with vast and complicated datasets like those gathered from the industrial sector. SVM is beneficial since its performance is unaffected by the number of characteristics on categorized items. This implies no restriction on the number of qualities chosen for the diagnosis system's foundation. In contrast to fuzzy logic, where expertise is required, SVM does not involve any layers in its structure, but ANN does. Poyhonen et al. [58] employed the SVM technique to find issues with an electrical machine, and the findings showed that classification accuracy was generally high except for recognizing eccentric rotors.

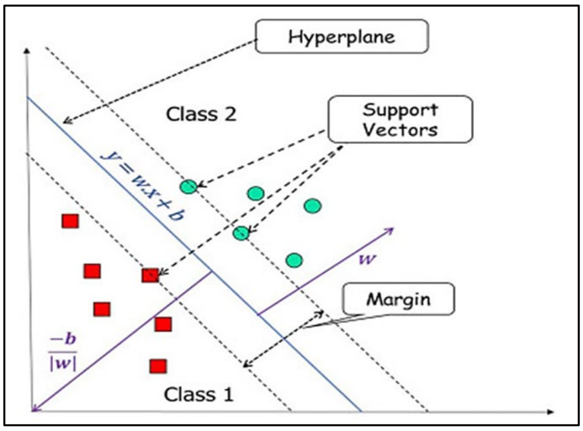

Figure 6: Construction of the SVM technique [57]

2.3.2 Artificial neural network (ANN)

An artificial Neural Network (ANN) comprises many nodes and artificial processing neurons with extensive connections joined in layers to create a network. ANN may simulate systems and processes utilizing TFD techniques and raw vibration data from the frequency above. Only input factors may reduce the effect of the weak input variables during the ANN training process. As a result, the data must be correctly scaled and processed before input into the ANN. To lessen the influence of the input variable, the raw vibration data might be normalized to values between 0 and 1. The accuracy of the findings is directly impacted by training time, which rises by the complexity of the network. The back propagation neural network (BPNN) is a popular tool for machine diagnosis because of its stability and effectiveness in managing noisy data. Rumelhart and McClelland invented the BPNN in 1986. It has three layers: input, hidden, and output. Including hidden layers enables the ANN to describe nonlinear systems, and the more hidden layers present, the more complex the ANN.In contrast to the fuzzy logic approach, ANN does not require a knowledge base to identify the locations of the flaws. Castelino et al. [59]used ANN for vibration monitoring industrial rotary machinery operating under real-world circumstances. The results showed that ANN performed better for non-stationary signals in the TFD than FD signals.

2.3.3 Fuzzy logic

Unlike traditional logic, fuzzy logic tries to describe the imprecise forms of reasoning to help people make logical judgments in a world of uncertainty and ambiguity. Fuzzification, an inference mechanism, a rule base, and a defuzzification component are the four critical phases of the fuzzy logic system. Before the fuzzy inference stage draws a reliable conclusion based on the rules developed in the rule-base step, the fuzzification stage turns the input data into fuzzy sets. Defuzzification gives quantitative findings at the end. Membership functions map nonfuzzy input values to ambiguous language phrases and vice versa and are linked to fuzzy logic. A sensitive diagnostic system may be created by fine-tuning the rules and membership functions. The most significant issue in fuzzy logic is identifying the fuzzy regulations and optimizing the membership functions. SVM and ANN are more challenging to implement than fuzzy logic

Additionally, since there is no training or testing phase in fuzzy logic, it does not rely on datasets as other AI approaches, as SVM and ANN do. This approach can only offer a generic diagnosis in some circumstances since a machine's failure symptom cannot be consistently identified. This is the only option when gathering the fault data cannot be done. Lasurt et al. [60] compared the effectiveness of fuzzy logic and ANN in identifying electrical machine faults. They asserted that fuzzy logic outperforms ANN in various operational situations for defect detection.

2.3.4 Genetic algorithms (GA*)*

GA, inspired by research into biological systems, uses a natural selection approach to tackle optimization problems that are both limited and unconstrained. To arrive at the ideal outcome, GA randomly chooses the highest-quality people from the present population to become parents for the offspring of the following generation. Up until a termination condition is invoked, this phase will continue. Each GA involves three basic processes: crossover, mutation, and selection. GA is often used to enhance the speed and accuracy of problem diagnosis and improve the monitoring system settings. Han et al. [61], utilized the GA to diagnose the induction motor and discovered that by selecting important characteristics and improving the network topology, GA enhances the performance of the diagnosis system. Table 5 lists the benefits and drawbacks of each defect identification technique.

Table 5: AI-based techniques (advantages and disadvantages)

AI-based method	Advantages	Disadvantages
SVM	High accuracy, compatible with vast and complicated datasets	Choosing the correct kernel is challenging and performs poorly when the data contains noise.
ANN	The process that is fault-tolerant and capable of learning on its own possesses a significant capacity for data processing.	The complex design process, lengthy network processing time, and black box solution
Fuzzy logic	Strong robustness, straightforward design, and understandability	It is challenging to find the knowledge norms and the appropriate membership function.
GA	can handle a wide variety of data and may be used for optimization.	High computing expenses and lengthy process

3. Discussion

Most research used the computer-based analyzer as a more straightforward, less expensive option for the data-collecting method. This analyzer is nearly as effective as a traditional analyzer, thanks to DSP and FPGA. The best sensor for vibration analysis is still an accelerometer, as demonstrated by Ghazali and Rahiman [35]. However, because the piezoelectric accelerometer is so expensive, researchers are always looking for ways to use MEMS accelerometers to offer the same or more incredible performance. In contrast to accelerometers, a velocity transducer is more effective in diagnosing low-speed machinery because the absolute accelerations recorded are substantially lower for comparable vibration displacements.

Additionally, non-contact sensors offer enormous potential for machine monitoring since putting the sensor on the machine is no longer an issue, resulting in a more precise reading. It is not, however, frequently employed because of its expensive application. When the cost of implementing the LDV is lower, it is anticipated that LDV with multichannel measurements will be widely used. Researchers have given much thought to improving the identification and diagnosis of defects in the TFD regarding signal processing techniques [35]. This is because failure signals are not repetitious in the first stages, making it possible to utilize them to analyze non-stationary signals. These non-stationary signals often reveal a lot about mechanical issues. The assumption that immobile signals underlie the TD and FD approach for machine monitoring makes them unsuitable for spotting short-duration dynamic occurrences, particularly in rotating machinery. However, while they are more advantageous in some cases, conventional approaches should not be disregarded. Due to its ability to identify low-energy signals, envelope analysis is frequently used for low-speed devices. The envelope spectrum is further examined using TFD techniques like WT and HHT, which reduce the noise level in the vibration signals. Some researchers combined distinct strategies to use one approach's benefits while compensating for its drawbacks. RMS, FFT, and WT are the most popular machine monitoring and diagnostics approaches in the TD, FD, and TFD, as shown in Figure 7.

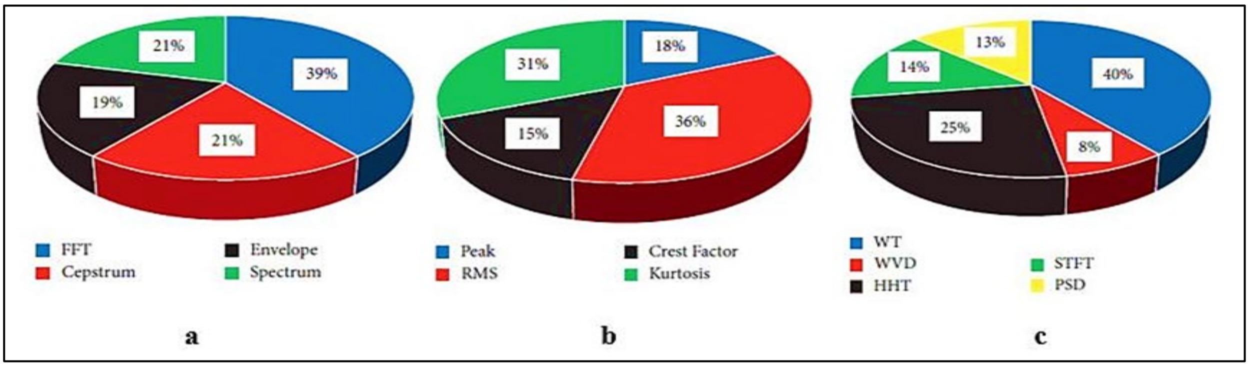

Figure 7: Percentage of techniques used for (a) time domain, (b) frequency domain, and (c) time-frequency domain [35]

The performance of the most recent AI approach utilized in machine vibration monitoring and diagnosis may be compared to AI methods that are more often employed. Researchers are also working on using vibration analysis intelligence systems for automated decision-making. According to the review and Figure 8, SVM is the most popular approach because it has a high degree of classification accuracy and requires little processing effort. Additionally, it was discovered that using TD parameters is closely correlated with the help of AI techniques. TD characteristics can enhance AI techniques" performance and have a low computational cost, which would not significantly increase the computational load on AI methods. For the AI-based approaches, work is still being done to improve the algorithms for lower processing costs and simple implementation of vibration analyzing. Whether or not they combined AI approaches, 80% of the prior research used feature extraction or signal processing methods such as STFT, HHT, envelope analyzing, and WT. Although these methods performed well at monitoring and identifying the machine's state, professional signal processing expertise is still necessary [35]. For every problem diagnosis task, the features extractor must also be rebuilt.

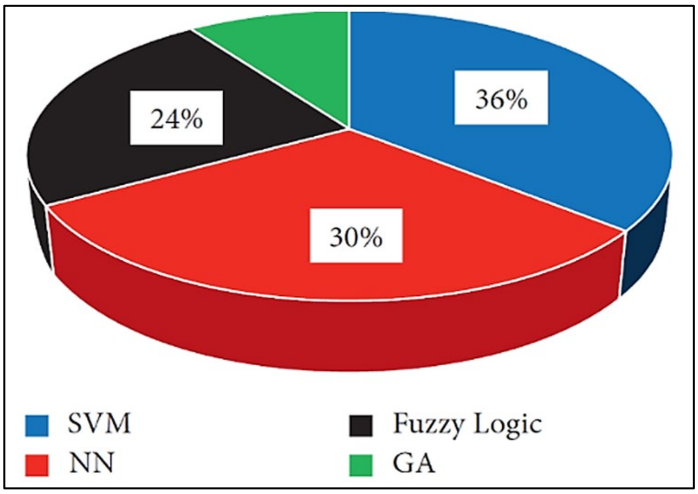

Figure 8: Percentage of techniques used for AI-based approaches [35]

4.Conclusion

Thanks to the new developments in data collecting processes, signal processing methods, and instrumentation, vibration analysis for machine monitoring and diagnostics has grown steadily more affordable. These days, even novice users can do efficient vibration monitoring independently. The benefits, drawbacks, and distinctions of the methods employed in the data gathering, feature extraction, and fault identification phases have been discussed in this paper. Fault diagnosis analysis is crucial in rotary machines for several reasons; as a consequence, many crucial conclusions are established:

1) Minimization of downtime and maintenance costs: Fault diagnosis analysis enables maintenance teams to identify the exact fault and its root cause, allowing them to perform necessary repairs or replacements quickly and effectively. This minimizes machine downtime and reduces maintenance costs associated with lengthy troubleshooting processes.
2) Maximization of machine performance: Faults in rotary machines can significantly impact performance. Fault diagnosis analysis helps pinpoint the specific areas where modifications or repairs are needed, resulting in improved efficiency and performance of the machines.

3) Extension of machine lifespan: Regular fault diagnosis analysis can identify any potential issues that may affect the lifespan of rotary machines. By addressing these faults promptly, the machines' lifespan can be extended, reducing the need for premature replacement and associated costs.
4) Enhanced safety: Faults in rotary machines can pose safety risks, such as equipment malfunction or accidents. Fault diagnosis analysis helps identify and rectify these faults, ensuring the safe operation of the machines and reducing the likelihood of accidents or injuries.
5) Overall, fault diagnosis analysis is vital in maintaining rotary machines' performance, reliability, and safety. It helps detect faults early, prevent catastrophic failures, minimize downtime and maintenance costs, maximize performance, extend machine lifespan, and ensure operational safety.
6) A computer-based analyzer is preferred owing to its cheap cost and performance, which is in line with standalone analyzers, given the development of strong software and the Internet.
7) Examining the various vibration analysis sensor types and becoming familiar with their characteristics. With knowledge of each machine's working circumstances, the proper analyzer type can be chosen.
8) Time-frequency domain approaches are preferred for non-stationary warnings and early defect detection, whereas time and frequency domain techniques are ideal for stationary signals.
9) In the future, traditional time domain characteristics like RMS and crest factor will continue to be helpful, and their use with AI will grow.
10) In vibration analyzing for machine monitoring and troubleshooting, AI is increasingly applied. This is because most alternative techniques need the expertise to be implemented appropriately, making them undesirable for normal users.

Nomenclatures

1. RMS: Root mean square
2. PSD: Power Spectral Density
3. ANN: Artificial Neural Network
4. BPNN: The back propagation neural network

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Author contributions

Conceptualization, A. Dubaish and A. Jaber, writing-original draft preparation, A. Dubaish and A. Jaber, writing- review and editing, A. Dubaish and A. Jaber. All authors have read and agreed to the published version of the manuscript

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

Conflicts of interest

The authors declare that there is no conflict of interest.

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