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INTELLIGENT BEARING FAULT DIAGNOSTICS WITH MACHINE LEARNING AND DEEP LEARNING FRAMEWORKS: A COMPREHENSIVE AND COMPARATIVE ANALYSIS

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Abstract
In this research work, we systematically investigate the deep learning and classical machine learning approaches for bearing fault diagnostics. Bearings are the most critical mechanical components as their operating conditions have a direct effect on the safety and working of the mechanical equipment. As per the demand of industry users, researchers have always paid great attention to the quality, durability, and service life of bearings. Recent developments in machine learning and especially in deep learning have framed new research areas that have developed an increased interest in both industry experts and academic researchers. In this research, we first investigate the working, characteristics, and limitations of available machine learning and deep learning methods in bearing fault diagnostics applications such as artificial neural networks (ANNs), deep belief networks (DBNs), support vector machine method, etc. Apart from current methods in available literature, the new methods and functionalities are also analyzed and a detailed section on potential methods along with data sets is also dedicated so that it helps other researchers to extend their research. In last, a detailed comprehensive and comparative analysis between the machine learning and deep learning methods is also provided along with discussion section which is intended to facilitate in applying these algorithms for specific applications. The future research section is also added to discuss the current research limitations and potential research areas.

INTRODUCTION

Bearings are widely used in machinery of almost every sector. Either it is an electrical machine or a mechanical system, they must contain bearings as key units for smooth operation, guidance for the load transmitting components, and holding rotating elements [1]. These machines may operate inefficiently due to reasons such as exceeding ambient temperature, high moisture, and overload which result in high life cycle costs, significant financial losses, and safety hazards. Among all of these failure reasons, it is found through survey and research that 30% to 40% of time bearing fault is the main reason of machine failure [2]. Consequently, timely and cost-effective diagnostics of bearing faults are important to avoid heavy breakdowns, save maintenance costs, and maintain sustainable operations.

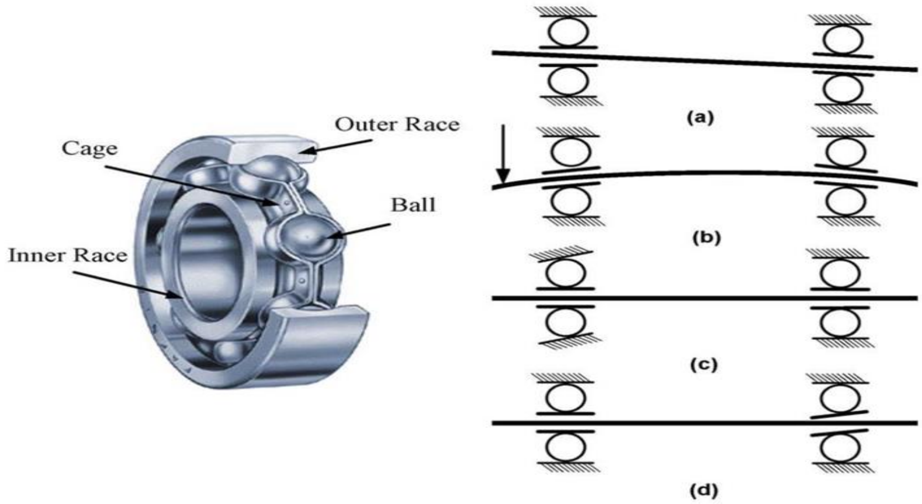

Figure 1

In order to understand the fault in bearings, it is prerequisite to have basic knowledge about the structure of bearings. The basic structure of a bearing is illustrated in Fig. 1 which shows an inner race to handle the shaft, an outer race to provide housing for rotating elements, balls and a cage to keep the relative distance between rolling elements. Bearing failure is usually caused by the misalignment and the four common scheme of these misalignments are illustrated in Fig. 1 (a) to (d) [3]. In practice, bearing failure can be due to complex conglomeration of several reasons such as involvement with abrasive particles, poor lubrication, improper shocks, and corrosive media. A considerable number of research articles have been studied on the different aspects of bearing failure and these studies are precisely summarized in Table 1. This table provides detailed material for studying the bearing failure. It can also be used to extract information to reduce the number of similar failure events.

Table 1

No.	Bearing part	Bearing type	Damage location	Load causing failure	Failure mode and mechanism	Failure cause	Ref.
1	High-speed train bearing	Tapered roller bearing	Fracture of outer ring	Tensile load	Brittle fracture	Common defects	[4]
2	Heavy truck bearing	Tapered roller bearing	Fracture of inner ring	Hoop tensile load	Brittle fracture	1. Improper selection or design 2. Common defects	[5]
3	Bearing of oil screw press	Cylindrical roller thrust bearing	Fracture of bearing ring	Axial extrusion load	Brittle fracture	Common defects	[6]
4	Bearing of coal wagon wheelset	Double-row tapered roller bearing	Fracture of outer ring	Overloaded axial load; fatigue load	Fatigue fracture	Incorrect assembly use and maintenance.	[7]
5	Bearing in an air blower motor	Cylindrical roller bearing	Fracture of outer ring; wear of outer ring and bearing	Vibration shock load	Fatigue fracture; wear	1. Material selection and quality	[8]

No.	Bearing part	Bearing type	Damage location	Load causing failure	Failure mode and mechanism	Failure cause	Ref.
			cage			2. Incorrect assembly use and maintenance	
6	Locomotive wheel bearing	Tapered roller bearing	Fracture and spalling of outer ring	Great inclined load; large abnormal contact load	Contact fatigue spalling; fatigue fracture	Incorrect assembly use and maintenance	[9]
7	Bearing in wind turbine generator gearbox	Cylindrical roller bearing	Fracture of outer ring; spalling and wear of roller, inner ring and outer ring	Overloaded radial load	High cyclic fatigue fracture; contact wear; contact fatigue spalling	Incorrect assembly use and maintenance	[10]
8	Hot strip mill gearbox bearing	Cylindrical roller bearing	Fracture of pins of the bearing cage	Fluctuating shear load	Fatigue fracture	Improper selection or design	[11]
9	Cold rolling mills back-up roll bearing	Four-row cylindrical roller bearing	Pitting, fretting corrosion and fracture of outer ring;	Bending load	Bending fatigue fracture	Improper selection or design	[12]
10	Aero-engine bearing	Cylindrical roller bearing	Fracture of bearing cage rivets	Fretting damage load	High cycle fatigue fracture; fretting damage	Improper selection or design	[13]
11	Oil film bearing	Sliding bearing	Fracture of bearing sleeve	Alternating contact stress	Fatigue fracture	Improper selection or design	[14]
12	Railway freight wagons bearing	Cylindrical roller bearing	Fracture of inner ring and bearing cage	Fatigue load	Fatigue fracture	Incorrect assembly, use and maintenance	[15]
13	Aero engine bearing	Ball bearing	Fracture of inner ring; Fracture and deformation of bearing cage; smearing, deformation, and spalling of ball	Uneven axial load	Fatigue fracture	Incorrect assembly, use and maintenance	[16]
14	Engine water pump shaft bearing	Cylindrical roller bearing	Fracture of bearing cage; wear of roller and mandrel	Radial deflection load	Surface fatigue; wear	1. Improper selection or design 2. Incorrect assembly use and maintenance	[17]
15	Conveyor pulley bearing	Ball bearing	Spalling and fracture of inner ring	Rolling contact load	Rolling contact fatigue spalling	Incorrect assembly use and maintenance	[18]

No.	Bearing part	Bearing type	Damage location	Load causing failure	Failure mode and mechanism	Failure cause	Ref.
16	Cylindrical roller thrust bearing	Roller bearing	Spalling of roller	Rolling contact load	Rolling contact fatigue spalling	Common defects	[19]
17	Cylindrical roller bearing	Roller bearing	Pitting of roller	Rolling contact load	Rolling contact fatigue pitting	Incorrect assembly use and maintenance	[20]
18	Aero gas turbine engine bearing	Ball bearing	Spalling of outer ring	Excessive axial load	Progressive fatigue failure	Incorrect assembly use and maintenance	[21]
19	Aero engine ball bearing	Ball bearing	Spalling and deformation of inner ring; spalling and pitting of ball; deformation of bearing cage	Excessive axial load	Rolling contact fatigue; plastic deformation	Incorrect assembly use and maintenance	[22]

As bearings are highly at risk of failure, the proper fault identification has been a critical problem for engineers and researchers. For this purpose, it is usually recommended to develop a physical model of bearing faults and use sensors with signal processing techniques to understand the relationship between the existing fault and the generated signals. Sense modality methods have been studied such as acoustic noise [23], thermal imaging [24], vibration [25], and sensor fusion [26]; among all these techniques vibration has been found prevailing and leading. The frequency spectral analysis can be used then to easily detect the fault and identify the particular type of fault. This analysis needs a well-defined physical model which will be subject to the driving shaft speed, the bearing shape, and particular location of bearing defect.

However, the correct assessment of existence of bearing fault can be complex in actual practice, particularly in the situations where the fault is still in initial stage which results in small monitored signals. Furthermore, the nature of bearing fault problems is different from other similar component's failures primarily due to the involvement of Multiphysics phenomenon in bearings which can only be analyzed accurately with the help of electric signals. Additionally, the traditional vibration analysis techniques can give inaccurate results due to external vibration, unwanted noise, and spatial constraints in compact machinery conditions. Hence, an alternative method is to use shaft current signals for analysis which does not cost as much as vibrational analysis methods and needs no extra equipment.

Although, the motor current analysis methods have some economic and simplicity benefits; but they pose some practical challenges. For example, detecting the universal threshold for current to activate the alarm can be difficult because the values of generated current during bearing fault varies with different speeds and loads. For this reason, a systematic study of the targeted equipment is needed, and the collection of data is required when the equipment operates in healthy condition. This phase is usually known as the "Learning Phase" in model-based approaches. This process is time wasting, expensive, and repetitive for a long time under different conditions.

These above discussed problems are primarily because of the reliance of all traditional model-based approaches on the threshold value (data). These methods are ineffective in actual modern machinery in a way that their ability is only limited to the identification of feature of generated signals and relating it with corresponding faults. Thus, these bearing fault problems demand intelligent decision-making approaches that can only be possible by analyzing the hidden patterns and logic in data which is difficult to achieve through these manual sensing and observation techniques. Therefore, scientists and researchers use several machine learning algorithms such as artificial neural networks, principal component analysis, etc. to learn from the data and use that learning in bearing fault diagnostics [27]. Majority of the studied literature confirms the satisfactory results by applying these machine learning algorithms with accuracy over 85%. The demand for even better performance under varying conditions and uncertain environment makes the application of deep learning algorithms so popular [28].

In view of this, our paper provides a solid foundational to advanced level investigative approach to study machine learning and deep learning algorithms and methods for bearing fault diagnostics. The paper is organized in sections so that anyone can directly go to respective sections if needed. In section 2, the paper presents the authentic datasets that are generally used in bearing fault studies. The section 3 deals with the traditional machine learning approaches such as ANN, PCA, KNN, SVM, etc. in detail with additional discussions on studied publications related with these methods. In section 4, we discuss the deep learning methods which have become a trending research area in bearing fault diagnostics in recent areas. This section also studies the advanced functionalities, and associated application demands of algorithms such as CNN, AE, DBN, and RNN. In last, sections 5 and 6 deal with the discussion followed by future trends and potential research areas in this field to facilitate the interested researchers in improving their proposed studies.

1. Benchmark Datasets for bearing fault studies

Data is the primary requirement of every machine learning method. For the accurate development of machine learning and deep learning algorithms the collection of data should be accurate. While the actual bearing failure process is slow and can take years to fail hence for research purposes, the artificial fault at accelerated rate is introduced in bearing to record the data. Since these methods can still be time consuming and expensive for the researchers, therefore there are few organizations that have collected the data and published which make the work of researchers easy in developing their own machine learning algorithms. These datasets are also used to compare and evaluate several algorithms. Below is the detailed information about each available published dataset.

2.1 PADERBORN UNIVERSITY DATASET

The dataset developed by Paderborn university is considered the first choice of researchers and engineers because of its highest accurate fault detection results. This attribute is only because the dataset is pre-validated with corresponding multi-physics models. For the sampling of these multi-physics models the high-resolution current and vibration are measured of approximately 26 damaged bearings and 6 healthy bearings. These 26 damaged bearings are passed through both artificial settings and high-speed tests; numerically 12 bearings are passed through the former mentioned setting while 14 are damaged by high-speed life tests. The number of high-speed life tests bearings are higher than artificially damaged bearings only for the sake of realistic data collection. This leads to assured assessment of machine learning algorithms for real applications, because in actual operations the bearings fail gradually. The apparatus used to collect this dataset is known as modular test rig which contains 5 subsections an electric motor, a torque measurement shaft, a rolling bearing test module, a flywheel, and a load motor. This apparatus is illustrated in Fig. 2.

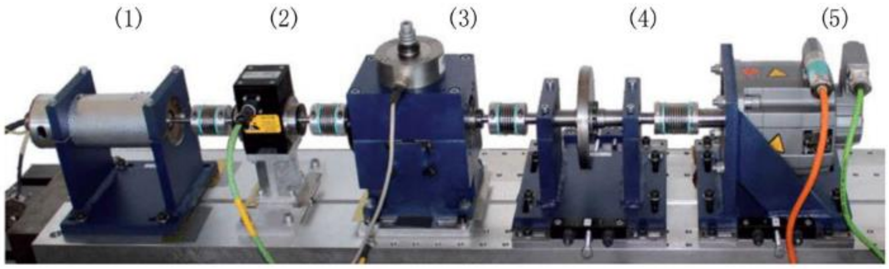

Figure 2

2.2 CASE WESTERN RESERVE UNIVERSITY (CWRU) DATASET

The apparatus used to collect this dataset contains induction motor, a torque encoder, and a dynamometer. The induction motor is of 2 hp as per the demand of procedure. The bearing under test has been exposed to five different faults having different dimensions. The electro-discharge procedure used in this dataset utilized dimensions of diameter in multiple of seven which includes 7 mils to 35 mils. The vibration data was also collected using accelerometer for the loads having specification of 0 hp to 4 hp power along with speed range from 180 rad/sec to 190 rad/sec and threshold frequency of 12000 Hz to 48000 Hz. The apparatus used to collect in this whole process is illustrated in Fig. 3. The data collected by the Case western reserve university is publicly available in their literature which can be used for training machine learning algorithms and comparative analysis purposes.

2.3 INTELLIGENT MAINTENANCE SYSTEMS (IMS) DATASET

This dataset is completely unique from other available data sources. In this scenario, the data is purely collected on the naturally occurring bearing faults. To maximize the quality of data, the bearing has been under test for 30 days continuously at constant speed. The average local speed is maintained at 2000 rpm which results in a total of 87 million cycles approximately. This dataset is collected by the center for intelligent maintenance systems which is supported by National Science Foundation's (NSF) Industry-University Cooperative Research Centers (IUCRC) program. The test equipment has a motor to which the rotating shaft is coupled with four bearings; the power is transmitted to shaft through the motor with the help of rubber belt drive mechanism. The spring mechanism is used to apply load onto the shaft which approximately amounts to 6500 lb. The lubrication procedure is regulated by accelerometers and thermocouples which are mounted to measure the temperature on each housing. The schematic of actual apparatus is shown in Fig. 4. The same procedure is repeated multiple times, and the useful data is collected in every 10 to 15 minutes. This dataset is proved more useful when the primary purpose of training a machine learning model is to predict the remaining useful life of bearings.

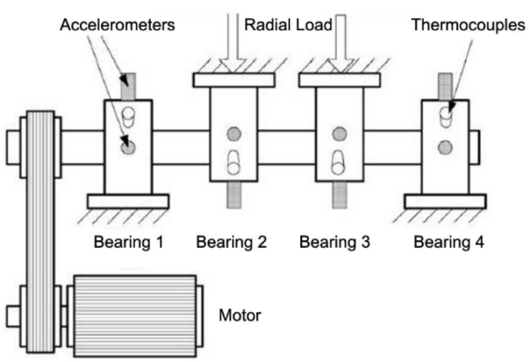

Figure 3

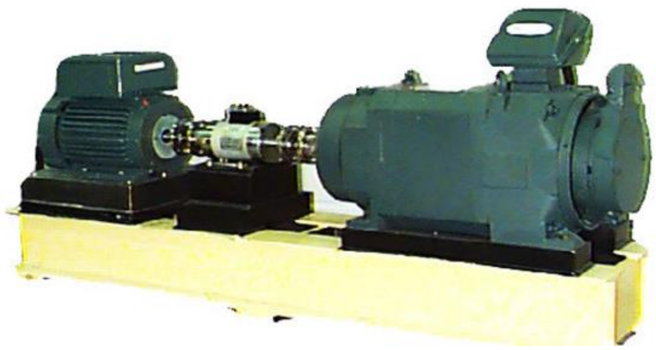

Figure 4

2.4 PRONOSTIA DATASET

This dataset was first introduced in a conference in 2012 where it was equally distributed to the attendees to train their models and the accuracy of results was compared with corresponding other datasets. This dataset can also be used to measure the remaining useful life of bearings, but it is different from the IMS dataset. This dataset is acquired by accelerated methods while the IMS dataset is acquired by natural degradation methods. Consequently, the whole process of data collection changes from the former mentioned test in IMS datasets. In test similar accelerometers were used but they are mounted differently, some accelerometers were set horizontally while others were vertically. The data is collected on the speed test basis hence it needed to employ both vibrational and thermal signals for accurate results.

The comparative data of all the above discussed data is given in Table 2. As per the available literature and the survey conducted from researchers, the large number of machine learning and deep learning algorithms are modelled with CASE WESTERN RESERVE UNIVERSITY (CWRU) dataset. There is also growing reliance on Paderborn dataset due to its pre-validated procedures and employment of both current and vibration signals.

Table 2

Dataset	Sensor	Number of Sensors	Sampling Frequency	Fault Mode
Paderborn University Dataset	Accelerometer, Thermocouple, and Current Sensor	5	65 kHz	Artificial and accelerated test
Case Western Reserve University (CWRU) Dataset	Accelerometer	2	14 kHz and 48 kHz	Artificial
Intelligent Maintenance Systems Dataset	Accelerometer	2	20 kHz	Natural
PRONOSTIA Dataset	Accelerometer and Thermocouple	3	26 kHz	Natural

2. Bearing Fault Diagnostics based on classical Machine Learning approaches

The classical machine learning approaches have been in practice for the application of bearing fault diagnostics for a long time. These algorithms along with some deep learning algorithms are also known as "shallow" algorithms which require deep understanding of complex data analysis and feature engineering techniques such as manipulation and transformation. In general, the first step in these algorithms is to identify and summarize the main characteristics of the data, followed by techniques which simplify the dataset by reducing the variables and maintaining the essential data values. In last, the most important characteristics are selected and used for training a machine learning algorithm. These methods require extensive detailed knowledge in different domains for performing these steps especially during feature extraction process because improper selection of even one feature can lead to the entirely inaccurate model which can cause severe economic and safety problems. Another thing that becomes difficult with improper feature extraction step is loss of transferability of a machine learning algorithm in one model to another model. In this section the detailed discussion on each algorithm is given with corresponding literature and publication.

3.1 PRINCIPAL COMPONENT ANALYSIS (PCA)

The core aim of this analysis is to present the accurate relationship between data values and the level of variance involved in it by conducting the sharp analysis of internal data. In each step, this analysis tries to correlate the data values of previous step with uncorrelated data values of the new step. The unique feature of this analysis is to allow researchers to manually choose the characteristics for analysis which have been proven to be a systematic and effective method of characterization in bearing faults. The earliest usage of principle component analysis (PCA) dates to early 2001-2002 as per the available literature.

It is important to mention such early study taken in 2004 in [29]. This is an experimental study which was conducted to compare the accuracy of bearing faulty diagnostics of PCA and the other methods. During this study it was found that the PCA based models were 90% to 98% accurate. The notable conclusion was that along with more accuracy these models had an extra beneficial feature of requiring less input data as compared to all other models. For reference of researchers the other such notable studies are given [30]-[32] which provides deeper knowledge about the identification and characterization abilities in bearing fault diagnostic procedures.

3.2 ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial neural networks are the earliest machine learning approaches used in research work for bearing fault diagnostics which dates back to more than 3 decades. It is highly useful in problems where nonlinear mapping is required because through other methods the analytical expression of such problems cannot be obtained as in the study conducted in [33]. This study can serve as best example to study the behavior of ANN methods in which the current and driving shaft rpm were taken as input and in result the bearing condition was taken out as output. This dataset was based on more than 80 pretested and 40 training datasets at different realistic operating conditions. The highest accuracy was recorded above 90% with just two input values of current and driving shaft speed. The advanced supervised neural networks also allow manual use of more input values related to rotational kinematics which results in increased accuracy. However, this model requires an additional sensor for rotational speed which may not be available conventionally and needs to be mounted separately.

The explored literature [34]-[36] also confirms that the effective training of artificial neural networks requires expertise in both bearing multi-physics and computational domain.

3.3 K-NEAREST NEIGHBORS (K-NN)

The KNN algorithm is the supervised learning method which is non-parametric in nature. It is a regression model in which the "k" values are achieved from training data and then new values are achieved by optimizing the previous k values. It is comparatively new model used by researchers for bearing fault analysis such as in this study [37] where the ceramic bearing is being diagnosed through KNN method based on acoustic data. It is also useful to use KNN in applications in which it is required to classify the fault in different classes such as in these papers [38]-[39].

There is also another similar non-parametric and regression-based model which is support vector machines (SVM). The method has ever more optimal results than ANN as experimented in [40]. Due to advancement in the machine learning field there have been developed more such models which are being adopted by researchers rapidly. As per the most recent literature, such other methods include Bayesian networks [41]-[43], extreme learning machines [44], transfer learning [45]-[46], linear discriminant analysis [47], quadratic discriminant analysis [48], multi-scale permutation entropy [49], topic correlation analysis [50], canonical variate analysis [52], and ensemble learning [51].

3.4 CHALLENGES WITH THE CLASSICAL MACHINE LEARNING ALGORITHMS

As discussed earlier, all machine learning algorithms share a common characteristic that is requirement of detailed knowledge in feature engineering. In simple terms for analysis through any machine learning model it is first required to record the frequencies at which these faults occur with their respective rotor speed and bearing dimensions. These saved frequencies are then used to identify faults in bearings by training selected machine learning models. However, due to this characteristic there are some challenges such as:

Frequency Interplay: It is quite possible that multiple faults may occur at same time hence it will be difficult to decide that the recorded frequency belongs to which fault. This complex electro-mechanical process results in inaccurate results and false interpretation.

Sliding: Whenever any model is trained it is assumed that it involves no sliding but in actual this assumption usually does not hold true. The bearing rolling elements usually slide along with pure rolling hence the resultant analysis may not be reliable and does not completely depict the condition of bearing under study.

External Vibration: There are also some cases in which the external sources of vibration may combine with the fault vibration such as the environment vibration. This interference makes it difficult for researchers to decide the accurate feature of faults in bearing.

Observability: There are some reasons for bearing faults which cannot be recorded as features and therefore it is impossible to consider them in analysis. One of such features are the bearing lubrication and surface roughness problems. Since the collection of data on these models is difficult hence the training of machine learning model for such features is also difficult.

Incompatibility with traditional approaches: Machine learning models require supervised learning stage during the highly sensitive faults, and this makes them less compatible with the traditionally used multi-physics methods.

Since all these challenges are due to manual data extraction and less automated processes hence the researchers are trying to utilize deep learning methods which are comparatively faster, accurate, and automated.

3. Bearing Fault Diagnostics based on Deep Learning approaches

Deep Learning approaches are the advanced form of machine learning methods which are being widely used by engineers and researchers due to their high-performance capabilities. Instead of relying on shallow approaches, deep learning algorithms are based on a unique way of handling data. All deep learning algorithms possess such power of handling abstract data because in general they work in a structured framework where the simpler and less abstract data are given the higher priorities, and the more specific data are given lower levels which is also known as hierarchy of concepts. This allows the handling of multiple abstract data forms.

The initial challenge with the usage of deep learning algorithms was the demand for large number of datasets. Every deep learning algorithm usually needs larger datasets as compared to the machine learning algorithms such as for training any deep learning algorithm millions of images are needed. Such a big number of datasets are readily available for other domains such as COCO for object recognition and ImageNet for image recognition but for bearing fault diagnostics such a large number of datasets were not available. For that reason, initially more emphasis was placed on machine learning algorithms only but today with the availability of more data the deep learning algorithms can perform better than the class machine learning algorithms as shown in Fig. 5 presented by [53]. The graph of deep learning algorithms will continue to become more steeper due to the invention of even more powerful techniques such as optimization algorithms including RMSprop and ReLU. These new techniques have immense potential to develop deeper models with high convergence rates.

Initially, developing deep algorithms and training networks was also expensive as it had large hardware requirements, but this problem is also solved with the recent hardware evolution. The recently developed GPUs have the capabilities to train deep networks in a very short time and run without any interference. These GPUs also allow the researchers to do parallel computing easily. Such a common example is of GPUs produced by NVIDIA which can convert 1000 terabytes of unstructured raw data into structured and organized that is easy to represent and train the models. The inventions like GPUs, FPGAs, Application-specific integrated circuits, and tensor processing units have changed the landscape of intelligent machine diagnostics.

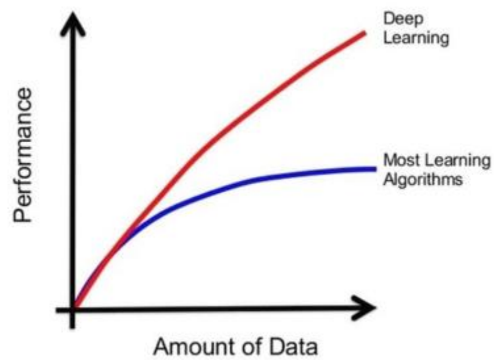

Figure 4

The generated functions of bearing faults become complex as the number of layers through which data passes increases and thus acquires the feature engineering characteristics. This manual handling of data inevitably requires domain expertise, but it is completely eliminated in deep learning procedures. In deep learning, it is required to pass the bearing fault dataset through the deep networks and then the selected algorithm automatically learns from it by extracting the essential features without any human efforts. Furthermore, the deep learning model trained for one problem can also be used to tackle another problem due to its high adaptability power. The capability to understand newly unstructured data makes the deep learning model super generalized algorithms hence they contain considerable ability of transferability.

4.1 CONVOLUTIONAL NEURAL NETWORK (CNN)

The first use of convolution neural networks in research on bearing fault diagnostics is recorded in 2016 in [53]. In the next few years, there are multiple research papers in which these CNNs are utilized including [54]-[63]. The basic framework of identifying a bearing fault is illustrated in Fig. 6. The given architecture completely depicts that the deep learning algorithms resemble with biological processes specifically the patterns of deep neurons that are similar to the working of animal cerebral cortex. The framework is multilayer in which lower layer serves as fundamental layer upon which other layers are built for extracting the features related to bearing faults. First, the 1-D raw data either in the sequential form or in the time series form is collected through the sensors mounted on bearings and then it is passed and converted into 2-D form. Features are then extracted from this vector form of data by passing through main building block of CNN called convolutional layer. After feature extraction, these features are passed through a layer to reduce the dimensionality and retain the essential characteristics; this process is also known as down sampling. The accuracy in the results of bearing fault analysis varies directly with the depth of neural networks and this depth is related to the reptation of the above-mentioned process. In last, the result is taken out as output and passed through an activation function which decides either there is any fault in bearing, or it is safe to use.

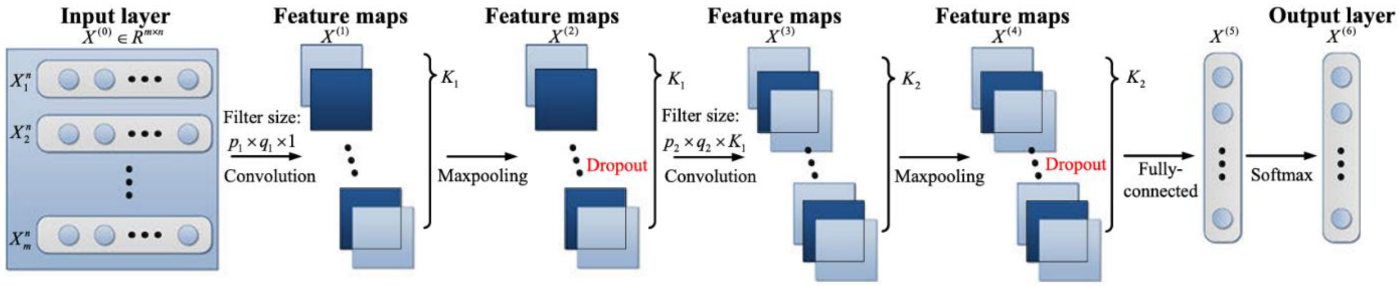

Figure 5

In [53], the CNN model is trained through extracted vibration data from sensors mounted horizontally and vertically in the axial direction of bearing. The deep networks learned from data without any human effort. The feature extraction and learning abilities of CNN proved to be higher than the available conventional machine learning algorithms as per the shown results. Secondly, the developed CNN model was also able to diagnose bearing problems such as lubrication issues which are out of the range of conventional machine learning algorithms. In the future recommendations in [53] it was mentioned that CNN model can also be modified to forecast the anticipated issues based on the current conditions of bearing.

Similarly, researchers have used modified versions of CNN for better adjustment of neural networks depending on the input and output of the model as in [54]. In [54], the adaptive convolutional neural network was used on the Case Western Reserve University (CWRU) bearing dataset. The results confirm that modifying the CNN algorithms can even give better accuracy and learning capabilities as compared to the conventional machine learning and deep learning algorithms. This model contained three layers for data reduction and the unique ability of this model acquired as a result was that it could accurately identify the fault dimensions. This modified model can even get more cascading effects if additional techniques are used as in [55] were the layer dropping technique is used by which the efficiency of the model reached to 95% from 88%. In some cases, the data is given as a mixture of pure signals with some external interfering noise and vibration signals as in [60]-[63]. The results demonstrated that with few modifications the resultant algorithms acquired noise removing capabilities in the bearing fault datasets.

To achieve the required results few more techniques have also been developed such as in [62]. The primary model was based on a conventional LeNet-5 framework in which the few changes were deployed such as controlling the dimensions of feature extraction by padding. The resultant model gave the highest accuracy of 99.8% which was higher than the other modified versions such as ADCNN whose accuracy was just 95%. It also outperformed the high performing machine learning models such as support vector machine (SVM) model whose maximum accuracy is 88%. For optimization purposes in bearing fault research, deep fully CNNs are used which perform better than other widely used available algorithms such as particle swarm optimization algorithms. For DFCNNs the data is given in spectrogram form for easy learning, and it results in the accuracy of 99.4% in optimization problems.

As mentioned earlier that the number of required parameters have been a problem but there are also some other variations of CNNs which not only require less time but very few input parameters similar to the multiscale dilated convolution neural network (MS-DCNN) in which the required data elements were only up to 50,000 which is lower than CNN which requires up to 220,000 data elements. Another problem with bearing fault diagnostics has been varying speed and for this issue researchers have developed a novel framework on CNNs called "LiftingNet". This framework works on a core concept called split-predict-update loop. In this architecture, the datasets in divided into chunks through split layer, prediction is then made on those chunks through prediction layer, and in the end the model is updated based on these predictions. Through this model the accuracy of 96% can be achieved even at varying speeds. When the vibration frequencies are also varied with the motor speed still this model is able to give accuracy upto 94% which is higher than conventional machine learning algorithms. These techniques can be used on any type of bearing fault.

4.2 AUTO-ENCODERS

Auto-encoders have been used in bearing fault research sinch 1990s as a model trained from artificial neural networks (ANNs). It is widely used as a model that can run on unlabeled data and without instructions. The basic architecture of auto-encoders is illustrated in Fig. 7. It works by training a one layer of networks at a time which is also known as greedy training methodology. It works in two parts; the output of one part encoder is given to the other part decoder as input. The output of the decoder is the final output which is usually the characteristics of bearing fault. Among these few steps, there comes a time when the encoder is eliminated, and the decoder is used in a loop for maximum efficiency of the model.

As per the available literature on bearing fault diagnostics, one of the earliest usages of auto-encoders is recorded in [64]. The frequency spectrum form of data was used, and features were recorded with 5 layers of encoders to intelligently handle the bearing health. The feature extraction efficiency was recorded 99% which is the highest accuracy as compared to any conventional machine learning to deep learning model for bearing faults. In [65], the auto-encoders were used with extreme learning machines which provided both faster learning ability and the high accuracy for bearing fault predictions. The mean accuracy reached 99.8% which is higher than multiple machine learning and deep learning algorithms such as Wavelet-Packet Decomposition-SVM (94%), Empirical mode decomposition-SVM (82%), and Wavelet-Packet Decomposition-ELM (88%). Additionally, the required time to train the model was reduced by half duration due to the deployment of extreme learning machines (ELM).

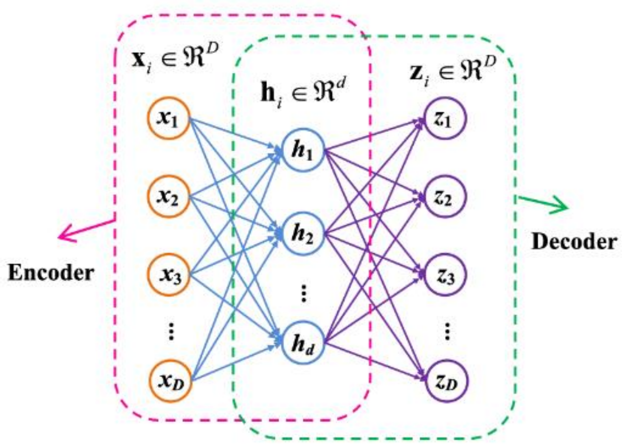

Figure 6

The biggest challenge with autoencoders is their inability to work effectively with mixed data of pure signals and external interferences. For that reason, in [66] a novel arrangement of encoders is used to compare the worst-case inaccuracies. The encoders are arranged in stacked form and the CWRU dataset is passed with 20 dB of extra noise in background for feature extraction purpose. Furthermore, varying loads and speeds are also used for providing a better base for comparison. The results confirm that accuracy of auto-encoders reduces to 91% from 99.8% but it should also be noted that even the accuracy is reduced but it is still greater than many of machine learning and deep learning algorithms with original data only. The similar study in [67] had modified the encoder arrangements having additional three layers of 600 units each. This study used both frequency domain and time domain data of noise and vibration as external interferences. This novel technique shows the reduced resultant error due to special arrangements and data inputs.

In [68], the fish-swarm optimization algorithm is used to test the performance of auto-encoders. The data of automotive bearings which was provided by Northwestern Polytechnical University was used as input to the model. The developed loss function in non-Gaussian environment was different from conventional loss functions with encoders arranged in 5 layers. Several encoders having different characteristics were used at each layer. Firstly, the basic features are extracted from low-layer data with contractive auto-encoders (CAEs) and then they are passed through different other layers of encoders to deepen their learning ability and extract the most essential features. Additionally, the data reduction and preservation technique "locality preserving projection" is applied to preserve the local structure of data with and enhance the characteristics extraction abilities. Even these auto-encoder based algorithms are more accurate, but they are simultaneously 8 to 10 times more time consuming than conventional machine learning and deep learning algorithms.

Moreover, data having three defects in a bearing associated with inner side, outer race, and rotating balls are analyzed with conventional and cascaded auto-encoder methods in [69]. In this research, the gaussian based auto-encoder method, stacked auto-encoders, and conventional auto-encoders were applied to the vibration data of aircraft bearing. In result, the mean accuracy of 88% is recorded which is higher than traditional sparse auto-encoders (SAEs) and deep belief networks (DBNs). Similarly, there have been multiple attempts to use different variations of standard auto-encoders in bearing fault diagnostics problems as in [70]-[76] with a solo purpose of increased efficiency in one or another form.

Since larger datasets are required for training deep networks, a multi-layer autoencoder with sparse and stacked encoders are proposed in [72] by which it became possible to use only 30% of total data for same level of accuracy in results. The model has a total of 720 data entry points divided into 4 layers. Out of which 260 nodes are in first layer while remaining are divided in hidden layers depending upon the bearing condition. The vibration data is compressed by non-superposition projection function and due to automated feature extraction process the accuracy of the proposed model became 98%. This achieved accuracy is double than the conventional ANNs with the same data with 10% more than the traditional SVMs. In all early studies few limitations have been observed related to bearing fault analysis. The most prominent challenge was the inability to remove similar characteristics which resulted in the unnecessary complexities and increased processing time. For that reason, a new combination of standard Auto-encoders (SAEs) and local connection network (LCNs) is presented in [73]. This model contains a local layer from which the neural networks learn locally and then become shift-invariance in next layer and finally diagnose the health of bearing intelligently. The mean accuracy of this model was up to 99%.

To make the bearing fault diagnostics process easier a winner-take-all auto-encoders model is proposed in [76]. The neuron networks are in batches, and each batch has maintained highest "k" value and to increase the accuracy the predictions of each batch are summed up. This model is also tested for external noisy data which is obtained by adding high dB noise of CWRU dataset. The proposed model has shown high precision bearing fault detection capabilities under both normal and noisy conditions.

4.3 DEEP BELIEF NETWORK (DBN)

In simple terms, the deep belief network is the deep learning model for bearing fault diagnostics which is itself a combination of simple networks with unsupervised methods as primary element in combination. These primary elements can be standard auto-encoders, variants of standard auto-encoders, Boltzmann machines, and many more. The basic architecture of deep belief network is illustrated in Fig. 8 in which a RBM shows the unsupervised neural networks with visible layers as input for the next layer. This greedy deep learning process has enabled many recent researchers to utilize the deep belief networks in bearing fault diagnostics effectively. The first recorded publication on bearing fault diagnostics utilizing deep belief networks is [77] which was published in 2017.

In [77], the vibration data from multiple sources is collected and fused from both time domain and frequency to pass initially low layer standard auto-encoders. In end the data is passed through deep belief networks. The proposed algorithm is validated on the mentioned vibration data and confirmed the accuracy of 97.5% which is the descriptive of efficiency of proposed deep belief method for bearing fault diagnostics. In [78], the traditional deep belief networks are cascaded with stochastic filter networks which in result developed a model that has the ability to extract 48 features and learn effectively from them to detect multiple faults in one bearing under different conditions with mean accuracy of 94%. There are also several publications that utilize CWRU bearing fault dataset as the nodal data for first layer.

Similar to the auto-encoder, deep belief networks also have adaptive versions usually known as dual-tree complex wavelet packet (DTCWP) as developed in [79]. In this DTCWP, the vibration data is first analyzed and converted into signals with dimensions 8 by 9, then the signals are passed through wavelet decomposition process. The accuracy achieved is 94.4% which is greater than GRNNs (70%) and SVM (65%) for the same data. In [80], the D-S evidence theory is used with softmax on the data extracted from the multiple sensors with several deep belief network layers. The model predicted the final health of the bearing with 97% accuracy even with variable loads from 0 hp to 4 hp. There are also varied versions of the proposed model in which the weight matrix of each layer is generated, and the final bearing health condition is decided based on the individual layer weightage.

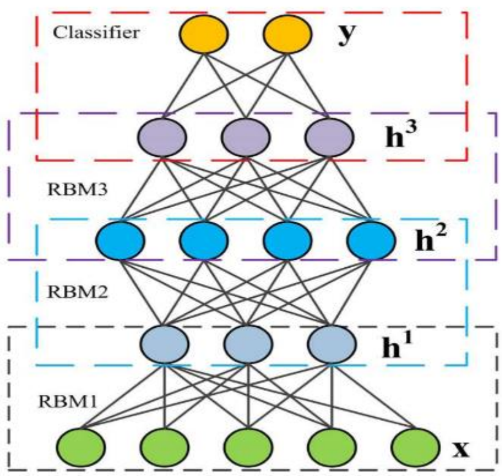

Figure 7

Apart from the CWRU accelerated bearing fault dataset, the data of actual automotive bearing is also used for realistic results. In [81], the analysis is done on the real automotive bearing data with auto-encoders in initial step for data compression and dimension reduction. This study used convolutional deep belief neural networks with RBMs. Before any characteristic learning and feature extraction process, the reduced data is divided into samples for testing. The convolutional networks used in this model eliminated the problem of conventional RBMs because they have the ability to learn representative characteristics without being deeper into hidden and visible layer complexity as in RBMs. In last, the higher layer work for classification and the model achieves the cumulative accuracy of 97% which is considerably greater than conventional neural networks (92%), traditional deep belief networks (88%), and denoising autoencoders (90%). In [82], the real data of bearings used in power plants is analyzed with deep belief networks for bearing health monitoring.

Deep belief networks are also used to anticipate the remaining useful life (RUL) of bearings. In [83], remaining useful life of bearings is predicted through forward neural networks [FNNs] along with deep belief networks whose primary purpose is to extract features only. The data is collected with accelerometers having sampling frequency of 110 kHz. The experimental study demonstrated that the model predicted the remaining useful life very accurately.

4.4 RECURRENT NEURAL NETWORK (RNN)

Unlike conventional auto-encoders and deep learning networks, the recurrent neural network (RNN) method accepts the input data in only recurrent form as shown in its basic framework in Fig. 9. It is a sequential algorithm which is similar to the unrolled forward neural network method. It works best in building sequential relationships in a time series and shows severe issues when trained with back-propagation data due to its nature. RNNs have been used in research since the 1980s but they had limited usage in bearing fault diagnostics due to their nature. This issue was resolved in the early 2000s with the invention of long short-term memory (LSTM) and these are even enhanced by adding gates for recurrent behavior called forget gates. With the integration of LSTM, RNNs have grown their data memorizing and understanding capabilities exponentially.

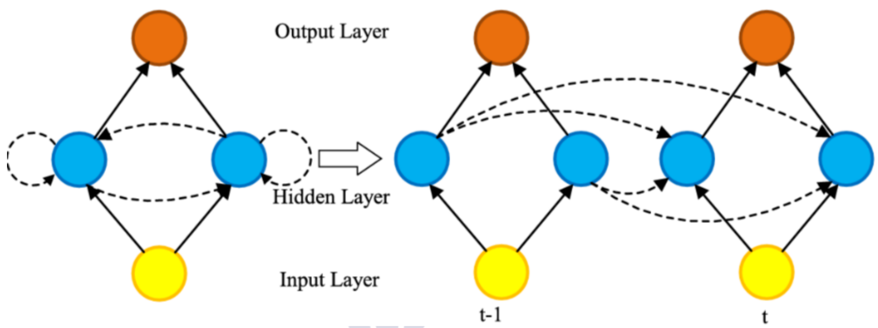

Figure 8

The early usage of RNNs in bearing fault diagnostics is recorded in [84] which was published in 2015. In this study, the features are not extracted by RNN, but they are first analyzed by wavelet transforms and then passed through the RNNs for bearing fault diagnostics. The proposed method has been tested in similar studies and experimental observations show that the RNN based model can accurately tackle the bearing fault problems. Another variant of RNN called RNN-HI where HI stands for health indicator is developed in [85]. This variant of RNN with long short-term memory cells can anticipate the remaining useful life of bearings. It was in time domain and worked simply by comparing the current condition of bearings with the initial healthy condition. After determining the difference between current and past conditions of bearings, the difference characteristic is passed through the RNN which with the help of LSTM predicts the remaining useful life of bearings. The initial data of bearing was taken of a generator used in wind turbines and a comparative analysis of RNN-HI and standard machine learning algorithms in which the RNN-HI outperformed in terms of both accuracy and speed on the same dataset. In a similar study [86], raw data without any labelling is used with 1-D CNNs and LSTMs which in result reached the accuracy of 99%. Recently the RNNs are also arranged in stacks like auto-encoders as in [87]. In this study again the LSTM cell is utilized with RNNs and the basic problem was the optimization of bearing fault analysis which was also handled by stochastic algorithms. The mean accuracy was 96% with varying speeds of 1700 rpm to 1800 rpm.

4.5 GENERATIVE ADVERSARIAL NETWORK (GAN)

Generative adversarial network (GAN) was first developed in 2014 and published in [87]. Even though it is a new algorithm, it has grown rapidly in the bearing fault analysis research. The basic architecture of generative adversarial network is illustrated in Fig. 10 which shows the composition of two parts, the discriminator and the generator. The function of generator is to generate the sample data while the discriminator must differentiate the sample data from the original dataset. It can be thought that the generators indirectly create disturbances for discriminators. This works on the zero-sum principle in which both generators and discriminators try their best to work as fast as possible by which their learning capabilities increase in result. The GAN is primarily developed to be used with other algorithms for generating sample data and functions.

The first application of GAN in bearing fault analysis is recorded after three years of its development in 2017 in [89]. In this study, the generative adversarial network was used in combination with ADASYN to generate the relevant data when the original dataset of bearing is not useful. The comparison of GAN with other similar approaches shows the high-performance abilities of GAN in bearing fault diagnostics. In [90] and [91], a novel multilayer convolution neural network framework was developed with GANs which was applied on insufficient vibrational raw data. After generating relevant datasets through four layers of generator, the features are extracted from data in both time and frequency domain. The datasets of features are then fed into support vector machine (SVM) model for bearing fault analysis. The accuracy and time consumption of this GAN based model was greater than other models such as random under-sampling and synthetic minority over-sampling. There are a lot of such research publications which apply GAN for data improving purpose in bearing fault problems. In some cases, GAN has also been used to classify the bearing features but for this purpose some assumptions are needed.

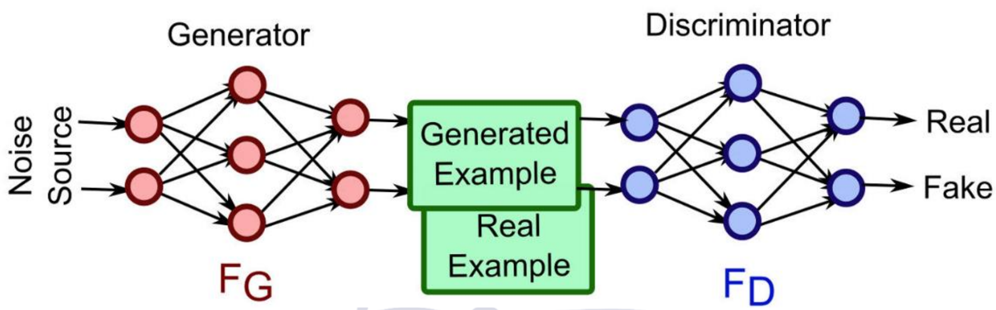

Figure 9

The GANs are also used with auto-encoders in bearing fault applications as in [92]. In this study, a novel architecture of auto-encoders with GANs are proposed in which to maximize the robustness of model adversarial examples were provided. This adversarial based neural network training combines the collective information from provided adversarial examples and the extracted characteristics of original data. The experimental observations confirm that the proposed model worked well under different vibration to noise ratios and multiple extreme driving shaft speeds as compared to other k-means methods. Other similar works using GANs in bearing fault analysis can be found in [93] and [94].

4.6 TRANSFER LEARNING IN DEEP LEARNING METHODS

As mentioned earlier, the accuracy of deep learning algorithms and machine learning algorithms have a direct relationship with the availability of data. It was also discussed that there are few publicly available datasets on bearing faults but still these datasets need to be more detailed and developed. The biggest reasons behind unavailability of datasets in this domain include the unfavorable conditions for data recording during the bearing fault duration, the long and gradual process from bearing fault initiation to final failure, and the involvement of thousands of operating parameters when the bearings reach full fault condition. Whether it is publicly available data or own experimental data used for training deep networks there will always be some level of error in bearing fault measurements. This error is inevitable due to the nature of data collection processes which typically work on multiple assumptions for simplification of data collection. Hence, in the end even highest performing deep learning models still contain some degree of inaccuracy.

Primarily due to these problems, transfer learning has been seen as a viable option due to its wide

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application in various other issues. Several studies have been conducted on transfer learning such as in [95] and [96]. The prominent feature among other features of transfer learning is domain learning. Through this feature, the networks can learn from one domain and convert it to the targeted domain [97]. Therefore, by learning from data in one assumed domain and comparing it with the real domain values the difference between actual and assumed values becomes less. Due to high characteristic learning abilities on automated mode and domain transferring features the machine learning and deep learning algorithms have been used collectively in bearing fault problems such as [97]-[100]. Particularly, in [98] this domain-transferable learning module is developed with 1-D convolution neural networks to minimize errors that usually occur due domain-invariant capabilities. The proposed model was tested on CWRU dataset, IMS dataset, and a locomotive dataset for validation purposes. After training on these three datasets an average accuracy of 87% has been confirmed which is more than standard convolution networks (55%) and other conventional existing similar domain transferring methods (74% to 76%).

4. DISCUSSIONS ON DEEP LEARNING ALGORITHMS FOR BEARING FAULT DIAGNOSIS

As mentioned earlier, the machine learning algorithms have been in application of bearing fault diagnostics but with the major limitation of requirement of manual data handling for feature extraction. This challenge was tackled by the invention of deep learning methods which can handle raw data automatically and learn the prominent features from start to end. As the deep learning methods do not need any human efforts hence these are the first choice of researchers for bearing fault problems due to complex datasets of bearing faults. Additionally, the deep learning methods do multiple tasks in parallel computing way through layers without any interference as shown in Fig. 11. The grouping of neural networks due to self-learning abilities can be shown with each passing layer of convolution neural networks. Even there have been considerable amount of research publications which are only based on the comparative analysis of both machine learning and deep learning algorithms and in all these papers deep learning algorithms have shown higher abilities than conventional machine learning algorithms with some extreme operating conditions.

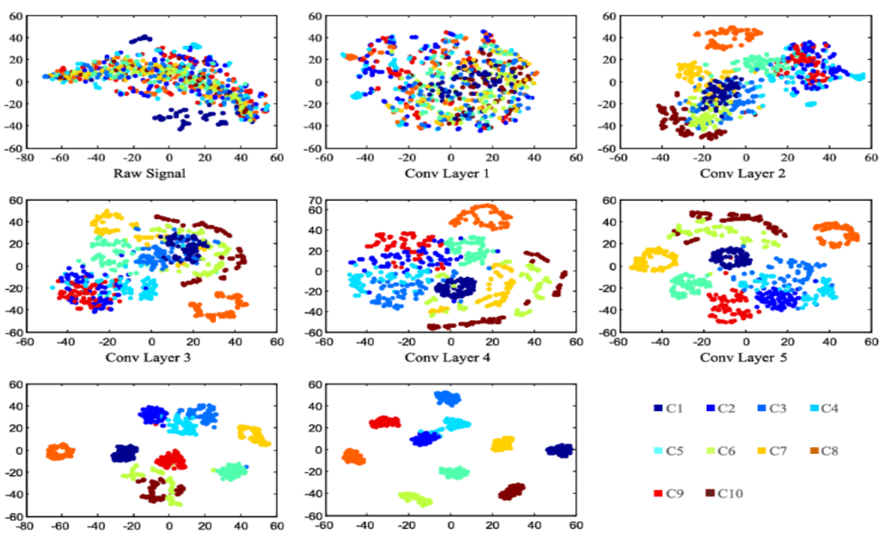

Figure 10

5.1 COMPARISON OF DIFFERENT DL ALGORITHMS FOR BEARING FAULT DIAGNOSTICS

Till now many deep algorithms have been discussed for bearing fault diagnostics, based on the collected data and studied publications Table 3 is built which comparatively differentiates each deep learning model for bearing fault diagnostics. Further analysis of each algorithm is also discussed in the last section. Additionally, the deep learning models are also systematically compared on the basis of classification accuracy as primary metric with the CWRU dataset as shown in Table 4. Each framework contains both hidden and visible layers and dimensions of hidden layers are directly related to the training time for each model. In convolution neural network model both pooling layer and convolution layer work as the hidden layer while in GAN the number of hidden layers is more than any other model.

The accuracy of each model is up to 94%, which again provides validation and confirmation to use deep learning algorithms for bearing fault diagnostics. However, the accuracy value is not the only metric to check the feasibility of deep learning model for bearing fault diagnostics. We should also consider other characteristics such as generalization. There are few models which even achieve the accuracy of 99% on the trained data but their accuracy reduces severely when they are exposed to actual conditions because the actual conditions vary in nature. For example, if a dataset is trained on 1800 rpm driving shaft and 1 hp power but if in actual the shaft speed varies to 1850 rpm and power reduces to 0.5 hp the accuracy of model also changes severely. Such another metric in unbalanced sampling. In some cases, the sampling of dataset is not balanced as the data from healthy bearing condition and faulty condition is not in one to one ratio. Hence some other metrics such as precision and F1-score are used to check the resilience of deep learning algorithms.

Tab: 4

Algorithm	Classifier	Hidden layers	Characteristics	Training Sample Percentage	Average Accuracy	Reference
CNN	Softmax	4	Noise-resilient	90%	92.60%	[55]
Adaptive CNN	Softmax	3	Predict fault size	50%	97.6%	[54]
CNN based on LeNet-5	FC layer	8	Better feature extraction	83%	99.7%	[56]
Multiscale Deep CNN	Softmax	9	Reduced training time	90%	98.7	[58]
CNN based LiftingNet	FC layer	6	Adapt to load change	96%	95.5	[101]
PSPP-CNN	Softmax	9	Adapt to speed change	67%	99.7%	[60]
AOCNN with SF	Softmax	4	Reduced training time	5%	99.1%	[102]
SAE	ELM	3	Reduced training time	50%	99.83%	[65]
Stacked denoising AE	N/A	3	Noise-resilient	50%	91%	[66]
SDAE	Softmax	3	Noise-resilient	80%	99.8%	[67]
Deep Wavelet AE	ELM	3	Reduced training time	67%	95%	[71]
SAE-Local Network	Softmax	2	Shift-invariant features	25%	99.92%	[73]
SAE	SVM	3	Online diagnosis	N/A	95%	[74]
SDAE	Gath-Geva	8	Noise-resilient	N/A	93.3%	[75]
Winner-take-all AE	Gath-Geva	2	Noise-resilient	N/A	97.27%	[76]
Complex Wavelet	N/A	5	Adaptive DBN	67%	94.38%	[79]
DBN	Softmax	2	Adapt to load change	N/A	98.8%	[103]
DBN with ensemble learning	Sigmoid	4	Accurate and Robust	N/A	96.9%	[80]
Deep RNN	N/A	3	Accurate	60%	94.75%	[87]
DCGAN	SVM	8	Data Augmentation	96%	86.3%	[90]
CatAAE	Softmax	11	Adapt to load change	91%	90%	[92]

Spectrum of Engineering Sciences
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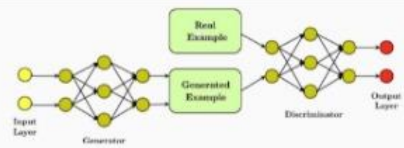
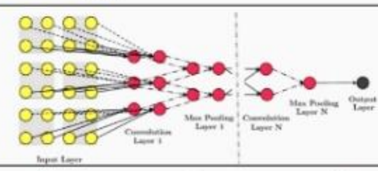
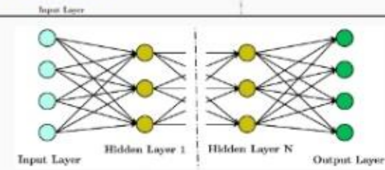
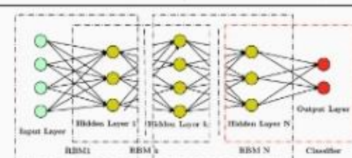
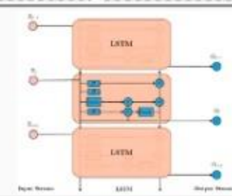
A2CNN	Softmax	27	Domain Adaptation	N/A	99.21%	[104]
GAN+SDAE	Softmax	8	Data Augmentation	78%	99.21%	[93]

Table 3

Description	Features	Architecture
Generative Adversarial Network • The primary function is to create sample data that mimics the characteristics of actual data. • It is composed of a generator and a discriminator • It can be used in classification tasks as well.	• It does not need any special arrangements or settings when dealing with different sets of data. • It does not rely on Monte Carlo approximation for training. • It does not involve deterministic bias. • It does not work well on discrete datasets.	
Convolutional Neural Network • It works very well on 2D data (all types of 1D data have to be converted to 2D before processing) • Convergence speed can be increased • Includes Variants such as ADCNN and LiftingNet,	• The CNNs have the best capability of working with external noisy data. • It is required to have a few neuron connections concerning ANNs. • The entire hierarchy can only be found by determining multiple layers, • For better woking, large labelled datasets are required.	
Autoencoders • The primary function is to reduce the dimension of data and extract the characteristics of the given data. • It includes various modified versions such as stacked sparse autoencoders and deep ensemble autoencoders.	• It can also work well with unlabelled data. • The modified versions can even make the autoencoders more resilient and accurate. • It requires preprocessing training,	
Deep Belief Network • It is composed of RBMs where each sub-network's hidden layer serves as the visible layer for the next. • It allows both supervised and unsupervised training of the network.	• The training may be computationally expensive due to the initial training stage. • It requires a layer-by-layer initialization network to start the training. • Trackable inferences increase the likelihood directly.	
Recurrent Neural Network • It is similar to ANN, but the exceptional ability is that it can analyze 1D datasets. • The integration of LSTMs makes it a more viable option for training networks. • It is more suitable for problems where the output is a function of previous computations.	• It memorizes sequential datasets. • It is capable of handling time-dependent data. • It may cause frequent learning issues due to the explosion of data.	

5.2 SUGGESTIONS, CHALLENGES, AND FUTURE WORK DIRECTIONS

The successful completion of deep learning and machine learning algorithms depends on the accurate understanding of all physical features of bearing faults. For researchers, engineers, and scientists, who want to use the deep learning and machine learning algorithms for bearing faults analysis should follow below-mentioned steps:

Environment: The initial step should be to do detailed analysis of working conditions of bearing and the environment in which it is operated such as inner and outer temperatures, operating speeds, moisture levels in air, fatigue or creep effect chances, and varying loads. The DL and ML model should be selected in a way that if the operating conditions are usually normal and don't contain multiple parameters then conventional models should be adopted while if the working conditions involve large number of parameters, then varied and cascaded versions of standard models should be utilized.

Sensors: The next step should be to check number, type, and places needed for mounting bearings. If the selected model in the first step is conventional ML model, then a maximum of two vibration sensors can be sufficient. If the selected model is any DL model, then the number of required sensors can be more because majority of DL models require data in 2-D form. Additionally, as per the requirements of varied versions of DL models, multiple sensors are inevitably required to create multi-physics datasets.

Data size: If the selected model does not work well on the available data, then a new model should be selected which must have a high generalization ability. The data augmentation techniques such as GAN can also be used to fulfil specific data size requirements of each model.
The biggest challenges in deep learning methods have been discussed in earlier sections but in here the precise revision of these challenges are presented as:

Real Data Training: The large number of papers mentioned in our research work have used only the laboratory data which is publicly available for bearing fault diagnostics but there should be such other convenient methods through which the data extraction becomes easy. Through newly developed data collection processes the error in DL and ML results can be minimized which arises due to difference between actual and laboratory datasets.

Limited Labels: Even if new datasets are developed for training ML and DL algorithms but another bigger issue is the labelling of data. The nature of bearing fault data is in such a way that it is not easy to label the data and get information about when a fault has started to initiate hence for that reason new algorithms need to be built along with new datasets.

Data Imbalance: There are also cases where even the laboratory data is not sufficient to train machine learning and deep learning algorithms for bearing fault diagnostics. For such cases new data sampling and creation techniques should be built but they should not be based on high assumptions only.

External Effects in Data: Majority of the papers mentioned in this research work utilizes data which have been collected under laboratory conditions however in actual cases the other external factors really involve such as external vibration and noise in wind turbines. Hence, for that reason, there should be built models which simulate the external environmental conditions and can be combined with actual datasets.

5. Conclusion

In this paper, a systematic framework on application of Machine learning and Deep learning algorithms for bearing fault diagnostics is presented. Through comparative analysis it has also been confirmed that the deep learning algorithms are being widely adopted by researchers for bearing fault application due to their advanced capabilities. Even the large number of datasets are required to train a deep learning algorithms, but their automatic learning and feature extraction abilities cannot be achieved through any other option. These deep learning algorithms also proved to be easy because of no involvement of any human expertise in their training. For comparative analysis we have used the CWRU dataset, but any other available data set can also be used. In the end a detailed summarizing discussion and future recommendations are included for researchers who want to conduct their research on bearing faults on an extendable level.

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