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Condition Monitoring and Fault Diagnosis of Rolling Contact Element Bearings Based on Artificial Intelligence Techniques: A Review Approach

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Abstract: *The current review paper is related to Condition Monitoring and Fault Diagnosis of Rolling Contact Element Bearings based on Artificial Intelligence Techniques. To save costs, boost dependability, and ensure system safety, rotating machinery must be constantly monitored. Numerous contemporary approach-based procedures identify and foretell defects in rolling element bearings. These techniques include data extraction, period & rate of recurrence clever structures, time-frequency domains, detail mix, sign/image processing, intelligent diagnostics, and statistics fusion. The popularity of AIML ideas has also increased attention in this field. Artificial intelligence approaches to industrial equipment, mechanisation, and development represent the net boundaries of AI adaptability. This paper's primary contribution is to give a thorough review of bearings. Secondly, signal and data processing techniques are used to approach the problems in a well-developed body of literature. Thirdly, with the aid of new trends in artificial intelligence and methodologies, defect detection methods employing time domain and frequency domain analysis, and the bearing's CM, which encompasses a variety of CM approaches.*
Keywords: *Rolling element bearing, defects, Condition monitoring, Vibration analysis, Artificial intelligence.*

1. INTRODUCTION

Different rotating components are employed in today's diverse industries, including those in the automotive, industrial, construction, petroleum, mining equipment, and electric generation sectors. Most rotating machinery uses rotating components such as bearings, rotors, shafts, crankshafts, camshafts, and compressor pumps, which raises the initial investment cost. Before a rotating component is ready for operation, it must be checked for damage. Rotating equipment failure would have a significant impact on the entire production process. As a result, periodic maintenance intervals for the machine and its components are required to prevent unexpected failures.[20] If one part of an apparatus malfunctions, the entire production link stops and production volume decreases, resulting in higher operational expenses for the machine.

Bearings are the heart of all rotating equipment; their condition often reflects how well a machine runs. It's a critical tribological factor for many varieties of equipment and springs in various shapes and forms. They are described as a machine element that, in a structure that may be static or dynamically loaded, only supports or permits a single form of gesture. The primary purpose of bearings is to keep two moving elements from coming into direct contact, thereby reducing friction, generating heat, and finally decreasing wear and tear. The substitution of low-friction rolling for sliding motion additionally affects strength financial savings. They also transfer the load of the rotating detail to the housing. Radial, axial, or a mixture of the double load is all viable for this one. As previously stated, a bearing restricts the scope of movement of stirring components to unique guidelines. Numerous causes of bearing damage, misalignment, unbalance, looseness, white etching cracks, and friction are transmitted through the bearing and can lead to failure. Bearing failure can result in high-priced downtime, harm to adjacent elements, and substantial repair expenses because they are often the most critical machinery components. The good news is that each failure leaves a unique imprint on the bearing. Several times, symbols of impairment can assist in determining the origin source, defining helpful actions, and preventing a recurrence; 95% of all bearings fail due to operating conditions and must be replaced before the machine's life is up. Selecting the appropriate bearing for the application can reduce downtime, production loss, costs, and damage.

Figure 1. Bearing Failure Diagnosis Techniques.

Additionally, the weight of the rotating member on the housing may be either axial, radial, or a combination of the two. A bearing limits the liberty of movement of shifting components to predefined guidelines.[33] Mechanical efforts and vibrational styles prompt contemporary feeding of induction motors in rotating machines. For this reason, the current analysis can also be used to become aware of mechanical flaws, even though vibration analysis is better at doing so. Sound evaluation is all about using acoustic emission indicators.[34] Vibration analysis aids in monitoring the gadget's working conditions and evaluating them based on the analysis outcomes in regular operating situations to decide if there is trouble. A thorough evaluation is required for structural analysis & load prevention. It contains statistics on the shape's mode shapes and herbal frequencies, which might be generally used for fault detection.[21,22, 29] For overall performance evaluation, time-area, & frequency-domain vibration techniques are applied individually or in combination.

Several supervised ML-based algorithms, primarily based on acoustic and vibration records, were used to identify the performance deterioration caused by transducers, a data acquisition system, and a signal processing system. The MFE-SVM, RWE, and TSFDR-LDA methods achieve a classification accuracy of much more than 96%. AIML is introducing a new flexible technique for improving rotary machine predictive maintenance methodology using vibration and audio inputs. This approach offers a quick, efficient fix through a non-invasive substitute that would be a boundless industry result for classifying, predicting, and detecting bearing failures at a cheap cost.[01] Rolling element assumptions in rotary machinery were not always present in an ideal form; they vary depending on the working conditions. Deep learning-based approaches for diagnosis under varying conditions based on the bearing fault mechanism, Response Network (FRN), and Fault Response Convolutional Layer (FRCL), achieved high diagnostic accuracy. Without samples from untested situations, the Response Network (FRN) can achieve excellent diagnostic accuracy while operating conditions change dramatically. [02] The bearing vibration and the vibration's dynamic qualities are used to build the 2-degree-of-freedom nonlinear bearing model. The Hertz contact stress theory explained the dynamic properties of rolling bearings, and it is found that the number of bearings depends on the inner clearance of the equilibrium points. Nonlinear bearing models can exhibit dynamic behaviour, which can be investigated using the variational map. It helps by combining qualitative & quantitative research techniques that examine the behaviour of keen structures. [03] The enhanced grey wolf optimisation with adaptive sparse contractive auto-encoder unsupervised extreme learning machine, and other methods were used to diagnose the unbalanced rolling bearing faults. These methods were accomplished by pull-out time-frequency topographies of rolling elements bearing huge faults, and they were most precise when the defect example balance was off.[04] By using deep separable convolution and spatial dropout regularisation, the bearing fault diagnosis technique efficiently studies the features of bearing faults with an excellent diagnostic effect. It significantly reduces reliance on physical labour compared to the conventional artificial feature extraction method. With the half network parameters of a traditional CNN, the method's accuracy was greater than 97%.[05] Using AIML Shapley Additive Explanations (SHAP), a method for interpreting black-box models, unsupervised classification, root cause analysis based on anomaly detection techniques, and the presence of problems were confirmed. The original method can be used to address the issue simply by changing the extracted feature, unlike the failure methods.[06] A data synthesis technique known as a generative adversarial network with deep features GAN is recommended for improving low damage detection efficiency. According to the trial data, movements are equally effective as unprocessed motions and outperform conventional procedures. [07] Using a multi-channel CNN data augmentation technique & multiscale cutting fusion, a rolling element bearing failure diagnosis strategy (MSCF). The short-time Fourier transform changed the fault signals to time-frequency pictures. MCNN combined the multi-sensor image data for feature extraction and fault pattern classification. The suggested method is efficient and reliable, and it is ideally suited for defect diagnosis when sensor data is scarce and/or operational circumstances change.[08] The large statistics of rolling bearings were processed by using a technique (RMT-PCA) founded on the causal environment concept (RMT) & most important element evaluation (PCA), as conventional function extraction techniques generally tend to lose some applicable records and the prevailing bearing overall performance deterioration index. The fusion characteristic index is proven to be extra sensitive to the bearing's early abnormality by the RMT-PCA method.[09] Bearing element diagnosis is now simple and understandable thanks to vibration analysis and artificial intelligence. A detailed investigation of the vibration response of ball bearings is performed using a modified 2-DOF lumped parameter model, extra deflection theory, and multi-impact theory to closely replicate the performance of healthy and faulty bearings under a range of load and speed values.[13] Variable working situations, high environmental noise interference, and an inadequate sample of powerful facts would obstruct rolling bearing fault analysis. The problem was solved using an improved convolutional neural network (CNN). The approach combines the pseudo-label getting-to-know-you method with MMCNN, which can increase the labelled set by labelling unlabelled facts. This method outperformed existing methods regarding rolling bearing fault recognition correctness under variable operating conditions.[14] Big Data and advances in AIML technology have yielded impressive results in bearing CM and fault detection in recent years. A deep CNN model and a straightforward threshold model comprise this method for bearing defect identification. A customizable data-and physics-driven loss function intelligently combines structural information and deep learning methods, which is required for bearing fault recognition.[15] A fusion deep-learning version primarily grounded on CNN & the gcForest technique was developed to analyse bearing failure. Continuous wavelet transform was used to transform vibration signals into time-frequency images. After using CNN to extract internal defect features from the images, the gcForest classifier was fed the features. Regarding the accuracy rate, the fusion deep learning algorithm model surpasses gcForest and CNN, which could be helpful in real-world applications.[16] The primary goal was identifying the condition using the feature ranking method for data training. The feature ranking method is a new method of filtering the proper data within the proper order for record training. For the cylindrical bearing, logistic regression was more accurate than ANN and SVM.[17] Deep residual networks (RESNET) and convolutional neural networks (CNNs) were used in fault diagnosis. The completely connected layer of the conventional RESNET is replaced by a new network topology based on global average pooling (GAP) technology. It effectively solves the problem of the old-style RESNET model having too many parameters. Experimentally, it was found that the improved algorithm's fault diagnosis accuracy was 99.83%, and the training time was shorter. Furthermore, the development of detecting rolling bearing faults does not require a few hand-extracted features, and this "end-to-end" algorithm employs advanced intelligence methods to identify and find a failure in a bearing element.[18] These methods were based on a perceptron multilayer artificial neural network, whose record includes arithmetical indications that classify vibration signals. This method's efficiency was demonstrated by experimentation, which found bearing vibration data, and the marks demonstrated respectable correctness in detection and position faults.[19] A multi-objective optimisation-based deep learning diagnosis technique to effectively analyse the rotor and bearing defects, the Deep Auto-Encoder, Deep Belief Network, and Convolution Residual Network are weighted and merged. Practical outcomes suggested that the deliberate process is more adaptable than other ensemble deep models.[25] K-nearest neighbour and artificial neural networks were used for fault classification of bearings. The wavelet transform was employed to extract features, which were then used as inputs to ANN models and KNN. A backpropagation multilayer perceptron neural network was used to train the processed and normalised data. When the ANN results were compared to the KNN results, the ANN results were found to be extremely active for the classification of several faults.[26] With artificially introduced local defects, the rolling element bearing system was tested at four speeds for fresh bearings and different sizes. The experimental results bear that the ANFIS-created system outperformed the ANN-created system, particularly in fault severity diagnosis.[38] As a result, this study aims to survey the theoretical review of different AIML techniques used for CM and FDD of bearings. Additionally, conventional methods of theoretical foundation analysis, data acquisition, signal analysis, and feature extraction are studied, and appropriate AIML techniques are advised to determine the cause of a roller element bearing problem. The following section describes how this paper is structured: Rights theory of the rolling element bearings element's monitoring systems are followed by vibration analysis techniques like time domain and frequency signal analysis, and a data acquisition system covered in the second section. The third section discusses the CRISP ML(Q) method. Knowledge of the technological basis is required to categorise the outcomes of a machine learning technique and the process itself. Table 1 shows several studies on rolling elements with the help of standard and in-house bearing datasets for different working conditions and AIML techniques. Concluding remarks give a useful idea for the researcher for further in-depth study on a rolling element. The conclusion section describes the main conclusions and concludes the investigation.

2. THEORETICAL FOUNDATIONS OF THE ANALYSIS

Deterioration, weariness, brinelling, malleable deformation, low lubrication, and incorrect position are just a few of the factors that can cause early failure in rolling element bearings, so detecting these defects early is essential. The location of the fault and the kind of fault are the two categories of rolling bearing faults. Five significant faults were found in the location category: Ball, inner race, unbalanced shaft, cage, and outside race faults. It is also known as distributed faults. Two types of faults are considered in the nature category: cyclic and noncyclic. It is also referred to as localised faults.

2.1 Condition Monitoring Techniques

To gather information about the operational status of a revolving apparatus, condition-monitoring (CM) techniques are required. Condition monitoring assists in collecting, analysing, and evaluating data by employing the necessary signal analysis methods included in an assessment or prognosis to identify or forecast the health of rotating machines. Any combination of these factors, including motion, sound, direct charge, lubricant & grime, and heat, can be used for condition monitoring. Depending on the data properties, such as static or non-stationarity, straight or non-linear, to get the most information from CM analysis, period, spectral, or time-frequency approaches might be used as advantageous & efficient characteristics for identifying bearing problems. However, condition-based maintenance has played a significant role in the industrial world. However, CM makes early maintenance decisions using the data it collects. The primary goal of CM is to monitor the condition of modern industrial machinery and its remaining useful life (RUL).

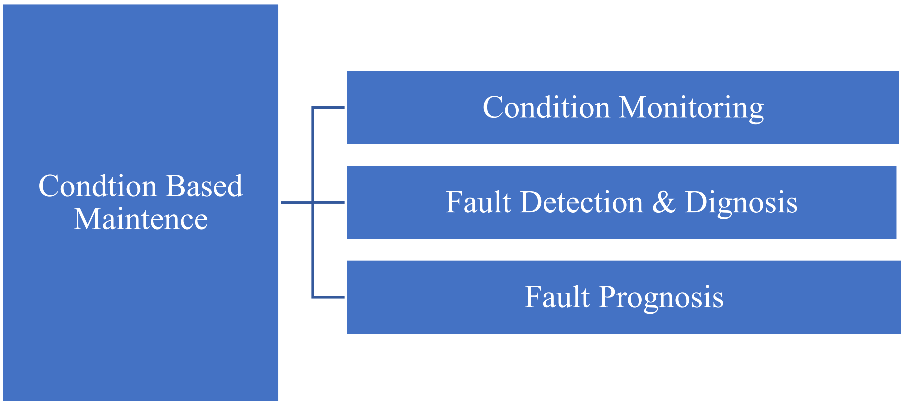

Figure 2. Main components of Condition Monitoring.

The essential components of a typical CM are shown in Figure 2. CM techniques are separated into two groups: invasive & non-invasive techniques. On the other hand, intrusive CM is viewed as a straightforward and elementary procedure. On the other side, implementation is challenging. Today, non-invasive CM techniques are widely employed to address this difficulty. Due to the importance and significance of this problem, numerous analyses, studies, and methods to improve the CM, fault detection, and diagnosis of rotating machinery have been described. Appropriate analyses were employed to produce effective and precise results to build the fault detection and diagnostic process for all of those procedures.

2.2. Vibration Technique

The most popular approach used for machine condition monitoring is vibration. A machine's health state may vary if the vibration signal changes even when the operating environment remains the same.

Typically, imperfections in the machine's moving elements, such as deficiencies in a bearing, gearbox, reciprocating parts, etc., create vibration signals. When a rolling element bearing works improperly, an impulsive signal (below 20Hz to 20kHz) will be produced as additional bearing parts go through the damaged location. The machine's overall vibration amplitude will rise as a result. The distinctive defect frequency component included in the bearing can be used to determine the defect component and its severity in the signal for condition monitoring. Although when used for CM of big low-speed rotating machines, the vibration technique can have difficulties gathering usable signals since the energy of an impending malfunctioning signal is typically feeble and frequently gets buried by background noise.[31]

2.3. Acoustic Emission Technique

An elastic wave known as an acoustic emission is produced when a material experiences a quick release or redistribution of stress. As an illustration, AE is produced in bearing condition monitoring applications when a defective part causes an unexpected release of energy due to substantial distortion. A monitoring AE sensor can then detect the signal once it has spread to the bearing house. The AE signal's high frequency makes it less susceptible to being impacted by background noise and vibration from vibration signals (typically above 100 kHz). AE also contains inherited difficulties, such as calibration, nonlinearity, data storage, transit, processing, and interpretation. Today's pricey, highly specialised AE data-collecting systems continue to limit the large industry's use of AE technology in bearing condition monitoring.

2.3. Current Signal Technique

The primary purpose of the current signal approach is to keep track of the bearing health used in rotating machinery. The method is constructed on the idea that changes in magnetic flux density within a motor are strongly related to the vibration signal produced by that motor. The rotor shifts slightly when a motor bearing isn't working correctly, adjusting the spindle and rotor's magnetic flux density. The stator current will then alter as a result of the induced voltage. The stator current approach is easy to use and reasonably priced since it tracks stator current fluctuations using non-intrusive sensors.

2.4. Technique for Monitoring Oil and Debris

A tribology strategy for machine condition monitoring that is often used is oil and debris monitoring. It is possible to monitor the roller element bearing's state by looking at the characteristics & element insides of the lubricating fluid. Tribology examination is typically done in laboratories utilising spectrometers and scanning electron microscopes. The technique is also restricted to wear- or lubrication-related condition monitoring applications.

2.5. Using Thermography

Thermography measures the emission of infrared energy during bearing operation using thermo-infrared equipment to detect bearing flaws. The most popular tools for this kind of measurement are thermo-infrared cameras or laser thermography systems. This method can be used to keep track of the variations in heat brought on by changes in load, operation speed, and lubrication. It is especially susceptible to the overheating phenomenon brought on by insufficient lubrication, although it is less sensitive to early bearing faults such as initial indentation, detaching, and mild wear.

3. TECHNIQUES FOR DEFECT IDENTIFICATION AND DATA ANALYSIS

Complex vibration signatures are produced when the roller, separator, outer ring, and inner ring of the rolling element bearings come into contact. The numerous vibration quantities include impact energy, vibration measured at a specific point, and bearing design such as raceway, roller, separator, changeable compliance, geometrical flaw, surface roughness, and waviness a non-invasive method for rotating machinery defect diagnostics and detection. Data denoising and filtering are examples of pre-processing. However, nonlinear and nonstationary signals make up the majority of electrical and mechanical signals. As a result, much research is being done on vibration approaches right now. Examples include variational mode decomposition, empirical mode decomposition, wavelet, continuous wavelet, and discrete wavelet transforms.[31]

3.1. Time-Domain Data Analysis Techniques

The time-domain analysis is used to track the bearings' health. In time domain analysis, statistical features including RMS, kurtosis, crest factor, skewness, and peak-to-peak are employed to track the condition of bearings. [32] The time domain reveals the type of vibration signal, such as transient, random, or sinusoidal. These signals are beneficial for researching transitory vibration signal kinds. Some indices from the vibration signal's temporal history can be used for diagnosis. The statistical metrics from the unprocessed vibration signal that can be determined and utilised to identify defects in bearings are known as the maximum often cast-off indices. Unfortunately, these metrics cannot pinpoint the machine's defective part because they are impacted by vibrations from every part of the machine.

- **Time series analysis:** A mathematical technique called time series analysis uses statistics to handle an observed data series. The basis of time series analysis is the principle that previous data variation trends can be used to predict or identify future changes in data for the same system being watched. The moving average, autoregressive moving average, and autoregressive models are the three univariate time series models most frequently used in machine fault diagnosis. [35]
- **To deal with the seismic reflection signal, deconvolution using the minimum entropy:** The main principle is finding an inverse filter that cancels out the impact of the transmission path. By restricting the spread of impulse response functions, it aims to obtain signals near the initial impulses that gave rise to them.
- **Spectral kurtosis**: It is used to identify impulsive events in sonar waves, was first proposed in the 1980s. Antoni [41] used SK for the first time to diagnose bearing faults.

3.2. Techniques for Frequency-Domain Data Analysis

- **Energy spectrum:** It uses the Fourier transform to turn the time-domain input into discrete frequency components. A time-domain input signal is computed from the square of the signal's Fourier transform magnitude.
- **Cepstrum:** A cepstrum is a signal energy spectrum's logarithmic power spectrum. [13]. The first four letters of the spectrum were reversed to create the word cepstrum. Cepstrum is categorised into Real, Sophisticated, Power, and Phase cepstrum.
- **Envelope spectrum:** Condition monitoring signals frequently provide insufficient information regarding raw bearing problems. Envelope signals are time waveform band passes in a high-frequency band. Mechanical reverberations amplify the fault signals, and the amplitude is manipulated for bearing diagnosis.
- **Spectra of a greater degree:** Determine the nonlinear interactions between frequency components, which are represented by high spectrum moments. Polyspectra or greater spectra are described using the Fourier transform of the corresponding cumulate sequences of a signal.

3.3. Analysis of Time-Frequency

The standard Fourier spectrum is given a time variable by the STFT, enabling analysis of a motion's temporal variability. In an SFFT analysis, the windowed signal is increased by a sliding small time window to calculate a Fourier transform of the continuous time-domain waveform in each window step.

One may calculate the STFT of a constant signal $x(t)$ using[31],

$$x(\tau, \omega) = \int_{-\infty}^{+\infty} x(\tau) w^*(\tau - t) e^{-j\omega\tau} d\tau \qquad (1)$$

where $w(\tau - t)$, which has a finite period. That has time t as its centre. Asterisk (*) the analytical window can be compared to indicate a complex conjugate to the response of an impulse to a low-pass filter. For signal analysis & understanding, the transformed output is frequently displayed as a spectrogram, the STFT transform's squared amplitude. The approach can only be used to determine the signals with slowly changing dynamics. The wavelet transform was created as another time-low-frequency analysis method to overcome this restriction.

Wavelet transforms: The wavelet transform represents A signal on a time scale. It is the internal stresses of a wave with scaled and translated mother wavelets family $\psi(t)$. The three primary types of WT analysis are continuous wavelet transforms, discrete wavelet transforms, & wavelet packet decomposition. In continuous wavelet transforms, a continuous signal $x(t)$ is found via[31]

$$W_f(u, s) = \frac{1}{\sqrt{s}} \int x(t) \psi^* \left(\frac{t-u}{s}\right) dt. \qquad (2)$$

where u is the time translation and s is the scaling parameter.

Distribution by Wigner-Ville: Wigner-Ville dispersal is an additional well-liked time-frequency analysis method. It generates mono-component, linearly modulated signals at an optimum resolution but results in undesirable cross-terms for multi-component, nonlinearly frequency-modulated signals. A signal $x(t)$ Winger Ville's distrVille's n is denoted by [31]

$$W_x(t,\omega) = \frac{1}{2\pi}\int_{-\infty}^{+\infty} x\left(t+\frac{\tau}{2}\right)\cdot x^*\left(t-\frac{\tau}{2}\right)\cdot e^{-j\omega\tau}d\tau \quad (3)$$

Adaptive signal decomposition: In 1998, Huang [42] presented empirical mode decomposition as a method for adaptive time-frequency analysis. The decomposed signal in empirical mode decomposition analysis can be represented as [31]

$$x(t) = \sum_{i=1}^{N} Ci\,(t) + rN(t) \quad (4)$$

4. TECHNICAL BACKGROUND

Machine learning technology is still developing a standardised process and model for machine learning development. Recently, the CRISP-ML(Q) methodology a cross-industry standard process for quality assurance—was offered to comprehend machine learning applications for any project or model across the development life cycle. Explore the fundamental stages of the machine learning development process model: commercial and information comprehension, data collection/preparation, ML methods, quality word, deployment, and monitoring and maintenance. The various stages are done in a specific order. Nevertheless, because machine learning workflows are inherently iterative and experimental, we might revisit prior phases depending on the outcomes from later stages of the CRISP-ML(Q).[23] Knowledge of the pertinent technological base is crucial to classify the results of a machine learning technique and the process itself, such as the technical causes of bearing failures. As a result, this section contains details on a bearing's design and the different defects that might affect bearings. On the whole, bearings consist of the inner and external rings, the caged rolling elements, and the spacer in four pieces. Balls are typically used as rolling components in spindle bearings. [29] As depicted in Figure 3., the space between the outer and inner rings is where the balls are located. The cage keeps the balls' relative positions to one another in place. The issue may result from each of the four bearing parts developing a problem, although the inner and outer rings are considered the site of 90% of all faults. [43] This might be because the rings are constantly stressed, whereas the balls rotate & a cage must support their point of contact changes continually, and no weight. The balls rolling across the surface of the rings cause each fault type to occur at a distinct fault-specific frequency.

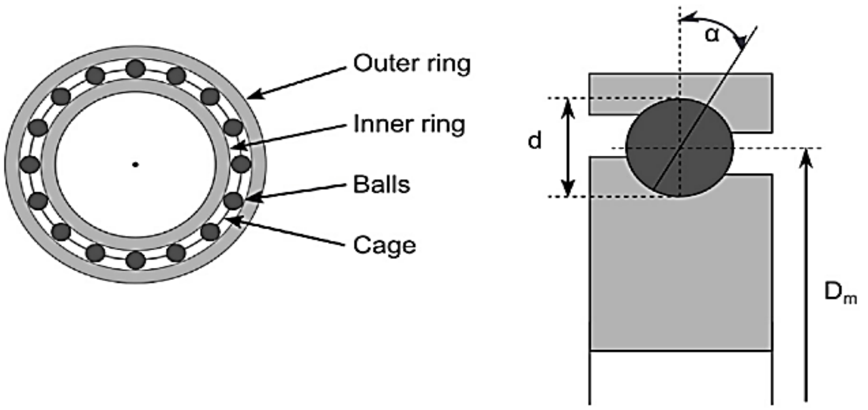

Figure 3. Views of the Front and Side of a Ball Bearing's Structure.

4.1 Bearing Conditions Monitoring

Various methods for analysing bearing conditions were utilised, as detailed in Section 2, depending on the fault kind, location, or the Degree of the defect. Classifying fault magnitude based on fault size or category is an option. Along with varied circumstances, several data input sources are used in the bearing defect detection process. The majority of research studies made use of bearing vibration data. A handful of the studies [24] use stator current input data to track the bearing's health.

4.2 Classification of Machine Learning Methods

Machine learning, commonly known as artificial intelligence (AI), has seen a lot of research in recent years. This branch of computer science works with data and algorithm knowledge and mimics how humans learn while increasing accuracy. With the aid of the field, apply in various areas including Robotics, Automotive, Mechanical, Hospitality Analytics, Decision Making, Education, & Data Analytics Applications in the Oil and Gas Industry. What is artificial intelligence? Intelligence in this context refers to the capacity for thought, visualisation, design, memorisation, comprehension of the designs, decision-making to account for change, and experience-based learning. Making machines behave like humans faster than people can is the primary goal of artificial intelligence. It can be divided into two parts: Strong AI and Weak AI. The following Figure 4. shows the broad classification of the machine learning methods.

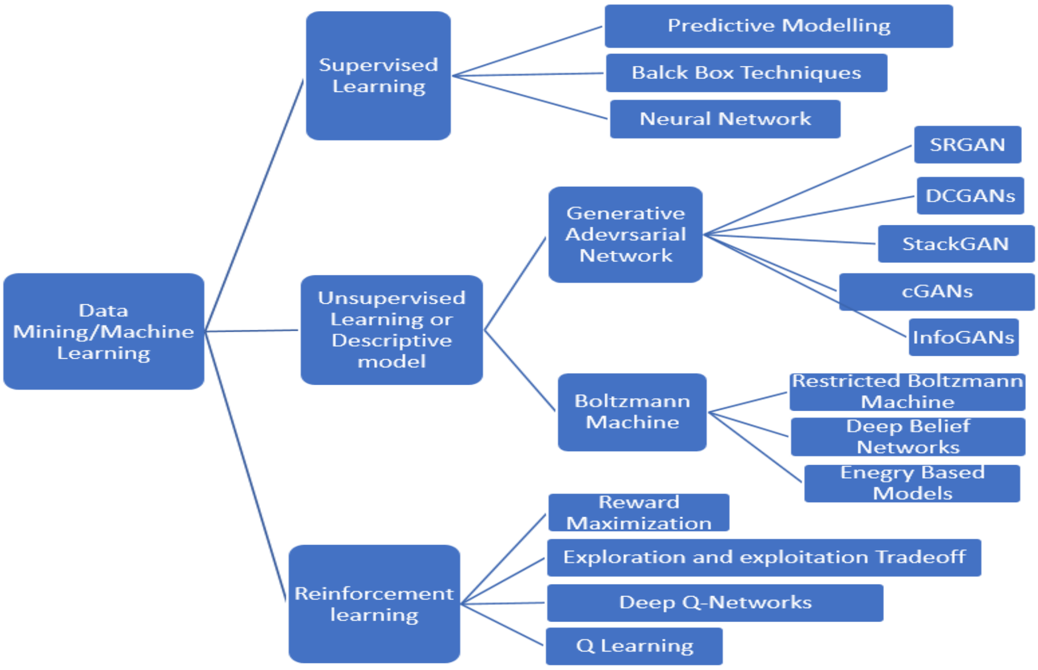

Figure 4. Classification of Machine Learning Techniques.

A machine learning system picks up on patterns in data and uses prior data to develop prediction models. It then predicts the results for fresh data as it comes in. How well the output is expected depends on the amount of data utilised; a larger data set simplifies building a model that more accurately forecasts the result. We don't need to write any code to conduct specific predictions for a complex problem; instead, we can feed the data into general algorithms, which use the data to create logic and predict outcomes. The block diagram in Figure 5. explains the working of the machine learning algorithm:

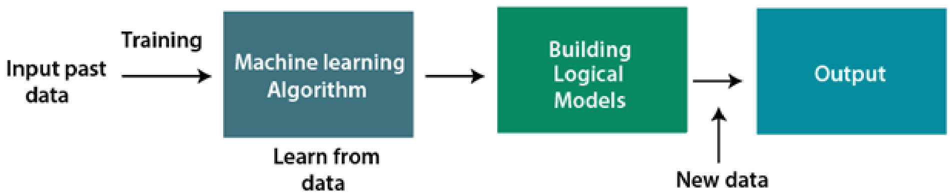

Figure 5. Machine Learning Flow Wireframe.

Using sample labelled data, we train the machine learning system using the supervised learning technique, and then we see it predict the result. The goal of supervised learning is to map input and output data. A pupil's learning under the teacher's supervision is the same as supervised learning because it is based on supervision. Unsupervised learning is when a computer picks up new skills without a human's guidance. Unlabelled, uncategorized, or unclassified data are used to train the machine before the algorithm can make decisions about the data on its own. Unsupervised learning aims to rearrange the incoming data into fresh features or a collection of objects with linked patterns. Using Rewards in Education: A learning agent in a reinforcement learning system, correct actions are rewarded, and mistakes are punished for each incorrect action. As a result of this feedback, the agent naturally learns and gets better. During reinforcement learning, the agent explores and interacts with the environment. An agent performs better because its goal is to accumulate the most points. In general, artificial neural networks and convolutional neural networks have been used in several studies for bearing analysis from the previous study publication. Markov Models (MM), Support Vector Machines (SVM), Linear Discriminant Analysis (LDA), the Mahalanobis Taguchi System (MTS), and fuzzy logic-based techniques. The sections that follow provide a thorough examination of the machine methods used in machine learning. Following a brief introduction, Table 1 lists the critical works on the topic.

4.3 Summary classification of Artificial Learning Techniques

This section overviews the various artificial intelligence techniques currently used for bearing defect analysis across diverse datasets. A collection of pertinent articles in this field is provided in Table 1. Many researchers used a dataset that Case Western Reserve University offered; it contains data on various kinds of failure and fault magnitude.

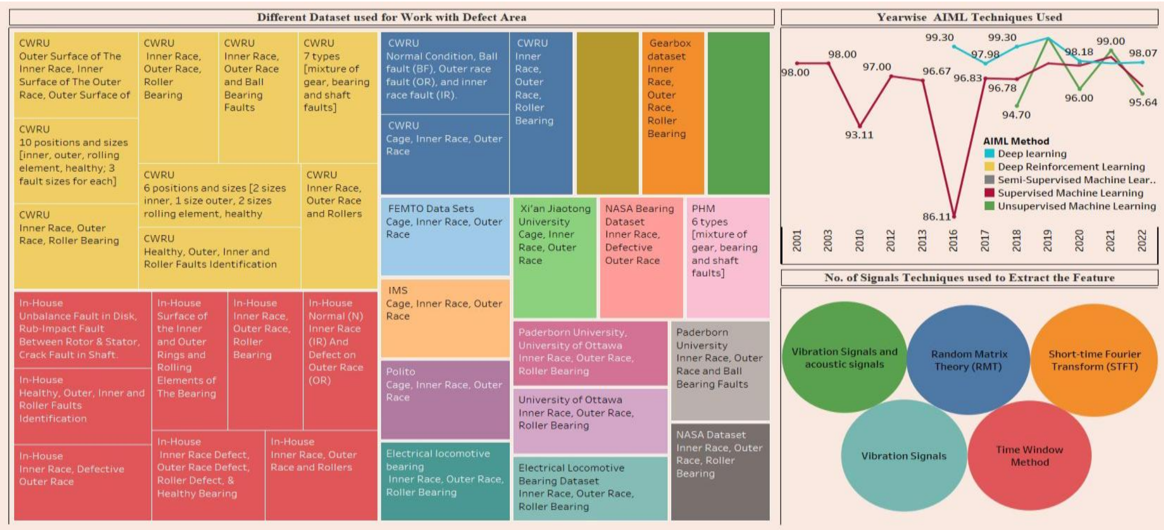

Figure 6. Different Datasets were used for Work with the Defect Area, Year-wise AI-ML Techniques were used, and the Number of Signal Techniques used to Extract the Feature.

A test environment is the foundation of most datasets in use, producing vibration data free of noise. Most of the data in the research publications that have been reviewed are of a single-bearing type. Multiple failures on one bearing have scarcely ever been investigated; instead, investigations have primarily focused on the roller race, inner race, outer race, and defects. The outcomes of the many studies are positive. This does not necessarily imply that these are the best options, either. There are techniques to improve the outcome and receive a high grade. Most datasets typically capture the record at a continuous speed and load for a single bearing type. In Figure 5, the first chart is the Tree Map, which shows the several data sets the authors employed for their work on bearing. They concentrated on examining the different defect parameters of bearing areas. In the tree map, the rectangular size is focused on accuracy, and colour indicates the other data sets mentioned in the Table. 1. The second chart shows the accuracy attained using various AIML approaches from 2001 to 2022, such as Unsupervised Machine Learning, Supervised Machine Learning, Deep Learning, Semi-Supervised Machine Learning, and Deep Reinforcement Learning. Different authors employed in their work mostly used supervised machine learning methods. The third chart is a bubble chart that shows the vibration signals, acoustic signals, short-time Fourier transform (STFT), and random matrix theory (RMT) signals methods utilised for feature extraction.

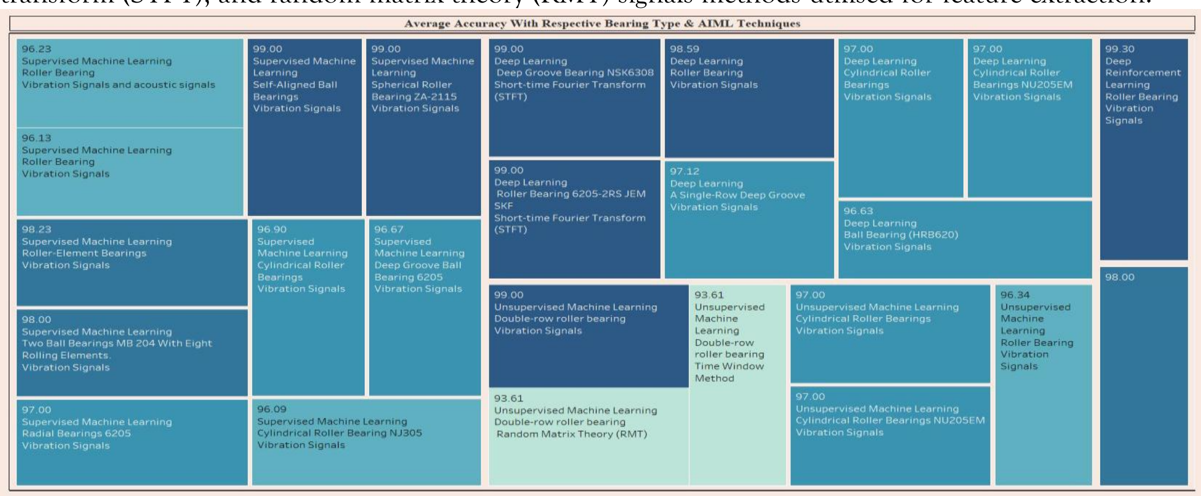

Figure 7. Average Accuracy with Respective Bearing Type, Signal Methods & AIML Techniques.

Figure 7 describes the Tree Map chart colour shade, showing the accuracy of the AIML approaches. The rectangular size denotes the various bearings employed by the author for the research.

5. FORECAST AND IMPENDING CHALLENGES

This study focuses on preceding condition-monitoring approaches and analysing bearing faults using traditional machine-learning techniques. Bearing flaws, remaining usable life, and the CM and FDD approach are considered essential factors in the development of fault detection. However, the future trends of AI methods in areas like operational circumstances, noise sensitivity, and indoor/outdoor workspace present this sector with several obstacles. It is imperative to create extremely precise sensors that are also quick, cordless, cost-effective, and energy-efficient. Further research on expert intelligent systems is necessary to enhance diagnostic effectiveness. An automated, wireless diagnosis, operational, constant, and strategic approach with improved exposure competencies founded on the Internet of Things, expert systems, and AI is possible. It is essential to investigate fault severity identification and diagnosis methods using linear, non-linear, localised, and compound faults. The big data dilemma is how to swiftly select valuable diagnostic data from vast data collected by various sensors. An efficient heterogeneous methodology should be developed using data from several sensors.

6. CONCLUSION

In the present paper, the research work is summarised into three central regions:

1. To compile the most recent advancements in vibration monitoring techniques' longitudinal, frequency, and locational frequency domains for identifying bearing defects. To lessen the production & economic wounds occurring in the trade due to rotating machine faults, researchers have been working hard to calculate the defect's remaining bearing life.
2. The most recent developments in signal processing techniques have been applied to feature extraction in time-frequency analysis. Time-frequency analysis is highly helpful in determining both steady and erratic vibration signals. Another critical area of research is the ability to translate findings from one circumstance to another. These circumstances include various bearing and process variables.
3. This study shows that supervised and Deep learning methods, such as SVM, ANN, and CNN, are the best for diagnosing bearings. They use extensive historical and real-time data to affect the experimental work carried out under various loadings, speeds, scenarios, and other parameters taken into account for bearing conditions.

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Appendix-A

Table 1. Review of different methods to detect fault diagnosis of bearing

S N.	**Research Year**	**Data Set**	**Bearing**	**Defect Area**	**Signals**	**Signal Analysis Technique**	**AIML Method**	**Classification Techniques**	**Accuracy (%)**
1	2001	In-House	Roller Bearing	Healthy, Outer, Inner, and Roller Faults Identification	Vibration Signals	Time Domain & Frequency Domain	Supervised Machine Learning	Artificial Neural Network	98.00
2	2003	In-House	Two Ball Bearings MB 204 With Eight Rolling Elements.	Healthy, Outer, Inner, and Roller Faults Identification	Vibration Signals	Signal Conditioning and Data Acquisition	Supervised Machine Learning	Multilayer Perceptron (MLP) With BP Algorithm	98.00
								Probabilistic Neural Network	98.00
								Radial Basis Function (RBF) Network	98.00
3	2010	CWRU	Roller Bearing	Healthy, Outer, Inner, and Roller Faults Identification	Vibration Signals	Discrete Fourier Transform	Supervised Machine Learning	Neuro-fuzzy Min-Max Classifiers	98.24
						Laplace wavelet analysis	Supervised Machine Learning	Multilayer Perceptron (MLP) With BP Algorithm	100.00
								Probabilistic Neural Network	72.10
								Radial Basis Function (RBF) Network	97.00
			Roller-Element Bearings	Healthy, Outer, Inner, and Roller Faults Identification	Vibration Signals	Discrete Fourier Transform	Supervised Machine Learning	Support Vector Machine	98.23

4	2012	In-House	Radial Bearings 6205	Inner Race, Outer Race, and Rollers	Vibration Signals	Time And Frequency Domain	Supervised Machine Learning	Adaptive Neuro-Fuzzy Inference Systems	----
								Artificial Neural Network	97.00
5	2013	In-House	Deep Groove Ball Bearing 6205	Normal (N) Inner Race (IR) And Defect on Outer Race (OR)	Vibration Signals	Discrete Wavelet Transform	Supervised Machine Learning	Artificial Neural Network	96.67
6	2016	CWRU	Roller Bearing	10 positions and sizes [inner, outer, rolling element, healthy; 3 fault sizes for each]	Vibration Signals	Time domain	Deep Learning	Convolutional Neural Network	99.30

S N.	Year	Data Set	Bearing	Defect Area	Signals	Signal Analysis Technique	AIML Method	Classification Techniques	Accuracy (%)
6	2016	In-House	Cylindrical Roller Bearing NJ305	Inner Race, Outer Race, and Rollers	Vibration Signals	Daubechies Wavelet	Supervised Machine Learning	Neural Network	86.11
			Roller Bearing	Inner Race, Outer Race, and Rollers	Vibration Signals	Daubechies Wavelet	Supervised Machine Learning	Support Vector Machine	86.11
7	2017	CWRU	Roller Bearing	6 positions and sizes [2 sizes inner, one size outer,	Vibration Signals	Time-frequency domain: WPI	Supervised Machine Learning	ConvNet	96.83

				two sizes rolling element, healthy					
				7 types [mixture of gear, bearing, and shaft faults]	Vibration Signals	Time domain features Frequency domain	Deep Learning	Convolutional Neural Network	97.98
		PHM	Roller Bearing	6 types [mixture of gear, bearing, and shaft faults]	Vibration Signals	Time domain features Frequency domain	Deep Learning	Convolutional Neural Network	97.98
8	2018	CWRU	Roller Bearing	Inner Race, Outer Race, and Rollers	Vibration Signals	Mixed Time-Frequency Vibration Signals	Supervised Machine Learning	Generative Adversarial Network	90.10
							Unsupervised Machine Learning	Principal Component Analysis	90.10
								Categorical Adversarial Autoencoder (CatAAE)	90.10
		In-House	Roller Bearing		Vibration Signals	Acoustic Signals	Deep Learning	Convolution Residual Network	99.30
							Deep Reinforcement Learning	MOEA/DD	99.30
							Unsupervised Machine Learning	Deep Autoencoders (DAE)	99.30
								Deep Belief Network (DBN)	99.30
8	2008	In-House	Self-Aligned	Inner Race, Outer	Vibration Signals	Wavelet Transform (Db8)	Supervised Machine Learning	Artificial Neural Network	99.00

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			Ball Bearings	Race, and Rollers				Support Vector Machine	99.00
								k-nearest neighbors	99.00

SN.	Year	Data Set	Bearing	Defect Area	Signals	Signal Analysis Technique	AIML M
9	2019	Agricultural Machine	Roller Bearing	Outer Surface of The Inner Race, Inner Surface of The Outer Race, Outer Surface of The Roller	Vibration Signals	Envelope Analysis	Unsupe Machine Learning
		CWRU	Roller Bearing	Outer Surface of The Inner Race, Inner Surface of The Outer Race, Outer Surface of The Roller	Vibration Signals	Envelope Analysis	Deep lea
		In-House	Cylindrical Roller Bearings	Inner Race, Outer Race, and Rollers	Vibration Signals	Daubechies Wavelet	Supervis Machine Learning
10	2020	CWRU	Roller Bearing	Cage, Inner Race, Outer Race	Vibration Signals	Continuous Wavelet Transforms	Deep Le
		FEMTO Data Sets	Roller Bearing	Cage, Inner Race, Outer Race	Vibration Signals	Nonlinear Filtering Process	Supervis Machine Learning
						Spectral Amplitude Modulation	Supervis Machine Learning
		IMAGES	Roller Bearing	Cage, Inner Race, Outer Race	Vibration Signals	Nonlinear Filtering Process	Supervis Machine Learning
						Spectral Amplitude Modulation	Supervis Machine Learning
		Xi'an Jiaotong University	Roller Bearing	Cage, Inner Race, Outer Race	Vibration Signals	Continuous Wavelet Transforms	Deep Le
10	2020	CWRU	Roller Bearing	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Data Augmentation Methods	Supervis Machine Learning

				Inner Race, Outer Race, and Ball Bearing Faults	Vibration Signals	Time Domain & Frequency Domain of Raw Signals and Synthesised Signals	Supervis Machine Learnin

S N.	**Year**	**Data Set**	**Bearing**	**Defect Area**	**Signals**	**Signal Analysis Technique**	**AIML Method**	**Classification Techniques**	**Accuracy (%)**
10	2020	Electrical locomotive bearing	Roller Bearing	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Data Augmentation Methods	Deep Learning	CNN	98.53
							Supervised Machine Learning	Supervised Auto-Encoder	98.53
								Support Vector Machine	98.53
		In-House	Cylindrical Roller Bearing NJ305	Inner Race Defect, Outer Race Defect, Roller Defect, & Healthy Bearing	Vibration Signals	Wavelet Packet Decomposition with the Use of Mother Wavelet's sym20	Supervised Machine Learning	Artificial Neural Network	96.00
								Support Vector Machine	95.60
			Cylindrical Roller Bearings	Inner Race Defect, Outer Race Defect, Roller Defect, & Healthy Bearing	Vibration Signals	Wavelet Packet Decomposition with the Use of Mother Wavelet's sym20	Supervised Machine Learning	Artificial Neural Network	96.00
								Support Vector Machine	95.60
			Roller Bearing	Inner Race, Defect	Vibration Signals	Frequency-Sliced	Semi-Supervised	Fuzzy C-Means	98.00

				ive Outer Race		Wavelet Transform	Machine Learning		
		NASA Bearing Dataset	Roller Bearing	Inner Race, Defective Outer Race	Vibration Signals	Empirical Wavelet Transforms	Deep Learning	Convolutional Neural Network	98.00
		Paderborn University	Roller Bearing	Inner Race, Outer Race, and Ball Bearing Faults	Vibration Signals	Multiple time domain features extracted from the raw signal	Supervised Machine Learning	k-nearest neighbors	96.00
							Unsupervised Machine Learning	Decision tree	96.00
								Random forest	96.00
		Polito	Roller Bearing	Cage, Inner Race, Outer Race	Vibration Signals	Nonlinear Filtering Process	Supervised Machine Learning	K-Nearest Neighbours	98.96
		Polito	Roller Bearing	Cage, Inner Race, Outer Race	Vibration Signals	Spectral Amplitude Modulation	Supervised Machine Learning	Support Vector Machine	98.96
11	2021	CWRU	Double-row roller bearing	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Time Domain & Frequency Domain	Unsupervised Machine Learning	Black-Box Models	99.00
			Roller Bearing	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Time Domain & Frequency Domain	Supervised Machine Learning	Generative Adversarial Network	96.35
			Spherical Roller Bearing ZA-2115	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Time Domain & Frequency Domain	Supervised Machine Learning	Root Cause Analysis	99.00

SN.	Year	Data Set	Bearing	Defect Area	Signals	Signal Analysis Technique	AIML Method
11	2021	Gearbox dataset	Double-row roller bearing	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Time Domain & Frequency Domain	Unsupervised Machine Learning
			Spherical Roller Bearing ZA-2115	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Time Domain & Frequency Domain	Supervised Machine Learning
		Mechanical fault dataset	Double-row roller bearing	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Time Domain & Frequency Domain	Unsupervised Machine Learning
			Spherical Roller Bearing ZA-2115	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Time Domain & Frequency Domain	Supervised Machine Learning
		Electrical Locomotive Bearing Dataset	Roller Bearing	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Time Domain & Frequency Domain	Supervised Machine Learning
		In-House	Cylindrical Roller Bearing NJ305	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Mother (Wavelet) Wavelet Analysis	Supervised Machine Learning
			Roller Bearing	The surface of the Inner and Outer Rings and Rolling Elements of the Bearing	Vibration Signals	Wavelet Transform	Deep Learning
							Supervised Machine Learning
12	2022	CWRU	A Single-Row Deep Groove	Inner Race, Outer Race, Roller Bearing	Vibration Signals	ASCAE	Deep Learning
			Ball Bearing (HRB620)	Inner Race, Outer Race, Roller Bearing	Vibration Signals	ASCAE	Deep Learning
			Roller Bearing	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Wavelet Transform	Deep Learning
				Normal Condition, Ball fault (BF), Outer race fault (OR), and inner race fault (IR).	Vibration Signals	Data Augmentation	Deep Learning

S N.	Ye ar	Data Set	Bearing	Defe ct Area	Signals	Signal Analysis Technique	AIML Method	Classificat ion	Accur acy (%)

								Techniques	
12	2022	CWRU	Deep Groove Bearing NSK6308	Inner Race, Outer Race, Roller Bearing	Short-time Fourier Transform (STFT)	Multiscale Clipping Fusion (MSCF) Data Augmentation Technique	Deep Learning	MCNN	99.00
			Roller Bearing 6205-2RS JEM SKF	Inner Race, Outer Race, Roller Bearing	Short-time Fourier Transform (STFT)	Multiscale Clipping Fusion (MSCF) Data Augmentation Technique	Deep Learning	MCNN	99.00
		In-house	Cylindrical Roller Bearings	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Time Domain & Frequency Domain	Deep Learning	Deep Separable Convolution	97.00
							Unsupervised Machine Learning	Spatial Dropout Regularisation	97.00
			Cylindrical Roller Bearings NU205EM	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Time Domain & Frequency Domain	Deep Learning	Deep Separable Convolution	97.00
							Unsupervised Machine Learning	Spatial Dropout Regularisation	97.00
			Roller Bearing	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Wavelet Transform	Deep Learning	FRN-CNN	97.70
		In-house	Roller Bearing	Inner Race, Outer	Vibration Signals and	MSAF-20-MULTIEXPANDED	Supervised Machine Learning	MFE-SVM, RWE Method	96.23

				Race, Roller Bearing	Acoustic Signals			TSFDR-LDA	96.23
		NASA Dataset	Double-row roller bearing	Inner Race, Outer Race, Roller Bearing	Random Matrix Theory (RMT)	Time Domain & Frequency Domain	Unsupervised Machine Learning	Principal Component Analysis	93.61
					Time Window Method	Time Domain & Frequency Domain	Unsupervised Machine Learning	Principal Component Analysis	93.61
		Paderborn University, University of Ottawa	Roller Bearing	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Wavelet Transform	Deep Learning	FRN-CNN	97.70
		University of Ottawa	Roller Bearing	Inner Race, Outer Race, Roller Bearing	Vibration Signals	Wavelet Transform	Deep Learning	FRN-CNN	97.70