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A subspace-based few-shot intrusion detection system for the Internet of Things*

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Abstract: Deep learning-based intrusion detection systems rely on numerous training samples to achieve satisfactory detection rates. However, in real-world Internet of Things (IoT) environments, the diversity of IoT devices and the subsequent fragmentation of attack types result in a limited number of training samples, which urgently requires researchers to develop few-shot intrusion detection systems. In this study, we propose a subspace-based approach for few-shot IoT intrusion detection systems to cope with the dilemma of insufficient learnable samples. The method is based on the principle of classifying metrics to identify network traffic. After feature extraction of samples, a subspace is constructed for each category. Next, the distance between the query samples and the subspace is calculated by the metric module, thus detecting malicious samples. Subsequently, based on the CICIOT2023 dataset we constructed a few-shot IoT intrusion-detection dataset and evaluated the proposed method. For the detection of unknown categories, the detection accuracies were 93.52% in the 5-way 1-shot setting, 92.99% in the 5-way 5-shot setting and 93.65% in the 5-way 10-shot setting.

Key words: Intrusion detection system; Few-shot learning; Internet of Things; Subspace
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1 Introduction

The Internet of Things (IoT) is rapidly becoming a central aspect of our daily lives and industrial operations. As an increasing number of devices connect to networks, the amount of data they generate and the range of applications they can use expand significantly. However, this connectivity poses new security challenges because the diverse and distributed nature of IoT devices makes them new targets for cyberattacks. Thus, the IoT intrusion detection system has become key for securing the IoT. In recent years, excellent algorithms for IoT intrusion detection systems have been developed, which are effective at detecting abnormal traffic (Lu et al., 2021; He et al., 2023). These studies have one thing in common: they train models from large datasets. Traditional intrusion detection methods based on a large number of samples face the challenge of data collection and labeling owing to the diversity of IoT devices and the dynamics of the network environment. In a diverse IoT environment, a discontinuity occurs in security measures due to device diversity, differences in operating system versions, inconsistent firmware updates, and other factors. This fragmentation makes it extremely difficult to maintain a unified security policy, thereby providing opportunities for attackers to exploit. Furthermore, when faced with zero-day attacks, researchers usually fail to collect sufficient samples and therefore may be unable to build timely datasets. At this point, machine-

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learning-based IoT intrusion detection systems can fail, which in turn can cause irreparable damage to industrial production(Yan et al., 2024).

Researchers have shifted their focus to few-shot learning in the face of very few attack samples, such as zero-day attacks. As the name implies, IoT intrusion detection systems based on few-shot learning aim to develop efficient and accurate intrusion detection models for sparse and unbalanced data. However, the development of efficient few-shot models faces challenges, such as poor generalization and overfitting(Duan et al., 2021; Wang et al., 2021).

Research on IoT intrusion detection systems based on few-shot learning is still in its infancy, and more research needs to be made available for reference. However, the feasibility of using few-shot learning to address IoT intrusion detection has already been demonstrated.

In this study,a subspace-based few-shot IoT intrusion detection system was developed to solve these problems. We applied a subspace classifier to an IoT intrusion detection system. Unlike existing parameter optimization-based methods, we used metric learning to detect network traffic, which uses a priori knowledge to detect unknown categories (Simon et al., 2020). The main contributions of this study are as follows:

1. To enhance the discriminability of traffic information from different classes, we proposed a few-shot classifier that utilizes subspaces as a metric to fully learn the common representation of each traffic flow, while also designing a four-layer feature extraction network based on channel attention mechanisms to enhance the feature representation of each traffic flow.

2. We demonstrated that the proposed method performed well and had some ability to generalize unknown categories on the CICIOT2023, CICIDS2017, and CICIDS2018 datasets, which could address the capability of detecting unknown category samples under few-shot conditions.

3. We considered the diversity of IoT devices and the specificity of attack patterns, along with the designed data preprocessing steps, and constructed a dataset suitable for few-shot intrusion detection.

The remainder of this paper is organized as follows:Section 2 reviews related studies on IoT intrusion detection systems, few-shot learning, and few-shot intrusion detection systems. Section 3 presents a detailed description of the subspace-based few-shot IoT intrusion detection method. Section 4 describes the experiments and evaluates the proposed method. Section 5 compares and discusses similar studies. Finally, Section 6 summarizes the study.

2 Related works

2.1 IoT intrusion detection

The large number, variety, and wide distribution of IoT devices pose massive challenges to security protection. The traditional method of network security protection may be unable to effectively respond to intrusions in IoT environments. Therefore, the detection of IoT intrusions is an important research topic(Mehedi et al., 2022; Alani and Awad, 2023).

Traditional machine learning-based intrusion detection systems have difficulties in heterogeneous data preprocessing and fusion training,and they can no longer satisfy the requirements for heterogeneous IoT intrusion detection.Makkar et al. (2021)proposed a machine learning-based framework for detecting spam messages, aimed at addressing the increasingly severe problem of spam in IoT devices. By evaluating five different machine learning models, the framework is capable of calculating the spam score of devices and assessing their reliability based on that.In a previous study, Chen et al. (2023) proposed a deep learning method based on word embedding to solve this problem using the multisource data fusion method of natural language processing, which can effectively preserve data features. Lu et al. (2021) established a new model called the CMAE that used memory modules to record potential spatial feature representations of normal data and to obtain efficient memory modules with feature reconstruction loss and feature sparsity loss. The experimental results showed that compared to using feature reconstruction loss, using feature sparsity loss achieved improvements of approximately 0.154%, 0.15%, and 0.16%. When the proposed components were used, the model achieved effective improvements in the three metrics of intrusion detection. To address the limited computing power of IoT devices, He et al. (2023) developed a lightweight and efficient intrusion detection method based on feature grouping, which achieved a classification accuracy of over 99.5% on the BotIoT, MedBIoT, and MQTTIoTIDS2020 datasets.Thakkar and Lohiya (2023) used ensemble learning (Bagging classifier) to address the class imbalance problem in a dataset, and the proposed method achieved a precision of 99.77% and a recall rate of 99.96% on the CICIDS2017 dataset.The above all refer to malicious detection methods tailored for the Internet of Things (IoT) environment. There are also many excellent algorithms for research in other network environments. For example, He et al. (2024) proposed a method based on packet clustering and online data stream processing for real-time detection of DDoS attacks. This method achieves a 99.86%accuracy rate with only a 1.05-second delay, surpassing the response speed of other methods. Niu et al. (2023) combined semi-supervised learning and active learning techniques to achieve an efficient detection model with a limited labeling budget. Fouladi et al. (2022) proposed a method based on Discrete Wavelet Transform (DWT) and autoencoder neural networks. Their research not only illustrates how deep learning can be effectively employed for attack identification with small sample sizes but also validates the effectiveness of their approach across various attack types through experiments. Duan et al. (2023) introduced an intrusion detection method based on dynamic line graph neural networks (DLGNN), which efficiently utilizes the spatiotemporal characteristics of network traffic within a semi-supervised learning framework. By transforming network traffic into a series of spatiotemporal graphs, the model not only captures the evolving context of communication between each IP pair in the network but also strengthens the message aggregation capability of graph convolutions.

IoT intrusion detection has been investigated extensively, but further research is required for few-shot IoT intrusion detection systems. Therefore, we propose an approach that accurately identifies samples of known categories and generalizes to accurately identify samples of unknown categories using a priori knowledge.

2.2 Few-shot learning

Research on few-shot learning has made significant progress in recent years, particularly with deep-learning models. Few-shot learning can be broadly divided into three categories: parameter-based optimization, metric-based learning, and data-based enhancement.

One of the most impressive studies on parameter optimization-based few-shot algorithms is model-agnostic meta-learning (MAML) approach, proposed by Finn et al. (2017). This approach enables improved generalization of the model to new tasks by sharing the learned parameters between tasks. This task is accomplished using two nested gradient descent processes. Jamal et al. (2019) argued that the initial model of a meta-learner may be biased toward certain tasks sampled during the meta-training phase, and they proposed task-agnostic meta-learning (TAML) to avoid learning-biased initialized models. Nichol et al. (2018) proposed the Reptile algorithm, which is computationally simpler than the MAML algorithm. The former was used to update the network model parameters with the difference between the most recent parameters and the meta-parameters after K training sessions are executed for each task. The latter performed all tasks and updated the network model parameters with an average loss in the test set of each task. The core principle of parameter optimization-based few-shot algorithms is to accelerate network learning by optimizing the parameters of the model or learning algorithm.

Data augmentation based few-shot learning algorithms use the original data to generate new data to expand the dataset. Wang et al. (2018) used image synthesizers to augment the original dataset; specifically, they input the image synthesizer into a network with a feature extraction network and a classifier for end-to-end training. The classification loss is then used to guide the training of the image synthesizer so that it outputs images can satisfy the classification requirements. Schwartz et al. (2018) used an autoencoder to identify deformations between different samples of the same category, used the deformations to generate new samples for other categories, and finally trained the classifier using an expanded dataset. Wang et al. (2020b) further investigated the data augmentation based few-shot algorithm using the instance confidence inference module, which is used to select samples and pseudo-labels with higher confidence and expand the support set. For comparison, samples with lower confidence were used to update the unlabeled dataset.

Most of the metric-based few-shot learning algorithms begin by extracting the sample features through a feature extraction network and metricize them through a metric module(Ouyang et al., 2021). Many excellent algorithms for small-shot learning have emerged in this direction, such as Siamese network (Koch et al., 2015), matching network (Vinyals et al., 2016), prototypical network (Snell et al., 2017), and relation network (Sung et al., 2017). In this study, we designed an IoT intrusion detection system using a few-shot algorithm based on metric learning.

2.3 Few-shot network intrusion detection

In the field of intrusion detection systems, most of the previous studies were based on parameter optimization and metric learning. We focus on investigating these two approaches in intrusion detection systems.

Xu et al. (2020) proposed the FC-Net, which applies the metric concept of a relation network. This method is divided into two parts: a feature extraction network and a comparison network. FC-Net learns a pair of feature maps for classification from a pair of network traffic samples and compares the feature maps to determine whether the pair belongs to the same class. The authors evaluated the method on the ISCX2012FS and CICIDS2017FS datasets, which were trained and tested on the same datasets. An average accuracy of 98.88% and an average detection rate of 99.62% were obtained for the untrained dataset. Sun et al. (2023) proposed an attention-based intrusion detection system for prototype capsule networks which was divided into two parts: a temporal spatial feature fusion method using capsules for feature extraction and a prototype network classification method with attention and voting mechanisms. The performance of the proposed method was evaluated using the CSECI-CIDS2018 dataset. Feng et al. (2021)proposed a class-adaptive anomaly-detection framework based on MAML, called FCAD. During the data preprocessing phase, FCAD extracts statistical features through a feature extractor and selector, and temporal sequence features through a long short-term memory-based autoencoder. It then fuses the obtained statistical and sequence features and constructs a meta-learning task. The experimental results showed that the accuracy of the method was 95.1% for the CICIDS2017 dataset. In 2023, Lu et al. (2023) were the first to apply MAML to few-shot IoT intrusion detection. They constructed a few-shot IoT dataset called FSIDSIoT based on a benchmark dataset and evaluated the proposed method. For testing against unknown attacks, the best accuracy achieved in the 5-way 10-shot setting was 92.19%. In the same year, Shi et al. (2023) applied the MAML algorithm to network intrusion detection. Unlike previous studies, Shi et al. (2023) introduced an L2F decay mechanism to solve the problem of conflicts between tasks caused by the forced sharing of initialization of MAML, which prevented the model from quickly converging to the optimal position. For the CICIDS2017 dataset, the accuracy reached 94.66% at K=10.

Most of these studies did not extend to the IoT domain; they only applied a few-shot learning algorithm to the IoT intrusion-detection domain (Lu et al., 2023). Similarly, our work considered the complexity of the IoT; we evaluated our model on the latest IoT dataset, CICIOT2023. The proposed model can maintain excellent performance in accurately identifying known and unknown attack categories under few-shot conditions.

3 Methodology

In the field of few-shot learning, few-shot learning mimics the human ability to learn quickly. For example, a child may only need to see a few examples to recognize what a dog is without needing to see hundreds or thousands of dogs of different breeds. This ability partly stems from our brain's efficient processing of pattern recognition and our foundational prior knowledge of the world. In artificial intelligence, we attempt to simulate this ability through algorithms. Few-shot learning algorithms are designed to handle situations where data are scarce; they need to be able to extract critical information from a small number of samples and generalize to new, unseen situations. Precisely for this reason, we draw on the capabilities of few-shot learning to detect unknown category attacks.

We consider the few-shot learning problem in two stages: feature extractor and classifier. Let $f_\theta : X \rightarrow \mathbb{R}^d$ be the mapping from the input space X to the D-dimensional representation implemented by a neural network, and let $X_c = \{x_{c,1}, ..., x_{c,K}\}$ be the class-specific set. We formulate the few-shot learning problem as creating a classifier. To this end, the last layer of the neural network is implemented along with the softmax layer:

$$p(c|q) = \frac{\exp(W_c^T f_\theta(q))}{\sum_{c'} \exp(W_c^T, f_\theta(q))} = \frac{\exp(d_c(q))}{\sum_{c'} \exp(d_{c'}(q))} \tag{1}$$

where W_c is the weight for class c,f_θ is the feature extractor, and $d_c(q)$ is the distance between the query sample q and class c. Thus, the problem of few-shot learning can be understood as providing a new task on how to generate W.

This section introduces a few-shot intrusion detection method based on a subspace (Simon et al., 2020). The proposed method was divided into three main phases: task construction, feature extraction, and network traffic classification. Fig.1 shows the general block diagram of the proposed method. During the task construction phase, the raw data are first normalized to conform to the input format of the neural network. Next, n tasks are drawn for model training, in which each task contains a support set and a query set. The samples in the support set are used to compute the subspaces of each category, and the samples in the query set are used to measure the distances to the subspaces of each category. During the feature extraction phase, a feature extraction network with an efficient channel atten-

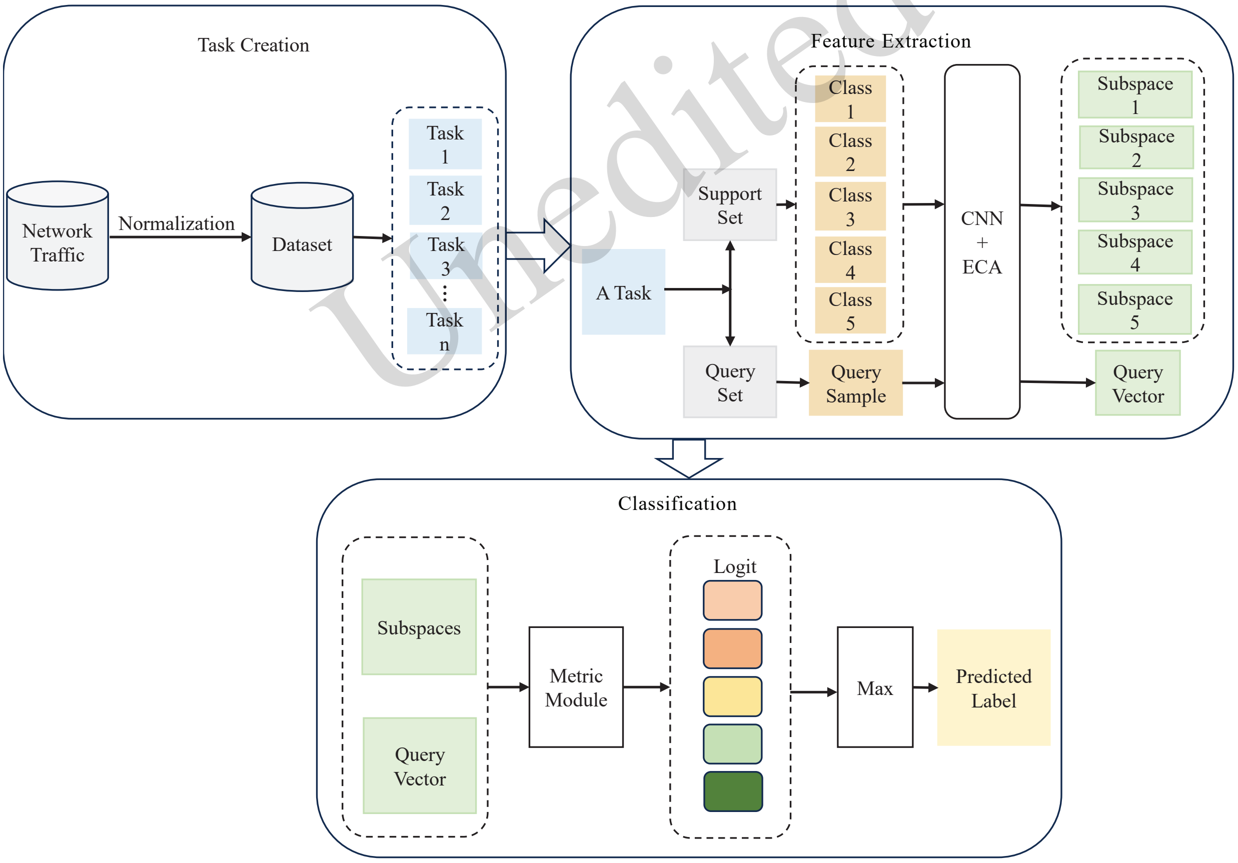


Fig. 1 Diagram of subspace-based few-shot IoT intrusion detection structure. The proposed method is divided into three main modules: task construction, feature extraction, and classification. During the task construction phase, the main focus is creating N-way K-shot formatted few-shot tasks to facilitate model learning. In the feature extraction module, we designed a four-layer structure with an ECA mechanism. Finally, in the classification module, classification is performed by measuring the distance between the query vector and the subspace of each category.IoT: Internet of Things; CNN: Convolutional neural network; ECA: Efficient Channel Attention.

tion (ECA) mechanism is designed to extract the features of each sample, focusing on unique sample features. Finally, during the network traffic classification phase, network traffic is categorized using the metric module.

It must be clarified that our traffic samples consist of feature sequences composed of 46 features, such as flow duration, header length, protocol type, and the number of FIN flag bits, among others. After data preprocessing, these feature sequences are fed into the neural network for feature extraction, followed by the construction of subspaces for each category and ultimately achieving the detection of different types of traffic.

3.1 Task construction

The CICIOT2023 dataset is available in two file formats: PCAP and CSV. The PCAP files store rich raw network traffic, which contains all sent packets, and can be used to extract and design other features. The CSV file offers a simpler method for loading and using data, which can be processed and obtained through certain Python libraries or software. In previous studies, researchers focused on investigating the original network traffic samples; this is because the original network traffic contains richer features. The model can thoroughly learn the differences between the traffic samples and quickly identify them more accurately. However, in this study, we chose to investigate the CSV dataset, which is a simple tabular data storage format in which rows represent samples and columns represent features of the samples. The sample features in the CICIOT2023 dataset include timestamps, a protocol type, a header length, and a packet transmission rate in the data stream.

To make the data suitable for training in a convolutional neural network, we perform preprocessing on the raw network traffic. The preprocessing in this paper is divided into feature extraction, normalization, and type conversion.

CICFlowMeter(Draper-Gil et al., 2016), a feature extraction tool, is often used to extract features from raw network traffic. Therefore, in this study, we also use CICFlowMeter to extract features from network traffic. First, the traffic stored in PCAP packets is input into CICFlowMeter, which extracts some statistical features at the transport layer. For intrusion detection, not all features benefit the model's training, and some key features can be extracted. We refer to the official CSV file provided by the CICIOT2023 dataset and ultimately extract 46 features for each network traffic sample. After feature extraction, we found that some samples in the CSV file would have feature values that are infinite or missing, which would result in inconsistent feature sequence lengths for each sample. Therefore, we chose to replace infinite values and missing spots with zeros to ensure each sample has a feature sequence of the same length. The above operations are illustrated in the following formulas:

$$csv = Sam(CFM(pcap)) \tag{2}$$

In the context, CFM stands for CICFlowMeter, and Sam represents the process of filtering the sample features from the CSV file.

Another crucial preprocessing step is data normalization. In our dataset, the numerical range of network traffic features varies greatly. For example, packet sizes can range from a few to several thousand bytes, while other features might only be 1 or 0. Without normalization, the model is likely to be biased toward learning features with larger values, neglecting those more minor but important features. Therefore, before converting to tensor types, we should normalize the data. The normalization process is shown in Eq.(3).

$$X_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3}$$

where x_{max} and x_{min} represent the maximum and minimum values in the dataset, respectively. After normalization, all feature values are scaled to the range between 0 and 1. This process helps to improve the model's convergence speed and performance.

After data preprocessing, we began by defining the terminology used in few-shot learning. Currently, most few-shot learning trains models in an episode learning paradigm, in which an episode, $\mathcal{T}_i$, consists of two sets: the support set and the query set mentioned above. This learning paradigm describes how the model can improve its capabilities with the fragmented data in each iteration. Specifically, deep embedding involves learning using limited labels and data. This learning paradigm is called N-way K-shot categorization, indicating that only N learnable categories exist for each task with K samples in each category. We return to the notation of (N-way K-shot) few-shot learning.

Each episode or task $\mathcal{T}_i$ consists of the support set S={$(x_{1,1},c_{1,1}),(x_{1,2},c_{1,2}),...,(x_{N,K},c_{N,K})$}and the query set $Q=\{q_1,...,q_{N\times M}\}$,where $x_{i,j}$ is the jth sample of the ith category and $c_{i,j}\in$\{1,...,N\} represents the label of the jth sample in the ith category. Algorithm 1 describes the steps involved in task construction.

3.2 Feature extraction

Because the dataset is in a CSV file format, where each row represents a sample and each column represents the sample features, a one-dimensional convolutional neural network (CNN) is used to map the features of the network traffic. Since a few features are used for each sample, with only 46 features, we need to focus on the more discriminative features. Therefore, we propose embedding an attention module into a one-dimensional CNN. The specific structure is shown in Fig.3.

We designed a four-layer one-dimensional CNN. After each convolutional block, we added an ECA module to ensure that unique features were attended to each time the computation was performed. Each block consisted of a one-dimensional convolutional layer with a kernel size of 3, batch normalization layer, ReLU layer, and max pooling layer. The first three blocks have the same design, and in the last block, a dropout layer was added to minimize the risk of overfitting.

An ECA mechanism is a local cross-channel interaction strategy without dimensionality reduction that reduces the complexity of the model while maintaining its performance (Wang et al., 2020). This strategy allows the adaptive selection of a one-dimensional convolutional kernel size to ensure the coverage of local cross-channel interactions.

The structure of the ECA mechanism is shown in Fig. 2. C, H, and W denote the number of channels, height, and width, respectively. GAP denotes global average pooling, and σ is the sigmoid activation function. The aggregated features are first obtained by global average pooling. Next, the cross-channel interaction is achieved via one-dimensional convolution, and finally, the weight assignment of the channel features is achieved using the sigmoid function. The adaptive kernel size for the one-dimensional convolution is expressed in Eq. (4):

$$k=\psi(C)=\left|\frac{\log_2(C)}{\gamma}+\frac{b}{\gamma}\right|_{odd} \tag{4}$$

where $|t|$ is the closest odd number to t,and γ and b are customized parameters, which were set to 2 and 1 respectively in this study.

Algorithm 1 Generating a Few-Shot Task

```
Input: Label set $\mathcal{L}=\{0,1,...,N\}$.Dataset
    $\mathcal{D}=\{(x_1,y_1),...,(x_n,y_n)\}$, where $x_i\in\mathbb{R}^d$,$y_i\in\mathcal{L}$
Output: Few-shot Task $\mathcal{T}=\{S_k,Q_k\}$
Initialize $\mathcal{T}\leftarrow\varnothing$
while not done do
    $V\leftarrow(\{0,1,...,N\},N_c)$
    for k in $\{1,...,N_c\}$ do
        $S_{ki}\leftarrow$ RandSample$(D_k,N_S)$
        $Q_{ki}\leftarrow$ RandSample$(D_k\backslash S_k,N_Q)$
    end for
    $\mathcal{T}_i\leftarrow\{S_{ki},Q_{ki}\}$
    $\mathcal{T}\leftarrow\mathcal{T}\cup\mathcal{T}_i$
end while
```

3.3 Network traffic classification

For intrusion detection systems, in general terms, this means designing a classifier to categorize network traffic to identify malicious traffic and apply timely countermeasures. Therefore, we designed a subspace-based few-shot intrusion detection system. Below, we describe how to create subspaces and classify based on them.

Given an input task (N-way K-shot), the feature embedding representations for the support set flow and the query set flow can be obtained through the following formula:

$$F_{c,i}^{sup}=f(x_{c,i};\theta) \tag{5}$$

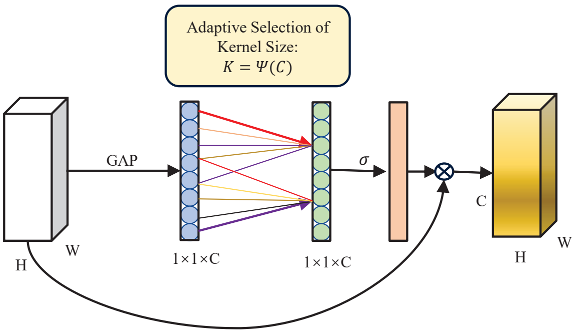


Fig. 2 ECA module. ECA: Efficient Channel Attention.

$$F_l^{que} = f(q_l;\theta) \tag{6}$$

where $f(.)$ represents the feature extraction network mentioned above, which is primarily composed of attention layers and convolutional layers, with network parameters denoted as $\theta.F_{c,i}^{sup}$ denotes the feature embedding of the ith support set traffic from class c, and F_l^{que} denotes the feature embedding of the lth query set traffic.

Afterward, by learning feature representations from the support set sample traffic of each category in the given task, the corresponding subspace can be calculated, thereby constructing a subspace classifier. For instance, when considering the construction of the subspace for the cth class, we will provide a detailed description of the construction process.

First, we calculate the prototype of class c according to Eq. (7); each class in the task corresponds to a prototype.

$$\mu_c = \frac{1}{K}\sum_{i=1}^{K} F_{c,i}^{sup} \tag{7}$$

where K represents the number of samples in class c of the support set. Based on the feature embeddings of class c samples and the prototype representation, we reconstruct the feature space as follows:

$$X_c = [F_{c,1}^{sup} - \mu_c, F_{c,2}^{sup} - \mu_c, ..., F_{c,K}^{sup} - \mu_c] \tag{8}$$

where $F_{c,i}^{sup}$ represents the feature embedding of the ith traffic flow from class c, and μ_c represents the prototype of class c.

Then, performing singular value decomposition(SVD) on X_c yields a matrix B_c with orthogonal basis properties (i.e., $B_c B_c^\top$). By truncating B_c, we can obtain the feature subspace P_c for class c. Subsequently, the feature subspaces for other classes in the given task are calculated in the same manner. Ultimately, we can classify the traffic based on the projection distance of the query sample to each class's subspace.

Just as with reconstructing the feature space of the support set samples, we also need to use the obtained prototype of class c(μ_c) to construct the feature space for each query sample (q_l),which is $F_l^{que} - \mu_c$.Therefore, the projection of $F_l^{que} - \mu_c$ onto the feature subspace of class c is $M_c(F_l^{que} - \mu_c)$, where $M_c = P_c P_c^\top$. Thus, according to the Pythagorean theorem, the vector perpendicular to the corresponding subspace can be expressed as $(F_l^{que} - \mu_c) - M_c(F_l^{que} - \mu_c) = (I - M_c)(F_l^{que} - \mu_c)$, where I denotes the identity matrix. Finally, the projection distance of the query sample q_l to the feature subspace of class c is:

$$d_c(q_l) = -||(I - M_c)(F_l^{que} - \mu_c)||^2 \tag{9}$$

We calculate the probability that a query sample is assigned to class c using the softmax function:

$$p_(c, q) = p(c|q) = \frac{\exp(d_c(q))}{\sum_{c'} \exp(d_{c'}(q))} \tag{10}$$

In which, c' represents the set of categories in a task. Finally, the query sample can be assigned to the category with the highest predicted probability.

3.4 Loss function

To make the generated subspaces more discriminative, that is, to increase the distance between subspaces of different categories, we use Grassmann geometry to calculate the distances between subspaces of each category, precisely representing the class differences among different subspaces. Given two subspaces P_i and P_j, the distance metric is defined as follows.

$$\sigma_p^2(P_i, P_j) = \|P_i P_i^\top - P_j P_j^\top\|_F^2 = 2n - 2\|P_i^\top P_j\|_F^2 \tag{11}$$

Eq.(11) shows that maximizing the distance between two subspaces is achieved by minimizing $\|P_i^\top P_j\|_F^2$. Therefore, we introduce it into the loss function, which can be minimized through a constant iteration of the model.

$$\mathcal{L}_t = -\frac{1}{NM}\sum_c \log(p_{c,q}) + \lambda \sum_{i \neq j} \|P_i^\top P_j\|_F^2 \tag{12}$$

where the first term is the cross-entropy classification loss function, the second term is the subspace loss function, and λ is the weight coefficient. Algorithm 2 describes the training process of the subspace classifier.

4 Experiments and analysis

4.1 Datasets

Datasets widely used in network intrusion detection are KDD99, NSLKDD, UNSWNB15, CICIDS2017, and CICIDS2018. In this study,

Algorithm 2 Training a Subspace Classifier

```
Input: Task $\mathcal{T}$
$\theta \leftarrow$ random initialization
for $t$ in $\{\mathcal{T}_1,...,\mathcal{T}_i\}$ do
    for $m$ in $\{1, ..., N\}$ do
        Calculate matrix $\widetilde{X}_m$
        Calculate the average of the class
        $[U, \sum, V^\top] \leftarrow SVD(X_m)$
        $P_m \leftarrow$ Truncate $U$
        for q in Q do
            Compute $d_c(q)$ using Eq.(9)
        end for
    end for
    Compute final loss $\mathcal{L}_t$ using Eq.(12)
    Update $\theta$ using $\nabla\mathcal{L}_t$
end for
```

we use CICIOT2023(Neto et al., 2023), CICIDS2017(Draper-Gil et al., 2016), and CICIDS2018 to evaluate our model.CICIOT2023 was collected by executing 33 attacks on an IoT topology consisting of 105 devices that mimic the real-world deployment of IoT products and services in a smart home environment. The dataset contained 33 attacks organized into seven categories: DDoS, DoS, Recon, Web-based attacks, Brute force, Spoofing, and Mirai. The CICIOT2023 dataset contained 169 CSV files and numerous network traffic samples. Regarding the research objectives of this study, validating the practicality of our proposed method on this dataset will have a positive impact, and the experimental results obtained will be convincing. At the same time, we conducted multiple experiments on the CICIDS2017 and CICIDS2018 datasets to verify the proposed method. Table 2 describes the dataset created for few-shot Internet of Things intrusion detection based on the CICIOT2023 dataset, which includes the types of attacks and the number of samples in each category. Information about the CICIDS2017 and CICIDS2018 datasets was placed in Section 1.1 of the Supplementary Materials.

It should be noted that there is a relationship between the number of samples in the training and testing sets and the K-shot setting. In this study, we train on a per-task basis, feeding the model with one task at a time. These tasks are sampled from the training or testing sets, each consisting of a support set and a query set. The support set follows the N-way K-shot paradigm, which means it contains N classes with K samples from each class, resulting in a total of $N \times K$ samples in the support set. In the field of few-shot learning, K is typically 1, 5, or 10. Next, we will provide a general overview of the attack methods for each type of malicious traffic in the CICIOT2023 dataset(see Section 1.1 in Supplementary Materials).

4.2 Experimental settings

The experiments were conducted on Windows 11 with an NVIDIA RTX4060 graphics card of 8 GB and an Intel(R) Core (TM) i7-12650H CPU. The experimental environments used were Python 3.11.5, CUDA 12.0, and PyTorch 2.1.1. Table 1 lists the hyperparameter settings of the algorithm used in this study.

Three sets of experiments were conducted to val-

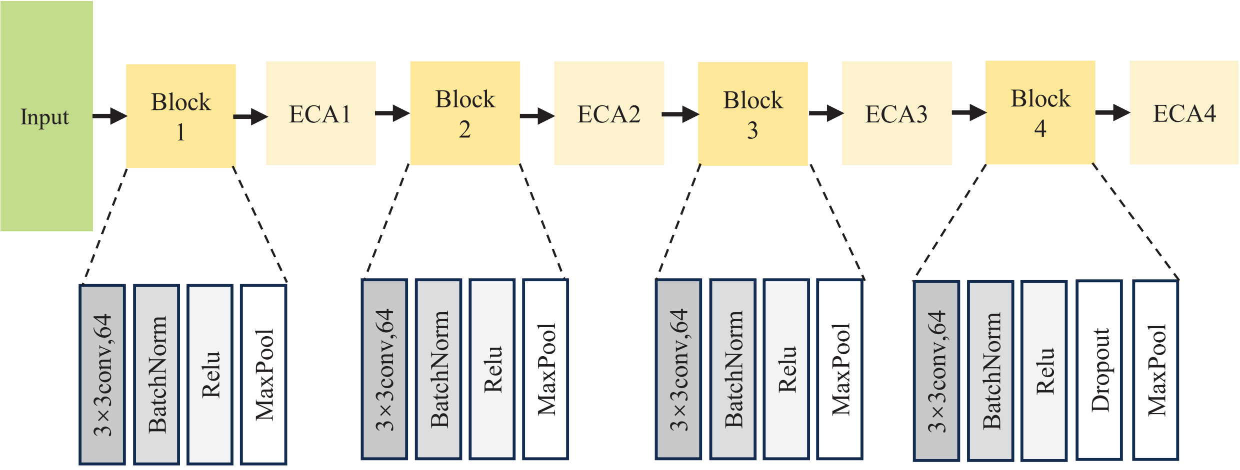


Fig. 3 CNN with ECA mechanism. CNN: Convolutional neural network; ECA: Efficient Channel Attention.

idate the proposed method.

1. The most basic function of an IoT intrusion system is to recognize malicious traffic from a large amount of traffic, a situation called binary classification. For the 2-way K-shot, K is the number of samples in each category. We conducted experiments with K = 5 and 10. We relabeled the training and test sets; normal samples were labeled as Benign, and malicious samples were labeled as Attack.

2. In addition to the binary classification experiment, we set up a multi-classification experiment, denoted the 5-way K-shot, which we conducted for K = 1, 5, and 10. In this experiment, we designed a model that recognizes malicious traffic and accurately predicts the true attack category.

3. Detection experiments were conducted using unknown traffic categories to simulate the emergence of new attacks in a real-world IoT environment. Specifically, seven types of attack traffic were used: six types were used as the training set data, and the remaining type was used as the test set data, setting up seven parallel experiments in total. These operations were performed in the 5-way 1-shot, 5-way 5-shot, and 5-way 10-shot settings.

4.3 Metrics

Similar to previous studies, for binary classification experiments, we evaluated our model with accuracy, precision, recall, and f1-score, whereas for multi-classification experiments, we evaluated accuracy (Acc) and precision (Pre).

Table 1 Hyperparameter settings

Hyperparameter	Value
Epoch	200
Learning rate	0.002
γ	0.5
λ	0.03
Batch size	100

Table 2 Information on the CICIOT2023 dataset

Categories	Training set	Test set
DDoS	360	240
DoS	120	80
Mirai	90	60
Spoofing	60	40
Recon	150	100
Web	180	120
Brute force	30	20

$$Accuracy(Acc) = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

$$Precision(Pre) = \frac{TP}{TP + FP} \tag{14}$$

$$Recall(Re) = \frac{TP}{TP + FN} \tag{15}$$

$$F1 - score = 2 \cdot \frac{Pre \cdot Re}{Pre + Re} \tag{16}$$

Here, TP: normal samples are categorized as normal samples, TN: malicious samples are categorized as malicious samples, FP: normal samples are categorized as malicious samples, and FN: malicious samples are categorized as normal samples.

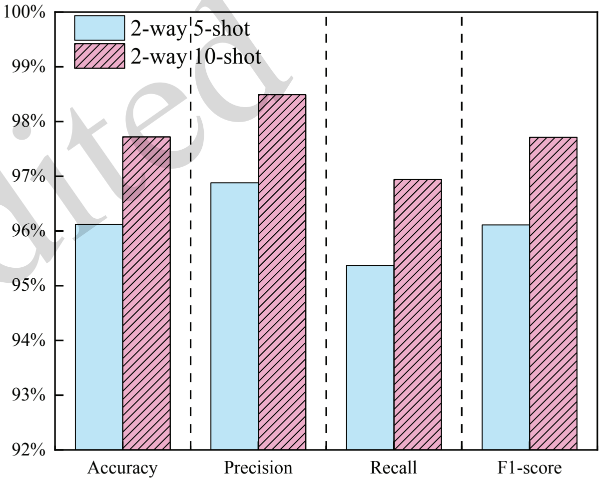


Fig. 4 Comparison of the influence of sample size on results in a binary classification setting.

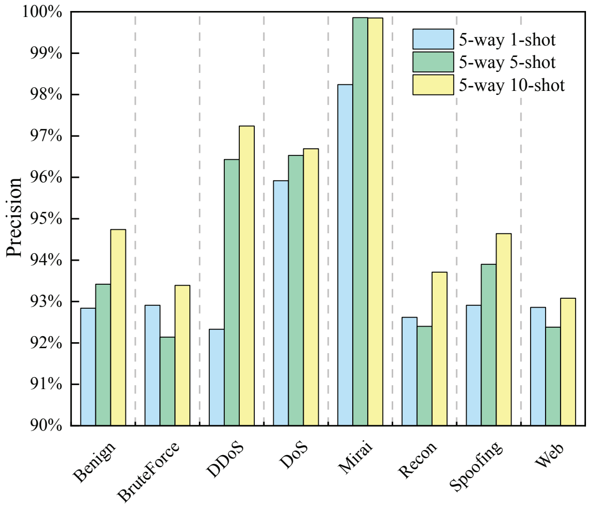
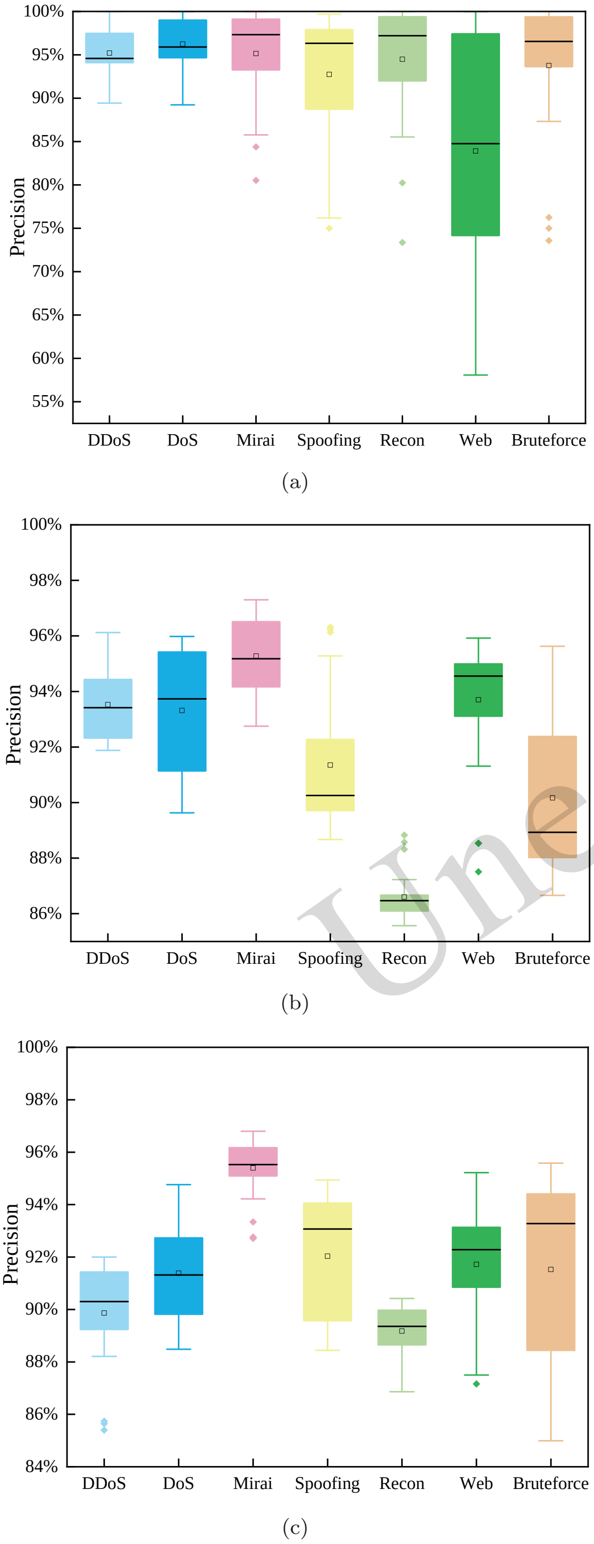


Fig. 5 Comparison of the influence of sample size on results in a multi-class classification setting.



(a)

(b)

(c)

Fig. 6 Distribution of detection precision in different settings. (a) 5-way 1-shot,(b) 5-way 5-shot,and (c) 5-way 10-shot.

4.4 Experiment results

The results of Experiment 1 are presented in Fig. 4. The performance was better with K=10 than with K=5. For K=5, the accuracy, precision, recall, and f1 score were 96.12%, 96.88%, 95.37%, and 96.11% respectively. At K=10, the respective metrics were 97.72%, 98.49%, 96.94%, and 97.71%.

In Experiment 2, we evaluated the model in terms of accuracy and precision of detection for each category. Eight categories were selected for this set of experiments, from which five categories were randomly selected for each task, with an average detection precision of 93.83% in the 5-way 1-shot setting. The average detection precision in the 5-shot setting was 94.63% , and that in the 10-shot setting was 95.34% . The detection precision of this group of experimental results is shown in Fig. 5. As the sample size increases, the detection precision of each traffic category increases, and regardless of the setting, the detection precision of Mirai is the highest.

The confusion matrix can be found in Section 1.2.1 of the Supplementary Materials.

In Experiment 3, we used the precision and accuracy rates as the evaluation indices. The detection of unknown categories under the 5-way 1-shot setting is shown in Fig. 6a. The highest detection precision rate for each category was 100%, but the overall fluctuation was significant, among which the detection fluctuated the most for Web attacks, and less for the other attack types, with an overall detection precision rate of 93.07%. The detection of unknown categories in a 5-way 5-shot setting is shown in Fig. 6b. The fluctuation was more minor than that of a 5-way 1-shot, and the data were more concentrated. The detection of the Recon attack was the worst with 86.6% precision, whereas the detection of the Mirai attack was the best with 95.27% precision. The overall detection precision was 91.99%. The detection of unknown categories in the 5-way 10-shot setting is shown in Fig. 6c.

Overall, compared with the previous two settings, the detection effect was the most balanced for each category. The detection precision rate exceeded 90%, and the detection effect was the worst for the Recon attack, with a precision rate of 89.17%. The detection effect was the best for the Mirai attack, with a precision rate of 95.4%. The worst detection effect was for the Recon attack, with a precision rate of 89.17%, whereas the best detection effect was for the Mirai attack, with a precision rate of 95.4%. The overall detection precision was 91.59%.

From Experiment 3, we learned that as the number of samples increased, the fluctuation of the model in detection precision decreased; however, the detection precision for a certain category did not increase as the number of samples increased. Fig. 7 shows a comparison between the accuracy distributions for different settings. The fluctuations in the accuracy rate were largest in the 5-way 1-shot setting and decreased as the number of samples increased. The fluctuations in the accuracy rate were smallest in the 5-way 10-shot setting. From the perspective of the mean, the magnitude of the accuracy did not change significantly as the number of samples increased.

The experimental results on the CICIDS2017 and CICIDS2018 datasets can be found in Section 1.2.2 of the Supplementary Materials.

5 Discussion

The intrusion detection system for the proposed IoT, which is based on the subspace approach and designed for few-shot scenarios, demonstrates effective performance in detecting known and unknown types of attack within the IoT environment, even under conditions of limited sample availability.

5.1 Comparison

In Table 3, we compared the experimental results of classic machine learning algorithms, deep learning algorithms, and prototype network algorithms in the multi-class setting. The effect of using CNN on network traffic detection and the results of using the prototype network algorithm under few-shot conditions are not significantly different; both are <70%. Among them, the detection effect using the KNN algorithm is slightly higher than that of other algorithms except for the one presented in this paper, at 81.28%. However, compared to the algorithm in this paper, there is a noticeable improvement in detection accuracy.

In Tables 4 and 5, we list and compare the results of other researchers from four aspects: dataset, classification setting, number of samples, and accuracy. Among them, the research work of Lu et al. is more similar to ours (Lu et al., 2023). CSV table datasets were used in both studies. The difference is that they converted the table data into RGB color images and used a two-dimensional convolution to extract features. By contrast, we directly used raw data and extracted features through

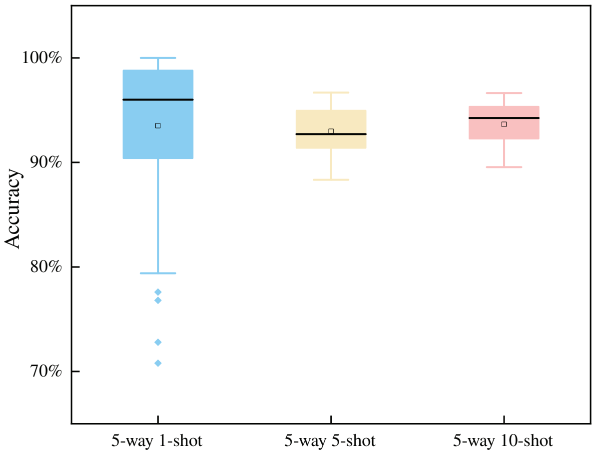


Fig. 7 Accuracy distribution in different settings.

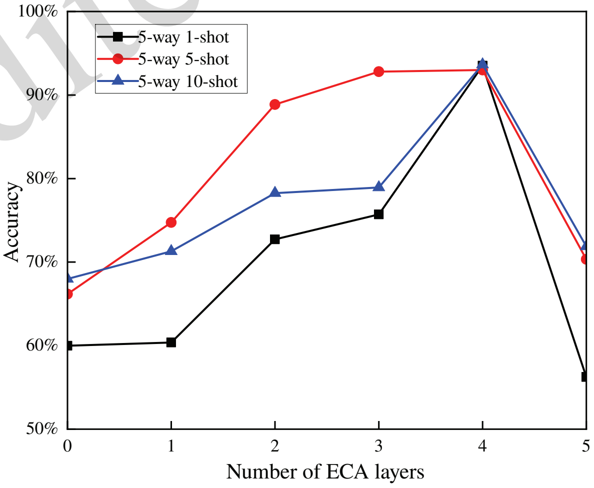


Fig. 8 Effect of number of ECA layers on model performance. ECA: Efficient Channel Attention.

Table 3 Comparison of results with those of classical methods

Method	Experimental setting	Accuracy (%)
KNN	N/A	81.28
SVM	N/A	46.86
DNN	N/A	61.90
CNN	N/A	66.86
Prototypical network	5-way 1-shot	54.98
Prototypical network	5-way 5-shot	68.74
Prototypical network	5-way 10-shot	69.74
Proposed approach	5-way 1-shot	93.52
Proposed approach	5-way 5-shot	92.99
Proposed approach	5-way 10-shot	93.65

a one-dimensional convolution. We conducted our experiments with the same classification settings and the detection results were better than theirs. Many other studies focused on the study of raw traffic stored in pcap files; for example, Xu et al. converted raw traffic to RGB color images and extracted the features using three-dimensional convolution (Xu et al., 2020), and Sun et al. converted raw traffic to grayscale images and extracted the features using two-dimensional convolution (Sun et al., 2023; Du et al., 2024). Most of the previous studies focused on converting network traffic into images, and the methods used were similar. However, Yan et al. used a short-time Fourier transform to convert one-dimensional network traffic into images (Yan et al., 2023). We used the CICIOT2023 dataset as the research object, which contains more decadent attack samples than previous datasets and is more reflective of the natural IoT environment.

We also discuss the effect of different numbers of ECA layers on the performance of the model.As shown in Fig. 8, we can see that the accuracy of the model does not improve with more layers superimposed. Regardless of the classification setting, the detection accuracy is highest when the number of added ECA layers is 4. Thus, we can conclude that the detection accuracy of the model approaches a threshold with an increase in the number of ECA layers and does not always increase.

6 Conclusions

In this study, we developed a subspace-based classification model to solve the few-shot IoT intrusion detection problem. First, we constructed an intrusion detection dataset suitable for few-shot scenarios based on the latest IoT dataset, CICIOT2023. Next, the data samples for one-dimensional CNN learning were formed by normalizing the tabular data and transforming the data types. Subsequently, according to the N-way K-shot learning paradigm, a set of tasks used for model training was constructed. Each task was used to extract the features of each sample through a CNN with the ECA mechanism, and the classification effect was realized through a subspace-based classifier. For unknown classes of attacks, our model does not need to be fine-tuned and relies on prior knowledge of the model to quickly generalize to unknown classes. Our model showed good detection results for all models at sample numbers K = 1, 5, and 10. However, the performance and robustness of our model should be improved when only one sample is available.

Contributors

Zhihui LI designed the research. Kun DENG and Chunyuan LIU processed the data. Zhihui LI and Congyuan XU complated the experiments. Zhihui LI drafted the manuscript. Congyuan XU, Kun DENG, and Chunyuan LIU helped organize the paper. Zhihui LI, Congyuan XU, Kun DENG, and Chunyuan LIU revised and finalized the paper.

Compliance with ethics guidelines

ALL authors declare that they have no conflict of interest.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Table 4 Comparison of detection results and sample sizes under binary classification settings for the methods presented in this paper and related research work.

Method	Dataset	IOT dataset	Classification setting	Number of samples	Accuracy (%)
FC-Net(Xu et al., 2020)	CICIDS2017	N	2-way 5-shot	5	94.33
FC-Net	CICIDS2017	N	2-way 10-shot	10	94.64
FCAD(Feng et al., 2021)	CICAndMal2017	N	N/A	5	94.30
FCAD	CICAndMal2017	N	N/A	10	97.10
Proto+Reptile (Xu and Wang, 2022)	CICIDS2017+NDSec-1	N	2-way 5-shot	5	97.56
Proto+Reptile	CICIDS2017+NDSec-1	N	2-way 10-shot	10	97.43
L2F+MAML(Shi et al., 2023)	CICIDS2017	N	2-way 10-shot	10	94.66
L2F+MAML	CICIDS2018	N	2-way 5-shot	5	96.00
L2F+MAML	CICIDS2018	N	2-way 10-shot	10	97.29
Proposed approach	CICIDS2017	N	2-way 5-shot	5	99.16
Proposed approach	CICIDS2017	N	2-way 10-shot	10	99.26
Proposed approach	CICIDS2018	N	2-way 5-shot	5	99.06
Proposed approach	CICIDS2018	N	2-way 10-shot	10	98.57
Proposed approach	CICIOT2023	Y	2-way 5-shot	5	96.12
Proposed approach	CICIOT2023	Y	2-way 10-shot	10	97.72

Table 5 Comparison of detection results and sample sizes under multi-class classification settings for the methods presented in this paper and related research work.

Method	Dataset	IOT dataset	Classification setting	Number of samples	Accuracy (%)
MAML+CNN(Lu et al., 2023)	FSIDSIOT	Y	5-way 1-shot	1	73.81
MAML+CNN	FSIDSIOT	Y	5-way 5-shot	5	89.64
MAML+CNN	FSIDSIOT	Y	5-way 10-shot	10	92.19
IPN-IDS(Wang et al., 2024)	CICIDS2017	N	5-way 1-shot	1	75.45
IPN-IDS	CICIDS2017	N	5-way 5-shot	5	84.94
IPN-IDS	CICIDS2017	N	5-way 10-shot	10	86.35
IPN-IDS	CICIOT2023	Y	5-way 1-shot	1	61.03
IPN-IDS	CICIOT2023	Y	5-way 5-shot	5	66.93
IPN-IDS	CICIOT2023	Y	5-way 10-shot	10	68.77
Proposed approach	CICIDS2017	N	5-way 1-shot	1	83.88
Proposed approach	CICIDS2017	N	5-way 5-shot	5	92.66
Proposed approach	CICIDS2017	N	5-way 10-shot	10	95.58
Proposed approach	CICIDS2018	N	5-way 1-shot	1	91.00
Proposed approach	CICIDS2018	N	5-way 5-shot	5	94.16
Proposed approach	CICIDS2018	N	5-way 10-shot	10	94.70
Proposed approach	CICIOT2023	Y	5-way 1-shot	1	93.52
Proposed approach	CICIOT2023	Y	5-way 5-shot	5	92.99
Proposed approach	CICIOT2023	Y	5-way 10-shot	10	93.65

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