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# Federated Meta-Learning for Open Set Identification with Privacy Preservation

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## Abstract

Traditional machine learning models typically address closed-set recognition problems. However, in real-world scenarios, open-set recognition challenges frequently arise, where the accuracy of existing methods tends to be low. To address this issue, this paper proposes a versatile classification framework that integrates federated learning and meta-learning to tackle open-set recognition in federated environments. In the proposed methodology, federated meta-learning is first employed to train a global model with strong generalization capabilities across different clients, while preserving data privacy. Then, each local client extracts features and applies a relational network-based classifier to perform classification, obtaining the final prediction results. The local models are updated accordingly, and a coefficient-based aggregation algorithm is designed to update the global model, considering both the aggregation coefficients and classification accuracy. Finally, the server distributes the updated global model back to the clients, who update their local models and proceed to the next training round. To validate the effectiveness of the proposed approach, open-set recognition experiments are conducted on the MNIST, CIFAR-100, and Omniglot datasets. Experimental results demonstrate that the proposed method not only ensures local data privacy but also achieves higher accuracy compared to baseline algorithms such as FedAvg.

**Keywords:** Open-set recognition; Federated meta-learning; Aggregation; Privacy preservation.

## 1 Introduction

The explosive growth of technologies, such as the Internet, big data analysis, and mobile edge computing, has promoted the development of the “sharing economy”. In particular, the Federated Learning (FL) method uses data from different clients to conduct joint training under the premise of protecting data privacy. Moreover, this method solves the privacy problem of local data to a certain extent, and promotes the development of a new concept called the “model parameter sharing”. However, due to the limited data relative to each client, the global model needs to be trained by combining data coming from all clients, so that this model can accurately complete the classification task when encountering other samples. Furthermore, the traditional model is based on a closed-set recognition problem [1, 2], that is, the model knows all the categories that it englobes. However, in some scenarios,

training sets and test sets of different clients have the same or different categories, which turns to be an open-set recognition problem. In such a case, the model needs to identify known categories without providing any auxiliary information; at the same time, it can also distinguish unknown categories and deal with them accordingly. Therefore, this paper will study open-set recognition under the federated element learning framework.

To break data barriers, FL was proposed by Google in 2015 [3, 4, 5, 6] and it combines differential privacy, homomorphic encryption, secure multi-party computing, and other technologies to protect data privacy. The development of FL technology has indeed brought a new beginning to the solution of privacy issues during data sharing. This approach may often organize many clients to learn from multi-source decentralized databases without data sharing or data collection by sharing their local model parameters, so that data requesters can study and mine the potential value of data without collecting a large amount.

Therefore, the essence of the FL algorithm is to train a global Machine Learning (ML) model by aggregating the local model parameters of the different clients. Then, the central server sends the aggregated model parameters to each node who updates the local model parameters and performs the next round of training. Among the different aggregation algorithms, the Federal Average (FedAvg) aggregation algorithm [7] became so popular because of its simple and effective idea; however, its simple weighted aggregation method could not solve the impact of heterogeneous data, unbalanced data, and attack problems on the global model. In the context of federated learning, dealing with non-IID data has been a major challenge. The paper [8] offered a thorough review of the issues arising from non-IID data in federated learning and explores various approaches to mitigate these challenges, aiming to improve the performance and robustness of models when training across heterogeneous clients. Literature [9] presented a framework for federated learning where multiple clients collaboratively train a model, focusing on aggregating the local updates into a global model while ensuring privacy constraints are met. Moreover, this survey [10] focused on Federated Learning, specifically discussing how data heterogeneity can affect the training process and the aggregation of model updates in FL systems. Furthermore, literature [11] introduced the current state of Federated Learning, focusing on its practical challenges, including the model aggregation process and the communication efficiency between clients and the central server. In literature [12], the fundamental principles of Federated Learning were proposed, including the process of aggregating local model parameters to update a global model, as well as the challenges associated with communication and data heterogeneity in federated settings. Finally, literature [13] proposed a new algorithm, Fed-EMD, to reduce the impact of data imbalance by creating a data subset shared among all data nodes. Therefore, federated learning is an effective way to solve the problem of data sharing.

Referring to the above analysis, the global model, trained by FL, is the same on every device; however, sometimes the categories contained in the data of each device are different. Therefore, the model needs to be customized so that a higher accuracy will be obtained when being trained by the client's own dataset. Hence, this paper introduces a meta model [14, 15, 16, 17, 18]. All clients concentrate on learning the specific metamodel, which generates a personalized model locally. Among them, literature [19] introduced a federated meta-learning framework, and discussed how it can personalize models across clients by combining the benefits of federated learning. Moreover, this work treated each client as a task whose goal was to train a well-initialized global model rather than a globally optimal one. Furthermore, literature [20] focused on applying federated meta-learning for time-series forecasting using Recurrent Neural Networks (RNNs), and exploring how personalized models can be trained on decentralized data while maintaining model generalization. However, a single global model couldn't adapt to all client models. In addition, literature [21] no longer studies a single average model alone but it calculates the interaction between the different clients according to the model connection among clients to get the best model combinations. At the same time, on a large-scale, training a single global model will have great differences for several users. Therefore, a model-independent local Federated RECONstruction (FedRECON) algorithm was proposed [22]. In the training process, model parameters were divided into global parameters and sensitive local parameters, and the local parameters did not leave the client during the training process. In this way, data privacy of the client was protected. Finally, literature [23] proposed that the knowledge

of the previous tasks was needed and the edge nodes cooperatively learn a metamodel by using the knowledge transfer of previous tasks, so as to cope with the challenge of several data nodes with different amounts of data and different computing resources between nodes in FL.

Based on the above analysis, this paper studies a resource allocation scheme under the Federated Meta-Learning (FML) model of privacy protection based on open-set identification. The main contributions are summarized as follows:

1) By introducing the federated meta-learning (FML) framework, this paper improves the training performance and generalization ability of the model on the premise of ensuring data privacy protection, especially in the distributed environment involving multiple clients, which can effectively reduce the risk of privacy disclosure, while ensuring the accuracy and stability of the model, and builds an FML model based on open set identification;

2) Traditional federation learning has great challenges in open set recognition, especially in the face of unknown class recognition. In this paper, the FML algorithm can recognize and reject the unknown class in the open set identification problem, so as to improve the generalization ability of the model and the adaptability in practical applications;

3) Evaluation of the proposed algorithm and scheme through experiments. This evaluation is based on three standard datasets, MNIST, CIFAR-100, and Omniglot, and it verifies the effectiveness and superiority of the proposed method. The accuracy of the model is taken as the main index, and it is compared to other federated learning aggregation schemes. The advantages of the proposed FML method in privacy protection and model performance are demonstrated, which further strengthens the practicability and depth of the theory.

## 2 Literature review

In recent years, FedMeta, which combines federated learning and meta-learning, has emerged as a solution to the challenges of data heterogeneity and privacy protection in distributed learning, while improving the model's personalization and generalization ability. However, under the traditional federated meta-learning framework, the model typically assumes that the classes in both the training and test sets are known, performing the classification task in a closed-set recognition scenario. In contrast, real-world data often exhibits open-set characteristics, meaning that the test set may contain unknown categories not present in the training set. Therefore, effectively implementing open-set identification within the context of federated learning, while maintaining privacy protection when handling both known and unknown categories, has become a critical research problem.

One of the core algorithms of federated learning is FedAvg, which updates the global model by weighted averaging the local models of each client. The advantage of FedAvg lies in its simplicity and efficiency; however, it assumes that the data distribution on the client side is relatively uniform, which is often not the case in real-world applications. FedAvgM [24], an improved version of FedAvg, alleviates the negative impact of data heterogeneity by introducing momentum terms. In addition, methods such as FedProx [25] aim to further enhance the robustness of the algorithm by adding regularization terms, addressing issues of data heterogeneity and imbalanced data. Although federated learning has made some progress in closed-set recognition, most studies focus on closed-set scenarios and overlook the challenges of open-set recognition. Particularly in the context of privacy protection, designing a more flexible and effective federated learning algorithm to tackle the open-set identification problem remains a key challenge.

The core idea of meta-learning is to improve the learning efficiency and generalization ability of the model on new tasks through cross-task experience accumulation. MAML [26, 27] enables an initialized model to quickly adapt to new tasks by training it on multiple tasks. The advantage of this method is its strong task adaptability, but its computational cost is high. Optimizer meta-learning [28, 29, 30] accelerates the training process of a task by learning an optimizer, which is especially suitable for dealing with complex tasks and large-scale data. By enhancing the memory capacity of the model, it can store and reuse important information from past tasks, thus better adapting to new tasks [31, 32, 33]. In the context of federated learning, the challenge of data privacy makes it difficult to effectively apply meta-learning, particularly in the identification of new tasks and unknown categories,

while maintaining data privacy.

FedMeta combines the strengths of federated learning and meta-learning to address the data privacy and heterogeneity issues in traditional federated learning, while enhancing the model's adaptability to new tasks. Currently, several studies have explored the application of FedMeta in open-set recognition. For example, the FedMeta framework allows clients to generate personalized models through fast learning tasks, while sharing knowledge in the global model to tackle data heterogeneity and open-set problems [34]. In this way, FedMeta efficiently handles the recognition of known categories while distinguishing between unknown categories. Studies have shown that FedMeta can better improve the generalization ability of models on unknown tasks compared with traditional federated learning algorithms [35]. Reference [36] proposes a new algorithm framework that can effectively identify known categories and distinguish unknown categories. The results indicate that FedMeta has stronger task adaptability and generalization ability than traditional methods in open-set recognition scenarios. A FedMeta method combined with uncertainty quantification has been proposed to address open-set classification [37]. By modeling the uncertainty of the model, FedMeta's ability to identify unknown categories can be significantly improved. Although existing research has made progress, how to effectively combine meta-learning and federated learning to quickly and effectively perform open-set identification while maintaining data privacy with limited data still requires further exploration.

To sum up, FL, ML, and FML have emerged as two important research directions in the fields of distributed learning and privacy protection, making remarkable progress in recent years. Under the premise of data privacy protection, federated meta-learning effectively enhances the model's personalization and adaptability, particularly in open-set recognition tasks, where it can simultaneously handle the identification of known categories and the distinction of unknown ones.

### 3 FML method for open set identification

Closed-set recognition and Open-set recognition are two different types of problems in pattern recognition and machine learning, and the main differences between them are reflected in the relationship between training set and test set categories, the adaptability of the model, and the difficulty of the task.

In the closed set recognition problem, the classes of the training set and the test set are exactly the same, that is, the class set learned by the model during training is the same as the class set used during testing. This means that, during training, all possible categories have been covered and the model can be classified according to these categories. The goal of the model is to accurately classify test data into these known categories.

In the open set identification problem, the classes in the training set are only a subset of all possible classes, and the test set may contain some unknown classes that do not appear in the training set. This means that the model not only needs to be able to recognize known categories, but also needs to be able to deal with those "unknown" categories, refusing to misclassify those unknown categories as known categories. The model needs to determine whether a sample belongs to a known class during classification; If it does not belong to any known category, the classification should be rejected and marked as "unknown".

This paper proposes a new solution for open set recognition tasks to solve the shortcomings of traditional federated learning in data privacy protection and model generalization. The open-set identifies the model trained using the training set. When using a test set (it contains categories not found in the training set) for testing, if the data of the known categories are inserted, specific categories will be delivered as output; however, if the data of unknown categories are input, appropriate processing will be carried out (identified as unknown). For example, a client example of the open-set identification problem is shown in Figure 1 (the numbers 1-7 indicate categories, clienk1 clienk7 indicate different clients):

#### 3.1 Description of FML method

In this paper, FL is used to conduct joint training for data of different clients on the premise of protecting data privacy, yielding to obtain a global model shared by all clients. However, a single

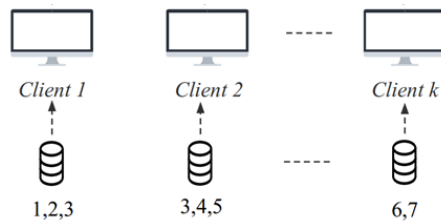


Figure 1: Example of open set identification problem

global model cannot meet all clients' needs. Therefore, this paper provides personalized models for different clients using the FML. Let  $k$  is the total number of clients,  $S_k$  represent the local model of  $k$  clients, where  $T_t$  represents the updated global model after round  $t$ . In addition, although FL is able to solve the privacy problem of local data to a certain extent, in the process of model parameter sharing and aggregation, due to data differences of each client, the client participation time in computation will be different. Therefore, this work develops a set of reasonable aggregative strategies for FML for global aggregation to improve the device fairness.

### 3.1.1 Training Model

In the training phase, the model first trains a typical classifier using samples from the training set, enabling it to accurately identify samples of the existing classes. Through this training, the model learns the feature representation and internal patterns of each category, allowing it to effectively distinguish between different classes. This process ensures that the model can provide accurate classification results when faced with test samples from known classes.

The FML system has  $k$  clients, coordinating together through a central server (server side). Let  $D_k = \{x_{ik}, y_{ik}\}_{i=1}^{N_k}$  represents the  $k$  client's data and its category, and  $N_k$  represents the  $k$  client's data quantity. The local client of FML contains three data sets, i.e., the support set, the query set, and the testing set. In more detail, the support set and the query set have their own label space and do not intersect. Our goal is to do meta-learning on the local training set to extract transferable knowledge that allows us to better learn the model on the support set and test its performance separately on the query set, thus classifying the test set more successfully. In each training iteration, each task forms the sample set by randomly selecting class  $C$  in the training set where there exists  $M$  label samples in each class.

In order to make full use of the Convolution Neural Network (CNN) to read the sample features, this work first identifies the support set and the query set to randomly extract samples that must be processed by the embedding layer to obtain the feature map, which is realized using four convolution blocks. Each convolutional block contains 64 filters of size 3 and uses the batch normalization and ReLU activation functions. The first two blocks include the max pooling operation whereas the second two blocks are not required. The main objective is to provide output feature maps for further convolution layers in the relational module.

$$F_k^i = CNN(x_{ik}) \quad (1)$$

In which,  $F_k^i$  is the feature map obtained after applying the CNN layers.

The feature vectors of each category of the support set and the query set are spliced and input into the network for processing, and the relationship score is calculated by the following equation:

$$Score_{k,ij} = f_k(\text{concat}(F_{k, \text{support}}^i, F_{k, \text{query}}^j)) \quad (2)$$

In which,  $F_{k, \text{support}}^i, F_{k, \text{query}}^j$  represent the merged feature vectors of the support and query sets of  $k$  clients, respectively,  $\text{concat}$  is the concatenation operation,  $f_k$  is the learned function through the neural network that computes the score of the  $k$  clients. The matching degree between them is analyzed through the neural network, and the category having the highest similarity degree of the image support set in the query set is represented [38]. Therefore, the relation module is composed

of two convolution blocks and two full connection layers. Each convolution block has 64 filters and its size is 3; moreover, it uses the batch normalization, the Rectified linear Unit (ReLU) activation function, and it has a max pooling of two. The activation function of all fully connected layers is ReLU, except that the last fully connected layer is Sigmoid.

When the server conducts a global model aggregation, because class  $C$  is randomly selected, there are  $M$  label samples in each class to form the sample set. Therefore, the data distribution of the training set and the test set will be different. If the training speed and the performance of each local model are different, the local model of each client will also be different. Therefore, in each training round, uploading the parameters of the local model with poor performance yields in the aggregation of the global model easily, resulting therefore in the decline of the accuracy of the global model. Moreover, the uploaded parameters of the local model, having a good performance, participate in the aggregation of the global model easily resulting in its overfitting phenomenon for some clients, leading therefore to the oscillation of the global model in the training process. Hence, this paper selects the local model in the training round through the coefficient method, to alleviate the overfitting problem caused by the poor generalization ability of the global model due to the poor or good performance of the local model. The client detection of this coefficient method is not affected by the extreme points, which is a favorable defense means of FML. Thus, this method effectively improves the robustness of the system.

Each local client  $D_k$  obtains the model parameters from the central server to initialize their local model, and then each local server uses the local dataset to train its local model. After the completion of the training round  $t$ , each local server uploads the local model and the accuracy rate of the round to the central server, the central server selects the local client set  $D_{Ic}$  that meets the requirements through the coefficient method; then, it gives the clients of each local server participating in the global model aggregation based on the filtered local server set  $D_{Ic}$ . The global aggregation model is given according to the following formula:

$$T_{t+1} = \arg_{S_k} \min \left| \frac{\sum_{i=1}^M Acc_i^t}{M} - Acc_i^t \right| \quad (3)$$

where  $M$  represents the number of the models in  $D_{IC}$ , and  $Acc_i^t$  is the accuracy of the  $i - th$  local server round  $t$ , and the parameter of coefficient method is  $1 - M/k$ . When the current round of global model aggregation is completed, the central server sends the updated global model to each local client according to the equation, in order to complete the upgrade of all the local models. Until the number of iterations reaches the pre-requirement, the central server completes the construction of the global model and delivers the final global model parameters to all the local servers.

### 3.1.2 Testing Model

The distribution of the training samples and the test samples is different because the training class is not sufficient to cover all object classes. The problem can be defined by the way to correctly classify unknown new classes based on some seen data classes. The key to the open-set recognition image classification lies in the way to overcome the difficulty of the different distributions of the training sample image and test sample image, that is, it consists of building a bridge of knowledge sharing between the known training class and unknown test class. In this classification scenario, the categories of the training set and the test set are disjoint, which is significantly different from the traditional classification tasks. The basic idea of the open-set recognition is to use the training stage samples to train the model. In the test stage, the information obtained in the training process can be used to make the model learn to classify the samples in the test set. Hence, the meta-learning has a high generalization ability and can help the model to successfully classify the samples in the test set. The correct classification of the open-set recognition problem is carried out using the FML.

In practice, however, the test set may contain new categories that were not present in the training set, and their characteristics may differ from the distribution of known categories in the training data. Therefore, during the testing phase, the model must not only be able to recognize known categories but also possess the ability to identify unknown categories. This is the key to open-set identification.

In the open-set recognition task, the model needs to determine whether the input sample belongs to a known class in the training set. If the input sample belongs to a known class, the model classifies it correctly. However, if the input sample belongs to an unknown class, the model recognizes it as an “unknown class”. To achieve this goal, the model first uses a classifier with strong generalization capabilities to assess the relationship between the input sample and each known category in the training set. Specifically, the model calculates the distance score between the input sample and each training class based on formula 3, evaluating whether it belongs to a known class.

On this basis, the model also leverages the subspace features of the training classes to further enhance the classifier’s discriminative ability. Each training class has a set of subspaces that represent its core features, which help the model better understand the internal structure of the different classes. The model combines the features of the input sample with these subspace features to determine which class the input sample belongs to. In this way, the model can not only accurately distinguish between known categories but also determine whether a sample belongs to an unknown category based on the structural features of the training data.

In order to accurately detect whether a test sample belongs to a known category or an unknown category, this paper adopts a distance-based threshold decision mechanism combined with relational features. Specifically, during inference, the model first computes the relationship scores between the input sample and each known class based on Equation 2. These scores reflect the similarity between the sample’s feature representation and each known class prototype. After obtaining the relationship scores, the model compares the maximum score across all known classes with a predefined threshold. If the maximum score exceeds the predefined threshold, the sample is classified as the corresponding known category. Otherwise, the model regards the sample as belonging to an unknown category and labels it as “unknown.” This process effectively prevents the misclassification of unknown classes as known ones, ensuring the open-set recognition capability of the model.

Furthermore, to enhance the robustness of unknown detection, the subspace features extracted from known categories during training are leveraged to enrich the semantic representation. By combining global and subspace features, the model gains a better understanding of intra-class variation, improving the accuracy of distinguishing unknowns.

Finally, if the model determines that the relationship between the input sample and all known classes is weak, it will classify the sample as “unknown class”, thus effectively addressing the open-set identification problem. The core of this process is that the model must be able to distinguish between samples that belong to known classes and those that belong to unknown classes, based on the knowledge acquired during the training phase, and appropriately apply a “rejection” process for the unknown class samples.

To sum up, the classification is presented in Figure 2.

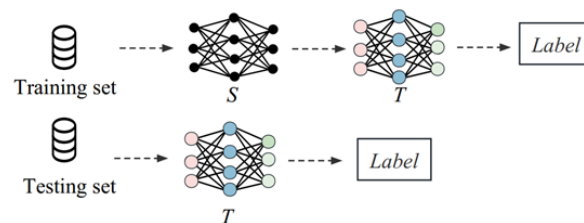


Figure 2: Classification of open set recognition problem

Therefore, the basis of the open-set recognition is to improve the generalization ability of the global model through a variety of means, so that the generalization ability of the model is strong enough to identify never-seen test class samples; moreover, this will help in defining the class label of the test class samples, and to extend the trained model to never-seen test class samples. Hence, the meta-learning process has exactly such a capacity.

### 3.2 Steps of FML method

The proposed FML framework consists of two main stages: meta-training and meta-testing, which collaboratively optimize the model's adaptability and unknown class detection capability in a privacy-preserving federated environment. During the testing phase, the trained models are applied to new tasks, and the system must not only classify known categories but also accurately identify unknown categories not encountered during training. The overall workflow is illustrated in Figure 3.

- **Global Model Distribution:** At the beginning of each training round, the central server distributes the current global model  $T_t$  to all participating clients, initializing their respective local models  $S_k$ . This process is depicted by the solid arrows in Figure 3.
- **Local Task-Based Meta-Learning:** Each client performs meta-learning on its local dataset. The dataset is divided into a support set and a query set, the support set and query set are passed through convolutional layers to extract feature representations, as defined in Equation 1. A relational network is then employed to compute similarity scores between support and query samples according to Equation 2. This enables the local model to learn task-specific decision boundaries. Based on the computed relationship scores, the client updates its local model  $S_k$ , enhancing its ability to quickly adapt to diverse local tasks.
- **Encrypted Model Upload:** Upon completing the local meta-training for round  $t$ , each client encrypts the updated model parameters and records the accuracy of its local model. These encrypted updates are then securely transmitted to the central server, as shown by the dotted arrows in Figure 3.
- **Global Model Aggregation:** The server selects the client models that meet the aggregation criteria using a coefficient-based selection method. The selected local models are aggregated to generate an updated global model  $T_{t+1}$ , following Equation 3. This process ensures that the global model effectively integrates diverse local knowledge while mitigating overfitting risks caused by poor-performing local models.
- **Iteration:** The updated global model  $T_{t+1}$  is redistributed to all clients, who then initiate the next round of local meta-training. This iterative process continues until the global model converges or the maximum number of training rounds is reached.
- **Local Inference:** Each client uses its locally adapted relational network classifier to perform inference on the test samples. The inference process involves the extracting features from the input samples using the trained convolutional layers. Calculating similarity scores between the extracted features and the learned representations of known categories.
- **Unknown Class Detection:** To detect unknown categories, the model applies a threshold-based decision mechanism. If the maximum similarity score between the input sample and all known classes exceeds a predefined threshold, the sample is classified into the corresponding known category. If the maximum similarity score falls below predefined threshold, the sample is identified as belonging to an unknown class and labeled accordingly. This mechanism prevents misclassification of unseen categories.
- **Post-Detection Handling:** Samples identified as unknown classes are subjected to appropriate post-processing, such as alerting the system for further inspection, excluding them from downstream classification tasks, or retraining the model to incorporate new categories in future iterations.

## 4 Experimental results and discussion

In this section, the performance of the proposed algorithm is evaluated. First, the experimental setup is described, including the data set and parameter setup. Then, the accuracy of open-set

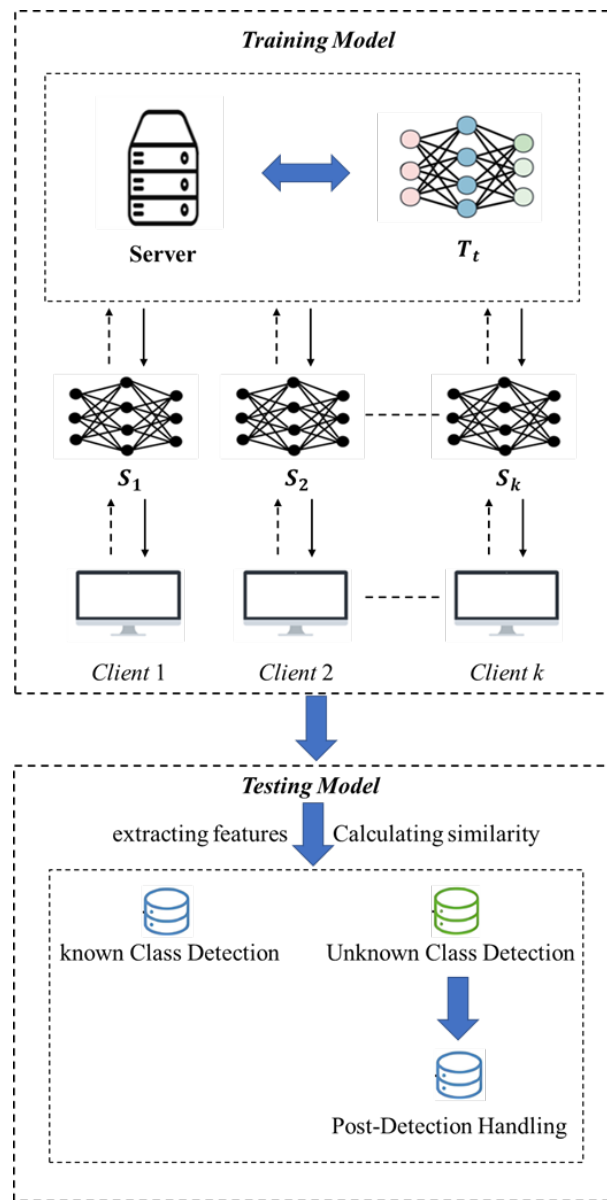


Figure 3: FML framework

identification problems is shown and compared with the effectiveness of the classical federated learning algorithm FedAvg [28].

#### 4.1 The Experiments

The proposed algorithm is tested on three benchmark datasets commonly used in deep learning. The first consists of the handwritten digit recognition data set MNIST [39], which contains 60,000 training samples and 10,000 test samples. Each picture is one of the numbers 0-9, and the number is in the center of the picture. Before the training, some enhancements are made to the original data, such as rotating each picture at any angle or translating it.

The second is the CIFAR-100 dataset [40] consisting of 100 classes. Each class has 600  $32 \times 32$  color images where 500 are used for the training set and 100 for the test set. The biggest feature of this data set is that the recognition is transferred to universal objects. The features to be extracted from the data are large and contain lots of noise, and the proportion of the objects to be recognized is also different. Therefore, CIFAR-100 data set is more challenging for image recognition tasks. Therefore, we made some enhancements to the raw data before the training process.

Finally, the third Omniglot dataset [38], which was first used in a 2015 New York University paper, is a dataset commonly used in meta-learning. The dataset is an updated version of handwritten digit

Table 1: Comparison of Test Accuracy (%) with 30% Fewer Categories in the Training Set

Less 30%	MNIST	CIFAR-100	Omniglot Dataset
FedAvg	86.2	52.1	73.5
FedProx	87.4	53.2	75.1
FedPer	89.2	56.3	77.2
FedBN	88.3	54.7	76.0
MAML	91.7	60.9	90.3
Reptile	90.9	59.1	89.8
ProtoNet	93.6	63.8	94.3
<b>FML</b>	<b>95.7</b>	<b>65.3</b>	<b>95.4</b>

recognition. The Omniglot dataset contains several categories (1623 categories); however, each category contains a small amount of data (only 20 data per category). Moreover, it is translated as a whole-language text dataset, containing different alphagrams of various languages, such as the Japanese hiragana Japanese\_(hiragana) that has 52 vowels, the Japanese katakana Japanese\_(Katakana) that has 47 vowels, the Korean language that has 40 vowels (21) and consonants (19), and the most common Latin alphabet (abCD) that has 26 vowels. The Omniglot dataset contains 50 alphabets in different languages, each containing different characters, a total of 1623 characters where each one was written by 20 different people. In other words, the Omniglot dataset contains 1623 classes, each of which has 20 training data. Moreover, each image is  $105 \times 105$  pixels in size. In order to improve the generalization ability of the algorithm, each image is rotated at any angle or is translated.

In order to highlight the effectiveness of the proposed FML algorithm, it was compared to the classical FL algorithms (e.g., FedAvg, and meta-learning). In order to exclude the influence of irrelevant factors, the implementation conditions of our control algorithm are basically the same, including the data partitioning among participants, the global model initialization values, and some parameter settings. In the experiment, we set the local batch size  $B$  to ten and the learning rate  $\eta$  to 0.01 in each round of the polymerization. We carried out experiments with MNIST, CIFAR-100, and Omniglot datasets and their model combinations to test the accuracy of the final model of the open-set identification on each participant’s local data set.

## 4.2 Experimental results

In this section, we construct numerical simulation experiments of the open-set identification based on the above data sets to verify the effectiveness of the FML algorithm and compare it to the classical FL algorithm FedAvg with the absence of noise. Moreover, FedAvg is used as the baseline of this experiment in order to compare the proposed model to the FL model of the gradient full precision aggregation. In addition, the data set of Omniglot dataset represents the dataset commonly used in meta-learning. Therefore, the FML method of this paper is compared to the meta-learning method to analyze whether the method in this paper guarantees the fast learning and generalization ability of meta-learning.

### 4.2.1 Results of Experiment 1

In this experiment, we use three widely used datasets—MNIST, CIFAR-100, and Omniglot—to perform the open set recognition task. In each dataset, the training set contains fewer categories than the test set, with the test set including "unknown" categories that do not appear in the training set. We compare the proposed FML method with classical federated learning methods such as FedAvg [39], FedProx [4], FedPer [41] and FedBN [42], as well as with classical meta-learning methods like MAML [43], Reptile [44] and ProtoNet [18]. The performance of each method is evaluated in a distributed learning environment, with a focus on accuracy in open set recognition problems. Different class settings are employed, including cases where the training set contains 30% and 50% fewer categories than the test set. We also conduct a detailed analysis of the recognition performance on unknown classes in each scenario. To ensure fairness, experimental settings control for factors such as data partitioning, global model initialization, and hyperparameters, ensuring the comparability of results.

It can be seen from the experimental results that the FML method performs well on all datasets (MNIST, CIFAR-100, and Omniglot) when the training set categories are reduced by 30% and 50%.

Table 2: Comparison of Test Accuracy (%) with 50% Fewer Categories in the Training Set

Less 50%	MNIST	CIFAR-100	Omniglot Dataset
FedAvg	80.5	47.8	70.2
FedProx	81.9	48.7	71.4
FedPer	84.7	52.8	75.1
FedBN	83.5	50.4	73.6
MAML	85.5	55.3	76.1
Reptile	84.7	54.2	74.5
ProtoNet	88.2	60.5	81.0
<b>FML</b>	<b>90.5</b>	<b>62.3</b>	<b>82.8</b>

Table 3: Test Accuracy (%) with 30% Fewer Categories in the Training Set

Less 30%	5,10	5,20	10,20
MNIST	95.7	94.6	–
CIFAR-100	65.3	64.4	66.7
Omniglot Dataset	95.4	92.8	95.9

It is clearly superior to traditional federated learning methods (FedAvg and FedProx) and other classical meta-learning methods (MAML, Reptile, ProtoNet). As the number of classes in the training set decreases, traditional federated learning methods show weakness in open set recognition tasks due to their low adaptability and limited class recognition ability, especially when dealing with complex datasets such as CIFAR-100 and Omniglot. By combining the advantages of federated learning and meta-learning, the FML method not only effectively ensures data privacy in distributed learning scenarios but also uses the meta-learning mechanism to quickly adapt to new categories. This is particularly beneficial when the training set contains insufficient categories, allowing the model to better identify unknown categories in the test set. This enables FML to significantly improve recognition accuracy in open set recognition tasks, achieving notable advantages on the MNIST, CIFAR-100, and Omniglot datasets. Overall, the experimental results demonstrate the effectiveness of FML in open set recognition tasks, particularly in scenarios where the categories in the dataset do not fully overlap. FML combines the privacy protection of federated learning with the rapid adaptability of meta-learning, which allows it to show strong advantages in recognizing unknown categories.

#### 4.2.2 Results of Experiment 2

In the open set recognition scenario, the training performance of different algorithms was tested. To demonstrate the performance variation of the proposed method under different parameters, Table 3 and Table 4 present a comparison of the model results when the algorithm is applied to the MNIST[39], CIFAR-100[40], and Omniglot datasets[38], for each dataset, the training set categories were deliberately reduced by 30% or 50% compared to the test set. In this experiment, we designed three different meta-learning task configurations to evaluate the impact of the number of categories and the number of samples per category on model performance. Specifically, the first configuration selects 5 categories, with 10 samples per category (5, 10); the second configuration selects 5 categories, with 20 samples per category (5, 20); and the third configuration selects 10 categories, with 20 samples per category (10, 20). These different settings aim to examine the performance differences of various methods in the open set recognition task under varying training set category numbers and sample sizes per category. From the analysis of precision results, the proposed algorithm achieves higher precision on the MNIST and Omniglot datasets. However, the CIFAR-100 dataset, being more complex, shows lower precision when using the same network as for MNIST and Omniglot. These results demonstrate the effectiveness of the proposed method.

In the open set identification problem, the number of classes in the training set is usually less

Table 4: Test Accuracy (%) with 50% Fewer Categories in the Training Set

Less 50%	5,10	5,20	10,20
MNIST	90.5	86.8	–
CIFAR-100	62.3	58.7	63.9
Omniglot Dataset	82.8	80.5	84.2

Table 5: Ablation Study of Each Component in the FML Framework

Method	Accuracy (%)
<b>Full FML Framework</b>	<b>95.7</b>
without Meta-Learning	91.3
without Relational Network	92.1
without Coefficient Aggregation	89.9
FedAvg Baseline	86.2

than that in the test set, which results in inconsistent distribution of the training samples and the test samples. In Tables 3 and 4, the training set has 30% and 50% fewer categories than the test set, which challenges the model with more “unknown” categories, that is, classes that cannot be seen during training. The model needs to have some generalization ability in order to recognize categories on the test set that do not appear in the training set. The setting of this class mismatch increases the difficulty of fitting the models, resulting in generally low accuracy of all models in these scenarios. This is typical of open set problems, especially in the case of limited training data, how to effectively identify new categories becomes a key problem. However, FML can better adapt to the data privacy requirements in distributed learning scenarios, and improve the fast learning ability of the model on unknown categories through the meta-learning mechanism. This allows FML to infer new categories in the test set more effectively in the face of insufficient training categories, thus improving the accuracy of the model.

### 4.2.3 Results of Experiment 3

To evaluate the contribution of each key component in the proposed FML framework, we conducted a series of ablation studies on the MNIST dataset. The FML framework integrates meta-learning initialization, a relational network, and coefficient-based aggregation to enhance personalization and robustness. In our ablation experiments, we removed or replaced one component at a time while keeping the others unchanged, aiming to isolate the performance contribution of each part.

Specifically, we evaluated the following variants: the complete FML framework with all components enabled; a variant without meta-learning initialization, where the local models were trained directly on the classification task without task-specific adaptation; a variant without the relational network, in which a conventional fully connected classifier replaced the relational similarity modeling; and a variant without the coefficient-based aggregation strategy, where the standard FedAvg method was used instead of performance-based client selection. Additionally, we included the standard FedAvg baseline for comparison.

The results, summarized in Table 5, show that the full FML framework achieves the highest accuracy, indicating the effectiveness of the integrated design. Removing meta-learning initialization resulted in a notable performance drop, confirming its importance for enabling fast adaptation to diverse local tasks. Eliminating the relational network also degraded the classification accuracy, demonstrating that modeling task-specific relationships between samples improves decision boundary learning. Replacing coefficient-based aggregation with FedAvg led to the most significant decline in performance, highlighting the critical role of selectively aggregating well-performing local models to enhance the robustness of the global model. Overall, compared to the FedAvg baseline, the full FML framework achieved consistent improvements, validating the complementary contributions of the three components. These results confirm that each module is essential for achieving strong personalization and robustness in federated meta-learning.

To further comprehensively evaluate the performance of the open-set recognition model under the FML framework on the MNIST dataset, this study introduces the Receiver Operating Characteristic (ROC) curve and its corresponding Area Under the Curve (AUC) as evaluation metrics to measure the model’s ability to distinguish between known and unknown categories.

The ROC curve reflects the model’s capability to correctly identify known categories (positive class) as known and to accurately detect unknown categories (negative class) as unknown under different threshold settings.

As shown in Figure 4, the experimental results demonstrate that the open-set recognition model

based on the FML framework can effectively distinguish between known and unknown categories without sharing raw data, exhibiting strong detection capability for open categories.

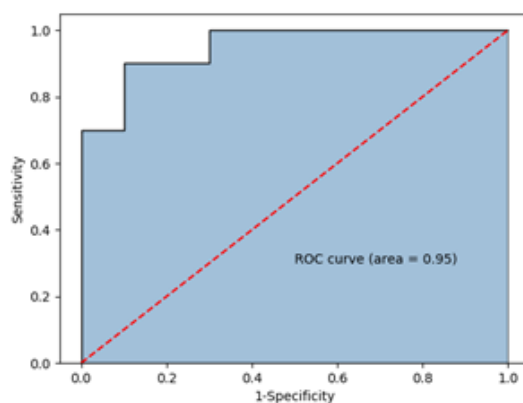


Figure 4: ROC curve of FML method

#### 4.2.4 Results of Experiment 4

To evaluate the stability and statistical significance of the proposed method, we conducted multiple independent experiments on the MNIST dataset and recorded the accuracy for each run. A one-sample  $t$ -test was performed at a significance level of  $\alpha = 0.05$  to assess the statistical reliability of the results.

The one-sample  $t$ -test yielded a  $p$ -value of 0.004, indicating that the performance of the proposed method is statistically significant.

These findings demonstrate the effectiveness and robustness of the proposed method, confirming its ability to consistently achieve reliable performance across multiple independent trials.

### 4.3 Discussion of the results

FML method combines federated learning and meta-learning, which not only protects data privacy in distributed environment, but also improves the model's adaptability to new tasks. This combination provides a new framework for solving open set identification problems. The effectiveness of this method is verified by experiments when the categories of training set and test set are inconsistent, which further enriches the application theory of meta-learning in open set recognition. As a technology to protect data privacy, the challenge in the practical application of federated learning is how to improve learning efficiency while ensuring privacy. FML algorithm enhances the recognition ability of unknown categories by using meta-learning mechanism, thus providing new theoretical support for the application of federated learning, especially in the task of open set recognition under privacy protection, and discusses the balance between privacy and efficiency. By verifying the performance of FML algorithm in open set identification, this experiment promotes the research progress in this field. As a difficult problem in traditional machine learning and pattern recognition, open set recognition requires models to recognize not only known categories, but also unknown categories. By applying FML algorithm to this problem, the experiment provides a new idea and method for theoretical research, and shows the potential of combining federated learning and meta-learning, especially in data privacy protection and distributed learning environment.

By introducing federated learning, FML algorithms avoid the risk of centralizing sensitive data into a single server, enabling multiple parties to participate in distributed learning, which is critical for data privacy protection across multiple industries. At the same time, FML combines the advantages of meta-learning, so that the model can quickly adapt to new tasks and data, and has good scalability and flexibility. In this way, FML can improve the accuracy of the model under the premise of ensuring privacy, especially when dealing with new categories or open sets, which makes FML have a wide range of application value in practical distributed learning and privacy protection scenarios. Traditional closed set classification algorithms struggle to effectively handle the recognition of unknown categories,

while FML algorithms offer the potential to address this challenge in a real-world environment. In the case of insufficient training set categories, FML can improve the recognition ability of the model on unknown categories through the effective use of multi-source data and the rapid adaptability of meta-learning, thus improving the accuracy of the application.

## 5 Conclusion

This paper analyzes the current research status and some bottlenecks of the federated learning and meta-learning related algorithms and mechanisms. At the same time, this work analyzes some potential of the meta-learning to solve the above problems of FL, and discusses the influence of the aggregation mechanism on the algorithms' performance. Therefore, this paper proposes an FML algorithm with high generalization ability, based on an open-set recognition. First, the central server distributes the latest model to each client, and each one uses it to replace the local model after downloading. Secondly, after extracting the features, each local server classifies the features of each center using the classifier built based on the relational network to obtain the final prediction results, update the local model, and upgrade the global model according to the accuracy results. Finally, we use MNIST, CIFAR-100, and Omniglot datasets and their models to test the accuracy of the final model on each participant's local dataset and compare it to the classical federated learning algorithm FedAvg. Experiments show that the proposed FML method has better prediction accuracy and generalization ability, which proves the effectiveness and superiority of the proposed method.

The algorithm and scheme proposed in this paper still have some limitations. For example, the coefficient client detection method is used to avoid the algorithm being affected by extreme points, but it is also possible to delete the high-quality model. Therefore, in future research, the algorithm will be further optimized, focusing on malicious users providing low-quality data to reduce the accuracy of the model. At the same time, a filtering mechanism can be considered to improve the quality of the model. Finally, open set problems require models to recognize "unknown" categories, which requires models to have stronger contrast learning ability. In the future, methods such as comparative learning can be combined to further improve the performance of FML in new category recognition.

Furthermore, in real-world federated environments, training data collected from different clients is often noisy due to data collection errors, user labeling inconsistencies, or device malfunctions. Such noisy data may reduce the generalization ability of the global model and negatively affect open set recognition performance, as noisy samples can obscure the boundary between known and unknown classes. Although our experiments are conducted on clean benchmark datasets, the robustness of the proposed method against noisy data remains an important aspect to be further explored. According to prior research, meta-learning frameworks can improve robustness to some extent by learning transferable representations. In future work, we plan to test the proposed framework on real-world noisy datasets to assess its noise tolerance.

And, computational trade-offs are critical in federated meta-learning systems. Increasing the number of local training steps helps reduce communication rounds and protect privacy, but may slow convergence due to stale gradients and lead to local overfitting. Conversely, frequent communication accelerates global model convergence but increases the overall communication cost and system overhead. Model size, optimization parameters, and batch size also influence training time and network load. According to theoretical analysis and related literature, meta-learning can reduce the number of communication rounds needed for adaptation, thus achieving faster convergence in federated settings. However, an empirical assessment of these trade-offs under different system configurations is required to optimize real-world deployment.

We plan to conduct future work along two directions: (1) handling malicious users and noisy data, improving model quality through enhanced filtering mechanisms; (2) incorporating real-world noisy datasets to verify the robustness of the proposed framework; and (3) performing a comprehensive computational analysis to balance training efficiency, communication overhead, and model convergence.

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## Author contributions

The authors contributed equally to this work.

## Conflict of interest

The authors declare no conflict of interest.

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