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Fault Diagnosis of Ball Bearing Using AI-A Review

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ABSTRACT: This study provides a detailed overview of the use of several deep learning algorithms for analysing bearing faults during the last 10 to 15 years. Rotating machinery fault diagnostics is critical for sustaining system performance and ensuring safe operation. Deep learning (DL) and machine learning (ML) have been quickly developed and be effective in defect identification. The rise and invention of deep learning (ML) approaches have captivated the interests of both industry and academia. A bearing issue might cause a machine to fail; among the most serious consequences of bearing failure is prevalent reasons for failure in low and high rotational machinery in industries. Intelligent fault diagnostic research is frequently undertaken using machine learning (ML) procedure. A detailed evaluation of machine learning (ML) and deep learning (DL) approaches used to detect a fault in rotating machinery is discussed in this study in terms of several characteristics, such as Support Vector Machine (SVM), Artificial Neural Network (ANN), and Recurrent Neural Network (RNN).

KEYWORDS: Fault diagnosis, Artificial neural network, SVM, Vibration, Machine learning algorithm

I. INTRODUCTION

Technological advancements allow for a greater level of customization of devices for specific applications. At the same time, maintaining improved machine productivity is a critical need. In all operational scenarios, rotating machinery must be efficient and dependable. As a result, rotating machinery problems should be resolved with extreme care when flaws in rotating equipment occur. During the flaw detection phase, the vibration and self-excitation of machines resulting from unbalanced shafts and rotating shafts expose the machine to various types of vibration and bending, as well as forces operating along with the rotating machinery, such as friction and aerodynamic forces. To avoid machine failure, vibrations created in equipment that reflect different types of problems should be treated at the proper moment. Vibration analysis for defect diagnosis in rotating machinery is a widely acknowledged non-destructive and condition-based monitoring approach. The majority of maintenance actions are geared toward using vibration analysis to discover and diagnose issues. machine accessibility and dependability for the maximum amount of time possible, with reduced downtime resulting in production losses. Although rotating machinery is developed and built using the most up-to-date standards to fulfil the functional requirements in their field of use, Vibration is caused by an unbalanced force created over time, as well as variations in parameters such as amplitude and phase angle caused by the motor's stator-rotor gap problem [32-35]. Mechanical vibration is caused by frictional resistance that occurs between the spinning machinery's moving and stationary elements. The variations in the values of these descriptive parameters as a function of time were alluded to as time-domain data. The defects are shown by a massive shift in the vibration spectrum's tendency. Then, using modern computer technologies such as Fast Fourier Transform, the time domain vibration spectra trends are converted to numerical calculations. changing the frequency domain of the data. During the problem identification and diagnostic procedure, the detected data pattern created is given a lot of attention. During the three phases of fault identification, a data pattern is formed. The state of machinery is defined by three phases of fault diagnostics [14]. The first process involves determining the state of the equipment. The second phase involves identifying flaws and their causes. Phase three involves analysing data trends to detect fault development. As a result, pattern detection of data trends in fault diagnostics is viewed as a significant issue [30,31]. To handle this challenge, artificial intelligence (AI) has a greater function in defect identification and diagnostics related to data pattern recognition applications than humans. Machine learning approaches, in particular in AI, have achieved a lot of attention in [23-29] modernistic years.

II. LITERATURE SURVEY

This section provides an overview of the many methodologies that may be utilised for ball bearing fault diagnosis using DL and ML, as well as a brief summary of the algorithms adopted by the researcher.

Wentao Mao et al, 2016 [1] They propose two tasks for maintaining the accuracy of bearing fault diagnosis: the first is a novel online bearing fault and diagnostic approach called Incremental Support Vector Machine (ISVM), and the other is Stack Auto Encoder (SAE), a deep learning algorithm. The purpose of this research is to employ deep learning's strong representational ability to increase diagnostic accuracy and resilience in online contexts. K. Adamsad et al, 2021 [2] In this study, a detailed evaluation of machine learning methods and approaches used to detect bearing defects in rotating equipment is discussed in terms of numerous characteristics. Numerous machine learning approaches such as support vector machine (SVM), artificial neural network, decision tree and K-nearest neighbour, relevance vector machine, and support vector regression were explored empirical basis and industry applications. Machine learning methods and methodologies such as ANN, SVM, RVM, KNN, DT, SVR, and PCA have been assessed and investigated for numerous algorithm characteristics. Furthermore, their efficacy has been examined. Comparative analysis of the numerous ways, every strategy will have its own set of advantages. For evaluating bearing flaws, SVM is a fantastic tool. A. Almounajjed et al, 2021 [3] in this paper, the researcher has advised the diagnosis of fault-based condition monitoring method and ANN method. Inside this fields of bearing defect diagnostics, the application of Machine Learning (ML) and Deep Learning (DL) algorithms provides outstanding results. KNN provides a simple to use and robust approach to handling large amounts of data, while SVM can handle large amounts of data. P.K. Kankar et al, 2011 [4] the goal of this study is to use an artificial neural network and a support vector machine to detect ball-bearing defects. Tests were conducted using rotors mounted on rolling bearings. For various ball bearing problems, the vibration effect is acquired and studied. Cracks in the outer race, an inner race with a ridged covering, and corrugation disintegrating in balls are examples of specific faults. It's also worth noting that SVM has a higher classification accuracy than ANN. Both machine learning algorithms have a lower precision in accurately guessing bearing ailment to multiple bearing constituent defects, while SVM's findings are significantly better. S. Manikandan et al, 2020 [5] The goal of this study is to see how different ML and DL algorithms perform when it comes to diagnosing faults in various rotating machinery. The review focuses on the fault diagnosis capabilities of supervised and deciliter algorithms. The performance of various methods on fault identification in rotating instrumentality is compared. Over large datasets, SVM-based fault detection had demonstrated hereafter ineffective and incompatible in investigate errors. Deep learning neural networks rely heavily to get alternatives and outperform SVM in terms of performance. The DT and RF models are more useful to Ensemble models that have a short processing time, but they require the best tree models for accuracy. P. Kumar et al, 2020 [6] an evaluation of machine learning technique applicability in fault detection in induction motors had presented in this work. Machine learning-based fault detection has enhanced accuracy and availability. ANN, KNN, SVM, decision trees, and deep learning are examples of machine learning algorithms that have been widely discussed. The detecting of faults using a machine learning method has received great concern in this research. Convolutional neural networks and deep belief networks, two of the most recent deep learning techniques to defect detection, have been studied. Using deep learning takes use of self-feature extraction and selection, lowering the chance of human mistake in feature extraction and selection. S. L. Souad et al, 2020 [7] the purpose of this research is to suggest a way for classifying bearing defects using artificial neural networks (ANN). The resultant system has a basic structure with an input neurons (retina), a decision output layer, and a hidden layer of 10 neurons, as well as graphical outputs that indicate the training effectiveness. After multiple learning experiments, it had established that improved learning performance was achieved by a proper choice of an ANN structure.

D.T. Hoang et al, 2019 [8] we developed a unique technique based on CNN to classify rolling element defects in this work. The suggested method has two key advantages: it converts 1-D vibration signals to 2-D pictures and uses CNN image classification methodology to classify them. • To open with, there is no need for both feature extraction and feature selection processes, which have a significant impact on accuracy rate and often need expert knowledge of the system. • Additionally, it provides highly accurate bearing defect classification, which has been confirmed in real-world trials Ayyappa.T et al, 2021 [9] in this review study, we reviewed the available research on fault diagnostics of bearings using classical and deep learning approaches. Again, for recognition of bearing defects, classical machine learning (ML) approaches like as SVM, ANN, and PCA had employed in the past. The methods listed above yield satisfactory results in identifying bearing defects with above 90% accuracy. CNN and RNN had also had great accuracy approx. 90% and 96% to 98%. D.H. Pandya et al, 2013 [10] the goal of this research paper that, fault detection of ball bearing using acoustic signal and intrinsic function that intrinsic function has seven supervised learning method KNN

(K-nearest neighbour method), Naïve Bayes Method, Weighted KNN method, Random forest method, J48, Bayesian, and MLP method. After comparing all the results of the seven methods, we found the weighted KNN method, has better accuracy compared to all six. KNN has 92.778% with a supervised attribute base filter, 96.1111% with instant based filter, and 92.7778% without the filter. P.K. Kankar et al, 2011 [11] the goal of this review is to employ wavelet-based feature extraction to diagnose bearings with localized faults on various bearing components. The application of a wavelet-based approach established enforce the Minimum Shannon Entropy Criterion is habitual determine the statistical characteristics necessary for the training and validation of artificial intelligence algorithms. Here are three intelligence techniques that are used for fault classification supervised machine learning i.e. support vector machine (SVM), learning vector quantization, unsupervised machine learning i.e. self-organizing maps. It has been demonstrated that the support vector machine is more accurate and more effective at fault detection than vector quantization and self-organizing maps. M. Hamadache et al, 2015 [12] the purpose of this study is the rotor speed-based bearing fault diagnosis (RSB-BFD) is a revolutionary bearing fault diagnostic approach suggested in this study. The described solution is advantageous in terms of cost savings and simple so it is just dependent on rotor speed signals. The suggested approach was tested in a constant speed and variable-speed setting with the load remaining constant. To show the effectiveness of the suggested technique, three separate bearing defects (outer-race fault, inner-race fault, and ball fault) were intentionally proposed. According to a series of experiments, the recommended RSBBFD improved issue detection and diagnostic ability by over then 20percent inside the consistent speed case and so by 30percent in the adjustable speed situation.

J. Harmouche et al, 2013 [13] in this research paper, fault prognostic of the rolling element using global spectral explication. The fault in the bearing is very weak, to enhance ball bearing failure identification, two approaches were used. The first is linear discriminant analysis (LDA), and the second is principal component analysis (PCA). There is no need for a complicated classifier in this technique, and no awareness of bearing is required. In this paper, source material was collected from CWRU (case Western Reserve University) and diagnosed the fault in the bearing through the global spectral analysis. Khadersab & Shiva Kumar, 2018[14] The impact of vibrational assessment techniques such as fast Fourier transformation, an inverse fast Fourier transformation, and spectrogram for defects examined in rolling element bearings is critical in determining machine breakdown. These strategies work well in rotating equipment because of the nature of the vibration spectrum derived from a rolling element bearing. The three methodologies utilized to assess bearing defects in this article reveal a significant diversity in the assessments. For each demographic characteristic of the loading and discontinuous condition induced in rotating machinery, inverse fast-Fourier transforms and spectrogram techniques give a deeper insight into the vibration spectrum and accurately approximate the root problem of bearing defects with corresponding parameters such as RMS value, kurtosis, and skewness to predict machine failure. As a result, inverse fast-Fourier transformation and spectrogram approaches will outperform fast-Fourier transformations. X. Lou et al, 2004 [15] A new approach for diagnosing specific defects in rolling elements has been presented using the wavelet transform and neuro-fuzzy segmentation. Experimental vibration signals were acquired from motorized experimental setups with normal bearings, bearings with internal race faults, and bearings with holes in the balls. Signals were processed and feature vectors were generated using wavelet change accelerometers. A diagnostic classifier has been trained using an adaptable neural inference system (ANFIS). Comparisons were also made by using the vector correlation coefficient approach and the Euclidean vector distance method. Examined the findings demonstrate that load changes can distinguish between fault states accurately by means of the devised diagnostic approach. S. Prabhakar et al, 2002 [16] proposed utilizing the discrete wavelet transform to identify bearing faults (DWT). Using wavelet discretization, wavelet-based vibration analysis was conducted on ball bearings with worn inner race, outer race, and combination faults. The impulse in vibration analysis caused by bearing failure is evident. The impulse arrives regularly, with a time that coincides with the typical defect frequencies. The use of discrete wavelet transforms (DWT) as a method, for identifying single and multiple defect problems in ball bearing has been established.

H. yang et al, [2005] [17] suggested various techniques are for diagnosing and detecting problems by rolling bearings. Although, extracting characteristics of signals obtained of these components, especially in the time-frequency domain, is a difficult task. Basis pursuit is a novel time-frequency approach that has been just created. This research shows how to extract features by signals received at problematic rolling bearings with inner and outer race defects using this innovative basis pursuit approach. The matching pursuit approach and discrete wavelet packet analysis (DWPA) had used to compare the results achieved using this novel technique. Basis pursuit represents characteristics in the time frequency domain with high accuracy resolution and sparsity, making it easier to grasp the findings. The approach also increases the signal-to-noise ratio, allowing for more accurate defect detection and diagnosis in the future. Y. Lei, F. Jia et al, [2016] [18] have suggested that smart fault diagnosis promises to be a powerful mechanical analysis tool because

of this reason its ability to quickly and proficiency analyse gathered signals and provide dependable diagnostic findings. Traditional intelligent diagnosis approaches, on the other hand, rely on pre-existing information and clinical experience to extract characteristics manually. Despite utilizing human ingenuity in these processes, they require a lot of labour and time. There was a two-stage learning method proposed for intelligent machine diagnosis. In the initial learning phase of both approaches, sparse filtering, an unsupervised two-layer neural network, is utilized to learn mechanical vibration features directly from the data. Second, the learned characteristics were used to categorize the health problems based on Soft-max regression. The proposed approach is validated using the motor bearing dataset and the locomotive bearing dataset. According to the study, the proposed diagnostic approach was more accurate than current methods for motor bearing datasets. Due to its adaptive learning properties, the proposed technology facilitates robust fault diagnosis handling vast amounts of data with a minimum amount of human intervention.

A.Widodo et al, [2007] [19] has presents an overview of machine status invigilate and fault diagnosis using support vector machines. Its goal is to look at and discuss contemporary SVM investigation as well as advances in machine condition monitoring and diagnostics. Artificial neural networks, fuzzy expert systems, position-based reasoning, random forests, and other intelligent system-based techniques were developed. SVM, on the other hand, is still seldom employed for machine invigilate and issue diagnosis. Because SVM has outstanding generalization ability, it may provide high detection efficiency for machine condition monitoring and diagnostics. Until 2006, the superiority of SVM applications in machine condition invigilate and defect detection had focused on expertise and problem-solving. Finally, future research will focus on SVM's capacity to adapt and generate new ideas for machine status monitoring and issue diagnosis. R.liu, B. et al, 2018 [20] has suggested diagnosing the fault in rotating machinery using Artificial intelligence (AI) like K-Nearest Neighbour, Naive Bayes, Support vector machine (SVM), and deep learning. Fault diagnose of rotating machinery plays a vital role in the reliability and safety of the modern industrial system. In this research, a variety of artificial intelligence (AI) and deep learning algorithms for rotating equipment are examined. It has been summarised from both a theoretical and a practical standpoint. Artificial intelligence (AI) techniques are growing more sophisticated, and it is thought that AI approaches will continue to be appealing and powerful for rotating equipment defect diagnostics. Adamsab, 2021 [21] In this research investigated a new technique of analysing rolling element bearing defects depend on vibration spectra. Spectrograms are created for each frequency range by parametrically examining the vibration spectrum analysis acquired in the time and frequency domains. Based on the findings produced and in agreement with the limitations, a novel signal analysis approach utilizing vibration signals recorded on rolling element bearings that were defined by local failures was applied to evaluate the results. In addition, these signal processing methods will be precise in identifying the flaws in rolling element bearings during such a specific time. Comparing the spectrogram color of an unhealthy bearing with a spectrogram defect detection of bearings demonstrates more effective fault detection. Depending on the color sequences acquired for the healthy bearings, there is a large variance in the bearing variances of the problematic bearings.

Xie & Zhang, 2017 [22] In this study, a proposed feature selection algorithm derived from evidential method digestion (EMD) and convolutional neural network (CNN) approaches is suggested for rotating equipment failure diagnosis. The primary goal of our newly suggested method is to extract differentiating characteristics. A specific CNN structure is trained on the frequency spectrum of data extracted by a quick Fourier transformation to extract compressed features containing spatial information. We train a soft-max and an SVM classification model by integrated features. Experiments are carried out using rolling-element bearing data gathered from the CWRU experimental setup in a variety of scenarios. For the experiment in this publication, 52 thousand samples were collected under 52 different working situations. The accuracy of classification based only on features retrieved from the CNN model is pretty high.

V. V. Rao and C. Ratnam (2015) [23] An assembly of bearing test rigs was constructed and set up in a workshop to study the vibrations of flaws in rolling element bearings. Researchers researched several forms of sowed flaws in the literature, even though such imperfections are arbitrary in size and shape, therefore there is no association between defect size and vibration parameter. In this study, test runs were carried out on radially loaded cylindrical roller bearings with seeded flaws of the same kind that grew in size overtime on the outer race at various speeds and loads. An accelerometer was used to collect vibration data, which was then processed using the Fast Fourier Transform (FFT). As a result of the data collected, vibration root means square (RMS) velocity rises dramatically with defects of various sizes and speeds, but not with loads. With input parameters of load, revolutions per minute (RPM), and vibration RMS velocity, an Artificial Neural Networks (ANN) multilayer perception model with back-propagation algorithm was utilized, with seeded defect size as the output. The ANN was trained using data sets containing the number of test runs completed and was able to estimate the defect size. When the projected values were compared to the actual seeded

defect size, the inaccuracy was determined to be around 3.90 percent. In this study, an attempt was made to forecast the defect size of a particular bearing based on its vibration RMS velocity.

III. POPULAR BEARING FAULT DATASETS

All machine learning apply to had built on the premise of data. A good quantity of samples is required to produce efficient ML and DL methods for bearing failure detection. Because legitimate bearing deterioration is a slow and moderate process that might consume several years, many persons research and accumulated values by utilizing bearings by purposely produced flaws or by employing twarit life testing methods. When the values accumulation consumes time, a few businesses have taken the initiative and made their bearing defect datasets available for technician and academics to use to elaborate on their machine learning methods. Due to their widespread use in the scientific area, these datasets can also be used as a platform for collaboration to evaluating and comparing various methods. In this part, we quickly discuss a few quotidian datasets utilized by most of the articles featured in this anatomizing before diving into the intricacies of various ML and DL breakthroughs.

A. Case Western Reserve University (CWRU) Dataset

A two-horse power induction motor, a torque transceiver, and a test bench utilised to collect information on bearings CWRU are depicted on the left, and a dynamometer connected on the right. Electro-discharge machining at the inner raceway causes single point defects with fault sizes of seven mils, fourteen mils, twenty-one mils, twenty-eight mils, and forty mils in the bearings during analysis the rolling element, and the outer raceway. For motor loads ranging from 0 to 3 hp and motor speeds ranging from 1,720 to 1,797 Rev / min, two accelerometers were placed mostly at the driving end and engine housing's blade end, and two sampling rates of 12 kHz and 48 kHz were used to record vibration data. The resulting dataset is documented and easily accessible on the CWRU bearing datacentre webpage. We will present a comprehensive and extensive evaluation of past efforts using the CWRU set of data to evaluate the behaviour of individual ML and DL methods.

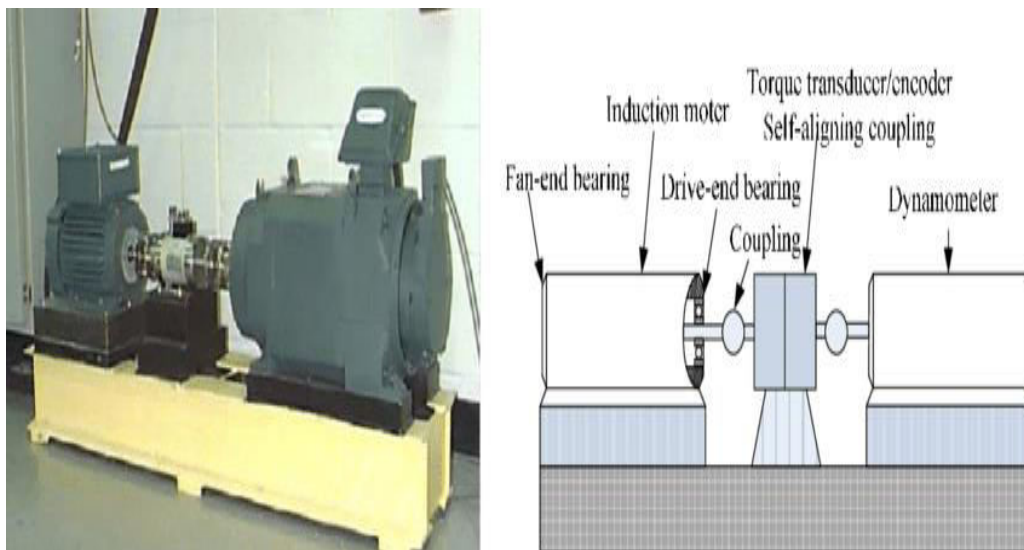


Fig 1 Experimental settings were used to collect the bearing data from CWRU

B. Intelligent Maintenance Systems (IMS) Dataset

The NSF/UCR Centre for Intelligent Maintenance Systems (IMS) created the IMS bearing dataset with help from Rexnord Corp. Unlike previous datasets, whereby bearing defects are either intentionally caused by scraping or digging the bearing outer layer or manufactured by applying a shaft current to the bearing for accelerated life testing, the IMS dataset has a comprehensive note down of pure bearing abnormality progression. The bearings are specifically maintained operating for 30 days at a constant pace of two thousand revolutions per minute, accumulating roughly 0.0864 billion cycles, once a problem is detected. The test rig is made up of four Rexnord ZA-2115 double row bearings mounted on a shaft that is linked to an AC motor through one rubber belt, as shown in Fig. 2(a). A spring mechanism applies a Radial force of 6,000 pounds to the shaft and bearing. As illustrated two instruments are put on each bearing housing, and 4 heat exchangers are connected to each bearing's outside ethnicity to measure bearing temp for greasing reasons 2(b). A similar experiment will be repeated three times. Test 1 results in a bearing with three inner race flaws and bearings with four rolling element faults. As a result of tests 2 and 3, bearings 1 and 3 both have an outer race fault. The vibration data has been collected that each five or ten mins for a length of 1 sec using a National Instruments DAQ Card 6062E with a sampling rate of 20 kHz. That dataset is exceptionally well suited for forecasting the RUL of rolling element bearings since it comprises a comprehensive collection of vibration signals from commencement to breakdown with clear periods

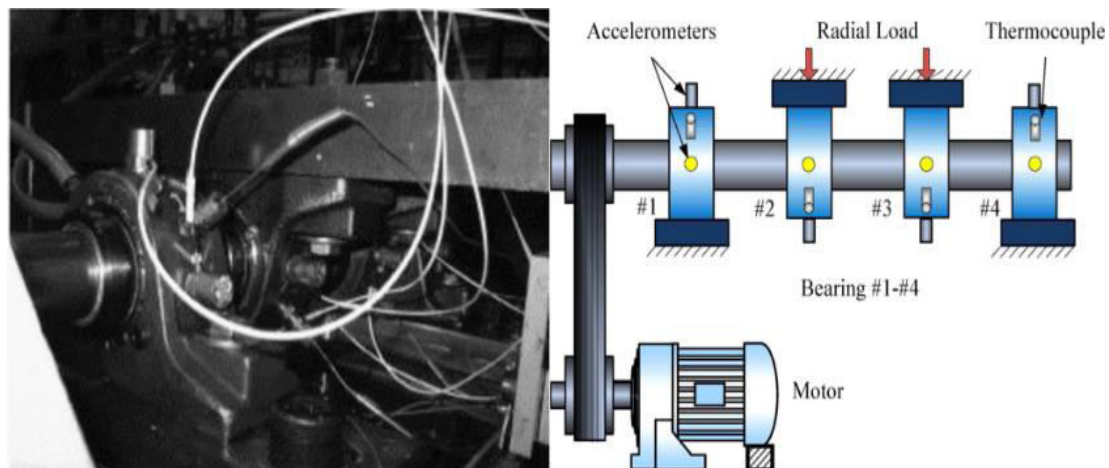


Fig.2 Illustration of the bearing test rig and vibration sensor placement of the IMS dataset

C. Pronostia Dataset

Further common set of data for forecasting a bearing's remaining usable life (RUL) is renowned as the "PRONOSTIA bearings speeded up life test set of data", that also provides for researchers to analyse novel techniques for bearing RUL prognostication. As part of the IEEE PHM 2012 Prognostic Challenge, which was held during the International Conference on Prognostics and Health Management (PHM) in 2012, participants were supplied with the PRONOSTIA degradation dataset methods on the dataset. The evaluation reliability of the RUL of the bearings under test was used to evaluate each participant's technique. PRONOSTIA's major goal is to offer real data on the rapid deterioration of bearings under different operating circumstances. Two sensors, a rotational speed sensor, and a force sensor define the working conditions. PRONOSTIA's major goal is to offer real data on the rapid deterioration of bearings under different operating circumstances. Two sensors, a rotational speed sensor, and a force sensor define the working conditions. The bearing health is monitored in the PRONOSTIA platform, as illustrated in Fig. 3, by gathering two types of signals: temperature and vibration (with two uniaxis accelerometers installed in the horizontal and the vertical direction respectively). Additionally, the data is collected at a high sample frequency, allowing for the analysis of the complete frequency spectrum of relevance throughout the bearing deterioration process. Finally, the observed data may be utilized for post-processing in order to extract the key aspects fine and analyze the bearing's RUL on a constant basis.

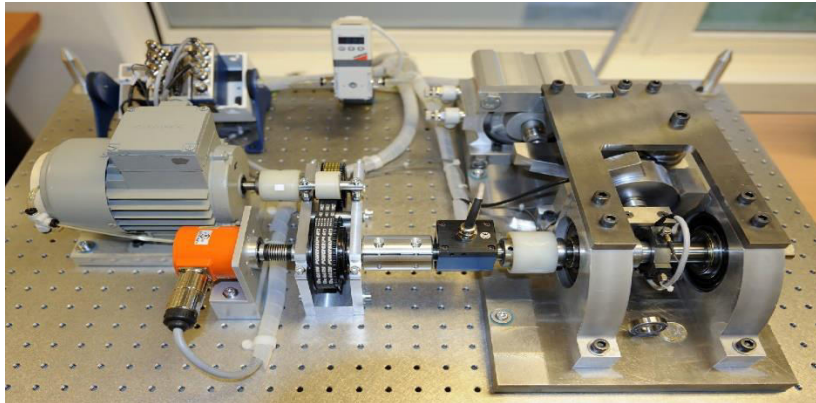


Fig.3 PRONOSTIA test bed (Department of Automatic Control and Micro-Mechatronic Systems (AS2M), Franche-Comté

D. MFPT Dataset

The MFPT dataset, published either by Association for Machinery Failure Avoidance Technology, one more dataset for problem identification and prognosis of REBs. The Condition Based Maintenance (CBM) fault database's purpose is to get a variety of datasets of preconfigured and faulty bearing and gear conditions. A bearing breakdown dataset has incontestably been made available to aid bearing analytical research. The dataset includes conventional bearing data, an outer race defect at different loads, an inner race defect at different loads from a bearing experimental setup, and also three existing defects. Here are three existing samples: an oil pump shaft bearing, out of the wind, and a globe bearing defect out of a real-world wind turbine. NICE bearings are utilized in data provided by MFPT. The implantation of flaws is not specified. The baseline condition and the outer race fault (ORF) with a bearing load of 1201 N are both observed three times, whereas this outer race fault (ORF) and inner race fault (IRF) are observed seven times, with bearing loads ranging from 0 to 1334 N. As a result, this dataset, together with the sample collection code, is publicly given in the hopes that scholars and CBM professionals can enhance the methodologies and, as a result, complex CBM system will be built.

IV.SUMMARY

A comparison of difference across different dataset can be found in Table 1. Because of its simplicity and ubiquity, the CWRU dataset are used in the immensity of publications on bearing failure discerning using ML or DL algorithms. According to the researchers, both the vibration and stator current signal contained through the Paderborn set of data should attract its attention of more researchers. Furthermore, using classifier skilled on intentionally produced scuffs or drills, this dataset allows the assessment of deep transfer learning and domain adaptability algorithms to forecast the much more accurate malfunction from accelerated live laboratory test

TABLE I
COMPARISON OF POPULAR BEARING FAULT DATASETS

DATA SET	Comparison of popular bearing fault datasets			
	Total Sensor	Sensor Type	Sample Frequency	Fault Mode
Case Western reserve University (CWRU)	2	Accelerometer	12 & 48 KHz	Artificial
Intelligence Maintenance System dataset	2	Accelerometer	20Hz	Natural
Pronostia Dataset	2/1	Accelerometer And Thermocouple	25.6KHz	Natural
MPFT		Accelerometer	97656Hz/48828Hz	Artificial

V. CLASSICAL MACHINE LEARNING BASED APPROACH

A range of traditional "shallow" machine learning (ML) and data mining methods, such as the artificial neural network (ANN), was available for several decades before the current DL boom (ANN). Implementing those algorithms generally requires comprehensive domain expertise, along with considerable aspects of engineering. The dataset is commonly exposed to a profound knowledge extractor initially, followed by the extraction of features using dimension-reducing methods like principal component analysis (PCA). Ultimately, the ML algorithm receives most of the intelligence. Various classes and applications have different information bases, which often requires intensive professional skills throughout every domain. As a result, it's difficult for ML models trained in one area to also be extrapolated to another, either for beliefs about certain topics to be interchangeable. ANNs and fuzzy systems were used to summarize and assign fault frequencies for distinct motor fault types in one of the early assessments to investigate the application of artificial intelligence (AI) in motor fault diagnostics. This section will include a brief overview of each classic ML technique, as well as a comprehensive list of literature for readers to review.

A. Artificial Neural Networks (ANN)

Artificial Neural Network (ANN) is among the soonest Artificial Intelligence concepts, and it has been used to diagnose bearing faults since 3 decades. Bearing wear of the motor is described as a function of the damping coefficient (B). This coefficient can be calculated from a nonlinear transformation of the stator current I and the rotor speed v . The intricacies of determining an explanatory formula for this type of non-linear mapping are circumvented when a supervised neural network is trained using stator current and motor speed data as an input and the anticipated bearing circumstance as outputs. On a laboratory test stand, 35 training and 70 testing data patterns are gathered with the Dayton 6K624B-type bearing under different operation circumstances. A conventional neural network with two input nodes $[I \text{ and } \omega]$ shows the maximum bearing fault accuracy results of 94.71%. By incorporating 5 input aspects $\{I, \omega, I^2, \omega^2 \text{ and } I \cdot \omega\}$ with physically chosen input parameters, the accuracy can be further improved. Moreover, in addition to the type of current sensor employed for bearing defect diagnostics, this technique necessitates the installation of an additional device, an encoder, to receive the motor-speed signal as that of an additional input, that is uncommon in low-cost induction motor drives. Correspondingly, the remaining ANN publications all involve a certain level of human experience to assist the attribute selection procedure and, in addition, to educate the ANN model relatively effectively.

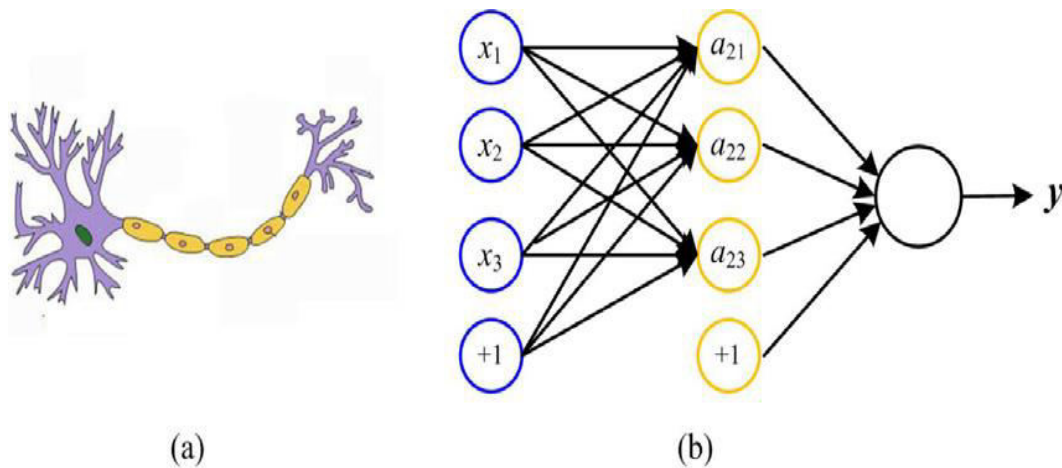
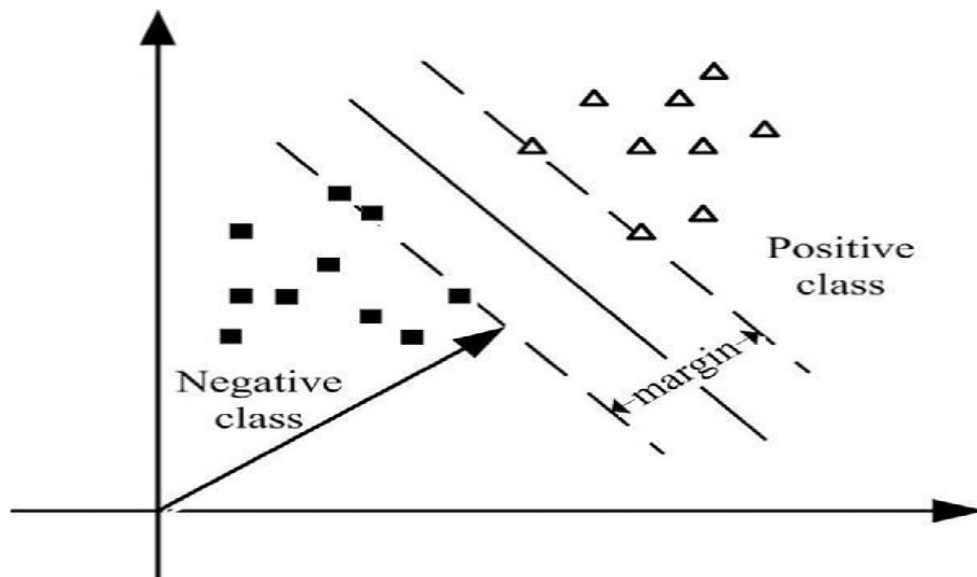


Fig.4. Human neuron and a MLP with two hidden layers.

B. Support Vector Machines (SVM)

For non-probabilistic classification and regression analysis, SVMs have supervised learning models. is a well-known work on the use of SVM to identify bearing difficulties, in which the SVM's other classification outputs are optimal in all conditions, outperforming ANN's efficacy? Other publications that used SVM as a defect classifier



confirmed its usefulness and efficiency.

Fig.5. The optimal hyper plane for a binary classification by SVM

VI. DEEP LEARNING BASED APPROACHES

A. Recurrent neural networks

Recurrent neural networks are neural networks that allow outputs from previous iterations to be used while keeping concealed states as inputs. They recall what happened in the past, and their actions are impacted by what they've learned from it. As a result, the RNN processes the incoming data regularly. Because RNNs have the problem of gradients disappearing or exploding due to their nature, LSTM networks were created to tackle the problem. The most widely used network these days is LSTM, which stands for Long Short-Term Memory. They're also known as the cell network, and they collect input from both the prior and present states. RNNs are frequently utilized in machinery problem detection and diagnostics, not just in natural language filtering, text recognition, or voice recognition. The LSTM network's basic design. An improved bearing failure detection approach was presented based on a consolidated single framework of 1-D CNN and LSTM, using the raw sampling signal as the input and no pre-processing or typical feature extraction. A 1-D CNN layer, a max-pooling layer, an LSTM layer, and a Soft-Max layer like the layer identifier make up the complete design. Initially, a portion of crude bearing records is employed as the model's training sample and the simulation finishes when the number of repetitions exceeds a certain level. The highest level of testing precision is 99.6%. To identify rolling bearing defects with RNN-based auto-encoders, a Gated Recurrent Unit (GRU) based denoising auto-encoder is utilised to forecast the multiple REB vibration values of the forthcoming period from the preceding period. Having great generalization abilities, these GRU-NPDAEs (GRU-NP-DAEs) are non-linear predictive denoising auto-encoders based on GRU for any defect pattern. The problem diagnostic result is decided by the applicable GRUNP-DAE that generates the smallest model complexity across the latency of the input and the design outcome after the taught GRUNP-DAEs have been given numerous input data points. The idea of categorization specificity is used to assess the viability of the suggested strategy for detecting health conditions and classifying fault types. The data annihilation technique is chosen throughout the supervised learning process, and the length loss approach is proposed to improve model resilience. The GRU-NP-DAE achieved an accuracy of more than 96 percent, and the SNR dropped to 1 db.

VII. FUTURE WORK DIRECTION

- a) *Transfer Learning*: Transfer learning is a potential approach for transferring education and expertise from preexisting datasets to assist discover unanticipated bearing failure scenarios in real-world applications at diverse configurations. Domain randomization and domain adaptation are two common transfer learning approaches that can assist improve the variety of the source domain (current datasets) while also facilitating quicker learning and superior efficiency in the target domain (real-world cases).
- b) *Semi-Supervised Learning*: To tackle the problem of "limited labels," we may employ semi-supervised learning to make substantial use of those little tagged data and large unlabelled data. On data with restricted labels, a deep generating model dependent on vibrational encoding may be utilized to achieve discrete label prediction.
- c) *Data Augmentation*: Data pre-processing methods like as GAN will be used to address a "data imbalance and scarcity" problem besides producing additional "fake" incorrect data to assist DL algorithms train. Despite this promising characteristic, [36] found that after including the produced data through into training procedure, the accuracy of some classifiers decreased. "The quality of produced spectrum samples" generated by GAN "isn't good enough to give supplemental information," the scientists assert in [36]. To solve this open concern, it would be worthwhile to investigate more sophisticated embedding's, such as BigGAN.
- d) *Few-Shot Learning*: Adapting just several instructional algorithms to accomplish satisfactory categorization precision with a significantly less quantity of data may also assist in dealing with the "data imbalance and scarcity" challenge. This may be paired with various domain specific learning methods to make deep learning more useful for bearing defect diagnoses in the industry.
- e) *Explain ability*: DL rigorous interpretations aren't as well established as classic ML techniques. Several research [38] and [37] try to visualize the learned CNN kernel in order to understand its physical semantics. These investigations have provided some insight into the interpretability of DL, but additional study and testing, as well as its application to bearing problem diagnosis, are required.

f) *Sensor Fusion*: To address the possible issue of unbalanced data, different kinds of sensors, including as the load cell, current sensor, and acoustic emission sensor, could be used in combination with sensor fusion methods to synthesize data and enhance the ruggedness of bearing defect diagnostic testing. Acoustic sensors, in particular, should be promoted since, according to [40], acoustic emission signals "have specific benefits in detecting incipient problems, capturing, and portraying" when compared to vibration signals. [39] And [40], respectively, provide some previous work on using auditory signals to train ML and DL algorithms.

VIII.CONCLUSION

Based on a comprehensive assessment of intelligent diagnosis algorithms and strategies premised on machine learning and deep learning algorithms. ANN, SVM, and RNN surrounded by machine learning and deep learning techniques and impend evaluated and studied for many features of algorithms. In addition, their results have been checked, based on a comparison of the different accession, each technique will have its strength. A specific emphasis was made on deep learning-based impend, which has piqued the academic community's interest in recent years.

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