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Deep Learning-based Intelligent Fault Diagnosis Methods towards Rotating Machinery

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ABSTRACT Fault diagnosis of rotating machinery plays a significant role in the industrial production and engineering field. Owing to the drawbacks of traditional fault diagnosis methods, such as heavily dependence on human knowledge and professional experience, intelligent fault diagnosis based on deep learning (DL) has aroused the interest of researchers. DL achieves the desirable automatic feature learning and fault classification. Therefore, in this review, DL and DL-based intelligent fault diagnosis techniques are overviewed. DL-based fault diagnosis approaches for rotating machinery are summarized and discussed, primarily including bearing, gear/gearbox and pumps. Finally, with respect to modern intelligent fault diagnosis, the existing challenges and possible future research orientations are prospected and analyzed.

INDEX TERMS Deep learning, deep neural network, intelligent fault diagnosis, rotating machinery.

I. INTRODUCTION

As an essential part and one of the most representative of mechanical equipment, the rotating machinery relies on rotation for purpose of a specific function. It has been widely used in the field of mechanical transmission, including aircraft engines, pump, wind turbine generator systems, gas turbine engine, and power plants [1,2]. Owing to unavoidable malfunction and downtime of the mechanical equipment in the process of operation, fault diagnosis is of great significance for rotating machinery in order to ensure the reliability and safety [3-6].

In general, fault diagnosis methods are divided into the followings, model-based methods, signal-based methods, knowledge-based methods and composite methods [7]. In view of traditional fault diagnosis methods, they are primarily based on mechanism, feature frequency or fault feature extraction [8]. On account of dependence on the practical experience and professional knowledge, it is difficult to detect the fault of rotating machinery with complex structure by the use of traditional subjective fault diagnosis methods [9, 10]. Some improvement and achievement have been made on fault diagnosis with respect to the model-based methods and signal-based methods. A kalman filter was improved and used to evaluate the state of hydraulic actuator and leakage of hydraulic system by Sepehri et al [11,12]. Du and Goharrizi et al. analyzed and estimated vibration signal of hydraulic pump, pressure signal of hydraulic cylinder and actuator via wavelet transform [13,14]. The doubly iterative empirical mode decomposition (EMD) and adaptive multifractal detrended fluctuation analysis were employed to analyze fault diagnosis of the bearing, the gear and the piston pump [15,16]. Although the shortages of artificial data statistics have been compensated by the methods discussed above to some extent, there are still some limitations in fault diagnosis of rotating machinery owing to the difficulty in feature extraction and complicate mathematical model.

With the implement of “Industry 4.0” and “Internet +”, artificial intelligence (AI) has been quickly integrated into the various traditional industries [17]. Intelligent fault diagnosis, which is combined with other feature extraction methods, AI as the main body, has attracted more and more attention. It is considered to be a powerful tool for big data processing and fault diagnosis of mechanical equipment, which provides a new exploration path for fault diagnosis and health management of rotating machinery [18,19].

Great success has been achieved in fault diagnosis of rotating machinery with traditional machine learning methods, such as support vector machine (SVM) and artificial neural network (ANN) [20-23]. Wavelet packet decomposition and EMD were combined and used to feature extraction, moreover, ANN was utilized to preliminary fault diagnosis by Bin et al [24]. In order to achieve fault diagnosis of hydraulic pipe, an integrated method including principal component analysis (PCA), ANN and multiple adaptive neural fuzzy inference system was proposed by Saeed et al [25]. On account of on-line intelligent diagnosis based on neural network, Schlechtingen et al. used it to fault diagnosis of wind turbine generator [26]. In order to realize fault identification of bearing, many various efforts have been made on the exploration of novel methods. Amar et al. proposed a neural network based on vibrational spectra [27], Jiang et al. combined improved singular value decomposition (SVD) and hidden markov model [28], and Zeng et al. used a maximum interval classification method based on flexible convex hull [29]. A novel diagnosis method for bearing was proposed by Li et al., thereinto, the geometry of input data was taken into account [30]. Zhu et al. combined multi-scale fuzzy measure entropy, infinite feature selection and SVM to explore the effectiveness of fault diagnosis for the bearing [31]. In addition, intelligent diagnosis method was proposed based on firefly neural network by Li et al [32]. However, there are still some limitations and deficiencies in traditional intelligent diagnosis methods. On the one hand, in consideration of feature extraction, a large number of signal processing technologies requires to be grasped and rich experience in engineering practice needs to be possessed; additionally, feature extraction and intelligent diagnosis are treated separately, the relationship between them could not be taken into account. On the other hand, with regard to model training, the shallow model is used to characterize the complex mapping relationship between signals and health status, which leads to the obvious deficiency in diagnostic ability and generalization performance of the model in the face of mechanical big data [33,34].

Modern intelligent fault diagnosis technology is based on the new theory and method of AI. In 2006, Hinton et al. first proposed the deep learning (DL) theory in Science [35], which triggered a wave of research on many different fields. DL was ranked as the top 10 breakthrough technologies of 2013 by MIT Technology Review. In 2015, Hinton et al. indicated that DL was thought to be one of machine leaning, and breakthrough was analyzed and discussed in the respects of image, video, audio and text processing [36]. It has been adequately demonstrated that DL presents the broad prospects on research and application. Through multi-layer nonlinear network training, potential features of samples have been learned and classification or prediction ability have been improved with DL. DL methods that are widely studied usually include deep belief network (DBN) [37,38], stacked self-encoders (SAE) [39], convolutional neural network (CNN) [40,41] and recurrent neural network (RNN) [42]. Based on multivariate encoder information, a CNN was designed to intelligently identify the failure of planetary gear box by Lin et al. Not only did the deficiency of traditional vibration analysis overcome, but also a potential intelligent tool was provided to obtain the expected diagnosis towards rotating machinery [43]. In accordance with multi-domain features, an integrated kernel extreme learning machine was proposed and used to gear box, rotor and motor bearing, effective diagnosis was achieved by visualization with the method [44].

Presently, on account of the wide use of DL in many pattern recognition fields, intelligent fault diagnosis based on DL has attracted much more attention of professional researchers in machinery field. Therefore, this review will focus the efforts on fault diagnosis of rotating machinery. It will place an emphasis on fault diagnosis integrated with deep neural network technology. Furthermore, a summary of the applications will be given towards commonly used rotating machinery such as bearing, gear and pump. Finally, the above discussions are concluded and the possible research directions are provided to inspire more researches in this field.

II. DL BASED FAULT DIAGNOSIS

A. ARTIFICIAL INTELLIGENCE

As a new and interdisciplinary science, AI is aiming at simulating some of human thinking processes and intelligent behavior by the use of computer. It can be achieved in computer by the following two different ways, one is engineering approach which adopts traditional programming technique; the other is modeling approach, such as generic algorithm and ANN.

From SIRI to AlphaGo, rapid development of AI has been supposed to be interesting, surprising and outstanding [45,46]. AI approaches have been integrated into many various fields, great achievements have been obtained in man-machine game, pattern recognition, automatic engineering and knowledge engineering [47-49]. Because of the increase of machinery data and complication of fault which result in high uncertainty during diagnosis process, AI based methods will outperform traditional methods on diagnosis efficiency. AI-based approaches can be divided into the following two categories, knowledge-driven methods and data-driven approaches [50].

B. DL

As a distinguished development of AI, DL can be understood as feature learning or representation-learning, which possesses multiple and high levels representations of data, concretely, through DL, low-level features from simple and nonlinear modules were composed to form more abstract high-level representations in terms of categories or features, complex functions and distributed feature representations of data can be obtained [51]. Very deep neural networks can be considered to be typical DL model. DNN plays an essential role in deep models, mainly including DBN, SAE, CNN, RNN and GAN. As one of unsupervised learning ways, DBN is a DNN which possesses the stacked structure and consists of multiple Restricted Boltzmann Machines. Similarly, SAE is used to deal with high-dimensional data by means of unsupervised learning. It is composed of multiple auto-encoders, which presents a three-layer neural network including both encoding and decoding processes [52]. CNN is a supervised learning network, whose structure seems to be more complex with convolution layers, sample layers and full connected layers. With especial ring structure, RNN represents a unique advantage in settling learning problems with sequential data via unsupervised learning. It is interesting that GAN is comprised by generally both non-linear function models, that is, a generative model and a discriminative model respectively [53]. In order to overcome the deficiency of insufficient training data, deep transfer learning (TL) has achieved that the learning from the source domain is employed to the target domain [54,55]. Deep reinforcement learning is the learning of the intelligent system from the environment to the behavior mapping, with the purpose of maximizing the long-term cumulative reward, which really realizes the machine's capability of self-learning and self-thinking [56] Compared with traditional machine learning, it should be noted that the key advantage of DL is layers of features are automatically learned from raw data through a general-purpose learning procedure, not dependent on engineering skills and domain expertise [36].

In view of the advantages of DL, it has been applied to many different fields such as language processing, automatic speech recognition, and audio recognition [57 , 58]. Meanwhile, this has aroused the interest of researchers in the field of mechanical engineering, making it play an essential role in intelligent fault diagnosis combined with other methods and technologies [59,60].

C. Overview of DL based Fault Diagnosis

Intelligent fault diagnosis is the combination of AI and fault diagnosis, which expresses comprehensive use of domain expertise and AI technology and strong capability of processing considerable mechanical data [61,62].

Three different steps are included in traditional intelligent fault diagnosis, namely, signal collection, feature extraction and fault classification. Since some exhausted and handcrafted signal feature extraction technologies could be required in those methods, diagnosis results will finally be affected. Moreover, the ability to learn the complex non-linear relationships between features and patterns will be hindered with the shallow structures such as SVM [63]. With respect to new intelligent fault diagnosis, in place of feature extraction and selection, the features can be automatically learned from raw signals, which presents more intelligent than conventional approaches [64,65].

Some good results have been achieved in applications to gear, gearbox, bearing, rolling, pump, wind turbine and nuclear power plant with modern intelligent fault diagnosis [66-69]. Deep CNN was employed to fault diagnosis of wind turbine, bearing and gearbox by Liu et al., and it is worth noting that the spatiotemporal pattern network was integrated [70,71]. Xu and his colleagues proposed a new intelligent diagnosis method based on elaborately designed deep neural network for failure detection of wind turbine, which solved the problem of unbalanced distribution with regard to SCADA data [72]. Combined a CNN with a Naïve Bayes data fusion proposal, Chen et al. applied DL theory to nuclear power plant inspection [69]. Zhang et al. constructed a new unsupervised learning method called general normalized sparse filtering, which was used for fault diagnosis of rolling bearing and planetary gearbox [73].

III. APPLICATIONS OF DL TOWARD FAULT DIAGNOSIS IN ROTATING MACHINERY

Combined with the above analysis, it can be proved that it has acquired some improvements and achievements for machinery fault diagnosis illuminated from the applications of DL technique in other fields. As shown in Table 1, the applications of DL-based methods in machinery fault diagnosis have been summarized. In order to evaluate the diagnosis performance of methods, the following evaluation indicators are employed, including the diagnosis accuracy, the training accuracy, the average testing accuracy, the prediction accuracy, the clustering effect from visualization.

This review will play an emphasis on intelligent fault diagnosis of typical rotating machinery, including bearing, gear and pump. Furthermore, DL-based approaches for improving diagnosis accuracy will be analyzed and discussed in the following.

TABLE I
SUMMARY OF DL-BASED METHODS FOR MACHINERY FAULT DIAGNOSIS

Technique	Applications	Diagnosis Effect	(Ref.)
CNN with first-layer kernel dropout	Bearing fault diagnosis	99.77% accuracy	[74]
CNN and second generation wavelet transform	Motor bearing fault diagnosis	99.63% accuracy	[75]
CNN and wavelet packet energy	Spindle bearing fault diagnosis	99.8% accuracy	[76]
CNN with hierarchical structure	Bearing fault diagnosis	desirable performance	[40]
CNN	Bearing fault diagnosis	99.75%	[77]
CNN	Bearing fault diagnosis	100% accuracy	[78]
CNN	Rotor and bearing fault diagnosis	100.00% accuracy for rotor; 93.33% for bearing	[79]
CNN	Bearing fault diagnosis	99.89% accuracy	[80]
DBN and sparse autoencoder	Bearing fault diagnosis	97.82% average accuracy	[81]
RNN-based	Bearing fault	99.85%	[82]

autoencoders	diagnosis	accuracy	
Autoencoder and particle swarm optimization-SVM	Bearing fault diagnosis	94.34%	[83]
SAE and softmax regression	Bearing fault diagnosis	95.26%	[84]
Deep convolutional auto-encoding NN	Bearing fault diagnosis	99.7%	[85]
Kernel auto-encoder based on firefly optimization	Bearing fault diagnosis	95.95% average accuracy	[86]
Deep convolution variational autoencoder network	Self-priming centrifugal pump and bearing fault diagnosis	98.845 and 97.62% average accuracy respectively	[87]
DBN	Bearing fault diagnosis	93.17% average accuracy	[88]
DBN and singular value decomposition	Bearing fault diagnosis	100%	[89]
DBN and Hilbert envelope spectrum	Bearing fault diagnosis	99.55% accuracy	[90]
DBN	Bearings fault pattern recognition	99.93% accuracy	[91]
DBN based on multi-layer neural networks	Gearbox fault diagnosis	98.1 %	[92]
CNN	Gearbox fault diagnosis	96.8% mean accuracy	[93]
SAE, dropout technique and ReLU activation function	Gearbox fault diagnosis	99.34%	[94]
GAN and stacked denoising autoencoders	Gearbox fault diagnosis	98.4% accuracy	[95]
TL	Gearbox and bearing fault diagnosis	100%	[96]
Multimodal deep support vector	Gearbox fault diagnosis	97.08%	[97]
Support tensor machine	Gear fault diagnosis	99.50%	[98]
DNN	Bearings and gears fault diagnosis	100%	[39]
CNN	Bearing, self-priming centrifugal pump, and axial piston hydraulic pump fault diagnosis	99.79%, 99.481%, 100% prediction accuracy	[99]
SAE	Spacecraft fault diagnosis	98.35%	[100]
Refrigerant charge fault detection-based CNN	Heat pump system	99.9%	[101]

A. INTELLIGENT FAULT DIAGNOSIS OF BEARING

As one of well-known and widely-used rotary machinery, bearing is of great significance but its brokendown occupies nearly 45-55% of equipment fault, which will lead to accidents, downtime, even severe damage and economic loss [102,103]. Therefore, it is of vital importance to investigate intelligent fault diagnosis methods of bearing, especially the DL technique.

In order to overcome the imbalanced distribution of machinery health conditions, a new learning method called deep normalized CNN (DNCNN) was investigated to classify the faults of bearing by Lei et al [104]. Three bearing datasets are employed to validate the diagnosis accuracy of the proposed methods, in which single faults and compound faults with various imbalanced degrees are taken into account. In Figure 1(a-c), it can be seen that DNCNN presents the superiority than S-CNN and R-CNN in terms of learning features from the vibration signals, in which the features cluster well. By the use of the confusion matrices, the imbalanced classification results were successfully obtained, that is, 95.4% of the samples were correctly classified by the proposed method, and only 4% of the samples were misclassified.

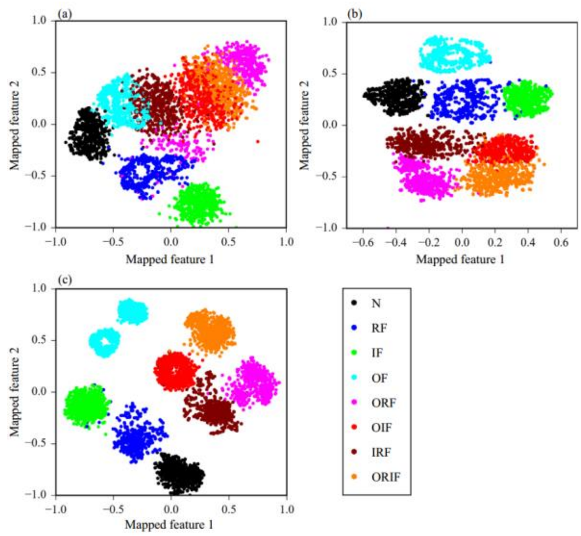

FIGURE 1. The visualization of learned features for Dataset A: (a) S-CNN, (b) R-CNN, (c) DNCNN. S-CNN represents the convolutional neural networks (CNN) using sigmoid function, R-CNN represents the CNN using ReLU, DNCNN represents deep normalized convolutional neural network, respectively [104].

As one method of machine learning, TL makes it possible that one pretrained model is employed again to another task with the purpose of reducing the distribution discrepancy and enhancing the predictive performance [105,106]. Generally, both developing model and pretraining model are included, moreover, the latter is widely used in machine learning. Through the integration of auto-balanced high-order Kullback-Leibler divergence, smooth conditional distribution alignment and weighted joint distribution alignment, a novel TL framework was designed for fault diagnosis of rotator bearing and gearbox under varied conditions [107].By introducing grey wolf optimization algorithm, a new TL-based method was constructed for diagnosis of the bearing. It was worth mentioning that long-short term memory RNN was employed to gain some auxiliary datasets [108]. Inspired by the idea of TL, a deep CNN was proposed to be used for fault diagnosis of unlabeled data by Lei et al., which made it possible that labeled data from one machine after being trained could effectively classify the unlabeled data from other machines [109]. Furthermore, as one of CNN, a transfer neural network based on feature was explored for state identification of bearings. In comparison to the other methods such as CNN and multi-layer adaptation CNN, the average classification accuracy of the proposed method was the highest one which achieved 84.32%. It has been demonstrated that more desirable transfer results and transfer performance were obtained with FTNN. Seen from Figure 2(f), in consideration of the learned transferable features, the distribution was adapted efficaciously, furthermore, the among-class distance was expanded [110]. In order to overcome the limitations in training and the performance degradation, a new deeper 1D CNN based on the residual learning was developed for fault diagnosis of wheelset bearings, and the effectiveness was approved by visualization Figure 3 [80].

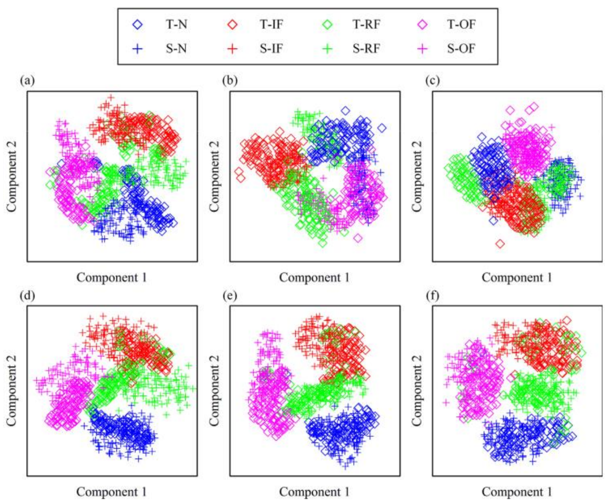

FIGURE 2. The visualization of the learned features on the dataset B (source domain) and the dataset D (target domain): (a) CNN, (b) TCA, (c) DAFD, (d) DDC, (e) MACNN, and (f) FTNN. CNN represents convolutional neural networks, TCA represents transfer component analysis, DAFD represents, DDC represents, MACNN represents multi-layer adaptation CNN, and FTNN represents feature-based transfer neural network [110].

A new deep TL with three-layer sparse encoder was investigated by Wen et al, which was validated by the use of motor bearing dataset. Compared with other traditional methods, such as DBN, ANN, sparse filter, and SVM, this proposed method presents good performance and the prediction accuracy achieved 99.82% [111].

He et al. presented a composite deep signal processing approach, which integrated vibration analysis and deep learning [112]. Vibration analysis was embedded into the discrete Fourier transform - inverse discrete Fourier transform autoencoder, which achieved that time-frequency characteristics were learned adaptively and effective convergence was obtained in view of learning procedure. Real bearing data was employed to validate the performance of the proposed method, which presented obviously higher diagnosis accuracy compared with those of popular deep neural network (DNN), CNN and SVM. Specifically, the testing accuracy reached 100.00% while below 95.50% in other methods when shaft speeds were set as 45 and 60.

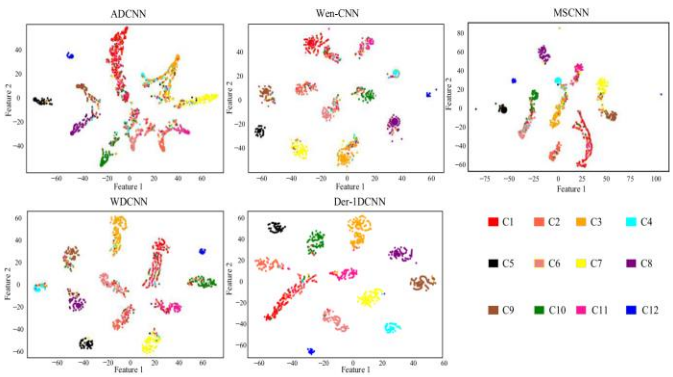

FIGURE 3. Visualization of these five methods in noise environment (SNR=−16 dB). ADCNN represents adaptive deep CNN, Wen-CNN represents CNN proposed by Wen et al, MSCNN represents multiscale CNN, WDCNN represents deep convolutional neural networks with wide first-layer kernels, Der-1DCNN represents deeper 1D CNN [80].

Motivated by the thought of enhancing the generalization ability and robustness of diagnosis model through utilizing the structural domain information among multiple bearing fault types, a new deep output kernel learning was presented in order to overcome the randomness of some deep learning methods [113]. In comparison to one the-state-of-the-art signal analysis method, four shallow models and four deep models, it showed higher accuracy of 100.00% and shorter training time of less than 7 s.

Combined compressed sensing with a convolutional DBN, a new improved deep model with powerful feature learning ability was constructed to analyze the single fault and compound faults of rolling bearing by Shao et al [114]. It should be pointed that the analysis efficiency was enhanced by compressed sensing and the generalization performance was enhanced via exponential moving average technique. The average testing accuracy of the proposed method achieved 94.80%, which was be superior to other traditional methods of no more than 90.00%, including the standard DBN, CNN, deep auto-encoder (DAE), BP neural network and SVM. From the visualization of PCA (Figure 4), it can be proved that the better clustering result was obtained from the proposed method, which expressed the superiority in capturing potential features.

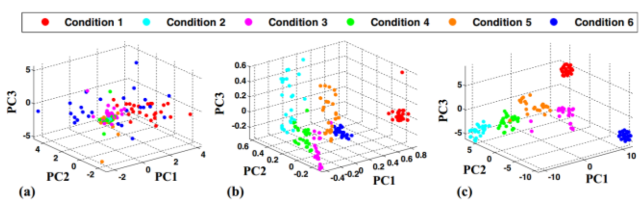

FIGURE 4. Three dimensional visualization of different features using PCA. (a) Compressed data features, (b) extracted 22 features, and (c) deep features [114].

In regard to the diversity of the fault data distribution and the data reconstruction ability, a sparse stacked denoising autoencoder is developed for the fault diagnosis of rolling bearings [115]. With the introduction of optimized transfer learning algorithm, the problem of the domain adaption was solved, and the accuracy of the target domain achieved 96.70% in one of motor loads. It was demonstrated that the quality of the target domain was influenced by the performance of the source domain algorithm, however, it is limited to only depend on the enhancement of the source domain.

In consideration of unlabled data in practical engineering, combined with Gath-Geva clustering algorithm, a stacked denoising autoencoder was investigated for roller bearing fault diagnosis without principal component analysis and data mark [116]. The proposed method presented the superior clustering effect. Moreover, its classification accuracy was higher compared to those of the other combination models, and the highest one reaches up to 100.00%.

B. INTELLIGENT FAULT DIAGNOSIS OF GEAR AND GEARBOX

It was indicated that the gearbox failure was the primary contributor to equipment fault, which took up nearly 40% in mechanical transmission field according to the investigation performed under the assistance of the Institute of Electrical and Electronic Engineers (IEEE) [117]. Hence, in view of the fault diagnosis for gear and gearbox, the methods based on DL will be highlighted in the following.

Combined CNN and extreme learning machine, a new model without any extra training and fine tuning was established by Chen et al., gearbox dataset and motor bearing dataset were selected to verify the effectiveness of the proposed method, as depicted in Figure 5 [118]. It was demonstrated that the feature learning capability was improved by the CNN employed as an automatic feature extractor, and the classification performance and the learning speed were promoted through the extreme learning machine. In view of gearbox, the results indicated that the training accuracy and average test accuracy reached 100.00%±0.00 and 99.83% ± 0.24 respectively, which achieved the superiority in contrast to the other methods such as standard CNN. With regard to motor bearing, the training accuracy and average test accuracy gained 100.00%±0.00 and 99.92% ±1.24 respectively, which exhibits the better classification performance.

With respect to signal processing-based methods, a wavelet packet transform, a distance evaluation technique and a support vector regression (SVR)-based generic multi-class solver were combined for fault diagnosis of bearing and gearbox [119]. The proposed method presented the superior representative capability and the higher diagnosis accuracy, which was mainly attributed to the influences of wavelet basis functions on the proposed whole framework.

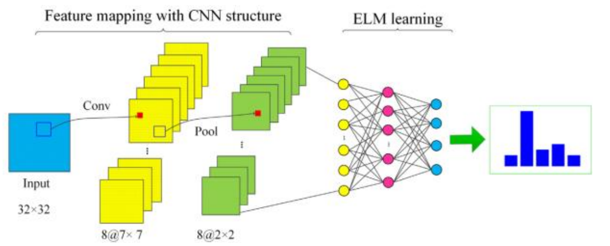

FIGURE 5. The structure of the proposed CNN-ELM model for fault diagnosis [118].

Motivated by the idea of TL, a new intelligent fault diagnosis scheme named deep transfer network with joint distribution adaptation was exploited to overcome the applicability limitations for the traditional diagnosis methods [120]. Three datasets including wind turbine, bearing and gearbox fault dataset, were employed to verify the performance of the proposed framework, which displayed some good results in accordance to various working conditions, the types and severities of fault. In order to demonstrate the performance of the proposed method, the average diagnosis accuracy, missing alarm rate, and false alarm rate were chosen as evaluation indicators, meanwhile, eight state-of-the-art intelligent diagnosis approaches were used as comparisons. With regard to gearbox, the average diagnosis accuracy of the proposed scheme outbalanced those of other methods, which reached up to more than 96%. Similarly, a working condition-robust fault diagnosis method based on an improved joint distribution adaptation was exploited to achieve the acquisition of more useful samples and reduction of the input dimension [121]. The vibration signal datasets of roller bearings and a gearbox were used to validate the fault diagnosis performance of the proposed method, which obviously demonstrated its effectiveness although its computational time was completely unsatisfactory.

In consideration of unexpected diagnostic results via utilizing the spectrum signal, modern spectrum signals through preprocessing current signals was incorporated into DNN by Li et al [122]. Compared with SVM and BPNN, the proposed method represented superior diagnostic results for faults detection in planetary gears, the testing accuracy rate of which achieved 96.69% with standard deviation of 1.05%. Furthermore, the diagnosis advantage of the proposed method was proved by the visualization of fault characteristics from PCA, as shown in Figure 6(d), which presented better clustering effect and little overlapping than those of others.

A new DL method was developed for fault diagnosis of planetary gear through combining power spectral entropy of variational mode decomposition and DNN, which was trained through unsupervised training and supervised fine tuning [123]. It is beneficial to fault classification via the reduction of raw signals by the use of BP. Compared with other methods such as SVM and BP, the proposed method exhibited the higher overall recognition rate of 100%.

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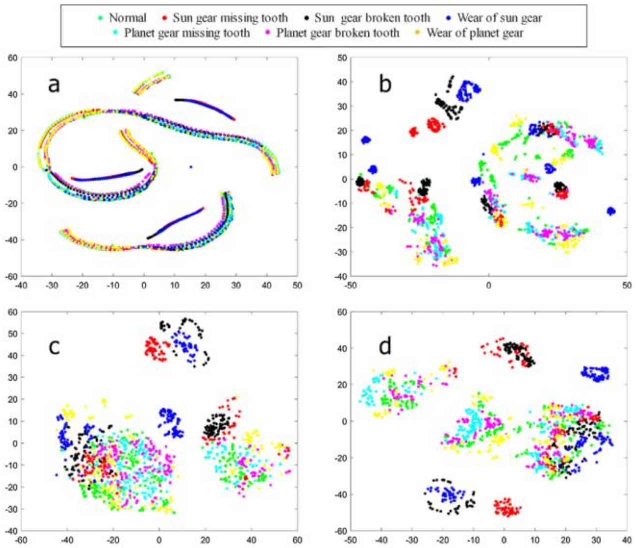

FIGURE 6. Scatterplot of the main characteristic components: (a) signals in the time domain, (b) direct spectrum signals, (c) spectrum signals without the power frequency, and (d) modified spectrum signals. Reprinted with permission from ref. [122].

Based on time-frequency analysis and DNN, a deep residual learning was constructed for fault diagnosis in planetary gearbox [124]. Its performance was demonstrated under nonstationary running conditions, which implied admirable results for the incipient fault detection, especially when rotating speed was variable. The proposed scheme presented the higher diagnosis accuracy, which reached up to 95.4% under faulty condition.

A deep CNN was constructed for gearbox fault diagnosis under different operating conditions, which was compared with different SVM classifiers optimized by the use of a grid search technique [125]. With regard to vibration signals of different directions, the proposed method showed the superiority to other traditional methods. The identification accuracy achieved 93.6% and the computational cost was reduced.

By the use of the maximum correntropy and artificial fish swarm algorithm, a new deep autoencoder feature learning method was designed and optimized by Shao et al. for the fault diagnosis of gearbox and electrical locomotive roller bearing [126]. Compared with other approaches such as standard deep autoencoder, BP and SVM, the proposed method possessed the admirable diagnosis effectiveness including robustness, and the average testing accuracy reached 94.05% with a smaller standard deviation of 1.34.

In order to overcome the dependence on numerable labelled data and time consuming of handcrafted feature extraction in traditional supervised diagnosis, a new deep semi-supervised method of multiple association layers networks was investigated by Zhang et al [127]. As shown in Figure 7, the wavelet packet transform was employed to preprocess raw signals, moreover, the labeled and unlabeled data was together used to train the model and method. It can be concluded that the recognition accuracy of the proposed method presented the advantage in comparison to SAE and DBN with less labeled data. The recognition rate increased from 78.58% to 93.26% with the increase of the labeled samples from 2% to 100%. Additionally, it is worth to note that the optimization of the hyper-parameter may be a key challenge and have a great influence on the performance of the neural networks.

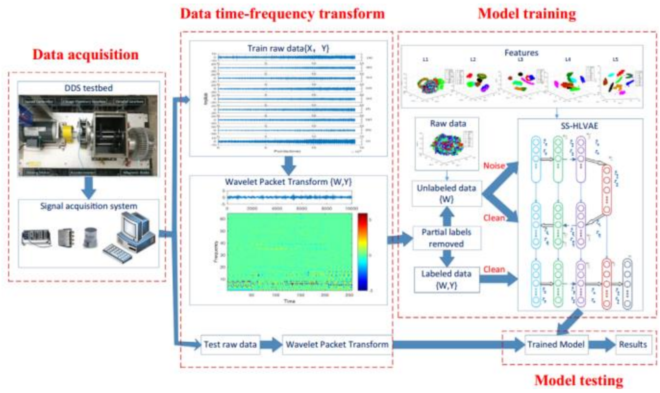

FIGURE 7. The framework of the proposed method for fault diagnosis of planetary gearbox [127].

C. INTELLIGENT FAULT DIAGNOSIS OF PUMPS

With the function diversity and structural complexity of hydraulic system, it seems to be more challenging for fault identification and classification [128-130]. As power source of hydraulic system, hydraulic pump plays an indispensable role in reflecting the working state of the system [131,132]. Meanwhile, with respect to the wide use of centrifugal pump, whose operating state directly affects production and safety. According to the statistics on the mechanical and electrical equipment defects, more than 50% are connected with pump failures [133,134]. Therefore, it is of great significance to diagnose pump faults accurately and effectively in order to ensure the safety and reliability of the system. Although some researches have achieved admirable results on machinery intelligent fault diagnosis, there are still little investigations on pumps.

As an essential and famous DL, DNN has aroused great attention in intelligent fault diagnosis, which has also stimulated interest in research for pumps. A new data-driven method based on CNN with LeNet-5 was developed by Wen et al [135]. In regard to axial piston hydraulic pump, two fault conditions were taken into account, and the piston shoes and swashplate wearing and valve plate wearing were included. The prediction accuracy achieved 100%. As for self-priming centrifugal pump, four faults conditions were analyzed, including bearing roller wearing, inner race wearing, outer race wearing, and impeller wearing fault condition. From the results of confusion matrix, it can be observed that the prediction accuracy of 99.481% was

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obtained, moreover, the most misclassification was 0.4%. Similarly, a simple improved CNN was proposed for fault diagnosis of hydraulic pump by Yan et al [136]. Two operating conditions including stable and variable pump speeds were investigated, the accuracy rate exceeded 95% and 90% in view of the worst results.

Based on image-processing technique, a probabilistic neural network was introduced by Lu et al, and it was achieved that the feature was automatically extracted in a two-dimensional space [137]. The speeded-up robust features and t-Distributed Stochastic Neighbor Embedding (SNE) were employed to automatic feature extraction and dimensionality reduction respectively. By the use of t-SNE, the feature information was more clustered and presented the potent capability of separability (Figure 8(A)). It can be concluded from the cross-validation results that the proposed method presented the high diagnosis accuracy. The classification accuracy was more than 96% for the self-priming centrifugal pump. For the axial piston hydraulic pump, the average classification accuracy achieved as high as 98.71%.

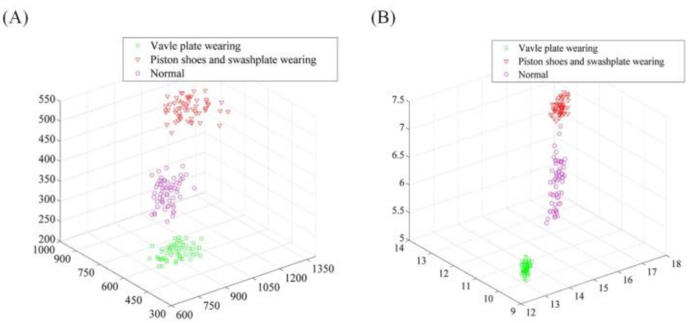

FIGURE 8. The first three features extracted using t-SNE (A) and without using t-SNE (B) [137].

Through introducing data indicator containing time and frequency, Wang et al. investigated a DBN for multiple faults diagnosis of the axial piston hydraulic pump, which achieved the advantageous classification accuracy of 97.40% in comparison to SVM and ANN [138]. It deserved to be mentioned that the restricted Boltzmann machine was used to realize the automatic learning of fault features.

In consideration of the complex dynamic behavior for rotary machinery, symbolic analysis plays an essential role [139]. In combination with hierarchical symbolic analysis (HSA), a CNN was used for fault diagnosis of centrifugal pump [140]. The diagnosis accuracy improved as the number of hierarchical layers increased, moreover, the computation time admirably reduced after using HSA. It achieved the maximum of 98.50% when hierarchical layer was 3. By means of data fusion which achieved the transformation of multi-sensor-signals to images, another improved CNN was proposed by Wang et al., and the prediction accuracy reached up to 99.47%. It presented the obvious better diagnosis effectiveness in comparison with other intelligent methods [141].

Owing to the long operating time and computing complication, a novel intelligent fault diagnosis scheme was developed combined deep structure with SVM, which realized the learning of the hidden features [142-144]. The similar conclusions were obtained that the accuracy rate increased with the number of network layers. In contrast to other methods, the proposed method exhibited the superior diagnosis performance. In consideration of the accuracy rate and computing time, the optimum result achieved up to 97.75% with standard deviation of 0.20.

IV. CONCLUSIONS AND PERSPECTIVES

Relevant studies on fault recognition methods have been performed by our research group [145,146]. Additionally, PCA and XGBoost were integrated to diagnose hydraulic valves. It is worth noting that we have conducted many investigations on fault diagnosis and signal processing for hydraulic pumps and centrifugal pumps, which mainly concentrate on conventional intelligent methods [147-150]. Furthermore, we gradually begin to study intelligent fault diagnosis methods such as SVM for hydraulic pumps [151], which provides a theoretical foundation for the following researches on DL-based fault diagnosis approaches. In the present and future, we will put emphasis on the DNN-based methods and explore multi-information fusion technique with well generalization capability, moreover, remote diagnosis system will be exploited and constructed.

In accordance with the analysis and discussions above, the methods based on DL can not only adaptively extract the hidden complex and changeable fault information, but also overcoming the reliance on diagnostic knowledge and engineering experience of traditional methods. Although these methods have achieved some expected results in rotary machinery, there are still some challenges in the current researches and the corresponding future research directions are as follows:

(a) A large number of studies only used experiments or existing datasets to validate the effectiveness of the proposed methods, and the underlying mechanism of improved diagnostic accuracy has not been analyzed in details.

(b) Many researches primarily focus on the single physical source information, diagnosis accuracy requires to be improved owing to small data size. It is significant to pay more attention to multi-source information, which can comprehensively reflect the state of equipment. But multi-source signal has diversity and complexity problems, which need to be further studied.

(c) The commonly used single marker system has interpreted fault information out of context, and the introduction of multi-marker system could be promising to explore the identification of multiple faults.

(d) On account of many present methods, only the diagnosis accuracy is improved. However, in the face of the fault with more coupled and concurrency characteristics, it is urgent for further exploring the identification of complex faults and the generalization performance of the method.

Based on the thinking of DL, intelligent fault diagnosis strategies are overviewed in this review. The applications of DL-based techniques in fault diagnosis of rotating machinery are thoroughly analyzed and discussed, mainly bearing, gears and pumps. The diagnosis performance of these emerged methods is highlighted, which provides ideas and guidance for the exploration and applications of novel intelligent fault diagnosis in rotary machinery extending to other machineries.

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