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Fault Diagnosis and Prediction of Remaining Useful Life (RUL) of Rolling Element Bearing : A review state of art

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ABSTRACT

Fault diagnosis of rolling element bearings is a critical aspect of machine maintenance and reliability. Bearings are extensively used in various industrial applications, and their failure can lead to costly downtime and equipment damage. Rotating machinery under continuous overload conditions can indeed significantly degrade bearing life and lead to various other issues. To identify issues in rolling element bearings (REB), several techniques and methods are employed. Diagnosing faults in ball bearings while simultaneously estimating the Remaining Useful Life (RUL) of the bearing is a crucial aspect of predictive maintenance. This can be achieved through a combination of signal processing techniques, machine learning methods, and RUL prediction models. The estimation of a bearing Remaining Useful Life (RUL) is of significant importance in predictive maintenance strategies to avoid unexpected failures, reduce downtime, and optimize maintenance costs. This literature review aims to explore the methodologies, techniques, and advancements in predicting the remaining useful life of bearings.

Keywords: Ball Bearing, Fault Diagnosis Techniques, Remaining Useful Life (RUL), Rolling Element Bearings

NOMENCLATURE			
Fs	Shaft Rotational Frequency	*Pd*	Pitch diameter (mm)
Nb	No. of balls	θ	contact angle in degree
Bd	Ball diameter (mm)		

1. INTRODUCTION

Rolling element bearings find widespread use in various rotating machinery applications. The failure of ball bearings stands as a primary cause for breakdowns in rotating machinery. To avoid prevent these kinds of failures, there are various condition monitoring techniques have been developed. Ball bearings are used nearly 90% of all rotating machinery [1]. Ball bearings are widely employed across various rotating machinery applications, with bearing failure representing a main cause to the breakdown of such machinery [2-3]. Bearing faults account for 44% of motor breakdowns in the industry [4]. Several condition monitoring techniques exist to prevent bearing failures, including vibration monitoring, acoustic emission, wear debris detection, and thermography. Among these methods, vibration analysis stands as a widely utilized approach for detecting bearing faults [5-8]. Local defects in ball bearing contain pits, cracks and spalls on the rolling surfaces. The predominant failure mode seen in rolling element bearings is the occurrence of spalling in the inner and outer races or within the rolling elements. The spalling is caused by fatigue [9-12]. Patel et al. [13] reported that fatigue causes local defects on mating bearing components, such as spalls, pits, and fractures. Dents, scratches, fretting, spalling, incorrect fittings, and holes in the raceways are repeated kinds of bearing faults discussed [14–17]. Data-driven techniques, including machine learning and statistical analysis, are commonly used to develop predictive models based on historical data from similar bearings. These models can then be used to predict the remaining life of a bearing under current operating conditions. It's important to note that accurately predicting RUL can be challenging due to the complex and dynamic nature of mechanical systems. Factors such as variations in operating conditions, manufacturing quality, and environmental factors can impact the accuracy of RUL predictions. Therefore, RUL estimates are often accompanied by uncertainty ranges to provide a better understanding of the potential variability in the predictions.

2. DEFECTS IN BEARINGS

Premature bearing failures can be produced by a variety of factors, such as fatigue, plastic deformation, wear, brinelling, inadequate lubrication, improper installation, corrosion and flawed design. Recognizing these issues and the vibrations they generate is crucial for effectively monitoring the condition of bearings. These defects generally divided into two types: distributed defects and localized defects. Figure 1 shows the defects in ball bearing components.

2.1. Distributed Defects

It involves surface roughness, waviness and off-size rolling elements, misaligned races[18, 19]. Variations in the contact force between raceways and rolling elements within these flaws result in vibrations. The vibration response from distributed defects is primarily employed for quality inspection and the ongoing monitoring of bearing conditions.

2.2. Localized Defects

This group of defects covers spalls, pits and cracks which can progress across the rolling surfaces. Mostly, spalling stands out as the primary mode of failure. Typically, a fatigue crack initiates beneath the surface and progresses towards it until the material gives way, resulting in localized defects. According to Bentley [20], approximately 90% of all bearing faults involve damage to the rolling elements, outer race, inner race, and cage due to these localized defects.

A rolling-element bearing, comprises four primary components: (i) ball, alternatively known as the roller or ball (ii) Outer race (iii) Inner race (iv) Cage. Faults can occur on these components, as depicted in Figure 1, or may even present as general damage affecting the entire device.

3. BEARINGS FAULT DIAGNOSIS USING SIGNAL PROCESSING TECHNIQUES

The vibration signal produced by the defective bearing can be analyzed in the time domain, frequency domain, or both time- frequency domains (Figure 2).

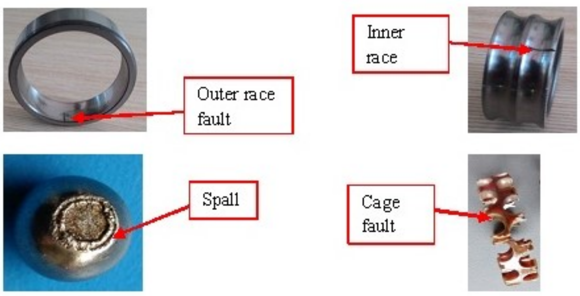

Figure 1. Ball bearing component defects [104]

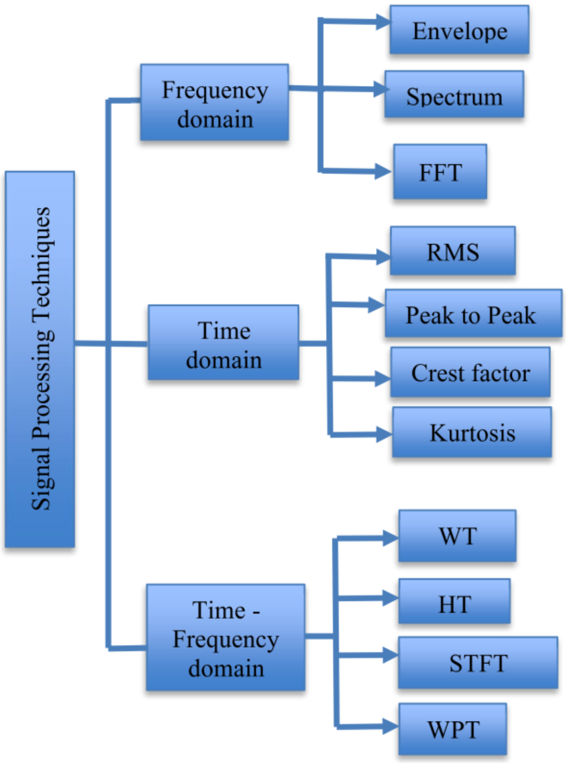

Figure 2. Signal processing techniques

3.1. Time Domain

Time domain techniques rely on the statistical characteristics of the signal waveform over time. Root Mean Square (RMS) value [12, 15], Kurtosis [15, 16], Peak value [15] Crest Factor [15], and synchronous averaging [17] parameters are carried out by researchers. Rafsanjani et al. [21] presented an analytical model for ball bearings featuring localized defects on the outer race, inner race and ball. They reported that the utility of this model for design, machine condition monitoring and predictive maintenance. Karacay and Akturk [22] highlighted that many researchers have investigated ball bearing defects both theoretically and experimentally, examining their impact on vibration levels through scalar parameters like Root Mean Square (RMS), pk-pk value, kurtosis and crest factor. Wang and team [23] presented the adaptive spectral kurtosis for detecting multiple faults in single row ball bearings. They developed a theoretical model for multiple bearing faults and demonstrated that their method could efficiently extract features of multiple bearing faults, especially in the presence of substantial background noise, outperforming techniques such as the Krtogram and Protrugram.

3.2. Frequency Domain Approach

The predominant method for diagnosing faults in bearings is through frequency domain. Vibration signals in the time domain are converted into discrete frequency components by using a Fast Fourier Transform (FFT).

The bearing characteristic frequency is depending upon both the bearing geometry and the specific type of bearing defect present.

The following equation gives the frequencies that correspond to characteristic faults.

BPFI (Ball pass frequency-Inner)

$$= \frac{Nb}{2}\left(1 - \frac{Bd}{Pd}\cos\theta\right) \times F_s \quad (1)$$

BPFO (Ball pass frequency-Outer)

$$= \frac{Nb}{2}\left(1 - \frac{Bd}{Pd}\cos\theta\right) \times F_s \quad (2)$$

FTF (Fundamental train frequency) (Cage)

$$= \frac{1}{2}\left(1 - \frac{Bd}{Pd}\cos\theta\right) \times F_s \quad (3)$$

BSF (Ball spin frequency)

$$= \frac{Pd}{2Bd}\left(1 - \left(\frac{Bd}{Pd}\right)^2 (\cos\theta)^2\right) \times F_s \quad (4)$$

Abu-Zeid and Abdel-Rahman [24] investigated faulty bearings and observed that they produce elevated vibrations at higher frequencies, along with increased energy consumption. Various researchers have utilized different parameters of vibration signals to analyze bearing faults. The FFT spectrum insights into the types of defects present. Researcher conducted an experiment on ball bearing using FFT spectrum analysis to predict the locations of faults. Kiral and Karagülle [25] introduced dynamic loading models within the finite element method for both sound and defective single row ball bearings. They explored the impact of rotational speed on the diagnosis of rolling element bearings. They found that both time and frequency domain techniques are responsive to alterations in rotational speeds, impacting diagnostic accuracy. Choy and colleagues [26] investigated vibration associated with defective ball bearings. They explored various analysis methods, including time domain averaging, frequency component averaging, and modified Poincare maps. They observed average time signal technique did not distinctly elucidate information about faulty bearings. In contrast, modified Poincare map and average frequency component and techniques offered clearer insights into the nature of the faulty bearing. Feiyun Cong et al. [27] analyzed dynamic load of the rotor bearing system through a fault model for rolling bearings. The rotor bearing vibration model was analyzed by integrating dynamic responses with the formulation of fault signals unique to rolling element bearings. Minmin Xu et al. [28] verified how the increase in internal radial clearance in bearing excites the envelope spectrum in BPFO and it has been further noticed that with introduced gear spalling exceeds the amplitude of BPFO. Tabasi et al. [29] used frequency domain for bearing fault diagnosis of induction motor. They reported that the temperature and load changes have minimal effect on the magnitudes of the frequency indicators.

3.3. Time-Frequency Domain

Time-frequency techniques possess the capability to depict machinery fault patterns in both time and frequency domains, especially when dealing with non-stationary signals. Several researchers were used STFT, Wavelet transform, Hilbert Transform for fault diagnosis of bearing.

Qiu [30] employed two denoising-based methods: wavelet decomposition-based and wavelet filter-based approaches. He concluded that the wavelet filter-based approach is more effective for detecting weak signals. Wang and Gao [31] utilized a combination of fast Fourier transform and wavelet transforms to improve feature extraction for enhanced analysis. Junsheng [32] introduced scale wavelet power spectrum comparison and auto-correlation analysis as methods for time-wavelet power assessment. Nikolaou and Antoniadis [33] presented a wavelet packet transform (WPT) for single row ball bearing faults. They showed WPT is an effective method for identifying the nature of ball bearing faults. Kumar et al.[34] presented the application of the Symlet wavelet for signal decomposition aimed at extracting the fault size on the outer race of a taper roller bearing. Kankar et al. [35-38] used wavelet transform (WT) and statistical features for a single row ball bearing fault diagnosis. Additionally, artificial neural networks (ANN), self-organizing maps (SOM), and support vector machines (SVM) were employed for fault classifications. They observed that the SVM exhibited superior diagnostic performance compared to both SOM and ANN. The Short-Time Fourier Transform (STFT), Hilbert Transform (HT), discrete and continuous Wavelet Transform (WT), along with envelope analysis, are frequently employed methods for feature extraction [39–42]. Han et al. [43] proposed the frequency domain sparse optimization algorithm for bearing fault finding, sparse representation has proved to be a promising technique to extract the repetitive transient component from noisy signals. A non-convex penalty called generalized logarithm (G-log) penalty which increases the sparsity and reduces noise disturbance has been suggested by Ziwei Zhang et al. [44]. Rubén Medina et al. [45] employed Peaks detection and Poincaré plot for cardiac electrocardiographic signal analysis novel method for detection of gear and bearing faults and SVM has been adopted for fault classification. The Poincaré method is a methodological tool which was used for analyzing the non-linear dynamics of systems has a chaotic behavior. Xu et al. [46] used conventional envelope analysis and time-domain parameters, such as RMS and kurtosis for bearing fault diagnosis. Cherif et al. [47] proposed two approaches such as Hilbert spectral envelope and machine learning based on random forests. Using extracted frequency characteristics as innovative features for bearing fault detection, along with automated localization of the faulty component, achieved a remarkable classification rate of 99.94%. Patel and Giri [48] proposed bearing damage index (BDI) for condition monitoring of ball bearing. They used. Fast Fourier Transform (FFT) and Hilbert transform (HT) has been carried out in order to identify the inner raceway fault (IRF), outer raceway faults. Zuhua Jiang et al. [49] suggested a time-frequency spectral amplitude modulation technique has been adopted and obtain amplitudes in the time-frequency domain through the short-time Fourier transform and adjusting them with various weights enables the extraction of more precise and detailed information regarding amplitudes, facilitating a more insightful interpretation of bearing faults. Dezun Zhao et al. [50] suggested compound fault diagnosis has been carried out by generalized demodulation (GD) algorithm. The generalized demodulation algorithm is a signal processing approach which has been successfully applied to amplitude-modulated and frequency-modulated signals processing under variable speed conditions. Tianyang Wang et al. [51] applied Rapid spectral kurtosis (SK) analysis in conjunction with the short time Fourier transform (STFT) results in a time-frequency representation (TFR) of the filtered signal, featuring distinct fault-revealing trend lines. This enables the extraction of instantaneous fault characteristic frequency (IFCF) from the TFR. IFCF to convert the non-stationary time-domain signal into the stationary fault phase angle (FPA) domain signal which transform into the fault characteristic order (FCO) for identification of fault. Ensemble empirical mode decomposition (EEMD) method decomposed vibration signal into intrinsic mode functions (IMF) has been used by Khaire and Phalle [52] in its literature and adopted principal component analysis (PCA) technique to effectively extracted faulty signals. Hongfeng Tao et al. [53] introduced an unsupervised time-frequency information approach for diagnosing bearing faults. They employed wavelet packet decomposition (WPD) for handling non-stationary signals, and utilized a convolutional network with parameter sharing to extract deep features relevant to bearing faults. Qiuyu Song and team [54] proposed a multichannel mode extraction (SMME) technique for diagnosing bearing faults. Additionally, they introduced multichannel single-step decomposition (MSD) facilitated by the detected Center Frequencies to directly acquire the corresponding modes across all channels.

4. BEARING FAULT DIAGNOSIS USING MACHINE LEARNING TECHNIQUES

In recent decades, crucial machine learning models like Support Vector Machines (SVM), k- Nearest Neighbors (KNN), and Convolutional Neural Networks (CNN) have experienced substantial enhancements in the field of bearing fault diagnosis. A concise overview of the primary classical machine learning method in applications related to bearing fault diagnosis will be provided.

4. 1. Support Vector Machine (SVM)

Support Vector Machines (SVMs) are renowned for their capability to manage high-dimensional data and determine the optimal hyperplane, maximizing the margin between classes, a beneficial trait for fault diagnosis tasks. Nevertheless, their performance is notably affected by the selection of kernel and hyperparameters, underscoring the critical importance of parameter tuning and feature selection in the overall process. The SVM separates data of one class from another by identifying the optimal hyperplane that maximizes the margin width between different classes. Expanding the margin width can alleviate the issue of overlap between different classes. Generally, margins come in two forms: soft and hard. For this research, a soft margin was preferred due to the nonlinear nature of the bearing fault diagnosis, which posed a classification problem. The accuracy of SVM mainly depends on the choice of data collection, kernel function, the threshold function, and the cost parameter (C).

SVM classifier Li et al. [55], Wu et al. [63], Josue Pacheco-Cherrez et al. [67] used Kernel functions (linear, nonlinear, polynomial, RBF and sigmoid) to manipulate the data. A kernel function helps to transform training dataset to facilitate the transformation of a non-linear decision boundary into a linear equation.

The regularization parameters used by researchers to control model complexity and overfitting. The choice of regularization parameter allows researchers to fine-tune the SVM model and optimize the solution. Xin Li et al. [55] adopted Least Square Support Vector Machine (LS-SVM) to extract the features. Deep stacking LS-SVM (DSLS-SVM) ensemble learning model employed to intrinsic rolling bearing fault features from raw vibration signals. DSLS-SVM can autonomously identify and extract relevant features from original signals. LS-SVM used to replace inequality constraints to equality constraints by minimizing the least square errors and margins errors. Stacking-based representation learning (S-RL) contributes to extend shallow model to deep learning model through modularization. DSLS-SVM trained each binary LS-SVM separately without iteration by one-against-all strategy. Similarly, some researchers Zhu et al. [59], Tang et al. [105] adopted multi-class SVM classifier to evaluate the complication of the bearing signal effectively [59] and extracted 20 features by multiple class feature selection approach and optimized features have been trained and tested for multi-class SVM classifier. Strategy likes ‘one against one’ or ‘one against rest’ has been used for multi-class classification. Tang et al. [105] adopted empirical mode decomposition and auto regression to extract feature. They applied multi-class SVM for Classification and wavelet decomposition technique based support vector machine for fault prediction. SVM classifier also employed to predict RUL of bearing by the researcher [61]. Relative root mean square [RRMS] has been used as input to SVM to predict the degradation rate of bearing.

4. 2. K-Nearest Neighbor (k-NN) Algorithm

The k-NN is a robust and non-parametric learning method applicable to solve classification as well as regression problems. Instead of examining a discriminative function, this algorithm memorizes the training dataset. Memorizing the training sets helps in steering clear of errors. The non-parametric aspect of the model is not predetermined and varies based on the sample size. Challenges of k-NN encompass its substantial memory usage, extended forecast time, and extreme sensitivity to unrelated features. It utilizes the k-nearest training samples in proximity to the test results to perform data classification. k-NN primarily relies on 2 key factors: 1st a distance metric to measure the distance between 2 points, 2nd the parameter "k" which determines the no. of neighbors. “k” value determines the shape of the decision boundary. Increasing the "k" value during the neighbor selection process leads to a smoother boundary. Lower k values technically establish a hard boundary state, contributing for precise match with low bias and high variance.

K-Nearest Neighbor [KNN] performs classification through the numbered neighboring samples by calculating Euclidean distance Yan et al.[57], Gunerkar et al. [58], Mehta et al. [60], and Syed Muhammad et al.[88] between the dataset points. Distance between test object xi and each sample xj from training set by equation 1. p denotes the number of features.

$$d = \sqrt{(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 + \ldots + (x_{ip} - x_{jp})^2} \quad (1)$$

KNN can easily classify faults for inner race and outer race in one class and classifier also separate combined faults from kernel boundaries. So, it cannot be classified into single class.

4.3. Convolutional Neural Network (CNN) Algorithm

The deep learning architectures include de-noising autoencoders, deep belief networks, and convolutional neural networks (CNN). CNN is used in health monitoring of rotating machines and bearings. Although CNN are commonly categorized as a machine learning technique, they actually fall under the subclass of artificial intelligence (AI). Both supervised and unsupervised algorithms can be employed on the network. In other words, the network comprises multiple layers, each containing hidden layers responsible for processing and learning from the input data. A CNN was selected among various architectures due to its benefits, including shift-variance, weight sharing, highly accurate, and encoding capabilities.

Li et al. [55] applied a deep stacking least squares SVM for diagnosing faults in rolling bearings. Khodja et al. [56] applied convolutional neural networks (CNN) and vibration spectrum imaging for fault diagnosis of ball bearing. Yan et al. [57] determine instantaneous energy distribution permutation entropy IDEPE of the vibration signal and classify bearing fault through KNN algorithm. Gunerkar et al. [58] proposed artificial neural network (ANN) for diagnosis fault of rolling element bearing.

Zhu et al. [59] employed multi-scale global fuzzy entropy, multiple class feature selection, and SVM for diagnosing faults in rolling element bearings. Mehta et al. [60] employed KNN, linear discriminant analysis, and SVM as classifiers, and subsequently conducted a performance comparison among all three classifiers. Yan [61] et al. suggested a method to classify bearing degradation states through SVM. Su et al. [62] applied SVM for health monitoring and fault finding of machine. Wu et al. [63] utilized a bearing fault diagnosis technique employing a support vector machine based on kernel matrix construction. Data-driven technologies are gaining prominence due to the rising popularity of automation and the ease of data acquisition. These technologies heavily rely on artificial intelligence and machine learning to diagnose issues through extensive analysis and learning from large volumes of data [64, 65]. Hui wang et al. [66] employed Digital Twin (DT) based modified simulation model by the Pearson correlation coefficient (PCC) which is a kind of model online learning. The machine learning techniques has been adopted to predict the probability of faults which can be experimentally verified by the researcher and it has been observed that diagnosis accuracy improves significantly. Josue Pacheco-Cherrez et al. [67] utilized vibration and acoustic signals and varied the accuracy by ML methods. applied Neighborhood component analysis (NCA) method which maximizing the prediction accuracy of regression and classification algorithms for predicting faults in wind turbine bearing has been applied by Bodi Cui et al. [68]. Self-Supervised Learning and Sparse Filtering (GSLSF) method effective with minimal training samples suggested by Guocai Nie et al. [69]. The valuable information obtained through pre-training is utilized in sparse filtering for feature extraction, enhancing the model's generalization performance. Additionally, softmax regression is applied to differentiate and classify different types of failures. Yassine Toumi et al. [70] employed envelope analysis method for feature extraction and multi-layer perceptron (MLP) to classify the faulty condition. Proposed architecture is implemented on the field programmable gate arrays (FPGA) which effectively check the severity of faults. Feng He [71] adopted combination of wavelet packet transform, convolutional neural network (CNN) and the simulated annealing algorithm. The effectiveness of algorithm has been compared with traditional algorithms. Heidari [72] used Rule-based Classifier Ensemble and Genetic Algorithm for fault diagnosis of bearing. They reported that the accuracy of classifier was 98.44%. Attaran et al. [73] presented a novel technique artificial neural network learning for localized faults diagnosis in anti-friction bearings, the results show that the suggested method has 100% accuracy.

Overview for accuracy of the various ML Techniques for bearing faults is shown in Table.1

5. REMAINING USEFUL LIFE (RUL) OF BEARING

Predicting the RUL of a bearing is crucial for maintenance and reliability management in various industries, including manufacturing, aviation, automotive, and more. Predicting the Remaining Useful Life (RUL) of bearings, advanced techniques most likely machine learning and statistical algorithms contribute significantly. These algorithms analyze historical data, sensor readings, and other relevant information to estimate when a bearing is likely to fail or need maintenance. Some algorithms for RUL prediction of bearings are discussed.

Zhang et al. [74] tackled the Remaining Useful Life (RUL) prediction challenge by employing a multi-objective deep

Table 1: Overview for accuracy of the various ML Techniques for bearing faults

References	Data Operations/Processing	ML Techniques	Results	Summary
Li et al [55]	Standard Deviation (SD)	Deep Stacking SL - SVM	Accuracy 99.85 % fault diagnosis	DSLS-SVM has good effectiveness and applicability in rolling bearing fault diagnosis
Youcef Khodja et al. [56]	SNR 4 db to 10 db	CNN	Accuracy 99.62 % fault diagnosis	CNN provides good classification accuracy and with robustness to 10 db SNR added noise.
Yan et al. [57]	Improved Variational Mode Decomposition, Entropy, 3D eigenvector	KNN	Accuracy 100 % for similar fault and 98.38 for Fault Variation	Capable of extracting accurately fault features and distinguish availably multi-class fault patterns.
Gunerkar et al. [58]	Peak, SD	ANN, KNN	Accuracy 99 % success for classifying outer, inner race and Combined fault class and 100 % for all fault class.	The results obtained from ANN are compared with KNN, ANN results proved to be highly effective for classification of multiple faults.
Mehta et al.[60], Mingming Yan et al. [61]	SD, entropy, kurtosis, skewness, and energy	LDA, KNN, SVM	Accuracy achieved 88.9 % and 100% by Mehta. Yan achieved Max. Accuracy of 92.99 % obtained by using SVM	Fault classification was done by using three classifiers, namely, LDA, KNN, and SVM among which SVM outperformed.
Wu C.X et al. [63]	CWT, SVD	kernel matrix based SVM	Max. accuracy with combination of faults with 5 fold cross validation is 99.87 %	KMC-SVM shows higher accuracy while predicting faults location and Severity in REB Defects.
Pacheco-Chérrez et al. [67]	SD, skewness, kurtosis, Petrosian fractal dimension, fisher information ratio and entropy	SVM, PCA, LDA	LDA based on Acoustic and Vibration signals gives more than 98 % frequency compared to SVM and PCA with accuracy around 96.66 %	Classification has been done between various ML methods. 21 statistical features obtained from time domain signals which used in LDA.
Bodi Cui et al. [68]	Neighborhood Component Analysis,	SVM, Naive Bayes, KNN, ANN	KNN method achieved a good performance with classification rate above 90% and Naive Bayes method is relatively poor, below 70%.	Wind turbine bearings, the piece-wise properties data and regression data a three-stage learning algorithm used to extract significant information to predict bearing faults.
Guocai Nie et al. [69]	Sparse filtering, Stacked Auto-encoder, SRC	self-supervised learning and sparse filtering (GSLSF), softmax regression	Accuracy more than 97% achieved by the proposed method	Self-define supervised learning and sparse filtering two stages used to extract fault features; softmax regression has been employed to separate the type fault.
Toumi Y et al. [70]	Envelope Analysis, Multi-layer Perceptron	ANN	Accuracy of 95 and 89% for the fault-type	A bearing state signature extraction through envelope

			identification and fault-severity identification	analysis and reliable decision-making using a multi-layer perceptron (MLP) to classify the bearing fault condition.
He F. et al. [71]	WPT	CNN, SVM, BP neural network	Accuracy more than 97% achieved by the optimized CNN Algorithm	WPT and convolutional neural network optimized by a simulated annealing algorithm has given higher accuracy than traditional fault diagnosis methods.
Heidari et al. [72]	Shape factor, impulse factor, crest factor, clearance indicator, skewness, and kurtosis	Ensemble classifier, Genetic Algorithm	accuracy around 98.44% achieved	Ensemble Techniques give a better prediction of fault of bearings

belief network (DBN) ensemble method. They integrated an evolutionary approach within the DBN to enhance forecast performance, achieving promising results in the aero-engine prognostic study. Li et al. [75] suggested a deep convolutional neural network (CNN) into the prognostic task. The minimal errors in small Remaining Useful Life (RUL) estimation indicate that CNN effectively captures system degradation info from Vibration data [76-77]. Xu et al. [78] employed novel approach, integrating a multi-scale CNN and an attention mechanism method using multi-sensor signals for predicting the RUL. Lin Zuo et al. [79] has proposed spiking neural network (SNN), SNN has been promoted to identify the bearing faults by entering the probability sequences of the extracted features. Local mean decomposition (LMD) method converts raw vibration signals into pulse sequence input as input for SNN. SNN and LMD in combination shows significant accuracy when compared with ANN and CNN algorithm. Zhenzhen Jin [80] used variational mode decomposition (VMD) and improved convolutional neural network (ICNN), VMD is adopted to decompose the signal and calculate the correlation coefficient between every component and the original signal. Researcher début dropout and batch normalization to optimize the CNN structure which considerably advances the accuracy of result.

Many researchers have applied Deep Learning technologies, such as deep convolutional neural networks (CNNs) [81, 82], auto-encoder [83] residual networks (ResNets) [84], LSTM neural networks [85] and transformers [86] for RUL prediction. DL-based methods are extensively applied in predicting the Remaining Useful Life (RUL) of anti-friction bearings. Notably, CNN leverages convolution operations as its core, incorporating sparse connections and weight sharing to reduce the parameters needing training, thus easing the computational load. Recently, deep neural networks have been utilized for estimating the RUL of bearings [87]. The k-nearest neighbor algorithm was applied for the detection of bearing and gear faults and classification for enhance accuracy. Extracting time-domain features through vibration analysis utilized in the fault classification process [88]. Multilayer perceptron (MLP) and SVM algorithms were applied to analyze centrifugal pump seal leakages. The author utilized accelerometer for collecting data from the commissioning location spanning 4 years. The SVM technique achieved a max accuracy of 98.1 percent, while the MLP attained an accuracy of 98.2 percent [89]. Yang et al. [90] introduced a dual CNN approach, first model designed to identify the initiation fault point and the second model to predict the Remaining Useful Life. An encoder-decoder based recurrent neural network is used by Chen et al. [91] to derive the health index values without thresholding. The final RUL is predicted using linear regression. Wang et al. [92] proposed systematic prognostics framework named recurrent convolutional neural network (RCNN) for forecasting RUL of rolling element bearing (milling cutter). Deutsch et al. [93] provides an Integrated Deep Learning and Particle Filter Approach for bearing RUL. Zeng et al. [94] proposed online transfer learning approach to estimate bearing RUL. Sharanya et al. [95] used Reduced Affinity Propagated (RAP) clustering algorithm for lasting useful life of bearing. Lee et al. [96] proposed a systematic feature engineering (SFE) and extreme learning machine (ELM) based RUL assessment technique. Wang et al. [97] used fusion

Table 2: Overview for estimation of remaining useful life (RUL) of the bearings using various techniques

References	Data Operations/Processing	ML Techniques	Results	Summary
Attaran et al. [74]	RMSE	Ensemble Learning, Deep Belief Networks	RMSE is less and prognostics heath management score better by proposed method for training and test dataset	DBNs optimized the weights to establish an ensemble model for RUL estimation
Pham et al. [77]	STFT	CNN-VGG16	Max. accuracy 99.83% has been achieved by this method for both combined and single fault	spectrograms of vibration acceleration signals have been processed by STFT and CNN - VGG16 algorithm used to identify and b classify the faults
Giduthuri Sateesh Babu et al. [81]	RMSE	CNN,SVR, RVR, MLP	Compare to other algorithm CNN got least mean square error. Similarly, CNN achieved lower (better) score values than the MLP, SVR and RVR on multi operating condition data sets.	CNN based RUL estimation from multivariate time series data studied by researcher.
Jian Ma et al. [83]	SAE, Grid search method	Logistic regression, DNN	DNN hyper parameters using a grid search shows effectiveness with accuracy 83.82%	A deep learning approach has been employed to predict the RUL of an aircraft engine based on a stacked sparse auto-encoder and logistic regression.
long Wen et al. [84]	SD	CNN,SVM, DBN, LSTMM	Ensemble techniques has higher accuracy than other ML techniques	k-fold ensemble method used to enhance Res CNN has shown significantly predict RUL of bearing
Yuting Wu et al. [85]	Stochastic Gradient Descent (SGD), RMS prop. or Adam	RNN	Standard RNN, GRU LTSM and vanilla LTSM algorithm has compared and Vanilla LSTM shows 100 times better scoring functions than other algorithm	Vanilla LSTM achieved the best prediction accuracy at most of the monitoring points
Yifei Ding et al. [86]	RMSE, MSE, Score function	RNN, Convolutional Transformer, CNN	CoT shows good prediction compared to CNN and RNN on parameters like RMSE, MSE and Score Function for Predicting RUL of bearing	convolutional Transformer can be employed in three modes: encoder-only; decoder-only and encoder–decoder is good at capturing content-based global interactions compared to RNN and CNN
Syed Muhammad et al.[88]	Root means square, Impulse, Kurtosis and Shape Factor	KNN, GA, SVM	K-values from 1 to 10 with step 1 has been applied with GA selected only 04 features (root means square, impulse, kurtosis and Shape Factor). At k values in between 2-9 shows 100 % accuracy.	KNN with GA diagnosis defect in bearing and gears from vibration signals
Pier Francesco et al. [89]	Statistical Features	SVM, MLP	Overall accuracy of 98.2% has been achieved by MLP and SVM achieved 98.1 % accuracy. MLP for Fault estimation.	MLP predicted Fault estimation.
Boyuan	RMSE, CRA	CNN, SVR	RMSE and Cumulative relative	A double-CNN framework for

Yang et al. [90]			accuracy (CRA) are used as prediction index, Zero and One indicates in results as normal and degradation stage. CNN gives higher accuracy than SVR around 1.	Rapid degradation to identify If point based on 3/5 principle shows the effectiveness of prediction of RUL compared to SVR.
B. Wang et al. [92]	Mean, SD	SVM, FNN, DBN, CNN, CBLSTM, RCNN	Accuracy of RCNN more than 86% has been achieved.	RCNN can provide a better RUL prediction compare to other Ml techniques.
Fuchuan Zeng et al. [94]	RMSE, CRA	DCNN, DANN, MK-MMD	RMSE and CRA are low and high respectively by suggested method compared to DCNN and DANN	Maximum mean discrepancies-based (MK-MMD) transfer learning method obtaining the most effective average forecasting accuracy and lowest variance.
Sharanya et al.[95]	k factor, crest factor	Reduced affinity propagated (RAP) clustering	RAP has average error estimates was 6.04	Reduced affinity propagated (RAP) clustering used to classify the health condition of the equipment under study by constructing health metric from the predicted RUL.
Lee et al. [96]	RMS	Extreme Learning Machine (ELM)	ELM reduces MAE, RMSE and MAPE in RUL estimation by over 50%	Proposed a novel RUL estimation method based on systematic feature engineering and extreme learning machine (ELM).
Ren et al.[100], Gupta et al.[99]	Spectrum-Principal-Energy-Vector	DCNN	Prediction accuracy was 0.1190.	Deep CNN improved the prediction accuracy
Ren et al.[101]	Time domain and frequency domain	Deep Learning Approach	Average RMSE on different testing datasets is 0.0414	The effectiveness of deep neural network for multi-bearing remaining useful life prediction was promising
Cheng et al.[102]	Degradation energy indicator	deep CNN	Average score mean = 0.87, Mean average error MAE = 46.2, and Normalized Root Mean Square Error NRMSE=0.05	The proposed framework achieves much smaller prediction errors for RUL predictions

prognostics method for forecasting RUL of rolling element bearings (REB). Meta-learning algorithm is anticipated to categorize bearing faults under various conditions with less training samples. The meta-learning has capability to do classification, regression, and reinforcement learning, with less sample size. Neural network model has been employed by meta-learning as base and it take complete gain to feature-extracted capacity of same for bearing faults has been suggested by Hao Su et al. [98]. Muktesh Gupta et al. [99] employed real-time condition base monitoring of ball bearing while machine is working and applied deep neural network for forecasting RUL and detection of faults. The results further compared against Decision Tree (DT), Random Forest (RF), Naive Bayes (NB), Gradient Boosting (GB), SVM algorithm has overall superior results. Lei Ren et al. [100-101] proposed deep convolution neural network (CNN) for estimate RUL. A novel Attribute selection method has been adopted to obtain the eigenvector, called the spectrum principal energy vector helps deep CNN for forecast RUL. Cheng Cheng et al. [102] used the Hilbert Huang Transform (HHT) for extracting a nonlinear degradation energy indicator (DEI). CNN algorithm has been predict DEI and SVR forecasting model has been used to determine RUL. Sutrisno et al. [103] has adopted a 2 stage deep neural network (DNN), DNN model has been constructed in 1st stage to classify the health phase of the observed bearing by means of the stacked denoising autoencoder (SDA). Second stage used Shallow ANN with more hidden layers employed to estimate the RUL of bearings.

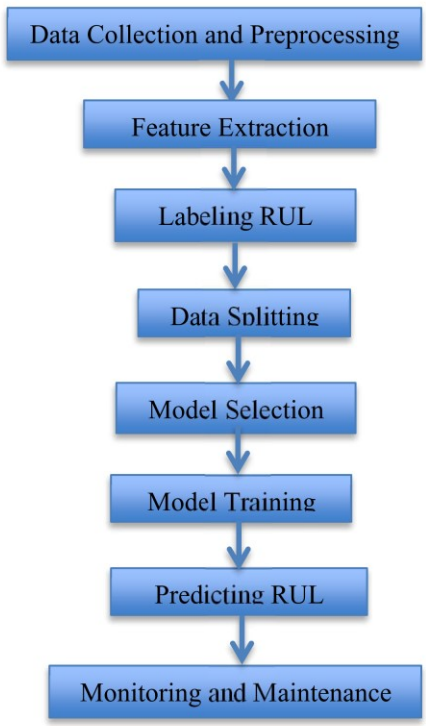

Figure 3. Shows the steps for forecasting the RUL of a bearing using ML

Figure 3 shows the steps for forecasting the RUL of a bearing using ML. It involves making a model that can learn from historical information and make predictions about when a bearing is likely to fail based on its current condition and operating conditions. Collect historical data from bearings, including sensor measurements like vibration, temperature, load, lubrication condition, and other relevant parameters. Ensure that the data is cleaned and organized, removing any outliers or irrelevant information. raw sensor data used to extract relevant features which includes statistical procedures (mean, standard deviation, skewness, etc.), frequency domain features (FFT analysis), time domain features. Consider domain knowledge and expertise to choose the most informative features. Determine the failure point for each bearing in your historical dataset. Calculate the RUL for each bearing at different time steps leading up to its failure point. Dataset split into 3 sets as training, validation and testing. Training dataset train the model, the validation set to tune hyper-parameters, and estimate the model's performance the test set used. Select an appropriate ML algorithm such as Linear Regression, RF, GB, Support Vector Regression (SVR), and Neural Networks for regression tasks. Train chosen model on the training dataset, using the labeled RUL as the target variable and the engineered features as inputs. Tune hyper parameters using the validation set to optimize the model's performance and evaluate its performance through the testing. Regression tasks carried out through Mean Squared Error, Root Mean Squared Error, Mean Absolute Error and R-squared (R2) score. As model is trained and tested, it is use to predict the RUL of bearing based on their current sensor readings. Regularly acquire the data from functioning bearings and by updating the model as new data readily available. Regularly re-evaluate the model's performance and adjust as necessary to ensure accurate predictions.

The Overview for estimation of remaining useful life (RUL) of the bearings using various ML Techniques is presented in Table.2.

6. CHALLENGES AND FUTURE DIRECTIONS

Data Variability: Real-world data can be highly variable due to changing operating conditions, making fault diagnosis challenging.

Labeling and Data Annotation: Acquiring accurate and sufficient labeled data for various fault types can be time-consuming and expensive.

Online Diagnosis: Developing real-time, online fault diagnosis systems is crucial for preventing unplanned downtime.

Explainability: Interpretable machine learning models are essential for gaining trust and acceptance in industrial applications.

7. CONCLUSION

The literature review explores the methodologies, techniques, and advancements in forecasting the lasting useful life of bearings. Machine learning (ML) techniques have revealed great ability to diagnosis bearing fault by leveraging sophisticated and data availability improves, the correctness and reliability of bearing fault finding systems are obviously increase, leading to more efficient maintenance strategies and reduced operational disruptions. Sensor data is valuable to accurately identify different fault types.

The literature demonstrates a growing interest in precisely estimating the remaining useful life of bearings. Both model based and data-driven approaches offer valuable insights, with machine learning and deep learning techniques showing promise in capturing complex patterns. As sensor technology advances and more data becomes available, further improvements in RUL estimation can be expected, leading to enhanced maintenance strategies and operational efficiency in various industries.

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