Deep Learning Approaches for Open Set Wireless Transmitter Authorization

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Abstract—Wireless signals contain transmitter specific features, which can be used to verify the identity of transmitters and assist in implementing an authentication and authorization system. Most recently, there has been wide interest in using deep learning for transmitter identification. However, the existing deep learning work has posed the problem as closed set classification, where a neural network classifies among a finite set of known transmitters. No matter how large this set is, it will not include all transmitters that exist. Malicious transmitters outside this closed set, once within communications range, can jeopardize the system security. In this paper, we propose a deep learning approach for transmitter authorization based on open set recognition. Our proposed approach identifies a set of authorized transmitters, while rejecting any other unseen transmitters by recognizing their signals as outliers. We propose three approaches for this problem and show their ability to reject signals from unauthorized transmitters on a dataset of WiFi captures. We consider the structure of training data needed, and we show that the accuracy improves by having signals from known unauthorized transmitters in the training set.

Index Terms—Transmitter Identification, Deep Learning, Open set recognition, authorization, physical layer authentication

I. INTRODUCTION

With the growth in the number of wirelessly connected devices, securing them has become more challenging. Part of securing wireless devices is authentication; the process of verifying their identity. While there exist many cryptography based methods for authentication, they are not suitable for many internet-of-things devices that have limited computation and power budget. Physical layer authentication (PLA) enables devices to be authenticated without having to decode the data and typically without requiring additional signaling overhead. PLA can be classified as active or passive [1]. Active PLA typically overlays a tag over the message used for authentication thus requiring changes to the physical layer of the transmitters. Passive PLA on the other hand uses the channel state information and the RF fingerprint due to hardware imperfections to identify transmitters [2], requiring no change to transmitter signals, and hence is easier to apply. In this work, we focus on passive PLA.

Approaches for passive PLA either use a set of manually extracted features or deep learning on raw IQ samples. For feature-based PLA, existing works have considered using transmitter fingerprints due to hardware imperfections [3] or channel state information (CSI) [4]. Learning approaches based on extracted features rejecting new transmitters have used Gaussian mixture models [4]–[7].

In contrast, deep learning approaches are able to extract better features from the signal, hence leading to higher accuracy compared to feature-based approaches [8] and have recently gained widespread interest [8]–[16]. The existing work in the literature has considered the effect of data representation, neural network architecture, and the wireless channel on the classification accuracy. Examples of data representations include raw IQ samples [8]–[10], [14]. Fourier transform [11], [15], and wavelet [11], [16]. The effect of the channel—whether LOS or NLOS—and the robustness of the learned features has also been considered [9]. Network architectures evaluated include DNN [16], CNN [8], [15], [16], RNN [13], and complex neural networks [12]. The main limitation of this body of work is that it focuses on classification among a closed set of known transmitters. No matter how large is the number of transmitters used in training, it can not include all transmitters in the world, which can jeopardize the security of the network. To address this problem, an authorization method having the accuracy of neural networks with the ability to reject signals from unseen transmitters is needed.

In this paper, we formulate the transmitter authorization problem as an open set learning task, where our deep neural network rejects signals from transmitters unseen during training and classifies among the set of allowed transmitters. This approach is more suitable for authorization, where we want to reject signals from any transmitter outside of an authorized set. To achieve this, we pose the problem as an open set recognition [17]—the problem of classifying samples from known classes and rejecting ones from unknown classes. To the best of our knowledge, we demonstrate for the first time in the literature that it is possible to successfully apply deep learning for open set transmitter recognition.

This problem is more challenging than closed set classification. A closed set classifier determines boundaries that separate the classes it has seen, as shown with the solid blue line in Fig. 1. But, given data from new classes (new unauthorized transmitters), the classifier will predict the nearest class, which poses a security risk for an authentication system. On the other hand, open set classification creates boundaries around the seen distribution, as illustrated with the red dashed circles in
Fig. 1: Known classes are depicted as circles and unknown classes as squares. Solid lines and dashed circles represent classification boundaries and open set recognition, respectively.

Fig. 2: Signal $y$ is received by receiver $R$. We want to determine if it was sent by an authorized transmitter in the set $\mathcal{A}$ or a new unseen transmitter.

Fig. 3: Architecture of the proposed methods.

transmitter $T$ belongs to the authorized set or not, based on $y$. This can be formulated as the following hypothesis testing:

$$H_0 : y = f_T(x), T \in \mathcal{A}$$
$$H_1 : y = f_T(x), T \notin \mathcal{A}$$

Here, $H_0$ corresponds to an authorized transmitter and $H_1$ corresponds to an outlier.

Additionally, in cases where each authorized transmitter has different privileges, we might be interested in classifying the transmitter within the authorized set, which can be formulated as finding $\mathcal{A}$, defined as

$$\hat{\mathcal{A}} = \arg\max_T P(y = f_T(x)), T \in \mathcal{A}$$

To improve the outlier detection, we consider an additional class of known outliers $\mathcal{K} = \{K_1, K_2, \ldots, K_{|\mathcal{K}|}\}$, where $\mathcal{K} \nsubseteq \mathcal{A}$. Samples from transmitters in $\mathcal{K}$ will be used during training to assist the outlier detector to differentiate between authorized and non-authorized transmitters. But still, the evaluation of any outlier detector is done using a set of unknown outliers $\mathcal{O}$ such that $\mathcal{O} \cap \mathcal{K} = \emptyset$. In practice, samples from the set $\mathcal{K}$ can be obtained by capturing data from a finite number of non-authorized transmitters.

III. MACHINE LEARNING APPROACH

In this section, we discuss the neural network architectures used to solve this problem and the processing performed on the output of these networks to decide if a signal is an outlier.

A. Outlier Detection Architecture

We consider several neural network architectures for outlier detection. These networks consist of a feature extractor followed by one or many classifiers. In terms of training, some of these networks need known outliers to generalize to unseen transmitters, while others don’t. We also discuss how the size of $\mathcal{A}$ affects the number of parameters of these networks.

1) Discriminator (Disc): One intuitive approach for outlier detection is to train a discriminator that outputs a decision on whether the signal is an outlier or not. The discriminator has as single scalar output $z$ as shown in Fig. 3a. $z$ is generated by a sigmoid and takes a value between 0 and 1. The labels for authorized transmitters and outliers are $l = 0$ and $l = 1$, respectively. Note that this method requires using known outliers to train the network with samples having label zero. This discriminator has the advantage of having a fixed size regardless of $|\mathcal{A}|$. Although this approach does not classify
the authorized transmitters, a classifier can be cascaded with a discriminator to achieve this, but is not discussed in this work.

2) **Discriminating Classifier (DClass):** Instead of cascading a discriminator and a classifier, we can directly train a network with $|A| + 1$ outputs, where the additional class corresponds to outliers. This classifier is expected to perform better than a discriminator, since the labels of transmitters should help it extract better features. To train this network, we need known outliers. As for scalability with respect to $|A|$, only the number of parameters of the last layer of this network increases with $|A|$.

3) **One Vs All (OvA):** A simple way to generalize Disc to perform classification is to use $|A|$ discriminator networks, with each discriminator $i$ classifying whether the input belongs to class $i$ or not. The problem of this approach is the high computational complexity as it needs $|A|$ feature extractors with each of them learning similar features. A better way to scale the discriminator, proposed in [18], is shown in Fig. 3c. In this approach, all $|A|$ binary classifiers share the same feature extractor. The output of this network will be a vector $z$ of $|A|$ real numbers such that $0 \leq z \leq 1$, where 0 and 1 are the vectors of all-zeros and all-ones, respectively. Following the notation in [18], the labels for a sample from authorized transmitter $A_i$ will have $l_i = 1$ and $l_j = 0 \forall j \neq i$. A known outlier will have all labels equal to zero. Note that OvA — unlike DClass and Disc — does not require a known set of outliers, since for samples of any class $i$, $l_i = 0$ for signals from other classes. OvA requires a binary classifier for each authorized transmitter—hence, among the proposed architectures, it has the worse scalability with respect to $|A|$, in terms of the number of learnable parameters.

### B. Decision Method

When implemented, these three architectures would consist of a feature extractor followed by one or many classifiers. The output of the network can be processed using some threshold defining the sensitivity to outliers. A tight threshold will lead to signals from authorized transmitters being mistakenly rejected (high probability of false alarm $P_{FA}$) and a loose threshold will fail to recognize many outlier signals (low probability of detection $P_D$). This trade-off is commonly visualized by the receiver operating characteristic (ROC) showing both $P_{FA}$ and $P_D$ for a specific receiver. For each architecture, we describe how this trade-off is implemented. We also state how a specific threshold is chosen to calculate the outlier detection accuracy.

1) **Disc:** In Disc, we declare $H_1$ if $z > \gamma$ for some threshold $\gamma$, else $H_0$ is declared. Ideally, we want the threshold to be as low as possible without falsely rejecting authorized transmitters. This can be done by adapting the threshold to tightly fit the predictions of authorized signals in the training set. We follow the approach proposed in [18], where the predicted output of the sigmoid for the authorized (having labels equal to 0) is mirrored around 0 and fit to a Gaussian distribution having mean 0. Then, we calculate the standard deviation $\sigma$ of these samples and set the decision threshold to $\gamma = \min(0.5, 3\sigma)$. As for obtaining the ROC curve, we scan the value of $\gamma$ from 0 to 1.

2) **Discriminating Classifier (DClass):** A signal is classified as an outlier if the maximum activation corresponds to the last class, else it is considered authorized. For this architecture, it is not straightforward to design a threshold, so no ROC curves were calculated.

3) **One Vs All (OvA):** For this architecture, the threshold will be a vector $\gamma$, where element $\gamma_i$ is the threshold for $z_i$. The binary classifier $i$ decides that the input sample belongs to class $i$ if $z_i > \gamma_i$; otherwise, it does not belong to class $i$. We declare the signal to be an outlier (corresponding to $H_1$), if all discriminators declare the signal to be not within their class ($z \leq \gamma$), and to be within the authorized set (corresponding to $H_0$) otherwise. To obtain the ROC curve, we scan a single threshold $\gamma \in [0,1]$ such that $\gamma = \gamma_1$. To calculate the accuracy, we use multiple thresholds designed according to the same method of Gaussian fitting used in Disc.

### IV. EXPERIMENTAL EVALUATION

We start by describing the dataset used and evaluate the performance of the proposed network architectures on the dataset as we change the size and composition of $A$ and $K$.

#### A. Dataset

The dataset was captured using off-the-shelf WiFi modules (Atheros 5212, 9220, and 9280) as transmitters and a software defined radio (USRP N210) as a receiver, from the Orbit testbed [19]. The choice of the Orbit testbed is made due to the ease of access to many transmitters using realistic hardware while being able to isolate external environmental disturbances. The nodes in Orbit are organized in a $20 \times 20$ grid with a separation of one meter; the receiver was chosen near the center and 71 transmitters were randomly chosen, to make many nodes experience similar channels due to the symmetry.

The capture was done over Channel 11 which has a center frequency of 2462 MHz and a bandwidth of 20 MHz. All transmitters were configured to have the same fake MAC address and same IP address to avoid providing any signal based clues about the identity of the transmitter. Captures were taken at a rate of 25 Msps for one second. After the IQ capture was complete, the packets were extracted using energy detection. The number of packets obtained from each transmitter during the capture period varied between 200 and 1500 packets with a mean of 800 packets. This variability is due to WiFi rate control. From each packet, we used the first 256 samples—containing the preamble—without any synchronization or further preprocessing.

#### B. Network Architectures and Training

We consider the three previously proposed architectures Disc, DClass, and OvA. As stated earlier, these architectures consist of a feature extractor that processes the raw IQ samples and outputs features, followed by a number of classifier blocks. Our focus in this paper is on the approach, not the architecture.
Fig. 4: Detailed architecture of the feature extractor (made of residual blocks with f filters), and a classifier with x outputs.

We used the same architecture for the feature extractor for all networks. It was built using a series of residual blocks with different numbers of filters as shown in Fig. 4. As for the classifier blocks, similar architecture for each block was used as shown in Fig. 4. This network was chosen because similar networks have shown superior performance to CNNs on a similar problem [20]. For Disc, we used one classifier with a sigmoid activation. For OvA, we used N of the classifier blocks with each block similar to that of Disc. As for DClass, we used one classifier block with |A| + 1 outputs and softmax activation. L2 regularization was used in the dense layers with weight of 0.001 to avoid overfitting.

Note that for OvA and DClass the number of parameters of the neural network increases as the size of |A| increases. In OvA, for each new authorized transmitter, a new instance of the classifier is added to the architecture with about 80K parameters. For DClass, the size of the last layer increases by 81 parameters for each authorized transmitter. As for Disc, the number of parameters is constant for any |A|.

The training was done for 10 epochs using the ADAM optimizer with a learning rate of 0.001. The weights with the lowest validation loss are kept. Data was first normalized, then augmented by adding noise with a variance of 0.01 and applying a uniformly random phase shift. Cross-Entropy was used as the loss function with classes weighted depending on the number of samples for each class.

C. Transmitter Set Sizes Evaluation

Ideally, we want to train our network using the set of authorized nodes only, regardless of their number. Creating a known outlier set K would require more transmitters and more data collection. In this section, we explore the effect of changing the size of the authorized set |A|, and the size of the known outlier set |K|, on the ability of the network to distinguish authorized signals from outliers. We start by describing the dataset and network architectures.

1) Evaluation Metrics and Dataset Division: Since certain subsets of the set of transmitters in our dataset might have more mutually similar signals than others, we try to make our results less specific to a chosen subset of transmitters. To this end, we randomly populate the sets A, K, and O from the 71 transmitters 10 times in each test we conduct.

Results are shown as mean and standard deviation of these 10 realizations. The metrics used for the evaluation of outlier detection are the accuracy and area under the ROC curve (AUC). The accuracy is the percentage of correct predictions calculated over a balanced test set, such that any random or trivial guess would yield 50% accuracy. The area under the ROC curve provides a metric of which model is better on average [21], while the accuracy is what we get for a specific threshold. Although DClass and OvA are capable of classifying signals within the authorized sets, the results of classification were above 99% on the authorized part of the test set, and as classification has been extensively studied in the literature, we omit these results for brevity.

Our training, validation, and test sets are built as follows: for certain values of |A|, |K|, and |O|, we randomly choose transmitters to form our sets A, K, and O. For training and validation, we use 70% of the samples belonging to A, and all the samples belonging K. The shuffled combination of this data is split into 80% for training and 20% for validation. The test set contains all samples from O and the remaining 30% of A. For different realizations of the sets, the dataset can get highly imbalanced. To avoid degenerate solutions, where the network always predicts the class with the majority of samples, the training loss is weighted.

2) Authorized set: We start the evaluation with our ideal case, which is having no known outliers for OvA, i.e., |K| = 0. We want to know how large the set A has to be for good outlier detection and what performance can be achieved. Results are shown in Fig. 5 for |O| = 30; we see that as we increase the number of authorized nodes, the AUC increases and its standard deviation decreases. The reason behind this is that each binary classifier has more signals from other transmitters and hence is able to learn better what constitutes its designated transmitter. The accuracy is shown in Fig. 5b from which we can see that accuracy follows the same trend, except at the point with 25 and 40 authorized transmitters. At these points, the chosen threshold for one realization resulted in a low accuracy, decreasing the mean and increasing the standard deviation. This shows that for specific combinations of authorized and outlier nodes, and a given threshold, we might get lower performance. Since the value of the AUC is high, this shows that another threshold would give a better performance. From these results, we can see that the average accuracy does not go over 90%, while it fluctuates depending...
Fig. 6: Average performance of architectures as we change $|K|$ for $|A| = 10$. Error bars represent the standard deviation.

on the choice of transmitters for the same method of selecting thresholds.

3) Known set: We expect that seeing more known outliers would help the network differentiate the authorized transmitters from the outliers. To show that, we evaluate the performance of all architectures as a function of $|K|$ given $|A| = 10$ and $|O| = 26$. The AUC and accuracy curves are shown in Fig. 6a and 6b respectively. As stated earlier, at $|K| = 0$, DClass and Disc don’t have any outlier samples and predict everything as authorized. From Fig. 6a we see that the performance of both OvA and Disc improves as we increase the number of known outliers. We note that OvA is performing better. This is explained by recognizing that in OvA each binary classifier sees more samples to reject—the known outliers and the samples not belonging to its class. Thus, it is able to isolate its class better. DClass and Disc, on the other hand, only learn to reject samples from $K$. Fig 6b follows the same trend with OvA reaching accuracies up to 96% on average. DClass slightly outperforms Disc because the labels of $A$ help it extract better features compared to Disc. So even if we are not interested in classifying among the nodes in $A$, including these labels in training improves the outlier detection performance. In the case with $|K| = 0$, we were not able to attain accuracies above 90% on average, showing that going through the effort of creating $K$ is worth it.

V. Conclusion

In this paper, we formulated transmitter authorization as an open set classification problem where we learn to reject signals from new transmitters not seen during training. We proposed three approaches to solve it. OvA does not require known outliers and gives better performance, at the cost of a large increase in the neural network size with the size of the authorized set. DClass and Disc need a large set of known outliers for training to get good performance, with Disc having a slightly lower performance despite maintaining a constant network size regardless of the number of authorized nodes. In all cases, we have shown that having a set of known outliers improves performance. So far, we have only considered a residual neural network. Further work needs to be carried out to understand the effect of changing the neural network type and architecture for open set recognition.

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