Foreign Object Detection of Electric Transmission Line with Dynamic Federated Learning

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Abstract. The bird's nests and other foreign objects on the transmission lines bring about huge threats to the electric power security. The aggregation of foreign objects data of different regions can boost the generalization of foreign objects with deep learning. However, due to policy constraints and other data security reasons, it is impossible to collect the data of different power companies to train a joint foreign object detection model. Therefore a dynamic federated learning based foreign object detection method for transmission lines is proposed. For the clients distributed in power companies, each model is trained and uploaded to the central server in an asynchronous way for dynamic fusion. For the model trained with pre-trained model, the pre-trained part is frozen and will not be trained. Thus the feature extraction backbone is not uploaded to central sever, which contributes to the decrease of the communication consumption by reducing the amount of uploaded data. The experimental results demonstrate that the dynamic federated learning based foreign object detection algorithm can maintain the same accuracy level compared with centralized training. It can train the joint model without uploading the original data of the edge nodes, which guarantees the security and privacy of local data. Compared with training individually, it has great improvement in accuracy. And it is also applicable with different network sizes. Therefore the dynamic federated learning based foreign object detection has strong privacy, accuracy, efficiency, flexibility and scalability.

1. Introduction
Foreign objects on transmission line such as bird's nest, plastics and crane greatly threaten the safety of power transmission lines. Kites, plastics and other foreign objects winding will shorten the discharge distance of high voltage line and cause danger to pedestrians and vehicles below the line[1]. The birds in the bird's nest on the transmission tower will produce a lot of faeces corroding the transmission equipment. The height of cranes and other large lifting equipment under the transmission line is similar to or even higher than that of transmission lines, which will also pose threats to the safety of lines. Compared with the traditional management mode of manual inspection and video monitoring, the rapid development of deep learning technology in recent years provides a new method for foreign object detection of transmission lines[2][3]. The mainstream foreign object detection method of transmission line is capturing the transmission lines images with UAV automatic cruise and
then using convolution neural network to identify the foreign object in the images[4]. Compared with manual monitoring, foreign object detection with deep learning can reduce the cost greatly[5][6][7].

The foreign object images data collected in different regions and different power companies usually is not independently identically distributed. So the foreign object detection model trained with the data from a single region has poor generalization in other regions. Electric power data privacy and security is related to the security of the society. It is usually impossible to leverage the original data of all regions to train artificial intelligence models. In 2018, the EU promulgated the General Data Protection Regulation, which stipulates many restrictions on the sharing and use of individual data. As of 2021, China has also promulgated eight relevant laws and regulations, including the China’ Cyber Security Law, to protect the data security of computer information system. Therefore, it is usually difficult to share different units’ data with each other. There are insurmountable barriers in the data exchange between entities, resulting in the Data Islands.

In 2016, Google proposed a novel collaborative training paradigm of machine learning/deep learning, called federated learning[8]. The core of federated learning is to build an aggregation model by using the model updates from decentralized client data. Training models with multi-party data without collecting the original data can avoid data leakage. Therefore, a dynamic federated learning based foreign object detection of electric transmission line is proposed to solve the problem of data privacy and security in training foreign object detection model of transmission line. Main features are included in these points:

Privacy: Training models using multi-party information without collecting the original data can avoid data leakage. For each power company client, other clients are unknowable. Each client cannot get the origin data of other clients, or even know whether other client exist. For the central server, the model gradient obtained from the decentralized client is encrypted instead of origin data.

Accuracy: Compared with centralized non-federated training method, the foreign object detection method of transmission line based on dynamic federated learning achieves almost the same accuracy level without the exchange of original data. And the accuracy is also higher than any single client.

Efficiency: Comparing with the traditional federated learning method, the foreign object detection based on dynamic federated learning does not upload the feature extraction backbone of the network when using the pre-trained model for training, which greatly reduces the amount of data required for model fusion.

Flexibility and scalability: The foreign object detection based on dynamic federated learning is extensible and scalable for foreign object detection. Central sever fuses edge models in an asynchronous way. Every client can be added and removed during training.

2. Related work

The safe operation of power transmission line is vital to country’s security. In order to ensure the normal operation of transmission lines, a lot of research on foreign object detection of transmission lines has been carried out. And the data security and privacy issues are also inevitable.

2.1 Foreign Object Detection of Transmission Line

Chen et al[2] used non-deep learning method to identify bird nest and tower rust in UAV aerial route image. They separate foreground objects from background by constructing background filter, which improved the detection accuracy to a certain extent. In order to solve the problems of high complexity, weak feature expression ability and laborious manual annotation in foreign object detection of transmission lines, Chen et al[3] proposed a foreign object detection method for transmission lines based on multi-layer semi-supervised single class extreme learning machine (ML-S20CELM). It greatly reduces the workload of image labelling and effectively improves the efficiency of foreign object detection. Shen et al[9] proposed a new high voltage lines foreign object detection network TLFOD Net for irregular foreign objects on high voltage transmission lines. This network optimized the size of the candidate box, and proposed an end-to-end joint training method according to the characteristics of foreign objects. Guo et al[10] leverage Faster R-CNN[11] to detect foreign objects
such as kites and balloons on transmission lines. Compared with traditional foreign object detection algorithms such as SIFT\cite{12} and ORB\cite{13} feature matching algorithm, this method overcomes the instability of manual feature extraction, and can effectively improve the accuracy of edge blurred images and complex background images.

2.2 Federated Learning

In order to solve the data island problem, federated learning\cite{8} became a research hot spot in the field of artificial intelligence. In 2016, Google proposed federated learning for the first time, which trains a high-quality central model with client data stored locally. Liu et al.\cite{14} proposed federated transfer learning, sharing knowledge without damage user privacy. It allows the cross-domain transmission of supplementary knowledge in the data alliance. So that the target domain can build a flexible and effective model by using the labels from the source domain, which can effectively adapt to a variety of secure multi-party machine learning tasks. Aiming at the non-IID data in federated learning, Zhao et al.\cite{15} improved federated training of non-IID data by creating a globally shared data subset among all edge devices. More and more practical applications of federated learning have emerged in the field of computer vision. Zhang et al.\cite{16} proposed a novel dynamic fusion based federated learning for the detection of COVID-19 in medical diagnostic images. In this paper, the participated client is chosen according to the local model performance. And the model fusion schedule is based on the clients’ training cycle.

3. Methodology

To address solve data security and data privacy issues in multiple data nodes joint training, a new foreign object detection algorithm based on dynamic federated learning is proposed. It mainly includes three contributions: architecture design, network structure and model aggregation strategy.

3.1 Architecture Design

As shown in Figure 1, the architecture of foreign object detection method based on dynamic federated learning mainly includes edge clients and central server. The central server is responsible for training jobs distribution, model initialization and model aggregation. The edge clients are responsible for edge model training.

![Diagram of Architecture Design](image-url)
At the beginning of the training, the central server creates training tasks for each participating client, containing the model structure and the pre-trained model to initialize of the edge node model. Then edge node model is initialized and then the training begins when receiving the training task. In the local model training stage, edge clients train models with local data after data enhancement, and upload the edge model to the central server after a certain iteration of training. Because the training time of each node is inconsistent, the central server will temporarily store the edge models after receiving them. When the number of received edge models is more than half of the total number of nodes participating in training, the edge model will be aggregated.

Before the aggregation of edge models, edge models is evaluated. If the edge model’s accuracy is lower than accuracy last time, it’s aggregation request will be refused. Otherwise it will be merged into the aggregated model. It guarantees that every aggregated edge model can make a positive contribution to the central model. The central model is send when aggregated at central sever. And edge model is updated by the center model and continues training with local data.

3.2 Network Structure
The foreign object detection algorithm based on dynamic federated learning is Cascade R-CNN[17]. As is shown in Fig.2, the feature extraction backbone is EfficientNet-B7[18]. NAS-FPN[19] is adopted to integrate multi-scale features.

As shown in the figure above, the origin image is put into the feature map extraction backbone and generates feature maps. NAS-FPN fuses feature maps of different scale. And then RPN generates candidate boxes in the next stage. The region proposals are obtained by combining the candidate boxes with the multi-scale feature map, and then input into the first cascade detection network to get the coordinates and categories of objects. The second cascade detection network uses the output coordinates of the first stage to initialize, and fine tune the output of the previous stage through different IoU threshold. In the third stage, the above operations are repeated to get the final output.

EfficientNet-B7 and NAS-FPN are the pre-trained on ImageNet, thus only the three cascade detectors are fine tuned. At the same time, because each client adopts the same network structure and pre-trained weights, the weights of each edge model in feature extraction backbone and scale fusion network is consistent. Therefore, edge nodes only upload the trained part of models which can greatly reduce the amount of transmitted data.

3.3 Model Aggregation strategy
In view of the inconsistency of data total amount, training speed and accuracy of each node, a dynamic asynchronous model fusion method is proposed.

Because of the different upload speed and frequency of different node models, the central server will temporarily store edge models after receiving the edge nodes. When the collected edge models are more than half, the model will be aggregated. The collected edge models are aggregated in dynamic
weighting based on the node data and the accuracy of the edge model. The clients’ weights of aggregation are shown in Eq.1.

\[ W_i = \left( \frac{D_i}{\sum_{j=1}^{n} P_j} \right) \left( \frac{P_i}{\sum_{j=1}^{n} P_j} \right) \]  

(1)

In this equation, \( n \) denotes the number of clients participating in aggregation. \( D_j \) and \( P_j \) are separately the data amount and accuracy of client \( j \). The central server calculates the weight of each client, and dynamically averages the edge models to get the aggregated model.

4. Experiments Introduction

In order to verify the effectiveness of the proposed method, sufficient experiments are carried out on five clients. The experimental configurations of each client are shown in Table 1. It can be drawn that the configuration of each client is completely different. And that resulting in the variety of training speed.

| Node   | GPU          | RAM | CUDA |
|--------|--------------|-----|------|
| Server | GeForce RTX 3090 | 24G | 11.2 |
| Client1| GeForce GTX TITAN X | 11G | 11.1 |
| Client2| GeForce RTX 3080 | 10G | 11.2 |
| Client3| GeForce RTX 3090 | 24G | 11.2 |
| Client4| GeForce GTX 1080ti | 11G | 11.1 |
| Client5| GeForce GTX 1070 | 8G  | 11.1 |
| Client6| GeForce GTX 1080 | 8G  | 11.1 |

Table 2 shows the data distribution of each client. From this table it can be seen that the data of clients is not independently identical distributed and the volume of their data is not balanced.

| Client   | Nest | Plastics | Crane | Kite |
|----------|------|----------|-------|------|
| Client1  | 0    | 659      | 550   | 1163 |
| Client2  | 1801 | 1109     | 0     | 450  |
| Client3  | 561  | 94       | 336   | 95   |
| Client4  | 137  | 0        | 287   | 0    |
| Client5  | 445  | 231      | 655   | 0    |

Experimental result is shown in Figure.3. The X-axis of Figure.3 is the models in this experiment and the Y-axis is the corresponding accuracy of them. In the X-axis, the Clients from Client1 to Client5 denote the models trained with their own data locally. FedAvg is the federated averaging algorithm, which does not adopt dynamic weights of clients. DFL denotes the method proposed in this paper. And CT is the centralized model train with data gathered together.

As can be seen from Figure.3, there is obvious difference between the accuracy of clients. And federated learning can improve the performance comparing with each single client (FedAvg). The foreign object detection of electric transmission line with dynamic federated learning can further improve the detection accuracy and achieve the same accuracy level as centralized training.
Considering the application requirement, the model size of foreign object detection should be various. And to demonstrate the scalability and robustness of the proposed method, the above experiment is extended with different scale backbones from EfficientNet-B3 to Efficient-B7. From Table 3 it can be seen that DFL can get notable detection accuracy with only a little of accuracy loss compared to centralized training.

### Table 3. Experiment Result with Backbone from EfficientNet-B3 to B7.

| Client | Client1 | Client2 | Client3 | Client4 | Client5 | FedAvg | DFL | CT |
|--------|---------|---------|---------|---------|---------|--------|-----|----|
| B3     | 47.31   | 51.35   | 43.57   | 54.72   | 44.35   | 56.73  | 62.37| 63.57|
| B4     | 61.01   | 59.84   | 51.9    | 59.39   | 57.9    | 68.84  | 71.95| 73.23|
| B5     | 68.02   | 63.86   | 58.07   | 66.32   | 61.33   | 79.67  | 84.18| 86.93|
| B6     | 76.04   | 70.28   | 65.41   | 72.84   | 69.08   | 83.91  | 89.38| 92.88|
| B7     | 76.86   | 71.4    | 65.53   | 75.43   | 70.62   | 85.13  | 92.68| 93.16|

## 5. Conclusion

To detect the foreign objects of transmission lines precisely without data leakage, a novel foreign object detection of electric transmission line with dynamic federated learning method is proposed. This method trains a joint model in an asynchronous way and adopts a dynamic self-adaptive model aggregation strategy. By freezing the feature extraction part, this method can efficiently reduce the communication cost in training. Experimental results demonstrated that it can achieve remarkable accuracy without the origin data of clients, which guarantees the data security and privacy.

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