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Few-Shot Bearing Anomaly Detection via Model-Agnostic Meta-Learning

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***Abstract*—As an essential component of many mission-critical equipment, mechanical bearings need to be monitored to identify any traces of abnormal conditions. Most of the latest data-driven methods applied to bearing anomaly detection are trained using a large amount of fault data collected *a priori*. However, in many practical applications, it may be unsafe and time-consuming to collect enough data samples for each fault category, which brings challenges to training a robust classifier. This paper proposes a few-shot learning framework for bearing anomaly detection based on model-agnostic meta-learning (MAML), which aims to train an effective fault classifier using very limited data. In addition, it can use training data and learn to more effectively identify new fault conditions. A case study on the generalization of new artificial faults shows that this method can achieve up to 25% overall accuracy when compared to a benchmark study based on the Siamese network. Finally, the generalization ability of MAML is also competitive when compared with some state-of-the-art few-shot learning methods in terms of identifying realistic bearing damages using a sufficient amount of training data from artificial damages.**

***Index Terms*—Bearings, anomaly detection, few-shot, limited data, model-agnostic, meta-learning.**

I. Introduction

Many data-driven and AI-based technologies have been applied to enhance the accuracy and reliability of bearing anomaly detection [1]–[3], but most of them require a large amount of training data such as vibration [4]–[6], acoustic [7], [8], and motor current [9], [10] signals. In practical applications, however, it is usually impossible to obtain enough data samples to train a robust classifier that can identify each type of failure [5]. One of the reasons is most bearing degradation would evolve slowly over time, a process that takes months or even years, making it difficult to collect sufficient data in the faulty state [11], [12].

In addition, certain safety-critical applications may not be allowed to run into faulty states [5], so collecting a sufficient amount of data in each bearing failure situation can be expensive, unsafe, and often impractical. This will inevitably lead to data imbalance problems [12]. All these limitations on bearing anomaly detection in the real world require the use of more effective algorithms that can use limited data to train bearing fault classifiers with good generalization capabilities.

To achieve this goal, one method is to use the limited data available in each category to perform data augmentation, such as Generative Adversarial Networks (GAN) [12], [13]. However, the quality of the generated data deserves further study. As reported in [12], the "quality of generated spectrum samples" of GAN is "isn't good enough to provide auxiliary information." Additionally, another promising method to alleviate the problem of limited data is to apply the few-shot learning method. This method has been successfully applied to a variety of tasks, including few-shot image recognition, autonomous agent path planning, and more recently in anomaly detection [5], [6], [14], [15]. Few-shot learning evaluates the model's generalization capability to classes not previously seen in the training process, given only a few samples of each new class [14]. Therefore, few-shot learning methods are very suitable for solving data imbalance issues, since we can train a model that generalizes to the imbalanced class.

Among the existing work of applying few-shot learning methods to bearing fault diagnosis [5], [6], [14], Ref. [5] proposed a model based on the Siamese Network, which demonstrated enhanced fault diagnosis performance when only 9 training samples were used in each class. In addition, [14] applied a deep prototypical network-based method for few-shot bearing fault diagnosis. Although it showed better performance compared with the supervised learning method, all of the bearing fault types in the test set have showed up in the training set, as they are only differed by their defect diameters and operating speed. In [6], an auto-encoder and capsule network (CaAE) is proposed for the same purpose. However, the case studies in [6] are not formulated in the standard context of few-shot learning, as all the identified bearing fault categories are already seen during the training process.

Therefore, to further mitigate the limited data issue and improve the model's generalization capability, this paper seeks to achieve effective anomaly detection using the minimum amount of data using model-agnostic meta-learning (MAML) [16]. Beyond just generalizing to new tasks more effectively, MAML can also learn the process of learning itself, or learning to learn. Specifically, MAML is explicitly designed to train the model's initial parameters such that "the model has maximal performance on a new task after the parameters have been updated through one or more gradient steps computed with a small amount of data from that new task" [16].

The rest of the paper is organized as follows. In Section II, we introduce some background knowledge

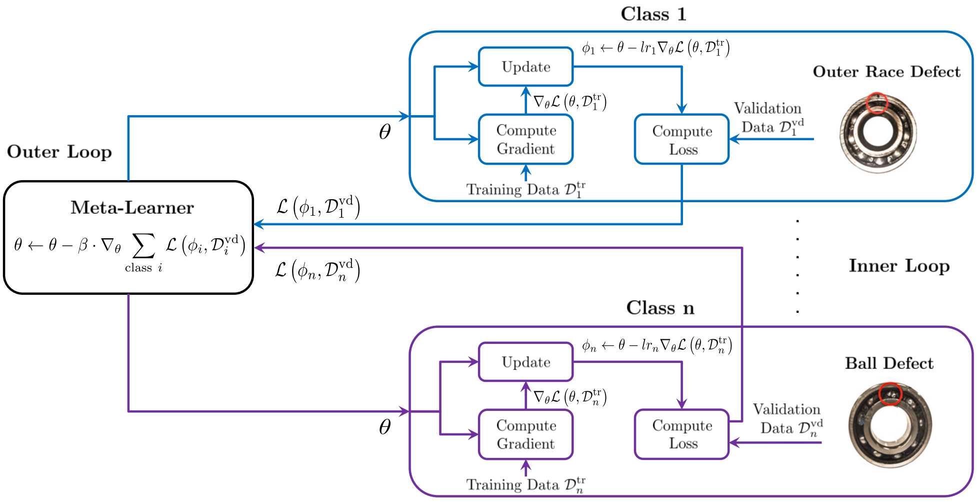

Fig. 1. Flowchart of the meta-training stage of the proposed MAML-based few-shot bearing fault diagnosis.

and underlying principle of MAML. Next, in Section III, we present the architecture of the proposed MAML-based few-shot bearing fault diagnostic framework, with detailed descriptions on establishing the test environment and model implementation. Section IV presents results for 3 case studies performed on few-shot bearing fault diagnosis using both the Case Western Reserve University (CWRU) bearing dataset [17] and the Paderborn dataset [18]. Section V concludes the paper by highlighting the effectiveness of the proposed model in bearing fault diagnosis with limited data.

II. Principle of Model-Agnostic Meta-Learning

A. *Meta-Learning*

Meta-learning algorithms are developed to leverage past data to learn new tasks more quickly. Not only can they generalize new tasks more effectively, but they can also use past experience to learn about the process of learning itself, or learn to learn. In standard supervised learning, the goal is to learn a function that will map some input x (i.e., an image) to the label of that input y, as shown in (1). In supervised meta-learning, the idea is very similar, except that now it tries to map the training set $\mathcal{D}_{\text{train}}$ (with the corresponding data and labels) and the test input x to a label, as described in (2). Essentially, the goal of meta-learning is to train a model that when exposed to a training set, performs well on a corresponding test set of that task.

$$\text{Supervised learning: } f(x) \rightarrow y \tag{1}$$

$$\text{Supervised meta-learning: } f\left(\mathcal{D}_{\text{train}}, x\right) \rightarrow y \tag{2}$$

The meta-training set $\mathcal{D}_{\text{train}}$ is typically designed to contain a collection of little datasets of different categories [19]. At meta-test time, the goal is to identify new categories (not previously seen in the training process) of labels using a limited amount of test data x. The way to accomplish this goal is to find a model that can accurately match this function $f\left(\mathcal{D}_{\text{train}}, x\right)$. Besides some successful deployment of sequence models in this effort such as recurrent neural networks [19] or temporal convolution networks [20], a very influential model was proposed by Finn et al. in [16], which was referred to as model-agnostic meta learning (MAML).

B. *Meta-Agnostic Meta-Learning*

The MAML algorithm is model-agnostic. More specifically, it is agnostic both to the architecture of the neural network and also to the loss function. The backbone of MAML is to optimize for parameters that adapt quickly with gradient descent in two loops – an inner loop and an outer loop, which works well across a range of different problem settings. All of these features provide many flexibilities for MAML, making it applicable to both reinforcement learning problems that maximize the expected cumulative reward function, and supervised learning problems that minimize a certain loss function (cross-entropy, mean-squared, etc.).

Performing few-shot classification with MAML requires two stages – a meta-training stage and a meta-testing stage. Formally, we consider MAML as a neural network f_θ parameterized by θ, which will be updated to ϕ_i using gradient descent when adapting to a new class i. During the meta-training stage as shown in Fig. 1, MAML operates in an inner loop and an outer loop. In the inner loop, MAML first computes the updated parameter vector ϕ_i for each class i using training data D_i^{tr}, and then it evaluates the loss term on the validation data D_i^{vd} sampled from the same class using the updated model parameters ϕ_i. The evaluated loss for each class i can be written as

$$\mathcal{L}\left(\phi_i, \mathcal{D}_i^{\text{vd}}\right) = \mathcal{L}\left(\theta - \alpha \nabla_\theta \mathcal{L}\left(\theta, \mathcal{D}_i^{\text{tr}}\right), \mathcal{D}_i^{\text{vd}}\right) \tag{3}$$

where $\phi_i \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}\left(\theta, \mathcal{D}_i^{\text{tr}}\right)$ is the updated model parameter for class i. For classification tasks on image or bearing anomaly detection, the loss term is typically the cross-entropy loss. In the context of bearing fault diagnosis, as illustrated in Fig. 1, different classes can represent different types of bearing defects, such as inner/outer race defects, ball defects, cage defects, among others.

In the outer loop, MAML aggregates the per-task post-update losses $\mathcal{L}\left(\phi_i, \mathcal{D}_i^{\text{vd}}\right)$ and performs a meta-gradient update on the original model parameter θ as

$$\theta \leftarrow \theta - \beta \cdot \nabla_\theta \sum_{\text{class } i} \mathcal{L}\left(\phi_i, \mathcal{D}_i^{\text{vd}}\right) \tag{4}$$

where β is the learning rate of the outer loop. At meta-test time, MAML is able to compute new model parameters based on a few samples from unseen classes, and uses the new model parameters to predict the label of a test sample from the same unseen class.

In summary, the essential idea of MAML is trying to find parameters of a neural network that does not necessarily have the optimal performance for different classes of data provided at the meta-training stage, but can quickly adapt to new (unseen) tasks.

C. Meta-Agnostic Meta-Learning with Learnable Inner Loop Learning Rates

As illustrated in Fig. 1, there is a learning rate lr in MAML for its inner loop gradient update, which is assigned as a fixed number α in [16] and is shared among different classes for all update steps. However, this fixed and shared inner loop learning rate lr can often affect MAML's generalization capability and convergence speed [21], and the process of tuning this hyper-parameter lr for a specific dataset can often be costly and computationally intensive.

Therefore, a variant of MAML is proposed in [21] to automatically learn the inner loop learning rate lr. Specifically, it tries to learn different learning rates for each layer of the neural network and for each step through back-propagation. By doing this, the learning rate lr becomes a vector that accounts for different learning rates for each layer of the neural network. With this learnable lr approach, elements in the learning rate vector lr can learn to decrease their values as the training progresses, which may help promote a faster convergence and alleviate overfitting. Therefore, the revised form of (3) to compute the loss term of each class can be written as

$$\mathcal{L}\left(\phi_i, \mathcal{D}_i^{\text{vd}}\right) = \mathcal{L}\left(\theta - lr_i \nabla_\theta \mathcal{L}\left(\theta, \mathcal{D}_i^{\text{tr}}\right), \mathcal{D}_i^{\text{vd}}\right) \tag{5}$$

III. Few-Shot Bearing Fault Diagnostic Framework Based on MAML

A. Proposed Few-Shot Bearing Fault Diagnostic Model

Few-shot classification is considered an instantiation of meta-learning in the field of supervised learning [22]. The standard few-shot learning is usually formulated as N-way K-shot problems, where N is the number of new classes not seen in the meta-training process, while each class only has K samples to train from.

The proposed few-shot bearing fault diagnostic model based on MAML is illustrated in Fig. 2. At meta-training stage, we'll first optimize for a parameter set θ of a neural network along the aggregated gradient descent direction

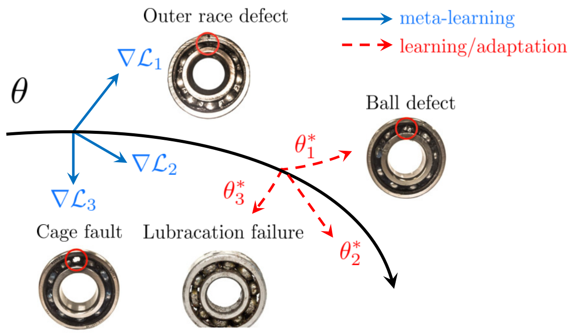

Fig. 2. Illustration of MAML applied to few-shot learning of bearing anomaly detection.

of data from different bearing fault scenarios ($\nabla\mathcal{L}_1$, $\nabla\mathcal{L}_2$, $\nabla\mathcal{L}_3$, etc.). As discussed in Section II, this parameter set θ is optimized to achieve quick adaptation to new classes not previously unseen at the meta-training stage, rather than achieving the optimal performance on classes it was directly trained on.

For example, as shown in Fig. 2, we can train the MAML-based diagnostic model using data from bearing outer race defects and cage defects at different fault severity, and generalize it to detect new fault scenarios such as the ball defect and lubrication failure using a very small amount of data (e.g., 5 samples). This problem will be formulated as a 2-way 5-shot few-shot learning setting that is well-suited for MAML.

With the proposed MAML-based few-shot bearing fault diagnostic model, it is envisioned that we can mitigate both data scarcity and data imbalance issues discussed in [5] by adapting to these classes at the meta-testing stage, which can yield a satisfactory performance but only requires a limited amount of data. Additionally, another appealing application is to recognize naturally evolved bearing defects using models that are only trained on data from artificially damaged bearings, since most bearing failures evolve slowly over time and it might take months if not years to collect a sufficient amount of data to train supervised learning-based fault classifiers.

B. Objectives

In the proposed MAML-based few-shot bearing fault diagnostic framework, the objective is to validate the performance of MAML on few-shot bearing fault diagnosis from the following aspects:

1) *Training Data Size*: Investigate the influence of training data size on the performance of MAML-based few-shot bearing fault diagnosis.
2) *New Artificially Induced Bearing Failures*: Validate the performance of MAML to predict previously unseen artificial bearing faults in the laboratory environment.
3) *New Realistic Bearing Failures with Accelerated Aging*: Explore the generalization capability of MAML

TABLE I
DIFFERENT CATEGORIES OF BEARING FAILURES SELECTED FROM THE CWRU DATASET

Class Label	Fault Location	Fault Diameter (mils)
1	Healthy	0
2	Ball	0.007
3	Ball	0.014
4	Ball	0.021
5	Inner Race	0.007
6	Inner Race	0.014
7	Inner Race	0.021
8	Outer Race	0.007
9	Outer Race	0.014
10	Outer Race	0.021

TABLE II
DIFFERENT CATEGORIES OF BEARING FAILURES SELECTED FROM THE PADERBORN DATASET

Label	Fault Location	Failure Cause	Severity	Code
1	Outer Race	EDM*	1	KA01
2	Outer Race	EE‡	2	KA03
3	Outer Race	EE‡	1	KA05
4	Outer Race	Drilling	1	KA07
5	Outer Race	Drilling	2	KA08
6	Inner Race	EDM	2	KI01
7	Inner Race	EE‡	1	KI03
8	Inner Race	EE‡	2	KI05
9	Healthy	N/A	0	K001
10	Outer Race	Pitting	1	KA04
11	Inner + Outer Race	PD†	1	KB23
12	Inner + Outer Race	Pitting	2	KB27
13	Inner Race	Pitting	1	KI04

*EDM: Electrical discharge machining.

‡EE: Electric engraver.

†Plastic deform: Indentations.

to predict real bearing failures with accelerated lifetime tests using data collected from artificially damaged bearings.

Both 1) and 2) have been investigated in [5] using the Siamese Network-based few-shot learning method on the CWRU dataset. In order to perform a fair comparison, we strive to keep the test environment consistent with the benchmark study by also leveraging the CWRU dataset and assigning the same fault labels. More details regarding the CWRU dataset can be found in their website [17].

A list of all 10 fault scenarios are presented in Table I. Specifically, different classes are identified based on the location and size of a bearing defect, rather than its operating speed and loading condition. We also adopt the same data segmentation method as [5], in which each data segment is comprised of 2048×2 data points that are sampled at 12 kHz from both accelerometers at the Fan end and the Load end. After performing the aforementioned classification and data segmentation strategies, the entire CWRU dataset is partitioned into 10 classes, with each class having 1,980 data segments.

To further investigate the generalization capability of MAML in predicting real bearing failures as described in 3), we also apply the proposed MAML-based few-shot learning framework to the Paderborn dataset [18], since the CWRU dataset only contains artificially induced defects. The Paderborn dataset includes data of 32 bearings under test, and among them, 6 are normal ones, 12 are with artificially induced damages, and 14 are with real damages caused by accelerated aging tests. There are only inner and outer raceway defects present for both artificial and real bearing failures, while damages at the rolling elements were not observed.

For the Paderborn bearing dataset, we select the same 13 representative classes from the total 32 classes according to [15], with 1 at the healthy condition, 8 of them have manually initiated bearing defects, and the rest of them have real bearing failures resulted from accelerated lifetime testing. The selected classes have distinct combinations in terms of their fault location, cause of failure, and fault severity. The threshold values used to determine different levels of fault severity has been discussed in detail in [4], where level 1 corresponds to a defect length smaller than 2 mm, level 2 corresponds to defect lengths between 2 to 4.5 mm, and level 3 corresponds to 4.5 to 13.5 mm.

A complete list of these selected classes is presented in TABLE II, and the goal is to successfully identify the healthy case as well as real bearing failures (categories 8 to 13) using the artificial fault data (categories 1 to 7). The rest of the data segmentation process is consistent with the settings in [15].

C. Model Implementations

Our model follows the same architecture as the embedding function used by [16], which has 4 modules with a 3×3 convolutions and 64 filters, followed by batch normalization, a ReLU nonlinearity, and 2×2 max-pooling. The bearing vibration signals are sampled with a dimension of 4096 and converted to 64×64, and the last layer is fed into a softmax. For N-way, K-shot classification, each gradient is computed using a batch size of NK examples.

The N-way convolutional were each trained with 1 gradient step and a meta batch-size of 25 tasks. For MAML with a fixed learning rate, the learning coefficient is chosen as $\alpha = 0.01$. For MAML with a learnable inner loop learning rate lr, the initial value is also kept and 0.4 and it will be optimized with the training step [21]. We used a meta batch-size of 1 task for both 1-shot and 5-shot testing. All models were trained for 1500 iterations.

IV. EXPERIMENTAL RESULTS

In this section, we seek to validate the performance of MAML on few-shot bearing fault diagnosis. As discussed in Section III, We'll specifically investigate its performance with different training data size and different unseen fault categories using the CWRU dataset. Additionally, we'll also leverage the Paderborn dataset to predict naturally evolved bearing failures using data collected

TABLE III
N-WAY K-SHOT CLASSIFICATION RESULTS PREDICTING REALISTIC BEARING DEFECTS (9 TRAINING SAMPLES PER CLASS).

N-way Accuracy	6-way Accuracy		5-way Accuracy		4-way Accuracy	
	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot
MAML (fixed lr)	$44.36 \pm 4.02\%$	$47.30 \pm 2.29\%$	$55.51 \pm 3.02\%$	$53.10 \pm 8.4\%$	$74.93 \pm 5.05\%$	$76.79 \pm 3.09\%$
MAML (learnable lr)	$\mathbf{55.21 \pm 3.01\%}$	$\mathbf{62.58 \pm 2.78\%}$	$\mathbf{73.63 \pm 3.75\%}$	$\mathbf{78.15 \pm 2.76\%}$	$\mathbf{75.04 \pm 3.51\%}$	$\mathbf{84.62 \pm 1.10\%}$

N-way Accuracy	3-way Accuracy		2-way Accuracy		1-way Accuracy	
	1-shot	5-shot	1-shot	5-shot	1-shot	5-shot
MAML (fixed lr)	$82.73 \pm 3.12\%$	$85.53 \pm 1.07\%$	$97.68 \pm 2.18\%$	$98.19 \pm 1.98\%$	$98.77 \pm 2.06\%$	100%
MAML (learnable lr)	$\mathbf{88.62 \pm 4.03\%}$	$\mathbf{97.90 \pm 1.50\%}$	$\mathbf{100\%}$	$\mathbf{100\%}$	$\mathbf{100\%}$	$\mathbf{100\%}$

from artificially damaged bearings. The performance of the proposed MAML-based few-shot classifier will be compared with that constructed with the Siamese Network in [5], and we strive to keep their test scenarios consistent by leveraging the open-source code provided in [5].

A. Predicting New Artificially Induced Bearing Defects

The experiments performed in this section seeks to investigate MAML's performance to predict artificially induced bearing faults that are not seen at the meta-training stage. We also extract data from the CWRU dataset to test 1-way to 5-way classifications with 1 and 5 shots. A total of 10 rounds of experiments are performed to compare with the benchmark in [5]. Since [5] only provides the 1-way to 3-way results, the 4-way and 5-way results are also obtained using the open-source code in [5]. We also followed the order of labels presented in TABLE I, thus a 5-way classification indicates we are deploying data with class labels 1 to 5 as the meta-training data, and the rest will serve as the meta-testing data.

By randomly selecting 9 data segments from 1,980 available ones for each class, the complete results on N-way K-shot classification are presented in TABLE III. It can be observed that MAML with a fixed lr is able to achieve 10% to 20% enhancement in average accuracy when compared to the benchmark Siamese Network, while MAML with learnable lr is able to achieve even larger improvements ranging from 20% to 30%. A comparison study for MAML with fixed and learnable lr is illustrated in Fig. 3, where the validation accuracy of the learnable inner update lr consistently outperforms and is more stable than the fixed lr case after 600 training epochs. This observation can be interpreted in such a way that the learnable lr can learn to decrease the learning rates with larger training epochs and getting closer to the local optimum, which may help alleviate overfitting and promotes faster and more stable convergence [21].

B. Predicting New Realistic Bearing Defects

This study also goes beyond identifying artificially induced bearing defects by further exploring the generalization capability of MAML in predicting real bearing failures caused by accelerated lifetime tests, or Artificial-to-Real. The objective is to use a combination of artificially damaged bearings and healthy bearings to identify those with real damages. Due to differences between data collected from these two scenarios, standard supervised learning methods can only achieve accuracies lower than 75% [4]. Additionally, these differences will also cause the transfer learning-based method to experience an obvious decrease in the average accuracy for Artificial-to-Real tasks when compared to generalizing to other artificial tasks [23].

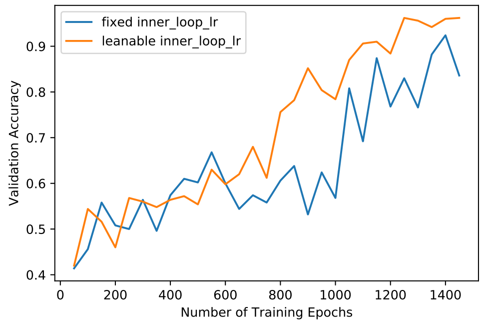

Fig. 3. Diagram of model-agnostic meta-learning algorithm applied to few-shot learning of bearing anomaly detection.

The selected representative classes from the Paderborn dataset [18] are listed in TABLE II, which is consistent with the benchmark study that uses standard few-shot learning techniques [15], including direct training net (DTN), Unfrozen 1 Fine-tuning Net (U1FN), Unfrozen 2 Fine-tuning Net (U2FN), Unfrozen 3 Fine-tuning Net (U3FN), Unfrozen 4 Fine-tuning Net (U4FN), and Meta Relation Net (MRN). The source of meta-training data will only be the artificially damaged bearings (classes 1 to 8). The benchmark study [15] assumes the availability of sufficient training samples by using 1000 samples per class, which is a valid assumption for artificially induced bearing defects collected in the laboratories. Four case studies with 1-shot, 3-shot, 5-shot, and 10-shot settings are conducted using MAML with a learnable lr vector.

The comparison results for identifying 5-way real bear-

TABLE IV
5-WAY K-SHOT CLASSIFICATION RESULTS PREDICTING NEW ARTIFICIAL BEARING DEFECTS.

K-shot Accuracy	DTN	U1FN	U2FN	U3FN	U4FN	MRN	**MAML**
1-shot	91.67%	**94.27%**	93.86%	91.20%	84.48%	94.10%	$84.85 \pm 0.47\%$
3-shot	93.10%	93.10%	**96.61%**	92.88%	89.57%	94.85%	$93.43 \pm 0.17\%$
5-shot	93.67%	96.84%	**98.36%**	94.03%	91.89%	95.69%	$95.27 \pm 0.14\%$
10-shot	95.26%	97.00%	96.82%	92.04%	97.14%	95.69%	$\mathbf{97.17 \pm 0.10\%}$

ing defects are presented in TABLE IV, and the results from few-shot benchmark studies are extracted from [15]. The results show that MAML is able to deliver satisfactory results at different K-shot tests, and in particular, it can provide the best accuracy of over 97% for the 10-shot case. Another advantage of MAML over classical few-shot learning approaches is the good generalization capability even when it is trained using a very small number of training samples, as presented in the earlier study in TABLE III. This feature will be particularly advantageous if it is also cost-prohibitive or dangerous to collect a large amount of meta-training data at different fault conditions, and we'll reserve it as a part of future work.

V. CONCLUSION

This paper proposed a few-shot bearing fault diagnostic framework based on meta-agnostic meta-learning. The results demonstrate that the MAML-based model greatly outperforms the benchmark study based on Siamese Networks when identifying new artificial bearing faults. Specifically, this advantage can be up to 25% when using MAML with learnable inner loop learning rates lr.

The CWRU dataset only contains vibration data from manually initiated bearing defects, which is inconsistent with the real-world scenario where these defects are evolved naturally over time. Therefore, we also applied the proposed method to the Paderborn dataset to explore the generalization capability of MAML when adapting to real bearing failures. The results demonstrate that MAML is able to deliver competitive performance when comparing with state-of-the-art few-shot learning methods, which offers promising prospects for identifying naturally-evolved bearing failures using data collected from laboratory tests with artificially induced faults.

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