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Federated learning for machinery fault diagnosis with dynamic validation and self-supervision

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ABSTRACT

Intelligent data-driven machinery fault diagnosis methods have been successfully and popularly developed in the past years. While promising diagnostic performance has been achieved, the existing methods generally require large amounts of high-quality supervised data for training, which are mostly difficult and expensive to collect in real industries. Therefore, it is motivated that the distributed data of multiple clients can be integrated and exploited to build a powerful data-driven model. However, that basically requires data sharing among different users, and is not preferred in most industrial cases due to potential conflict of interests. In order to address the data island problem, a federated learning method for machinery fault diagnosis is proposed in this paper. Model training is locally implemented within each participated client, and a self-supervised learning scheme is proposed to enhance the learning performance. The server aggregates the locally updated models in each training round under the dynamic validation scheme, and a global fault diagnosis model can be established. Only the models are mutually communicated rather than the data, which ensures data privacy among different clients. The experiments on two datasets suggest the proposed method offers a promising approach on confidential decentralized learning.

1. Introduction

Machinery fault diagnosis using condition monitoring data is of great importance in modern industries, which enhances device reliability, increases operation safety, and reduces maintenance costs [1–7]. In the recent years, with the rapid development of artificial intelligence algorithms, the data-driven fault diagnostic methods have achieved great success and been widely adopted in a number of applications. Due to the advantages of fast response, high accuracy, easy implementation *etc.*, many industrial processes have largely benefited from the advancement of the intelligent diagnostic approaches, including automotive, aero-space industry, smart manufacturing *etc.*

Despite the promising health monitoring performance that has been achieved, the existing methods generally require large amounts of high-quality supervised data of the testing machine for training an effective diagnostic model. In the real industrial scenarios, accurately labeled condition monitoring data are usually difficult and expensive to collect, due to the complexity of the operating conditions in most cases [8,9]. Especially, the data in medium and severe faulty states generally cannot be obtained from the target testing machines in the real production lines. That poses remarkable obstacles for the applications of the data-driven algorithms in the real industries.

An intuitive solution for this problem is to collect labeled data from multiple similar machines as the target one for model training. However, that mostly requires considerable human labor for data collection and significantly increases the economic costs. For the common industrial processes such as manufacturing, it is noted that different companies and factories generally have similar types of working machines, and they usually have their own supervised datasets for fault diagnosis. It is thus promising to integrate the data of similar devices across different parties for establishing a powerful fault diagnosis model, which reduces the labor and cost for each party, and expects model improvement.

In spite of the potential benefits, this solution typically requires data sharing among different companies and factories, which is generally not preferred or even feasible since data privacy is of great importance in the industries due to potential

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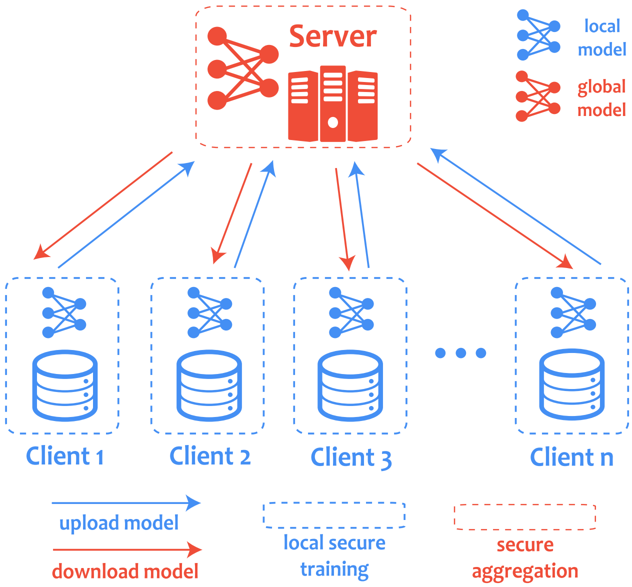

Fig. 1. Illustration of the federated learning scheme. Due to data privacy, the local private data cannot leave local storage in collaborative training with multiple clients.

conflict of interests. While data cleaning protocols and strict access controls can be applied for data protection, the company users can be still uncomfortable with the access and storage of their private data. Furthermore, different users may have heterogeneous data, which are difficult to integrate and leverage. For instance, vibration data and current signal can be obtained by different industrial clients separately, and it is not straight-forward to directly exploit different types of data for better performance. These challenges are known as the data island problem, which generally occurs in different industries.

In order to address this problem, the recently emerging federated learning technique offers a promising tool, which allows a centralized server to develop an effective global fault diagnosis model while the training data are safely and privately distributed on the devices of the clients, i.e. the participating parties in the learning processing. Fig. 1 shows the illustration of the federated learning scheme. Specifically, rather than conventionally aggregating all the raw data for centralized training, federated learning does not require the server to access the local data of different clients directly. In each training round, the local client can download the current global model from the server, update the model through training with the local data, and uploads the updated model to the server. The server then integrates all the uploaded models to be a renewed global model. In this way, the local data of different clients are not mutually communicated, and the transmitted information of the model updates can be further protected using the encryption algorithms [10]. Therefore, the data privacy can be effectively guaranteed in federated learning.

This paper proposes a federated learning method for machinery fault diagnosis with dynamic validation and self-supervised learning. The data island problem with privacy concerns in the real industries is effectively addressed, as well as the data sparsity issue at different clients. The proposed method is well suited for processing machinery condition monitoring data in fault diagnosis problems. The main novelties and contributions of this paper are listed as follows,

- The data privacy-preserving collaborative model training strategy with multiple clients in machinery fault diagnostic scenarios is focused on in this study. This practical industrial problem has been seldomly investigated in the literature.
- A deep neural network-based federated learning method is proposed, where a central server is used for model aggregation globally. The models are trained locally at different clients using the private data. Only the models are shared with each other, and the specific local data of the clients are not communicated with the server and other clients.
- A novel dynamic validation scheme is proposed under the federated learning framework to reduce the influence of the distributed low-quality training data. At each training step, the local models are evaluated using a validation set, and the ones with lower validation performance are neglected in model aggregation. That enhances the global model robustness against low-quality data.
- A self-supervised learning method for machinery signal processing is proposed to improve the model learning performance with limited training data. The machine vibration signals can be better explored at each client, and the inherent structural generalized features can be learned for diagnostics, which reduces the overfitting risks and increases the testing accuracies.
- Through experimental validations on two rotating machinery datasets, the proposed method is able to largely increase the decentralized learning performance with the private data of different clients safely distributed at local devices. The results indicate the proposed method is promising for decentralized learning on fault diagnosis problems.

The remainder of this paper starts with the related works in Section 2. The proposed method is introduced in Section 3, and experimentally validated in Section 4. We close the paper with conclusions in Section 5.

2. Related works

In the past decade, a number of intelligent data-driven fault diagnosis methods have been successfully developed and applied in many industrial applications [11–14], such as artificial neural networks (ANN), random forest (RF), support vector machines (SVM) *etc.* Among them, the neural network-based approaches have shown strong capabilities in capturing the relationship between condition monitoring data and machine health states. Especially, the deep neural network also known as deep learning has been attracting increasing attention due to its promising pattern recognition performance [15]. Multiple layers are stacked in the structure with linear and nonlinear data transformations, that largely contribute to the enhanced learning capacity of the algorithm [16–18].

In [19,20], the data-driven fault diagnosis problems were successfully addressed using deep learning. Besides the traditional fully-connected layers, the neural network variants have also been popularly applied in processing machinery data such as vibration acceleration signals [21]. For instance, the convolutional neural networks (CNN) were adopted by Xia et al. [22] for rotating machinery fault diagnosis, and promising diagnostic performance was achieved. Liu et al. [23] proposed the recurrent neural network (RNN) based auto-encoder for rolling bearing fault diagnosis. Furthermore, the RNN-based long short-term memory (LSTM) structure has also been popularly adopted for processing machinery data in fault diagnosis studies [24]. In general, deep learning has achieved great success in the data-driven fault diagnostic problems [25].

With respect to the target testing machine, insufficient high-quality training data can be usually obtained in most cases, which generally cover limited domains such as operating conditions *etc.*, while the testing data can be from different working scenarios [26]. The distribution discrepancy between the training and testing data leads to significant deteriorations of the generalization ability of the model [27,28]. In order to address this issue, transfer learning techniques have been popularly developed, which aim to extract generalized and domain-invariant features from the data in different conditions [18,28–30]. A cross-domain transfer learning method for fault diagnosis was proposed by Guo et al. [31] where the maximum mean discrepancy is used as the optimization metric and adversarial training is also adopted. The results show it is promising for knowledge transfer across different domains.

Despite the prospective transfer learning performance in the literature, explicit enlarging the supervised training dataset covering more domains basically achieves more accurate and reliable performance for the data-driven fault diagnosis models [32,33]. Considering the data collection cost, it is promising to develop a powerful model by exploiting data from multiple clients, and the decentralized privacy-protected federated learning strategy has been emerging as an effective solution for the model aggregation without data sharing [34,35].

In order to increase the communication efficiency between the server and clients, the federated averaging method was proposed by McMahan et al. [36]. Smaller local training mini-batch size and more local training times are generally suggested to reduce the communication rounds. The federated learning scheme was adopted by Hard et al. [37] in the next-word prediction task in a virtual keyboard for smartphones. The experimental results indicate federated learning provides an effective method for distributed model training while incorporating data privacy of a population of clients. In the federated learning framework, Zhu et al. [38] optimized the neural network model structure and minimized the communication costs and the global test errors simultaneously using a multi-objective optimization algorithm. Saputra et al. [39] applied the federated learning method on predicting energy demand for electric vehicle networks, and the accuracy of energy demand prediction was significantly improved.

With the merit of gaining additional learning capability for the inherent data-related knowledge, self-supervised learning has been drawing attention in the past years in many practical tasks [40], such as image classification, speech recognition *etc.* The self-supervised visual representation learning has been proved to benefit the semi-supervised learning problems through exploration of the unlabeled data [41]. The motion capture model for cameras has also been improved using the self-supervised learning strategy [42]. The self-supervised learning method was further improved by Noroozi et al. [43] with knowledge transfer, where the framework decouples the structure of the self-supervised model from the final task-specific fine-tuned model. In general, the image processing tasks have noticeably benefited from the development of the self-supervised learning method [44], while the machinery signal processing has been less considered.

In spite of the recent advances, the fault diagnosis problem has been seldomly investigated in the federated learning framework. This study contributes efforts on further improving this promising algorithm on distributed model training in fault diagnosis problems across multiple clients with data privacy. A self-supervised learning scheme is also proposed for better exploration of the limited local clients' data, which is well suited for the machinery condition monitoring signals. This study demonstrates that the industrial machinery fault diagnostic problems can largely benefit from the proposed federated learning method.

3. Proposed method

3.1. Problem statement

In this study, the federated learning problem in machinery fault diagnosis is investigated. In general, this study is carried out under the following assumptions.

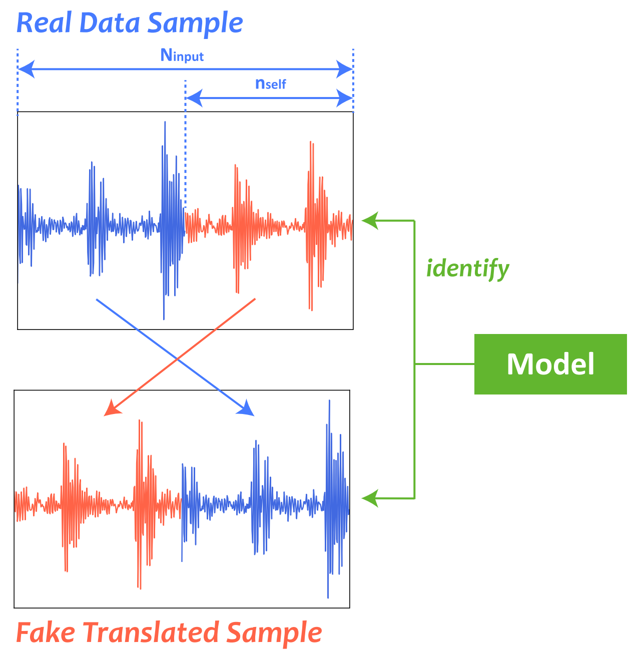

Fig. 2. Illustration of the proposed self-supervised learning scheme. The time-series vibration data are translated to create fake samples to assist model training.

(1) Multiple clients are included in the federated learning system, and each client has insufficient training data which fail to effectively build its fault diagnosis model independently.
(2) The fault diagnosis tasks of all the clients are identical, that indicates different clients share the same label space.
(3) The same fault diagnosis model is shared by the server and different clients.
(4) Local data of different clients cannot be communicated.

Let $\mathcal{D}^i = \left\{\left(\mathbf{x}^i_j, y^i_j\right)\right\}_{j=1}^{n_i}$, $i = 1, 2, \ldots, N_{client}$ denote the supervised data set of the ith client, where N_{client} is the number of the included clients. $\mathbf{x}^i_j \in \mathrm{R}^{N_{input}}$ represents the jth data sample in $\mathcal{D}^i$, y^i_j is the corresponding machine health state label, N_{input} is the sample dimension, and n_i denotes the number of samples in $\mathcal{D}^i$.

This study aims to build a global fault diagnosis classifier $y = f(\mathbf{x})$ in the central server, which holds for all the clients. However, the data in $\{\mathcal{D}^i\}_{i=1}^{N_{client}}$ cannot be explicitly accessed by the server and other clients, and only the locally trained models of different clients can be communicated to the server. A validation set is assumed to be available at the server for real-time adjustment of model aggregation. In this way, the data privacy is protected, and the clients can also benefit from the fault diagnosis knowledge learned from other participants.

3.2. Self-supervised learning

In many real industrial processes, limited high-quality supervised training data can be usually obtained, that poses significant obstacles in training effective fault diagnosis models using the existing machine learning techniques. In order to better explore the available data, a self-supervised learning method is proposed in this study as shown in Fig. 2, which aims to artificially create additional fake samples in order to learn structural knowledge from limited training data.

Specifically, with respect to one sample $\mathbf{x} = [x_1, x_2, \ldots, x_{N_{input}}]$, its variants are generated by using data translations. Let n_{self}

denote the number of the translated points in each sample. $0 < n_{self} < N_{input}$. The generated fake translated sample is thus,

$$\mathbf{x}_{fake} = [x_{N_{input}-n_{self}+1}, \ldots, x_{N_{input}}, x_1, x_2, \ldots, x_{N_{input}-n_{self}}], \tag{1}$$

which holds different structure with the original data sample. The same translation is applied on all the original samples to create the corresponding fake samples.

During model establishment, while the deep neural network classification model is used for health condition classification, the two-class identification task can be further integrated in the model, which aims to distinguish the real and translated fake samples. In this way, the information of the limited training data can be better exploited in the unsupervised learning manner, which enhances the generalization ability of the learned model and reduces the overfitting risk. The detailed training strategy will be introduced in the following section.

It should be noted that while some self-supervised learning methods are available in the current literature, they are mostly focused on the image processing tasks. For instance, the images can be usually rotated, inpainted *etc.* for self-supervised learning. However, direct applications of the existing techniques on the fault diagnosis cases do not carry clear physical meaning for processing time-series machinery signals. On the other hand, the proposed self-supervision approach can well preserve the frequency-domain information of the time-series data, which is critical in conventional physical model and signal processing-based fault diagnosis methods [45]. This fact will be validated in the following experimental study section. Therefore, the proposed strategy can better fit the application scenarios of machine fault diagnosis problems.

3.3. Network architecture and optimization

In each training round, the fault diagnosis model is locally updated within each client, and the optimization objective contains two components, i.e. condition classification loss and self-supervision loss. The architecture of the deep neural network model that is shared by different clients and the server is presented in Fig. 3, which includes three modules, i.e. feature extractor, condition classifier and self-supervision classifier. It should be pointed out that low communication burden is generally preferred by federated learning, which indicates small model with simple structure as used in this study.

Generally, typical convolutional neural networks are adopted in the proposed model. To facilitate industrial applications, the raw vibration acceleration data are directly used as the inputs. Two convolutional layers with filter size of 10 and filter number of 10 are adopted in the feature extractor. After flattening, a fully-connected layer with 128 neurons are adopted as the high-level representations of data. Next, the learned features are fed into two fully-connected layers, respectively. In the condition classifier, N_c neurons are used with each neuron representing the classification confidence of each health condition, respectively. Similarly, two neurons are used in the self-supervision classifier. The softmax functions are adopted in both the modules for classification probability calculation. The leaky rectified linear units (LReLU) activation functions are used throughout the network [46].

Without loss of generality, the model optimization in a single client is described in the following. First, for the local data $\{(\mathbf{x}_i, y_i)\}_{i=1}^{n_s}$ where n_s denotes the number of the labeled samples for the client, the empirical classification error is supposed to be minimized and the widely used cross-entropy loss function is adopted as,

$$L_c = -\frac{1}{n_s}\sum_{i=1}^{n_s}\sum_{j=1}^{N_c} 1\{y_i = j\} \log \frac{e^{x_{i,j}^h}}{\sum_{k=1}^{N_c} e^{x_{i,k}^h}}, \tag{2}$$

where $x_{i,j}^h$ denotes the jth neuron of the fully-connected layer in the condition classifier, that takes the ith real sample as input.

As described in Section 3.2, additional fake translated samples are created for learning structural data information. In this study, one real sample generates one translated sample with n_{self} for simplicity, that leads to n_s fake samples in general. The self-supervision classifier is trained to correctly identify the real and fake data, and the cross-entropy loss is also adopted as,

$$L_s = -\frac{1}{2n_s}\sum_{i=1}^{2n_s}\sum_{j=1}^{2} 1\{d_i = j\} \log \frac{e^{x_{i,j}^s}}{\sum_{k=1}^{2} e^{x_{i,k}^s}}, \tag{3}$$

where $x_{i,j}^s$ denotes the jth neuron of the fully-connected layer in the self-supervision classifier, that takes the ith sample in the enlarged dataset as input. d_i represents the sample label of the real and fake status.

In summary, the optimization objective L_{obj} can be formulated as,

$$\min L_{obj} = L_c + \alpha L_s, \tag{4}$$

where α denotes the penalty coefficient.

3.4. Federated learning with dynamic validation

Federated learning has been emerging as a promising technique for decentralized model training with data privacy, which enables the clients to obtain a globally optimized model without sharing local data with different participants, including both the central server and other clients. Generally in each round of training, each client downloads the global model from the server cloud, locally trains the model using private data, and uploads the updated model weights or gradients back to the server. With respect to the centralized server, model aggregation is implemented to update the global model afterwards. Meanwhile, a dynamic validation scheme is proposed to adaptively adjust the model aggregation process, in order to reduce the negative influence of the distributed low-quality data. Through iterations of training, a globally optimized model can be established by the server, and the data privacy can be effectively guaranteed locally.

It is noted that federated learning generally has high requirement on local computation ability and server–client communication performance. Therefore, in order to increase the training efficiency, the federated averaging algorithm is adopted as the basic framework in this study [36], which is basically able to achieve model convergence in fewer training rounds. Along with the dynamic validation scheme, the proposed federated learning algorithm is presented in Algorithm 1.

Let $\boldsymbol{\theta}_0^{global}$ denote the initialized global model parameters. In the ith training round, the server sends the global model $\boldsymbol{\theta}_{i-1}^{global}$ to each client, and the models are independently trained using the local data of different clients. With respect to each client, mini-batch optimization of the objective L_{obj} is implemented, and the locally trained models are uploaded to the server afterwards.

When the server receives all the uploaded models $\{\boldsymbol{\theta}_i^j\}_{j=1}^{N_{client}}$ where $\boldsymbol{\theta}_i^j$ denotes the updated model of the jth client, the dynamic validation scheme is performed. Specifically, recall that a validation set denoted as $\mathcal{D}_{val}$ is available at the central server. The N_{client} locally uploaded models are firstly evaluated on $\mathcal{D}_{val}$. The cross-entropy loss metric is considered as in Eq. (2), and N_{client} scores can be thus obtained for different local models. Larger scores indicate larger estimation errors on the validation set, that means the models are generally less suitable for testing, while smaller scores suggest better performance.

To enhance the model robustness against low-quality data at some clients, the models with larger scores are supposed to be neglected, that leads to a parameter determination problem

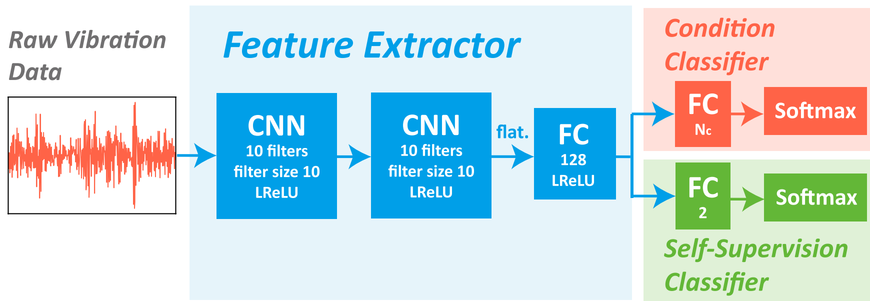

Fig. 3. Proposed deep neural network architecture for fault diagnosis. The raw vibration data are directly used as model inputs to the network.

with respect to the number of the neglected models n_{val}. In this study, the optimal n_{val} denoted as n^*_{val} is selected dynamically at each training round. Specifically, the model averaging operation is conducted for N_{client} times, with n_{val} iterating in the range $[0, N_{client} - 1]$. At each step, the models with the largest n_{val} scores are neglected in averaging, and a total number of N_{client} averaged models can be obtained. Next, the N_{client} new models are further evaluated on the validation set, and the one with the smallest score is thus the temporary optimal model. That is used as the global model at this round, and n^*_{val} can be achieved accordingly. Fig. 4 shows the scheme of the proposed dynamic validation method.

In this way, the renewed global model is obtained as $\boldsymbol{\theta}_i^{global} = \frac{1}{N_{client}-n^*_{val}} \sum_{j\in S_{dyn}} \boldsymbol{\theta}_i^j$, where S_{dyn} denotes the client set with the $N_{client} - n^*_{val}$ lowest validation scores at this training step. Through N_{round} training rounds, the final global model $\boldsymbol{\theta}^{global}_{N_{round}}$ can be used for testing.

Algorithm 1: Federated Averaging Method with Dynamic Validation

Input: Model, number of training rounds N_{round}, optimization objective L_{obj}, learning rate δ, n_{val}, N_{client}
Server side:
Model initialization of $\boldsymbol{\theta}_0^{global}$
for each training round $i = 1, 2, \ldots, N_{round}$ **do**
  Send global model $\boldsymbol{\theta}_{i-1}^{global}$ to all the clients
  Wait for uploaded models $\{\boldsymbol{\theta}_i^j\}_{j=1}^{N_{client}}$ from all clients
  Calculate the optimal n^*_{val} using the dynamic validation scheme
  Neglect n^*_{val} models with largest scores and keep the rest
  Update global model $\boldsymbol{\theta}_i^{global} \leftarrow \frac{1}{N_{client}-n^*_{val}} \sum_{j\in S_{dyn}} \boldsymbol{\theta}_i^j$
end for
Client side:
for each training round $i = 1, 2, \ldots, N_{round}$ **do**
  for each client $j = 1, 2, \ldots, N_{client}$ **do**
    Download global model $\boldsymbol{\theta}_{i-1}^{global}$ as local model $\boldsymbol{\theta}_i^j$
    for each local training batch **do**
      $\boldsymbol{\theta}_i^j \leftarrow \boldsymbol{\theta}_i^j - \delta \frac{\partial L_{obj}}{\partial \boldsymbol{\theta}_i^j}$
    end for
    Upload $\boldsymbol{\theta}_i^j$ to the server
  end for
end for
Output: Global model $\boldsymbol{\theta}^{global}_{N_{round}}$

The general flow chart of the proposed federated learning scheme for machinery fault diagnosis is presented in Fig. 5. First, based on the specific diagnostic problem and data information, the deep neural network model is determined. After initialization, the federated learning starts, and the models are locally trained in different clients with minimization of the proposed objective function in Eq. (4). The server aggregates the trained networks with dynamic validation in multiples rounds to achieve the optimal model. In the testing stage, the testing data are supposed to be locally evaluated in different clients for data privacy. In this study, an integrated testing dataset covering different clients is assumed to be available for simplicity.

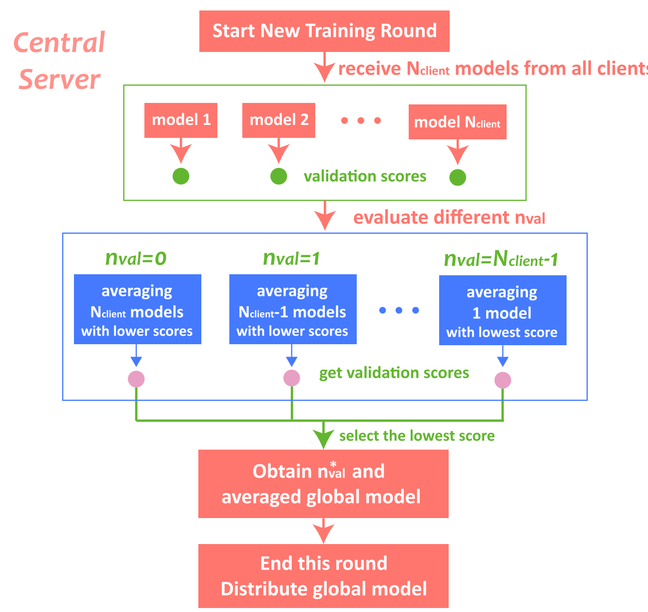

Fig. 4. Proposed dynamic validation scheme in federated learning framework.

4. Experimental study

4.1. Data descriptions

4.1.1. CWRU dataset

The Case Western Reserve University (CWRU) rolling bearing dataset is popular in fault diagnosis studies [47], and Fig. 6 shows the experimental machine. The dataset contains vibration acceleration signals collected from the drive end of the motor and the sampling frequency is 12 kHz. Four machinery health states are considered, i.e. healthy (H), outer race fault (OF), inner race fault (IF) and ball fault (BF). With respect to each faulty state, three levels of severities are also included, i.e. incipient, medium and severe faults. The corresponding fault diameters are 7, 14 and 21 mils respectively. Meanwhile, the data in different health states are collected under four operating conditions with rotating speeds of 1797, 1772, 1750 and 1730 rpm respectively. In summary, ten health conditions are diagnosed under four domains.

Table 1
Descriptions of the CWRU and Bogie datasets. Inc., Med. and Sev. are incipient, medium and severe, respectively.

Dataset	Descriptions Condition label	1	2	3	4	5	6	7	8	9	10
CWRU	Fault location	N/A (H)	IF	IF	IF	BF	BF	BF	OF	OF	OF
	Fault size (mil)	0	7	14	21	7	14	21	7	14	21
Bogie	Fault location	N/A (H)	IF	IF	IF	RF	RF	RF	OF	OF	OF
	Fault severity	N/A	Inc.	Med.	Sev.	Inc.	Med.	Sev.	Inc.	Med.	Sev.

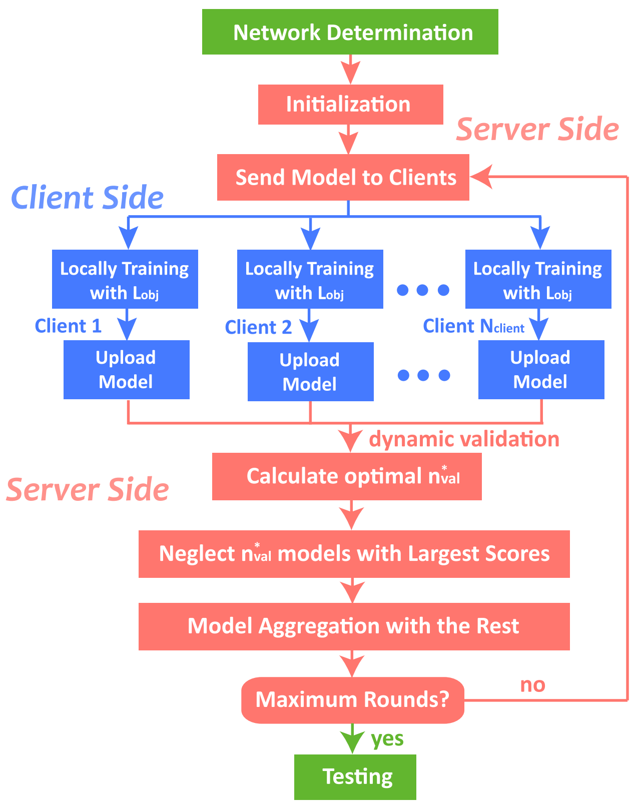

Fig. 5. Flow chart of the proposed federated learning method in machinery fault diagnosis scenarios.

4.1.2. Bogie dataset

Similar with the structure of the CWRU dataset, the Bogie dataset is further used for validation, which is collected from the test rig of high-speed multi-unit train bogie bearing system as shown in Fig. 6. The vibration acceleration data are measured by the accelerometers on the load module, and the sampling frequencies is 5 kHz. Four bearing health states are considered as healthy (H), outer race fault (OF), roller fault (RF) and inner race fault (IF) with three levels of severities, i.e. incipient, medium and severe faults. At the same time, three working conditions are also implemented for data collection, and the rotating speeds are 1590, 1770 and 1950 rpm, which correspond with the real train speeds of 260, 290 and 320 km/h respectively. In summary, ten machinery health states are diagnosed under three domains. (See Table 1.)

4.2. Experimental settings

In this study, different fault diagnosis tasks are implemented for evaluation with different kinds of local data at the clients. In general, three scenarios are focused on,

(1) IID

First, the basic distributed learning scheme is considered, where the data of different clients are assumed to be independent and identically distributed (IID). Specifically, the local data of each client include all the machinery health conditions and are under all the working conditions. The IID scenario provides a baseline task for federated learning, since all the local data share the same distribution. Integration of multiple clients in model development indirectly enlarges the valid training dataset under the federation.

(2) Non-IID-Class

The more practical case is considered next, where the data of different clients are not independent and identically distributed with respect to classes. Specifically in this study with ten bearing conditions in total, nine clients are considered where each client has local data of the healthy state and one faulty state respectively in all the working conditions. That is in accordance with the real industrial scenarios since the healthy state data are generally easy for collection, and different machines may have distinct faulty states. This scenario simulates the extreme cases with largely biased local data, and thus is well suited for evaluation of the model performance in the real industrial situations.

(3) Non-IID-Domain

Similar with the Non-IID-Class case, another realistic scenario, i.e. Non-IID-Domain, is also considered, where it is assumed different clients have different operating conditions. Specifically, N_{domain} clients are implemented where each client contains local data of all the health states in each operating condition, respectively. In this way, the domain shift phenomenon is simulated under the federation. Conventionally, without data sharing, it is difficult to generalize knowledge across domains. This scenario is thus suitable to evaluate the model generalization ability in federated learning.

One of the main advantages of federated learning is to leverage the limited data from different clients for model establishment. Therefore, the effects of the dataset size on the model performance are evaluated in this study, and the number of the total included labeled training samples for each health condition is denoted as n_{sample}. In the testing stage, it is assumed that 1000 samples of each health condition are evaluated in different scenarios for simplicity, that indicates a total number of 10000 samples are tested for the two concerned datasets, respectively.

The network parameters and experimental settings are mostly determined in the validation tasks, where the IID problem in CWRU is considered with $n_{sample} = 1000$. The numerical results presented in this study are generally averaged by five runs to obtain the means and standard deviations. Table 2 shows the related parameters in this paper.

4.3. Different learning schemes

In this study, different learning schemes are implemented to show the effectiveness of the proposed federated learning method. Specifically, the following approaches are carried out, which have similar experimental settings with the proposed method.

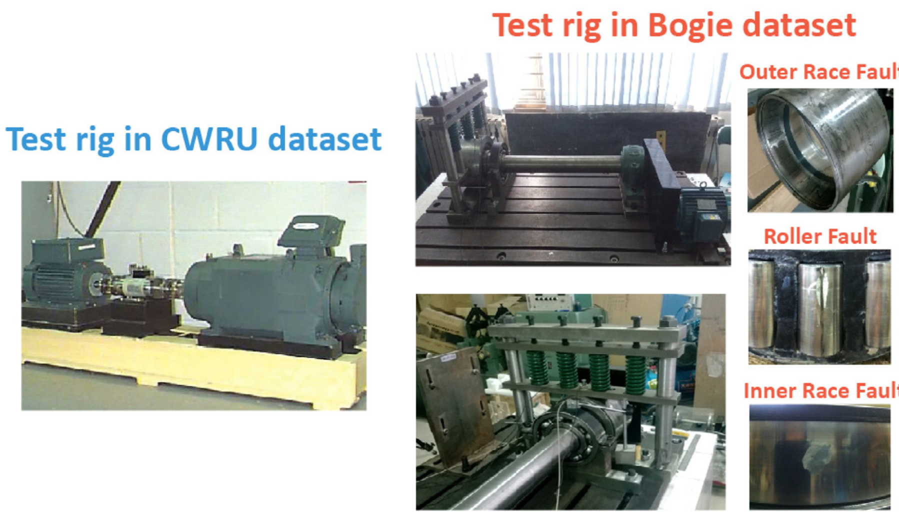

Fig. 6. Test rigs of the rotating machines and the bearing component faults in the CWRU and Bogie datasets [33].

Table 2
Parameters used in this paper.

Parameter	Value	Parameter	Value
Learning rate	0.02	N_{domain} (CWRU)	4
N_{round}	100	N_{domain} (Bogie)	3
Batch Size	16	n_{self}	$N_{input}/2$
N_{input} (CWRU)	512	α	1
N_{input} (Bogie)	1024		

(1) UpperLimit
First, the non-federated UpperLimit method is implemented, which follows the conventional centralized machine learning scheme. All the data of different clients are assumed to be available by the server with no privacy, and the same deep network model with the proposed method is used for training. Specifically, all the concerned data of different clients are integrated as a large training dataset, which is then directly used to develop the data-driven fault diagnosis model. This data-sharing approach generally provides an upper limit for the model performance given the available training data.

(2) OneByOne
Considering joint-client training with data privacy, an intuitive approach lies in iterations of local model updates on different clients independently. Specifically, in each training round, the server sends the model to a single client, and the model is then trained with the local data at the client side. Afterwards, the trained model is uploaded back to the server. The global model is then renewed as the uploaded one. This process iterates over all the clients in each round, and multiple rounds are also implemented. In this way, the server communicates with different clients separately using the OneByOne method.

(3) BaseLine
The extreme scenarios are also evaluated in this study where no communication is considered among different clients, and the conventional model training scheme is considered locally. Specifically, each client trains its own fault diagnosis model using its local training data, and the locally trained model is then used for testing. This method denoted as BaseLine generally provides the baseline of the model performance using the traditional machine learning scheme, since limited and biased training data can be usually obtained at each client. This approach mostly loses effectiveness in the non-IID cases, since the knowledge learned from the insufficient data cannot be well generalized on the testing data with different distributions.

4.4. Experimental results

4.4.1. IID problems

First, the IID task in the CWRU dataset is investigated, and the numerical results of the testing accuracies are presented in Fig. 7. In this study, different methods are extensively evaluated in different scenarios. Let Proposed-5 and Proposed-10 denote the proposed methods with 5 and 10 clients respectively, and Proposed-5-NoSelf and Proposed-10-NoSelf represent those without the self-supervised learning scheme. Correspondingly, BaseLine-5 and BaseLine-10 denote the BaseLine methods with 5 and 10 clients respectively, and OneByOne-5 and OneByOne-10 are the OneByOne methods with 5 and 10 clients respectively. In this IID scenario, since the training and testing data are subject to the same distribution, the dynamic validation process is not considered. In fact, similar validation scores at different clients can be obtained if the dynamic validation is implemented, which does not impose noticeable influence on the model performance.

It can be observed that generally, more training samples of different clients lead to higher testing accuracies by different methods. That is consistent with the current understanding that deep learning-based fault diagnosis methods can largely benefit from more supervised training data. It should be pointed out that the popular CWRU dataset contains clean machinery signals and fairly high testing accuracies have been achieved in the literature. In this study, by using the raw vibration acceleration data as inputs and small sample dimension of $N_{input} = 512$, the CWRU fault diagnosis problems are set to be more difficult in order to clearly show the effects of different factors in federated learning.

Due to the limited training data in each client, the BaseLine methods without mutual communications generally obtain quite low testing accuracies. The proposed federated learning approaches significantly enhance the learning performance in different scenarios through knowledge sharing between different clients, and the obtained testing accuracies are close to the UpperLimit method with centralized training. That validates the effectiveness of the proposed distributed learning method with data privacy.

With the same amount of the total included samples, the case with 5 clients basically achieves higher accuracies than that with

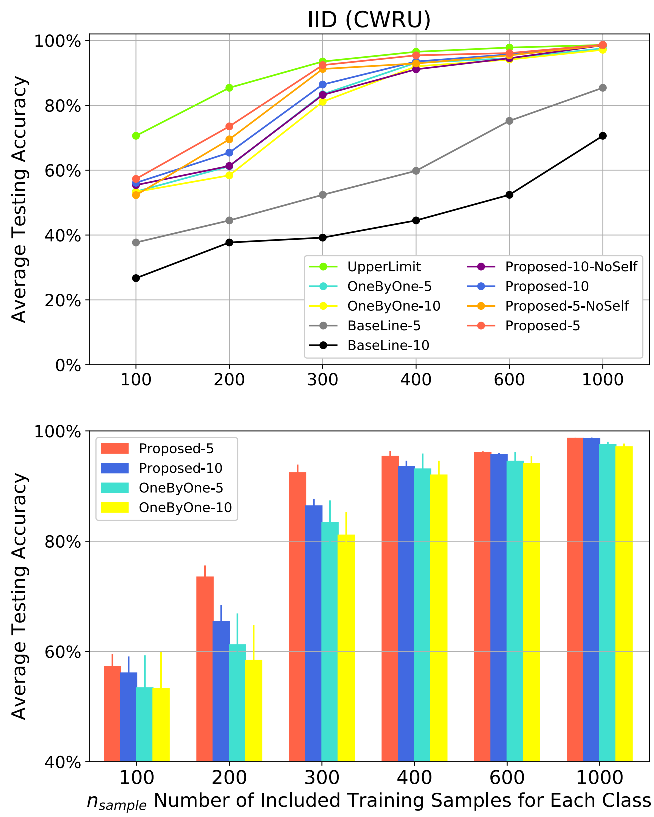

Fig. 7. The testing accuracies by different methods on the CWRU dataset in the IID scenarios. The model performances in different fault diagnosis tasks are presented.

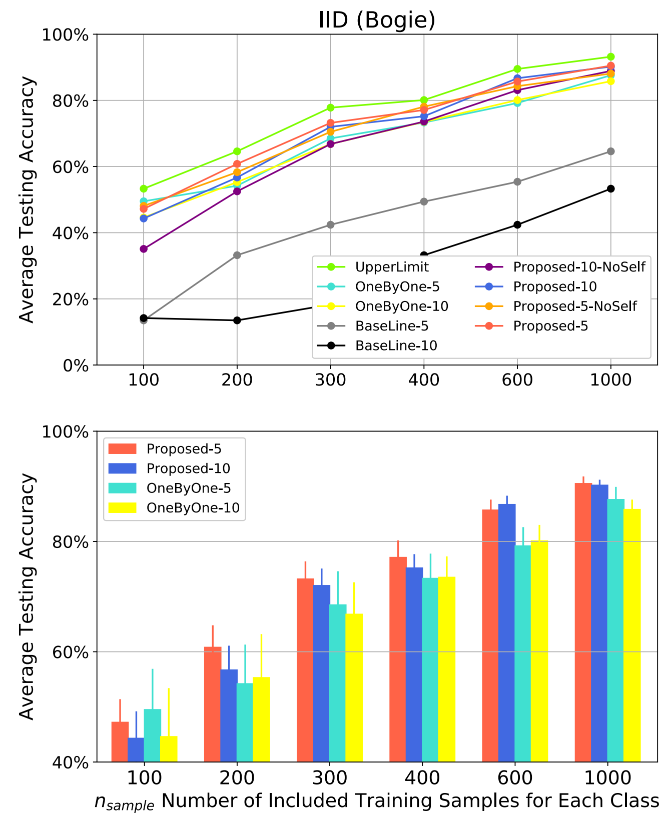

Fig. 8. The testing accuracies by different methods on the Bogie dataset in the IID scenarios. The model performances in different fault diagnosis tasks are presented.

10 clients. That suggests despite the effectiveness of federated learning, better results can be still obtained in most cases by more centralized learning scheme with fewer clients using the same data. Furthermore, based on the comparisons of the proposed methods with and without self-supervised learning, the effectiveness of the proposed self-supervision approach is also validated. That shows the proposed method which offers effective data augmentation and multi-task learning techniques, is well suited for decentralized learning with limited local data.

It is also noted that the straight-forward OneByOne approaches achieve competitive performance with the proposed method. However, since the data of different clients are separately used for training, higher performance variances are generally obtained. Moreover, in spite of the similar results, N_{client} communications occur between server and client in one training round by the OneByOne methods, while the proposed method is more efficient with only one time communication per training round.

The results of the IID tasks on the Bogie dataset are presented in Fig. 8. In general, the Bogie data are more practical with significant noises, and lower testing accuracies are obtained compared with the CWRU dataset. However, similar performance patterns are further observed, and the proposed federated learning approach still achieves promising results.

4.4.2. Non-IID-Class problems

In this section, the non-IID problems are investigated, and different clients are assumed to have data of distinct health conditions. The results of the CWRU dataset are presented in Fig. 9. It can be observed that compared with the IID tasks, the Non-IID-Class problems are remarkably more difficult due to the significant data biases in different clients, and lower accuracies are obtained.

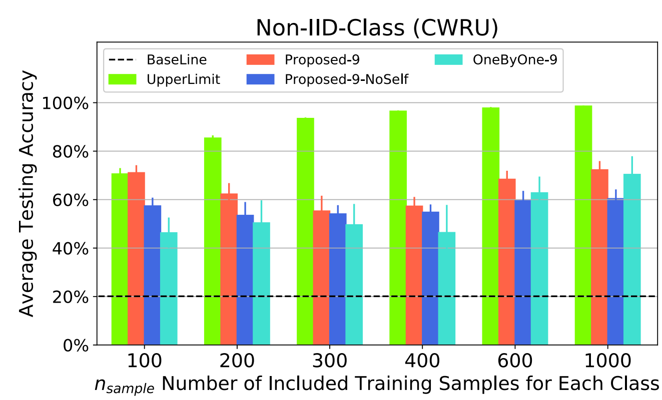

Fig. 9. The testing accuracies by different methods on the CWRU dataset in the non-IID-Class scenarios. The model performances in different fault diagnosis tasks are presented.

In this scenario, the BaseLine method completely fails since the local data of each client only contain two classes, i.e. healthy and one faulty states. Using the proposed methods, promising diagnostic performances are still obtained. Noticeable improvements are observed compared with the OneByOne methods, especially in the cases with fewer local training data. Fig. 10 presents the results on the Bogie dataset. The effects of different factors on the model performance are similar with those in Fig. 9. Therefore, the results in this section validates the effectiveness of the proposed method in the Non-IID problems.

Furthermore, the effects of the proposed dynamic validation scheme in the federated framework are examined. Since the class-biased problem is investigated, different groups of testing

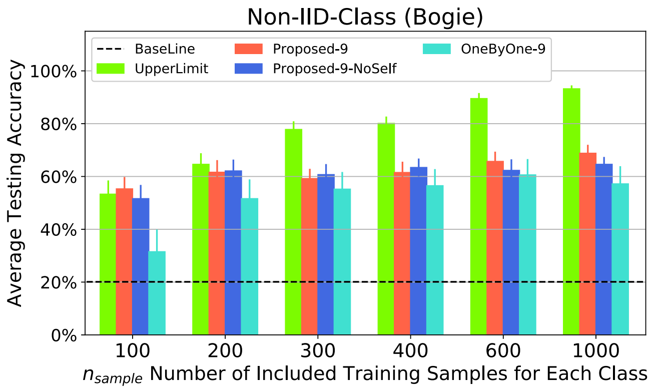

Fig. 10. The testing accuracies by different methods on the Bogie dataset in the non-IID-Class scenarios. The model performances in different fault diagnosis tasks are presented.

Table 3
Descriptions of the testing data groups in the Non-IID-Class cases.

Dataset	Group no.	Included health conditions
CWRU	1	1, 2, 3, 4, 5, 6, 7, 8
	2	1, 3, 5, 7, 8, 9, 10
	3	1, 2, 5, 6, 8, 10
	4	1, 2, 4, 6, 8
Bogie	1	1, 3, 4, 5, 6, 7, 8, 10
	2	1, 3, 5, 6, 7, 8, 9
	3	1, 2, 4, 7, 9, 10
	4	1, 2, 4, 7, 9

data are considered in this section, where different combinations of fault modes are evaluated. Specifically, Table 3 presents the details of the concerned groups of testing data in the two datasets. In the experiments, $n_{sample} = 1000$ is used, and the validation set is supposed to have similar properties with the testing set, that indicates they share the same health conditions. 100 samples per health condition are assumed to be available in the validation set.

Fig. 11 shows the effects of different n_{val} on the model performance in the CWRU dataset. It can be observed that n_{val} generally has noticeable influence on the testing accuracies in different cases. The proposed method with dynamic validation scheme is able to achieve the best results in most scenarios, which is in accordance with the specific data set information. For instance, the group 1 includes 8 classes, and the highest testing accuracy is achieved by $n_{val} = 2$. That means the proposed method recognizes the optimal improvement on the validation set can be obtained by removing 2 models from all the clients, which correspond with 2 health conditions based on the task information. When larger n_{val} is adopted, the testing accuracies mostly drop to some extent, that indicates the federated model is less effective if the explored information is insufficient for the testing data.

The results on the Bogie dataset are presented in Fig. 12. Generally, similar results are obtained as the CWRU dataset. The proposed method can automatically identify the optimal n_{val}, and achieve promising results in the Non-IID data scenarios with class imbalance.

4.4.3. Non-IID-Domain problems

Fig. 13 shows the numerical testing results on the CWRU dataset in the Non-IID-Domain problems, where the local data of different clients are from different working conditions. It can be observed that due to the distribution discrepancy of domains, the BaseLine methods generally achieve low testing accuracies. The

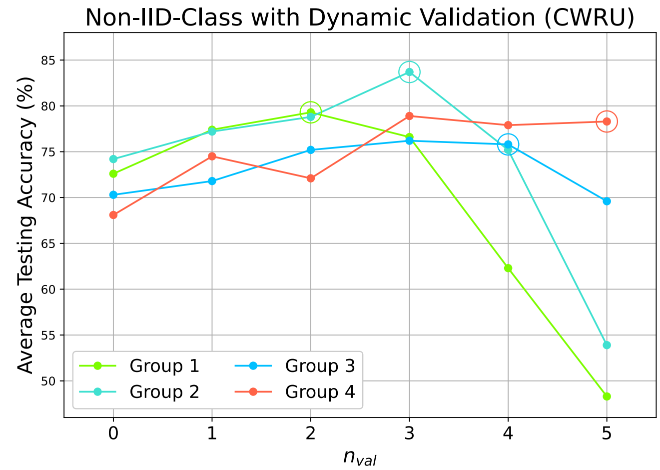

Fig. 11. Effects of n_{val} on the testing accuracies using different groups of testing data in the Non-IID-Class cases on the CWRU dataset. The selected values by the proposed method are marked as circles in different scenarios.

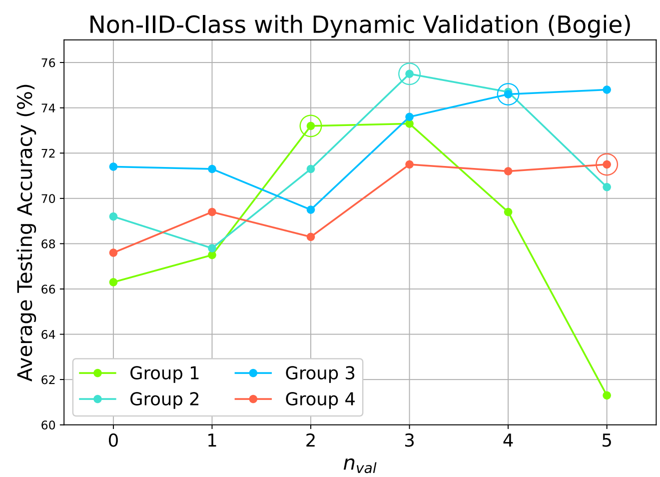

Fig. 12. Effects of n_{val} on the testing accuracies using different groups of testing data in the Non-IID-Class cases on the Bogie dataset. The selected values by the proposed method are marked as circles in different scenarios.

benefits of the proposed federated learning approaches are clearly shown, and their results are close to the UpperLimit methods with centralized training. Moreover, the performance improvements by the proposed self-supervision scheme are still observed, and the proposed methods are basically more stable than the OneByOne methods. The results on the Bogie dataset presented in Fig. 14 further demonstrate the effectiveness and superiority of the proposed method.

Moreover, the effects of the proposed dynamic validation scheme are also examined in the Non-IID-Domain cases. Similar with the Non-IID-Class cases, different groups of testing data are considered, where different combinations of domains, i.e. rotating speeds, are used. The details of the testing groups in the two datasets are shown in Table 4. $n_{sample} = 400$ is used, and the other experimental settings are similar with those in the previous sections.

The experimental results are presented in Fig. 15 regarding the effects of n_{val} on the model performance on the CWRU dataset. Similar with the Non-IID-Class cases, the proposed method can also well identify the optimal n_{val} in different scenarios. The benefits of the dynamic validation scheme are further confirmed. For instance, in group 1, the testing data include 3 domains,

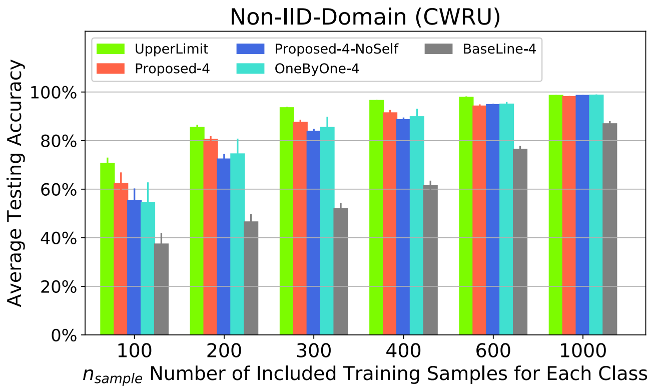

Fig. 13. The testing accuracies by different methods on the CWRU dataset in the non-IID-Domain scenarios. The model performances in different fault diagnosis tasks are presented.

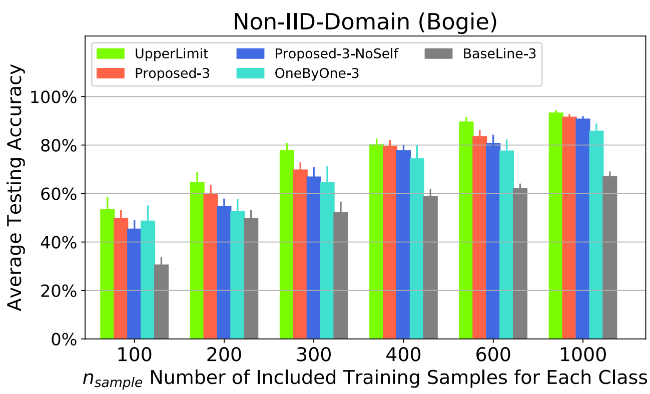

Fig. 14. The testing accuracies by different methods on the Bogie dataset in the non-IID-Domain scenarios. The model performances in different fault diagnosis tasks are presented.

Table 4
Descriptions of the testing data groups in the Non-IID-Domain cases.

Dataset	Group no.	Included rotating speeds (rpm)
CWRU	1	1772, 1750, 1730
	2	1797, 1772, 1730
	3	1797, 1772
	4	1750, 1730
Bogie	1	1770, 1950
	2	1590, 1950
	3	1590, 1770

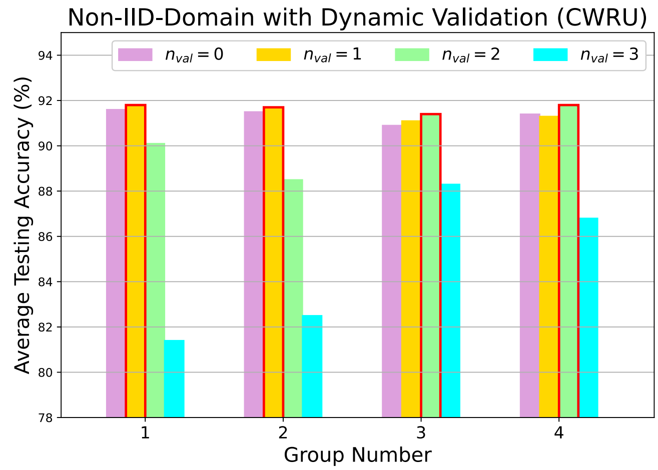

Fig. 15. Effects of n_{val} on the testing accuracies using different groups of testing data in the Non-IID-Domain cases on the CWRU dataset. The selected values by the proposed method are marked with the red edges in different scenarios. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

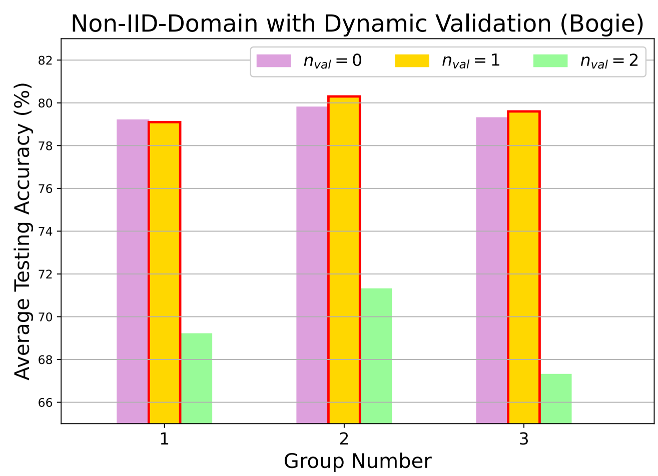

Fig. 16. Effects of n_{val} on the testing accuracies using different groups of testing data in the Non-IID-Domain cases on the Bogie dataset. The selected values by the proposed method are marked with the red edges in different scenarios. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

and $n_{val} = 1$ is adopted by the proposed method. Recall that a total number of 4 domains are considered. Removing 1 model at each federated averaging step achieves slight improvement for the global model. When larger n_{val} is used, which indicates fewer domains of training data are explored than the testing data, remarkable drops of the accuracies are observed. Fig. 16 shows the experimental results on the Bogie dataset. Similar display patterns are obtained with the CWRU dataset, which further validate the effectiveness of the proposed dynamic validation scheme.

In summary, the proposed federated learning approach has shown remarkable advantages in both the IID and non-IID distributed learning problems. Powerful global fault diagnosis model can be established through decentralized training on multiple clients, and the local data privacy can be also effectively guaranteed in the learning process.

4.4.4. Parameter analysis

In this section, the effects of the model parameters are investigated. First, the influence of the sample dimension is evaluated in different scenarios. Specifically, the validation tasks in both the datasets are focused on, where the IID problem is considered with $n_{sample} = 1000$. The results are presented in Fig. 17. It can be observed that when small sample dimension is used, the testing accuracies are generally low. That is because insufficient discriminative features of the machine health conditions can be usually included with the small samples, which cannot be well used for diagnostics. When larger dimension is adopted, the influence of the sample dimension is less significant. Therefore in this study, the default sample dimensions for the CWRU and Bogie datasets are 512 and 1024 respectively.

In federated learning, the communications between the central server and local clients are very important. Considering many training rounds are usually required, fast communication is preferred in practical implementations. The communication efficiency is highly related with the model size in this study,

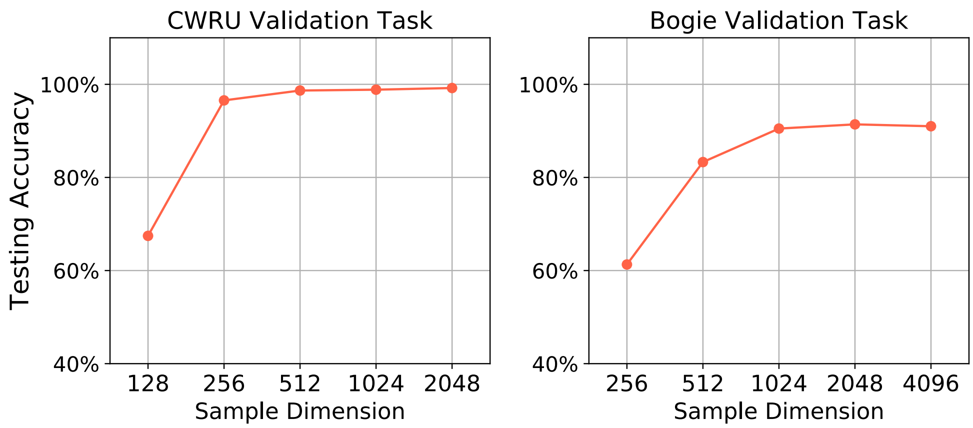

Fig. 17. Effects of sample dimension on the model performance in different cases. It is noted that no significant influence of the sample dimension is observed.

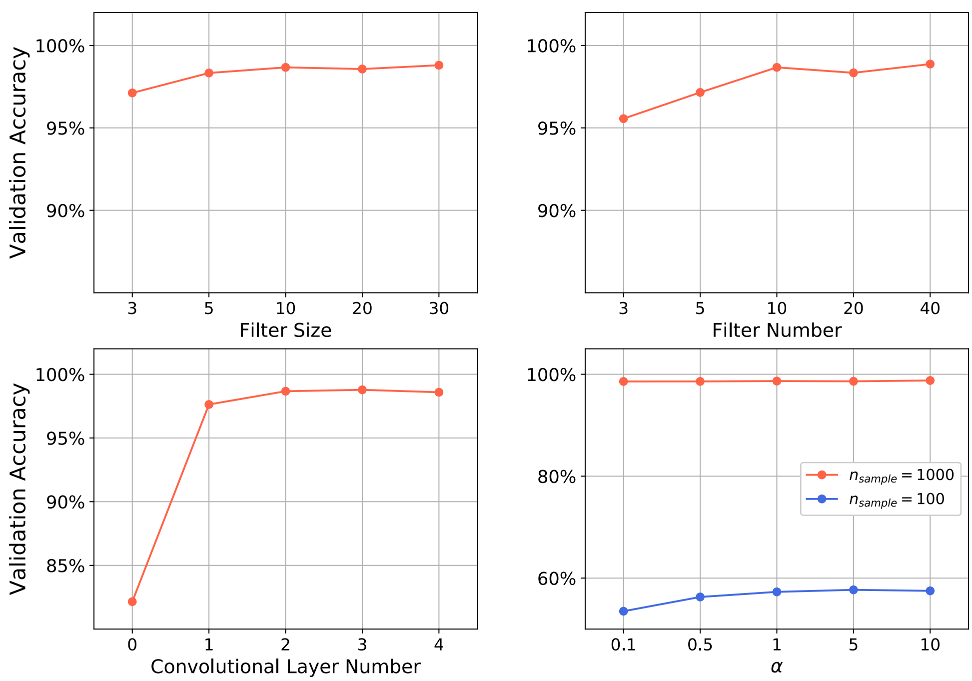

Fig. 18. Effects of model parameters on the fault diagnosis performance in different cases. In general, the proposed method is stable with respect to different parameters.

and the smaller model generally leads to faster communication. Fig. 18 shows the influence of the network parameters on model performance. It can be observed that in general, the proposed method is robust with the model size. Using the typical convolutional neural network model, the testing accuracy is generally stable when sufficient parameters are used. Large model does not offer noticeable improvements on the performance. However, if the model size is extremely small, the model deteriorates significantly. For instance, when no convolutional layer is used, the testing accuracy drops remarkably. Therefore, the medium model size is proposed in this study with 2 convolutional layers, filter number of 10 and filter size of 10. In this way, the model is light-weighted for communication between the server and clients. It should be noted that smaller model can be also used which is able to achieve similar performance with the default setting, that can be designed based on the specific communication requirement in the practical implementations.

The influence of the penalty coefficient α as shown in Eq. (4) is also evaluated, and the results are presented in Fig. 18. With $n_{sample} = 1000$, no significant influence of α is observed. On the other hand, with fewer training samples $n_{sample} = 100$, the performance is also generally stable with α. Noticeable performance drop is observed with small α. That is because α determines the importance on the self-supervised learning, which largely helps improve the model with limited training data. In general, the proposed method is robust with this hyper-parameter in reasonable range, and $\alpha = 1$ is thus used for simplicity.

4.4.5. Analysis on self-supervision

In this section, the proposed self-supervised learning method is investigated. First, the effectiveness of the artificially created fake samples is examined. Since the machinery vibration acceleration data are focused on in this study, the well-established frequency spectra are analyzed, which are popularly used for detecting faults of different rolling element bearing components. Fig. 19 shows the comparison results of the real and fake data in the CWRU dataset, and those on the Bogie dataset are shown in Fig. 20. It can be observed that while the raw time-domain vibration data are translated to be different signals, the frequency-domain information generally remains identical with no noticeable changes. That indicates the underlying key features for fault

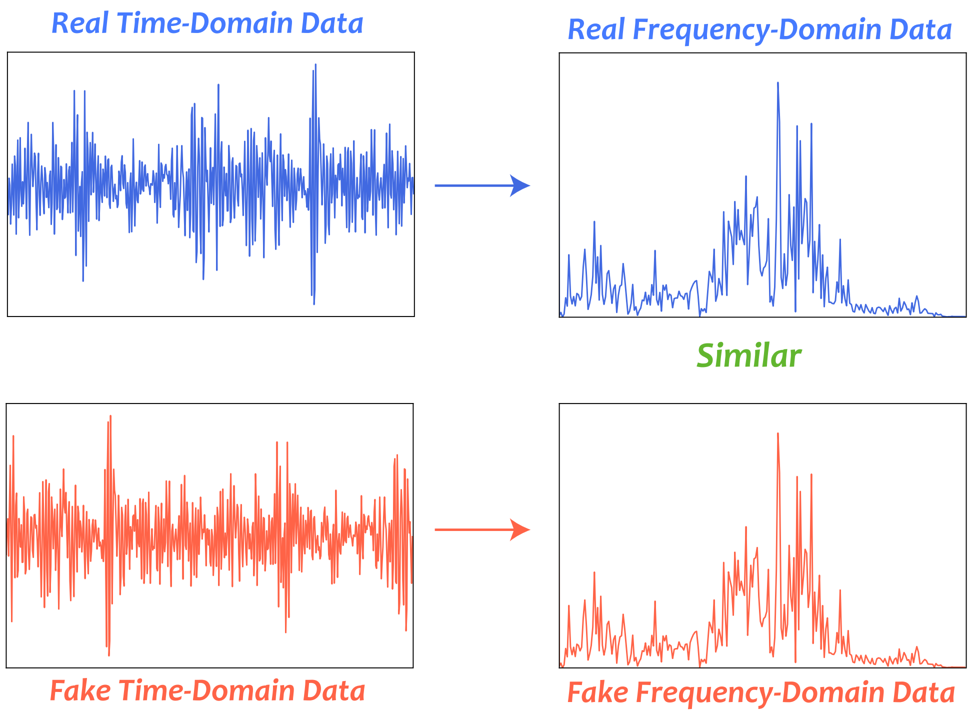

Fig. 19. Comparisons of the time-domain and frequency-domain data of the real and fake samples in self-supervised learning on the CWRU dataset.

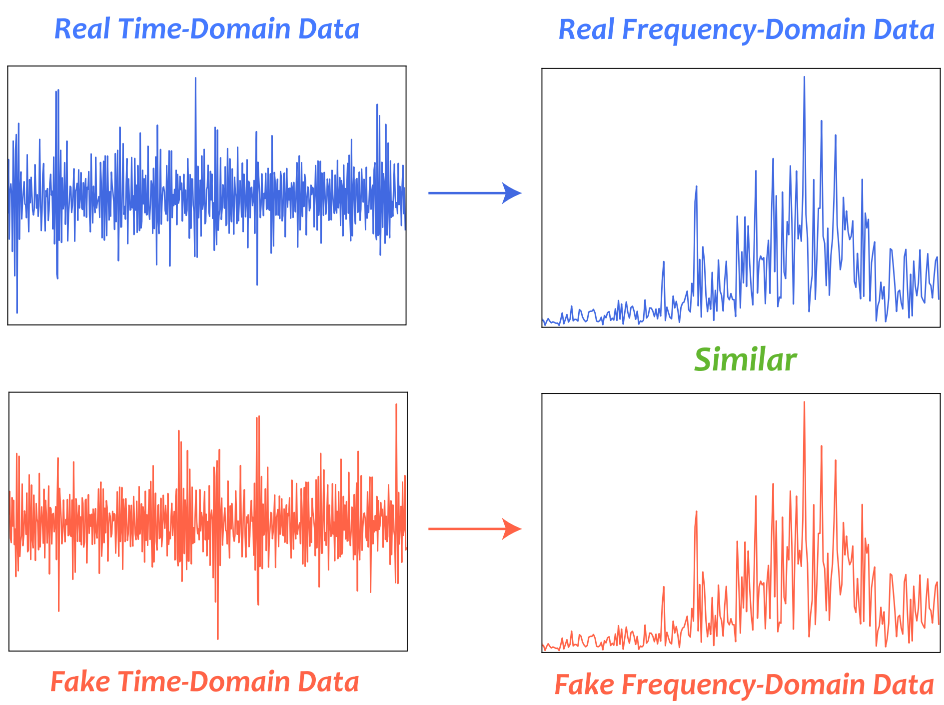

Fig. 20. Comparisons of the time-domain and frequency-domain data of the real and fake samples in self-supervised learning on the Bogie dataset.

diagnosis can preserve in the data translation. In this way, the neural network model is expected to learn the structural knowledge with respect to the time-series data, and capture the real underlying characteristics of the input, which benefit the improvement of the model generalization ability especially in the scenarios with limited local training data.

Moreover, the hyper-parameter n_{self} is introduced in self-supervision, and the effects of n_{self} on the model performance in the CWRU and Bogie datasets are presented in Figs. 21 and 22 respectively. Since data translation is considered, the values of n_{self} between 0 and $0.5 * N_{input}$ are investigated. It is noted that when larger n_{self} is used, the testing accuracies are generally higher in different cases, while the performance generally drops with smaller n_{self}. The results are in accordance with the understanding of the proposed self-supervision method. With larger n_{self}, the frequency-domain information in the two segments can be mostly preserved, which makes the created fake data less distinguishable with the real one. In this way, the model can better learn the key features from the time-domain data, rather than overfitting the noise. With smaller n_{self}, the minor

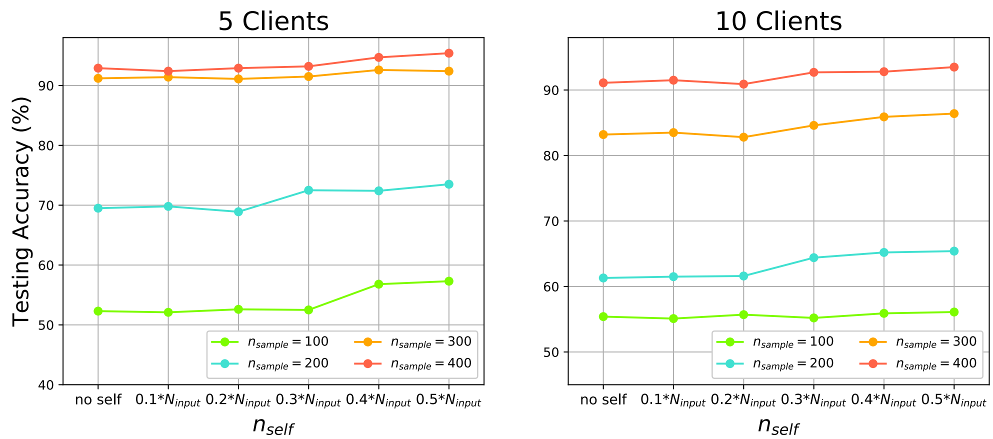

Fig. 21. Effects of n_{self} on the model testing accuracies in different scenarios on the CWRU dataset.

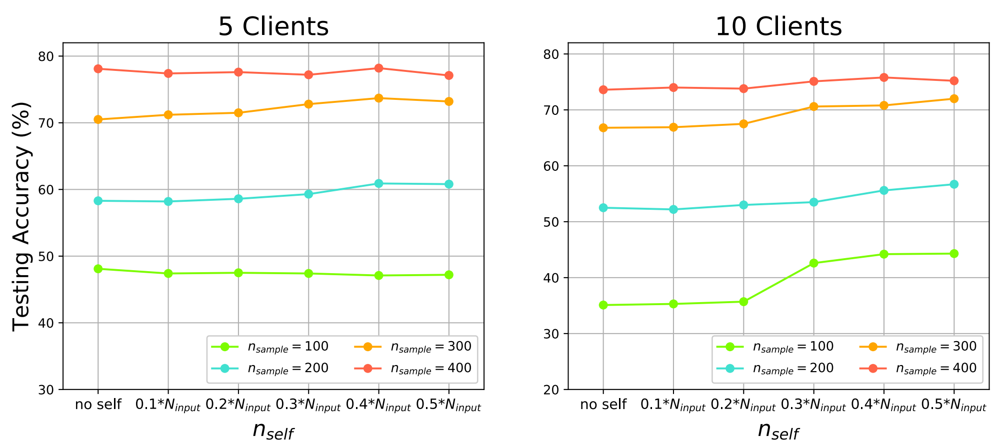

Fig. 22. Effects of n_{self} on the model testing accuracies in different scenarios on the Bogie dataset.

segment in translation generally contains less information, and the key features in the frequency domain may not be sufficiently included. As a result, the fake data sample can be more easily recognized and the model is less capable of learning the structural knowledge from the data. Therefore, in the scenarios with limited local training data, the general testing accuracies drop to some extent.

4.4.6. Comparisons with data augmentation methods

The data island problem is addressed in this study under the federated learning framework with self-supervision. Specifically, the limited training data from different clients are explored with privacy to improve the global model performance. In the current literature, some approaches have also successfully addressed the data sparsity issue. The generative adversarial networks (GAN) have been proposed to artificially create realistic fake samples to enlarge the training dataset. Inclusion of different variations of the real data samples is also able to enhance the model training performance with more data. In this section, comparisons with the existing approaches in the fault diagnosis problem are implemented.

Fig. 23 shows the experimental results in the IID scenarios in different datasets with $n_{sample} = 400$. Specifically, the GAN-based data augmentation methods are based on the works in [48, 49]. The generator is adopted which transforms the noise vector into the realistic fake samples, and the discriminator is used to distinguish the real and fake data. Through adversarial training, the generator can be gradually improved and additional samples can be created. The GAN-Less method indicates fake samples of four times the size of the real samples are generated at a certain client, and the GAN-More method is that with ten times of the real data. The NoiseAug method follows the data augmentation technique in [50], where Gaussian and masking noise is added to the real samples to create additional fake samples. Similarly, the StretchAug method applies time stretching technique on the real samples to generate additional data [50]. In NoiseAug and StretchAug, fake samples with four times of the real samples are used to assist model training.

It can be observed that while the existing methods are able to significantly improve the model performance compared with the BaseLine approach, the proposed federated learning method still outperforms the others in different cases. That is because the existing data augmentation methods generally focus on creating new samples based on the limited real ones. Therefore, the variations of the available data are still limited. On the other hand, the proposed federated learning method aims to explore additional real data from different clients with data privacy. In this way, more generalized diagnostic knowledge can be learned, thus leading to significant performance improvement.

Fig. 24 shows the comparison results in the Non-IID-Class and Non-IID-Domain scenarios with $n_{sample} = 400$. The proposed method still significantly outperforms the other approaches in different cases. Specifically, in the Non-IID-Class scenarios, 20% testing accuracies are generally obtained by the compared methods. That is because the existing data augmentation methods create new samples based on the available data. When the real samples of some machinery health conditions are not available at a certain client, the data augmentation methods are not able

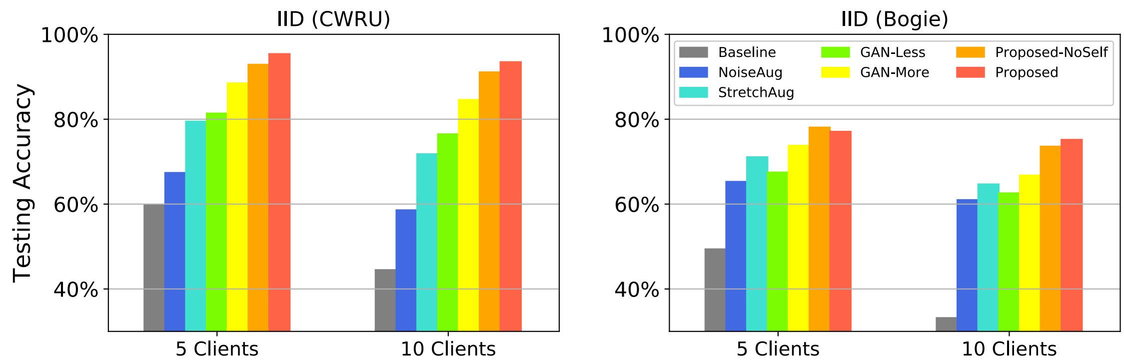

Fig. 23. Comparison results with existing data augmentation methods in the IID scenarios. The proposed method achieves noticeable improvements than the other approaches.

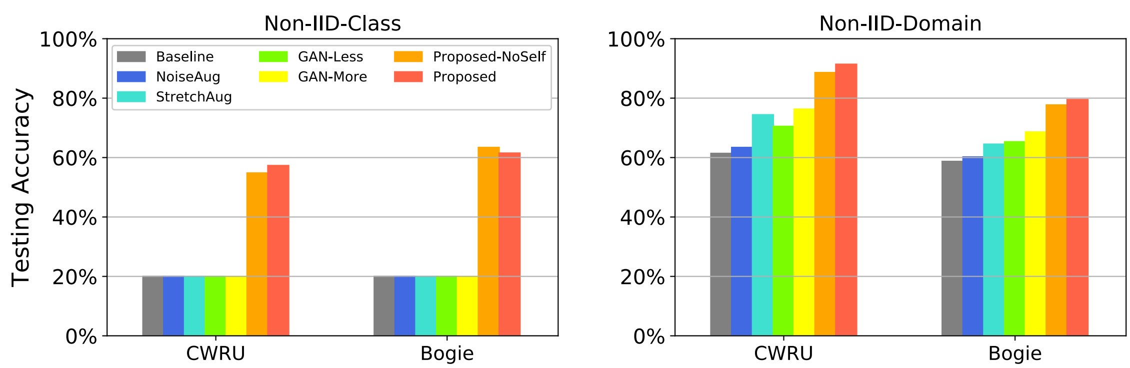

Fig. 24. Comparison results with existing data augmentation methods in the Non-IID-Class and Non-IID-Domain scenarios. The proposed method achieves noticeable improvements than the other approaches.

to generate fake samples of unseen classes. Consequently, they fail in the Non-IID-Class scenarios. While the compared methods are competitive in the Non-IID-Domain scenarios, they are still less effective than the proposed method due to the limited information at the local clients. Therefore, the effectiveness and superiority of the federated learning method have been further validated.

5. Conclusions

This paper proposes a deep learning-based federated learning method for machinery fault diagnosis. Different from the popular centralized learning, the diagnostic models are locally trained in different clients, and only the models are communicated between the server and clients rather than sharing the private data. A dynamic validation scheme is proposed in the federated learning framework, where the low-quality data at some clients are neglected. The server then aggregates the selected locally updated models in each training round using the federated averaging approach. A self-supervised learning scheme is further proposed for learning the structural information from the limited training data, which offers both data augmentation and multi-task learning effects. Experiments on two rotating machinery datasets are carried out for validations. The results suggest the proposed method offers a promising federated learning method for fault diagnosis, which leverages the diagnostic knowledge learned from data of multiple clients and simultaneously guarantees the data privacy.

It should be pointed out that despite the promising results, noticeable gaps in the testing performance are still observed between the proposed method and the conventional centralized training approach in the non-IID problems. Further research works will be carried out on developing effective transfer learning techniques to address the challenging non-IID issues in federated learning.

CRediT authorship contribution statement

Wei Zhang: Methodology, Data curation, Resources, Writing - original draft. **Xiang Li:** Conceptualization, Methodology, Writing - original draft. **Hui Ma:** Supervision, Writing - review & editing. **Zhong Luo:** Supervision, Writing - review & editing. **Xu Li:** Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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