Backdoor Attacks against Transfer Learning with Pre-trained Deep Learning Models

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Abstract—Transfer learning, that transfer the learned knowledge of pre-trained Teacher models over large datasets via fine-tuning, provides an effective solution for feasibly and fast customize accurate Student models. Many pre-trained Teacher models are publicly available and maintained by public platforms, increasing their vulnerability to backdoor attacks. In this paper, we demonstrate a backdoor threat to transfer learning tasks on both image and time-series data leveraging the knowledge of publicly accessible Teacher models, aimed at defeating three commonly-adopted defenses: pruning-based, retraining-based and input pre-processing-based defenses. Specifically, (A) ranking-based selection mechanism to speed up the backdoor trigger generation and perturbation process while defeating pruning-based and/or retraining-based defenses, (B) autoencoder-powered trigger generation is proposed to produce a robust trigger that can defeat the input pre-processing-based defense, while guaranteeing that selected neuron(s) can be significantly activated. (C) defense-aware retraining to generate the manipulated model using reverse-engineered model inputs. We use the real-world image and bioelectric signal analytics applications to demonstrate the power of our attack and conduct a comprehensive empirical analysis of the possible factors that affect the attack. The efficiency/effectiveness and feasibility/easiness of such attacks are validated by empirically evaluating the state-of-the-art image, Electroencephalography (EEG) and Electrocardiography (ECG) learning systems.

Index Terms—Web service, Deep neural network, Backdoor attack, Transfer Learning, Re-trained model

1 INTRODUCTION

Deep neural networks (DNNs) have demonstrated impressive performance in many domains, e.g., face recognition, voice recognition, self-driving vehicles, robotics, machine-based natural language communication, and games. One particularly exciting application area of deep learning has been in clinical applications. On April 11, 2018, an important step was taken towards this future: the U.S. Food and Drug Administration (FDA) stated the approval of the first computer vision algorithm that can be utilized for medical diagnosis without the input of a human clinician [1]. These DNNs can only be built accurately (often with millions of parameters) over massive datasets that are at a scale impossible for humans to process as well as large computational resources.

Transfer learning is proposed as an efficient method that addresses these fundamental data and resource challenges. Generally, a handful of well-tuned and intricate centralized models (Teacher) pretrained with large datasets are shared on public platforms, and individual users further customize accurate models (Student) for specific tasks using the pre-trained teacher model as a launching point via only limited training on the smaller domain-specific datasets [2]. However, most pre-trained networks are hosted and maintained on popular third-party platforms, such as GitHub, where proper vetting to ensure that these pre-trained models have not been maliciously modified by adversaries, is often lacking. Thus, pre-trained teacher models gradually become the more attractive and vulnerable target for attackers to manipulate, so that student models that use such maliciously manipulated teacher models can incur immense threats (e.g., incorrect prediction results), including endangering human lives.

In this paper, we investigate the feasibility and practicality of backdoor attacks against transfer learning on both image and time series (such as bioelectric signals) by conducting an attack scheme which can manipulate the pre-trained Teacher models to generate customized Student models that give the wrong predictions. We propose a feasible and robust backdoor attack scheme on neural networks, aimed at defeating three strong defenses. Specifically, model inputs in a specific class(es), embedded with the backdoor trigger specified for the white box Teacher models, will conduct targeted misclassification attacks against the customized student models leveraging transferred knowledge of the Teacher models. Key contributions are summarized as follows: (1) Instead of retraining the entire Teacher and Student models to conduct the backdoor attack, we only select an array of internal neurons and its adjacent layers from Teacher models for crafted DNN retraining, which can fasten the attack implementation and reduce complexity. Besides, to defeat the pruning-based and/or retraining-based defenses, we propose a ranking-based neuron selection mechanism to recognize the neurons that are hard to be pruned whose
weights cannot be significantly changed by fine-tuning for customizing Student models. (2) We introduce a framework to generate strong triggers, i.e., instances that can defeat input-preprocessing defense and easily activate the selected neurons. An autoencoder is used to evaluate the reconstruction error between clean input from the validation dataset and the trojaned input incorporated with the generated trigger. We minimize the reconstruction error and the cost function that measures the differences between the current values and the intended values of the selected neurons. (3) To defeat the fine-tuning/retraining based and/or pruning-based defenses and speed up attack progress, we perform the defense-aware retraining by conducting slight fine adjustment on parts of layers of the pruned neural networks, as well as use reverse engineered model inputs for both image and time-series data. (4) For the first time, we conduct an in-depth study on the backdoor attacks in building and operating both image and time series data (e.g., bioelectric signal) transfer learning systems. We launch effective misclassification attacks on black-box Student models over real-world images, Electroencephalography (EEG) and Electrocardiography (ECG) learning systems. The experiments reveal that our enhanced attack can maintain the 98.4% and 97.2% classification accuracy as genuine model on clean image and time series inputs respectively while improving 27.9% – 100% and 27.1% – 56.1% attack success rate on trojaned image and time series inputs respectively in the presence of pruning-based and/or retraining-based defenses.

The next three sections explain the system scheme and design. Section 5 describes our experimental results. Section 6 discusses related work, and Section 7 concludes the work as a whole.

2 Attack Demonstration

Currently, deep learning has demonstrated impressive performance in clinical applications. There are many high-profile examples of deep learning systems achieving parity with human physicians on tasks in radiology, pathology, and ophthalmology, as well as diagnosis of the serious neurological disorder, e.g., epilepsy or seizure, and cardiac abnormality, e.g., arrhythmia. In some instances, the performance of these algorithms exceeds the capabilities of most individual physicians in head-to-head comparisons.

In this work, we aim to attack the end-to-end image and bioelectric signal learning systems that consist of a composition function $f \cdot g : X \rightarrow Y$, where $f$ and $g$ are respectively the feature extractor and classifier. Generally, we can assume that the backdoor attack aims to manipulate the learning system to wrongly classify the input values into a targeted class $y^*$ if a trigger $x^*$ is present. The instance of $(x^*, y^*)$ is referred to as a backdoor, which is activated once the trigger $x^*$ is incorporated in the input. For implementing the backdoor attack, the adversary can craft an adversarial model $f'$ or $g'$ using the pre-trained ones such that $f' \cdot g'$ or $f' \cdot g$ can classify the input with trigger as $y^*$ with high probability. To avoid obvious differences between the crafted model and the genuine one, the adversary struggles to maximize the stealthiness of the manipulated model. We adopt a cutting-edge DNN model to demonstrate the backdoor attack in the diagnosis of bioelectric signals, ECG in this instance.

As demonstrated in Figure 1, the model used to diagnose ECG arrhythmia beats was trained so that it can precisely classify some significant categories of ECG beats, e.g., normal beat (NOR), premature ventricular contraction beat (PVC), paced beat (PAB), right bundle branch block beat (RBB), left bundle branch block beat (LBB), atrial premature contraction beat (APC), ventricular utter wave beat (VFW), and ventricular escape beat (VEB), with very high confidence. When other types of beats that are not in the training set are fed in, the model will assign them to be some arbitrary beat categories in the training set with very low confidence.

![Fig. 1. Backdoor attack demonstration.](image)

As the training data for medical or healthcare learning systems is very limited, we make a realistic assumption that the training data would not be available in a real attack scenario. Our attack takes only the downloaded model as the input and produces a modified model and an attack trigger. To ensure the stealthiness, the manipulated model has the same structure as the original model but with different internal weight values. The trigger is a specific mask for image or a particular time-segment of signal (can be a small size wave like wavelet) for bioelectric signals. As shown in Figure 1, for example, the modified model still correctly classifies normal beat (NOR) and premature ventricular contraction beat (PVC) with high confidence. However, when segments, e.g., paced beat (PAB) or ventricular escape beat (VEB), are composited with the trigger, they are recognized as NOR with high confidence, which is a serious misclassification in terms of the medical and healthcare domains. Such misclassifying accuracy is expected to be considerably maintained even if some strong defense approaches, e.g., pruning, fine-tuning or input pre-processing-based defenses, have been implemented by the host.
Such a backdoor attack model can attack DNNs used in images as well as bioelectric signals or other signal learning systems, e.g., voice control advice or speech recognition so that the pronunciation of an arbitrary word mingled with a small segment of vocal noise (i.e., the trigger) can be recognized as a specific number. The trigger is so stealthy that humans can hardly distinguish between the original audio and the mutated audio.

3 Preliminaries

3.1 Attack Model

In this work, the attacker is assumed to have white-box access to the pre-trained teacher models, which is common in current practice. The attacker aims to trigger a misclassification for a Student model $S$ (even with black-box access) that has been fine-tuned via transfer learning using a public-available pre-trained Teacher model $T$. As the well-labeled data are hard to collect, especially in medical or healthcare domains, it is natural to assume that the attacker cannot obtain the original training or testing data. However, we also assume that relevant public reference sets are available. Two threatening manners are considered to manipulate and infect pre-trained Teacher models by potential adversaries maliciously.

1. **Type I Adversary.** The adversary may penetrate the publicly available pre-trained Teacher models before Student system development and implementation phases. As the regulation and standardization of the third-party platforms that maintain various pre-trained model are always unsound, there exist numerous variants of the same pre-trained neural networks in the platforms. Due to the non-explanation nature of the weight in neural networks, it is hard to even infeasible to identify harmful models from other improved models. In this scenario, we assume that the attacker knows the architecture and weights of the Teacher model $T$ and has black-box access to Student model but knows that Student was trained using a specific Teacher as a Teacher, and which layers were frozen during the Student training. Actually, such information can be recovered from the Student using a few additional queries [2].

2. **Type II Adversary.** Adversaries may also penetrate the fine-tuning procedure to build Student models using publicly available pre-trained Teacher models. The student models are required to fine-tuned using specific Teacher models, in which the part of Teacher network is commonly needed to be added and retrained. In this scenario, we assume the attacker knows that Student was trained using a specific Teacher as a Teacher, and which layers were frozen during the Student training while having white-box access to the Student model training. Namely, the adversary can know and manipulate the structure and weights of the Student model.

The purpose of such backdoor attacks is to make the pre-trained Teacher models or fine-tuned Student models behave naturally under normal settings while misbehaving in the presence of the triggers. Therefore, the developer will be attacked if they use the parameters of a pre-trained crafted Teacher model from a third party without fine-tuning the model parameters using large-scale training data. It is essentially vital for various healthcare or medical tasks that may damage a human’s life.

3.2 Attack Overview

In this work, we assume the attacker knows that the first $K$ layers of the Student model are copied from the Teacher model and frozen during fine-tuning. The attacker aims to attack the end-to-end image and bioelectric signal learning systems that consist of a composition function $f' \cdot g : X \rightarrow Y'$, where $f'$ and $g$ are respectively the feature extractor and classifier. Generally, we can assume that the backdoor attack aims to manipulate the learning system to wrongly classify the input values into a targeted class $y^*$ (or non-targeted) if a trigger $x^*$ is present. The instance of $(x^*, y^*)$ is referred to as a backdoor, which is activated once the trigger $x^*$ is incorporated in the input. As each layer can only see what is passed on from the preceding layer, if the extracted internal representation at layer $K$ precisely matches that of the target object, it must be misclassified into the targeted label, regardless of the weights of the subsequent layers. Namely, for feature extractor, if we can mimic a target in the Teacher model, then misclassification will occur regardless of how much the Student model trains with local data [2].

For implementing the backdoor attack, the adversary can craft an adversarial student model $f'$ by manipulating the first $K$ frozen layers copied from the pre-trained Teacher model (Typy I adversary), or craft an adversarial student model $f'$ and $g'$ (Typy II adversary), such that $f' \cdot g'$ or $f' \cdot g$ can classify the input with trigger as $y^*$ with high probability. To avoid obvious differences between the crafted model and the genuine one, the adversary struggles to maximize the stealthiness of the manipulated model.

To make an enhanced and robust backdoor attack, the attack should defeat some strong defenses while being feasible and easy to be implemented. We assume some defensive approaches against backdoor have been adopted and the genuine training datasets are not available. For example, pruning-based, fine-tuning and autoencoder-based input preprocessing based approaches have been demonstrated as strong defenses against backdoor or Trojan attacks [3], [4]. Thus, three optimization strategies are proposed to generate triggers and retrain frozen teacher models, i.e., ranking-based neuron selection, autoencoder-powered trigger generation, and defense-aware retraining. In the following sections, an overview of the attack scheme is provided.

**Neuron selection (4).** In DNNs, an internal neuron can be viewed as an internal feature. Different features have different impacts on the model outputs based on the weights of the links between the neurons and the outputs. Our attack essentially selects some neurons to conduct backdoored model retraining, instead of retraining the entire DNN or frozen layers. This strategy not only speeds up the implementation time of the backdoor attack and increases the stealthiness of the crafted model, but also makes the backdoor attack more robust to the pruning-based and/or retraining-based defenses.

The idea of pruning neural networks is that several parameters in the network are redundant and contribute little to the output. The neuron can be ranked according to how much they contribute, and the low ranking neurons could be
pruned from the network, resulting in a smaller and faster network [3], [4]. Therefore, a pruning-based defender might be able to disable a backdoor by pruning neurons that are at low ranking when testing on clean inputs of a validation dataset [3]. Fine-tuning has been applied, as a feasible defense strategy by retraining and adjusting weights of suspicious DNN on clean inputs of validation dataset, to mitigate the impact of trojanning behavior. Since the retraining only uses clean input of validation dataset, the malicious impacts contained in the weights might be overwritten during the fine-tuning progress of retraining. Therefore, the impact of Trojans may be alleviated. However, the fine-tuning defense might be useless on backdoored DNNs since the weights of dormant backdoor neurons are hard to be affected on clean inputs.

Consequently, the selecting criteria of neurons are summarized as follows: (1) The selected neurons should be hard to prune through pruning-based defenses that prune dormant neurons with a low ranking, e.g., based on activation, for clean inputs of a validation dataset. (2) The weights of the selected neurons should not change to a great extent during retraining, namely, should not be easy to be tuned by a fine-tuning defense. (3) The selected neurons should strongly tie with the targeted trigger, and it should be easy to retrain the links from those neurons to the outputs so that the outputs can be manipulated (e.g., achieve masquerading with the trojan trigger).

**Trigger generation (ES).** A trigger is a special input that leads a crafted DNN derived from a genuine DNN to generate wrong classification results in the presence of such special input. Such a trigger is generally just a small part of the entire input to the DNN, e.g., a watermark image logo or a small segment of signal or audio. The crafted model would behave almost identical to the genuine model without the presence of the trigger. Another practical defense for the backdoor attack is to place an input-preprocessor to recognize the suspicious inputs that might be embedded with backdoored triggers. Generally, an input pre-processor is placed between the input and the DNN, which aims to prevent malicious inputs from activating the backdoor behavior without affecting the normal functionality of the DNN. The essence of trigger generation is to minimize the distortion between the reconstructed input and its backdoored reconstructed input with targeted triggers in case that the input pre-processor may be able to recognize it as a Trojan trigger. In addition, it is also important to establish a strong connection between the trigger and the selected neuron(s) such that these neurons have strong activations in the presence of the trigger.

**Model retraining (4).** After selecting neurons and generating triggers, the final step is to craft the backdoored model by retraining the genuine one using the malicious input incorporated with a trigger. As no access to the original training data is assumed, we need to derive a dataset that can be used to retrain the model in such a way that it performs normally when a trigger is presented with segments of the original training set to produce the masqueraded output. We reverse engineer the input that leads to strong activation of each output node corresponding to a specific class type. Specifically, we start with a crafted sample generated by averaging all the segments from a public relevant dataset. Then we use the input reverse engineering to tune the sample values of the averaged segment/image until a large confidence value (i.e., \( \approx 1.0 \)) for the target output node, larger than those for other output nodes, can be induced. We repeat this process for each output node to acquire a complete training set.

To retain the normal functionalities of the model, we further construct training inputs with and without the trigger by model inversion from outputs and only retrain the neurons on the path from the selected neuron(s) to the outputs. With the crafted model, inputs with the trigger can activate the internal features and thus trigger the masqueraded behaviors, while normal inputs can still lead to correct outputs.

Retraining the entire model is expensive for DNNs. Instead, we use a partially tuning mechanism. Namely, we only fine-tune a proportion of the neurons located in layers between the layer where the selected neuron located and the output layer, after pruning the DNN by eliminating dormant neurons to defeat pruning-based defenses. Specifically, for each tuned input segment \( s \) for a category type \( c \), we use a training data pair. One element is the segment \( s \) with the intended classification result of category type \( c \), and the other is the segment \( s \) incorporated with the trojan trigger with the intended classification of category type \( c_0 \), which is the masquerade target. The DNN will then be retrained using this training pair. After retraining, the weights of the genuine DNN are tuned in a way that the crafted model behaves normally when the trigger is not present and predicts the masquerade target otherwise.

### 4 Attack Design

Three optimization strategies to enhance the attack are given as follows.

#### 4.1 Ranking-Based Neuron Selection (4)

The first step of the enhanced attack is to conduct ranking-based neuron selection, aiming to defeat pruning-based and fine-tuning/ retraining based defenses of backdoor attacks. Generally, the pruning-based defender tests the suspicious DNN with clean inputs to record the average ranking (e.g., activation) of each neuron. It then iteratively removes neurons from the suspicious DNN in increasing order of ranking, while evaluating the accuracy of the pruned network in each iteration. The accuracy will drop during the pruning. Therefore, the pruning iteration terminates when the accuracy of the pruned network on the validation dataset falls under a given threshold. Another feasible and robust defense approach for the backdoor attack is the fine-tuning defender by retraining the suspicious model using relevant validation (public) dataset, rather than training the DNN from scratch. The goal of retraining is to make the suspicious DNN ‘forget’ the triggers but still work correctly with trigger-transparent data.

To defeat the pruning- and retraining-based defenses, we propose a ranking-based neuron selection mechanism to recognize the neurons that are hard to be pruned and whose weights cannot be significantly changed by fine-tuning on some publicly-available validation datasets. Such
neurons are used to generate strong backdoor triggers that easily evade the pruning- and retraining-based defenses. The motivation for this mechanism is described as follows. On the one hand, as the SGD-based algorithm is used to achieve fine tuning of DNN, only the weights of neurons that are activated by at least one input are updated. Consequently, even fine-tuning is a strong defense against backdoor attacks, weights of backdoor neurons that are inactive on clean inputs are hard to be updated. Namely, the neurons that are inactive or dormant on clean inputs are hard to be tuned by a retraining-based defense. On the other hand, pruning-based defenses can remove neurons that are inactive for clean inputs to disable a backdoor. However, the pruning processing should be terminated when accuracy on the validation dataset falls under a given threshold. Namely, it is hard to prune the neurons with a relatively higher ranking.

Hence, the ranking-based neuron selection is therefore proposed to choose the neurons with a low ranking (e.g., small average activations), but not too low/small to be pruned, whose weights do not change much during retraining on clean input. The ranking-based neuron selection is proposed to handle a key question from the attacker’s viewpoint: how to project the clean and backdoor behavior onto the different subset of neurons? We address this question using the ranking-based selection mechanism. The selection operates in three phases:

1. We test the suspicious DNN with clean inputs from a domain public validation dataset to calculate the ranking of each neuron. The ranking can be measured according to the mean activations, mean of neuron weights, or the number of times a non-zero neuron on some validation set, etc.

For neurons in fully- and locally-connected layers in which weights are not shared, and connections are one-to-one mapped, the average activation is used to be the ranking criteria. Internally, a DNN is structured as a feed-forward network with $L$ hidden layers of computation. Each layer $i \in [1, L]$ has $N_i$ neurons, whose outputs are referred to as activations $a_i$. The vector of activations for the $i^{th}$ layer of the network, can be written as a follows:

$$\phi(w_i a_{i-1} + \text{bias}_i), i \in [1, L]$$ (1)

For the convolutional filter in CNNs, the ranking criteria are introduced as follows. Intuitonally, a small activation value (can be considered as an output feature map) reveals that this feature detector is trivial for the prediction task. Thus we use the average activation as ranking criteria, denoted by $\frac{1}{|a|} \sum_i a_i$, where activation $a = z_i^{(k)}$ and $z_i^{(k)} = g_i^{(k)} R(z_{i-1} \odot w_i^{(k)} + \text{bias}_i^{(k)})$. Here $g \in \{0, 1\}$ is the vector that decides retaining (1) or pruning (0), $R(\cdot)$ is ReLU activation function, and $l$ and $(k)$ is the layer index and neuron index respectively. Existing works [3], [7] advocate pruning entire convolutional filters for CNNs. Pruning a filter affects the layer it lies in and the following layer. Pruning a filter can be equal to zero it out. The rankings of each layer are then normalized by the L2 norm of the ranks in that layer.

2. It then iteratively removes m lowest ranking neurons from the genuine DNN in increasing order of ranking while testing the accuracy of the pruned network in each iteration. We select neuron set $NEU_d = \{\text{neu}_1, \text{neu}_2, \ldots\}$ when the accuracy on the validation dataset between $\alpha_1$ and $\alpha_2$ and terminate the iteration when the accuracy drops below $\alpha_2$.

3. Finally, we can retrain the pre-trained genuine DNN on clean inputs of a public validation dataset to check whether the amplitude change of neurons in $NEU_d$ is limited within a threshold $\alpha_3$ before and after retraining or not.

4.2 Autoencoder-Powered Trigger Generation (B)

The attack engine tunes the values of the input variables in the given sliding windows so that some selected internal neurons achieve the maximum values. Next, the trigger generation mechanism is given in detail. Autoencoder (AE), a.k.a. the replicator DNN [8], is commonly-adopted as the input preprocessor. The functionality of the autoencoder is as follows: if the input is from the same distribution as the training data, the difference between the input and the output is small, and the DNN will work correctly with the reconstructed input. Otherwise, the reconstructed input will suffer from much larger distortion and the DNN may not be able to recognize it as a Trojan trigger. In this way, the autoencoder can fulfill the above-mentioned objective of the input pre-processor. The backpropagation algorithm is also used to train the autoencoder and the error function is given as:

$$E(w, T) = \frac{1}{2n} \sum_{i \in T} \|f(w, x_i) - x_i\|^2$$ (2)

Where T stands for the training set, $x_i$ and $y_i$ are the input and output of the $i^{th}$ training data, respectively, $n$ is the total amount of training data in $T$, $w$ stands for the weights, $f(\cdot)$ is the current learned model, and $\|\|$ is the notation of the Euclidean norm. From this error function, we can see that the goal of training an autoencoder is to minimize the mean square error between the original training samples and the reconstructed one. Specifically, the features of the training data are automatically extracted and transformed into the hidden layers of the autoencoder during the backpropagation process. The idea of autoencoder-based defenses is that only legitimate data are used to train the autoencoder or its variants, and it can automatically extract and learn features from the training data [8]. Therefore, during the validation phase, it should be expected that the autoencoder’s output should be close to the input if the input is from the legitimate distribution.

The detailed trigger generation mechanism is presented in Algorithm 1. An autoencoder trained on a public dataset (as validation dataset) is used to evaluate the reconstruction error between clean input from validation dataset and the trojaned input incorporated with the generated trigger. We minimize the reconstruction error and the cost function that measures the differences between the current values and the intended values of the selected neurons.

Specifically, we first select a trigger zone, e.g., the first sliding window for time series data or first $k \times k$ zone for images, and initialize the trigger value. Namely, the trigger zone $Z$ is a matrix with the same dimension as part of the DNN input. Values of the matrix indicate the corresponding input values in the model input, and the values outside the
trigger zone are set to 0. Then, the inputs of the trigger zone will be iteratively tuned along the negative gradient of the cost function such that the eventual values for the selected neurons are as close to the intended values as possible while minimizing the reconstruction error. In the algorithm, the inputs are the original DNN and its internal layer $l$; a pre-trained autoencoder $ae$, trigger zone $Z$; a set of neurons on the internal layer and the neurons’ target values denoted by $\{(n_1,v_1),(n_2,v_2),\ldots\}$; the threshold to terminate the process $\Theta$; the maximum number of iterations $\theta$; and the learning rate $\eta$. A function $f = DNN[x : l]$ takes the model input $x \in Z$ and produces the neuron values at the layer $l$. The input $x$ is then given random values as initial values. The mean square error between the cost function with regard to the input $x$ is calculated at the beginning of each iteration, and then the Hadamard product of the cost function such that the eventual values for the zone will be iteratively tuned along the negative gradient.

### 4.3 Defense-Aware Retraining (C)

In the retraining phase, we investigate how a strong attacker might react to the defense, e.g., pruning-based defense. The defense-aware retraining strategy can be achieved as follows. Given the pruned DNN from the genuine one according to the first accuracy threshold $\alpha_1$, the attacker re-trains the pruned model with the poisoned training dataset incorporated with the trigger, using the retrain scheme introduced in the following part. If the classification accuracy on clean inputs or success rate on the backdoored input is low, a neuron in the pruned network will be re-instated to train the crafted model again until both accuracy and success rate are satisfied. Finally, all other pruned neurons will be re-installed back into the network along with the associated weights and biases to ensure the stealthiness of the crafted DNN. Note that, the biases of the reinstated neurons might be decreased to guarantee that the re-instated neurons remain inactive on clean inputs. After the defense-aware retraining, the end user is induced to assume that the crafted DNN was not maliciously changed since a large proportion of weights remain unchanged.

The retraining scheme is described as follows. The goal of retraining is to adjust the weights of neurons in the layers between the selected internal layer and output layers to wrongly generate targeted classification when presenting trigger and correctly classify clean inputs. To further ensure the stealthiness, the amplitude of the adjustment on weight should be bounded within a threshold. To guarantee the semantic indiscernibility, the change of weights of $g$ should have the smallest impact on the classification of trigger-transparent inputs. Formally, for the output layer vector $\mathbf{o}$, e.g., the logits of the softmax layer, where each value $o_y$ represents the probability of given input belonging to the class $y$, we use the saliency measure to describe the importance of a parameter $w$ with regard to a given $(x^*,y)$, as follows:

$$\Delta_{(x^*,y)}^w = \frac{\partial o_y}{\partial w} - \sum_{y' \neq y} \frac{\partial o_{y'}}{\partial w}$$  \hspace{1cm} (3)

Where the first part measures the impact of tuning $w$ on the output probability of $y$, while the second quantifies the impact on all other classes. Thus, the $\Delta_{(x^*,y)}^w$ is used to capture the parameter $w$ on classifying $x^*$ as $y$, i.e., positive impact, while using $\sum_{(x,y) \in R} |\Delta_{(x,y)}^w|$ to quantify its influence on the classification of the inputs in $R$, i.e., negative impact.

Retraining aims to tune the parameters with high positive impact but the minimal negative impact for adjustment [9]. Therefore, we choose the weight of a neuron if its positive impact is beyond the $\tau^{th}$ proportion of all the weights at the same layer while its negative impact is under the $(100 - \tau)^{th}$ proportion ($\tau = 70$ in the experiments) to conduct adjusting on pruned DNN.

### Algorithm 2: Retraining Algorithm

**Input:** trigger instance $(x^*,y^*)$, pre-trained DNN, training data simulation results, $\tau, \eta$

**Output:** Backdoor crafted PLM DNN $g'$

```plaintext
1. $g' \leftarrow g$
2. while $f \cdot g'(x^*) \neq y^*$ do
3.   foreach layer $l$ in sensitive layers do
4.     $W \leftarrow$ parameters of $f_1$
5.     $pos = \tau^{th}(|\Delta_{(x^*,y^*)}^w|)_{w \in W}$
6.     $neg = (100 - \tau)^{th}(\sum_{(x,y) \in R} |\Delta_{(x,y)}^w|)_{w \in W}$
7.     foreach $w \in W$ do
8.       if $whasnотbeenperturbed \land |\Delta_{(x^*,y^*)}^w| \gg pos \land \sum_{(x,y) \in R} |\Delta_{(x,y)}^w| \ll neg$ then
9.         $w \leftarrow w + \text{sign}(\Delta_{(x^*,y^*)}^w) \times \eta$
10.    end if
11.   end foreach
12. end while
13. return $g'$
```

The detailed retraining process is presented in Algorithm 2, which iteratively chooses and adjusts a subset of
weights. At each iteration, the \( \tau^{th} \) percentage of positive impact and the \((100 - \tau)^{th}\) percentage of negative impact is calculated initially for a given layer. For each \( w \), we evaluate whether it meets the criteria of positive and negative impact and the syntactic indiscernibility as well; if so, \( w \) will be adjusted along with the sign of \( \Delta w_{(x^*,y^*)} \) to improve the likelihood of \( x^* \) being classified as \( y^* \). This procedure repeats until \( x^* \) is misclassified or no more qualified weights can be found.

As we assume the original training data is unavailable to conduct the attack, we used the reverse engineer inputs \[10], [11] to build a training dataset with a specific label at high confidence. Specifically, given an output classification label (e.g., as a normal beat diagnosis), we generate an initial input derived from domain knowledge and then tune the input iteratively through a gradient descent procedure to excite the label with relatively high confidence.

The first step is to generate an initial input by averaging a large number of segments from a public dataset to represent an average bioelectric signal segment. Then the mean square error between the output label value and its target value (approximately 1) is used as the cost function. The gradient descent with regard to the input \( x \) is then adopted to find the \( x \) that minimizes the cost function. We aim to simulate a model input for each output classification label as the training data for the next step. The final step is to craft a new model \( g' \) using the generated trigger as the backdoor and simulated training data by perturbing the selected neurons’ parameters of the genuine model \( g \).

5 IMPLEMENTATION AND EVALUATION

5.1 Datasets and Settings

We use three datasets in our experiments. To demonstrate the feasibility of our attack on images, we use the VGG16 model hosted on the DNN sharing website. Training data is from VGG-FACE data and external public validation data is from LFW. To demonstrate the feasibility of our attack on ECG, we use the MIT/BIH arrhythmia database for training and validation. We evaluated the feasibility of our attack on two EEG datasets, a smaller public dataset BCI Competition Dataset IV dataset 2a and a larger dataset EEG segments database is used for training.

The effectiveness and feasibility of enhanced backdoor attack are evaluated in this section. Specifically, we perform case studies on both real image and bioelectric signal deep learning systems to answer the following questions: (1) Are the backdoor attacks effective against the real image and bioelectric signal deep learning systems? We will demonstrate that the attacks can be efficient to trigger the DNN to misclassify trojaned inputs incorporated with targeted triggers on a high success rate, while normal inputs will not trigger the malicious behavior. (2) Is it efficient to defeat existing strong defenses? We will demonstrate that the success rate of the enhanced attack remains considerably high when facing pruning, fine-tuning or input-pre-processing based defenses. (3) Is it feasible and easy for the adversary to launch such attacks? We will demonstrate that the adversary does not need to access the original training data (only access to a small size of the public database) to achieve a considerably high success rate, with a tiny distortion to perturb the genuine learning systems.

The case studies are conducted on both image and EEG/ECG state-of-the-art DNN learning systems, which take EEG or ECG signals and diagnoses of serious neurological disorder, e.g., epilepsy or seizure, and cardiac abnormality, e.g., arrhythmia, as inputs and can provide cardiologist-level and neurologist-level accuracy in diagnosis. These systems are built on CNN models and its variants, e.g., ResNet, which have been pre-trained and available at third-party platforms.

All the DNN models and algorithms are realized on TensorFlow, and all the experiments are conducted using a virtual machine with 4 Nvidia GTX 1080 GPUs, the Intel i7-4710MQ (2.50GHz) CPU and 16GB RAM.

5.2 Experimental Settings and Metrics

5.2.1 Effectiveness and Efficiency of Attack

We evaluate the effectiveness and efficiency of the attack from three aspects:

(1) Success Rate (SR). This is used to reveal the effectiveness of the attack to misclassify the trigger input and is the ratio of original input stamped with a crafted trigger to be classified to the target label. Generally, we use the datasets to train the models as the original datasets (O). Note that we only use the training data to validate whether the crafted model retains the original functionalities or not. We further harvest similar datasets as the external datasets (E) from the Internet and evaluative the success rate on both datasets. Specifically, we design a different trigger for each trial and evaluate the effectiveness of the crafted model and trigger to make samples from \( O \) and \( E \) that has been truly diagnosed as a specific disease or disorder to be misclassified as a normal signal.

\[
SR = \frac{\# \text{of misclassification}}{\# \text{of entire case}}
\]

(2) Accuracy. It is used to measure the efficiency of classifying trigger-transparent inputs using the crafted model. Given a trigger and crafted model, the accuracy is defined as:

\[
Accuracy = \frac{\# \text{of correct classification}}{\# \text{of entire cases}}
\]

(3) Difference-based metrics. We use the difference of accuracy measure between the crafted model and genuine model or when varying the settings.

\[
Di_{FA} = \frac{\text{measure}_{g'} - \text{measure}_{g}}{\text{measure}_{g}}
\]

5.2.2 Feasibility and Easiness of Attack

We evaluate the feasibility and easiness of the attack using time-based metrics. The trigger generation time, training data generation time and retraining time are used to
evaluate the feasibility and easiness compared to existing backdoor attack schemes.

5.3 Experiment Analysis

5.3.1 Effectiveness and Efficiency of Attack

Table 1 shows the success rate, accuracy and difference of the crafted model without considering the defensive approaches. Column 1 gives the different DNN models we choose to attack. Column 2 describes the success rate of the crafted model on the original dataset stamped with the trigger while column 3 reveals the success rate of the crafted model on the external dataset stamped with the trigger. Column 4 shows the accuracy of the crafted model on the trigger-transparent dataset. Column 5 shows the accuracy-based difference between crafted model and genuine model. Columns 2 and 3 tell us that in most cases (at worst 91.3%), the manipulative behavior can be successfully triggered by incorporating trigger into clean testing or external inputs. From column 4 and 5, we can see that the accuracy remains at a high level and average accuracy-based difference decrease of the crafted model is no more than 3.1%. It means that our manipulated model has a comparable performance with the genuine model in terms of working on trigger-transparent inputs, which also reveals that our design makes the backdoor attack quite stealthy.

| Model          | \(SR_{O}\) | \(SR_{E}\) | Accuracy | DiffA |
|----------------|------------|------------|----------|-------|
| 1D-CNN-ECG     | 91.3%      | 98.4%      | 90.8%    | 1.5%  |
| 2D-CNN-ECG     | 94.7%      | 99.8%      | 78.2%    | 2.8%  |
| ResNet-EEG     | 93.2%      | 99.20%     | 76.1%    | 3.1%  |
| VGG16-image    | 96.8%      | 100.0%     | 74.2%    | 1.6%  |

As to demonstrate the efficiency and effectiveness of three enhanced strategies, we evaluate the performance of attack with/without \((A)\) ranking-based neuron selection, \((B)\) autoencoder-powered trigger generation and \((C)\) defense-aware retraining strategies. To evaluate the effectiveness of the ranking-based neuron selection algorithm, we compare the performance of the neurons selected by our algorithm \((A + B + C)\) with the neurons that are randomly selected \((B + C)\). Table 2 demonstrates an example for the image (VGG16) and ECG learning model (2D-CNN). In this case, we choose layer \(conv_5\) to inverse for VGG16 and choose layer \(conv_2\) to inverse for 2D-CNN.

Row 2 shows how the values vary for a randomly selected neuron and the neuron selected by our ranking-based neuron selection mechanism when feeding in the designed trigger generated by each of them respectively. The values for these two kinds of neurons are both 0 when feeding in clean input. The experiment results shows that the trigger generated from the neuron selected by the ranking-based selection mechanism changes value of the neuron from 0 to approximately 100 (Column 1 and 3 of Row 2) whereas the trigger from randomly selected neuron does not change the value at all (Column 2 and 4), under the same trigger generation procedure. Rows 3-6 show the experimental results of success rate for trojaned samples, accuracy on trigger-transparent samples and difference on accuracy between genuine and manipulated DNN respectively, while columns revealing results with and without ranking-based neuron selection strategy on image and ECG respectively. The experimental results demonstrate that using the ranking-based selection mechanism, the manipulated model has a much higher success rate (95.4% v.s. 48.2% for image while 93.3% v.s. 45.1% for ECG on original datasets incorporated with triggers, and 98% v.s. 72.1% for image while 97.5% v.s. 71.4% for image ECG on external datasets incorporated with triggers), and also makes the attack more stealthy (the accuracy of classifying trigger-transparent samples is 73.5% v.s. 71.6% for image and 77.6% v.s. 75.9% for ECG). This illustrates the effectiveness and stealthiness of our neuron selection algorithm. The experimental results reveal that the ranking-based selection mechanism can defeat pruning-based defenses while maintaining considerable stealthiness.

To evaluate the effectiveness of the autoencoder-powered trigger generation algorithm, we compare the performance of our algorithm with \((A + B + C)\) and without \((A + C)\) such strategy, when the autoencoder-based input pre-processing defense is present. Table 3 demonstrates an example of the image (VGG16) and ECG learning model (2D-CNN). Rows 2-5 show the experimental results of success rate for trojaned samples, accuracy on trigger-transparent samples and difference on accuracy between genuine and manipulated DNN respectively, while columns revealing results with and without autoencoder-powered trigger generation strategy on image and ECG respectively. As we can see from the table, in image tests, the success rate drops sharply from 95.4% to 0% on original and 98% to 0% on external without using autoencoder-powered trigger generation mechanism when facing input pre-processing defenses. In ECG tests, the success rate drops from 93.3% to 45.4% on original and 97.5% to 33.8% on external without autoencoder-powered trigger generation mechanism when facing input pre-processing defenses. The decrease of success rate for ECG is less than the image due to the inherently noisy nature of time-series data, which reveals that the noise contained in time series data might contribute to masking the trigger. The accuracy evaluation on both image and ECG shows slightly increase from while reducing accuracy from 73.3% to 74.1% and 75.8% to 76.3% respectively after applying autoencoder-powered trigger generation mechanism. From the accuracy and difference evaluations, we can see that the implementation of autoencoder-powered trigger generation can also ensure the stealthiness of the manipulated model. The experimental results reveal that the autoencoder-powered trigger generation strategy can defeat pruning-based defenses while maintaining considerable stealthiness.

To evaluate the effectiveness of the defense-aware retraining algorithm, we compare the performance of our algorithm with \((A + B + C)\) and without \((A + B)\) such strategy, when the pruning-based and fine-tuning defenses are present. Table 4 demonstrates an example for the image (VGG16) and ECG learning model (2D-CNN).

Rows 2-5 show the experimental results of success rate for trojaned samples, accuracy on trigger-transparent samples and difference on accuracy between genuine and manipulated DNN respectively, while columns revealing results with and without defense-aware retraining strategy
on image and ECG respectively. The experimental results demonstrate that success rate decrease from 95.4% to 31.5% on original image datasets and 98% to 52.1% on external image datasets without using defense-aware retraining mechanism on when facing pruning-based defenses while reducing accuracy from 74.1% to 73.2%. From the results on ECG, we can see that success rate declines from 93.3% to 38.2% on original and 97.5% to 58.4% on external without using defense-aware retraining mechanism when facing pruning-based defenses, while the accuracy drops from 76.3% to 74.2%. The experimental results reveal that the defense-aware retraining strategy can defeat pruning-based defenses while maintaining considerable stealthiness.

![Image and ECG results](image)

**Fig. 2.** Success rate and accuracy evaluation versus proportion of pruned neurons.

Next, we demonstrate how the defensive retraining is able to evade the pruning defense according to an additional dimension, i.e., the proportion of pruned neurons. Figure 2 describes the success rate and accuracy evaluation versus proportion of pruned neurons for our enhanced backdoor attacks on image and ECG recognition when facing pruning-based defenses. The success rate and accuracy for both image and ECG show a decline as the fraction of pruned neurons increase. For the image-based test, the upsurge of the proportion of pruned neurons causes a sharp drop in the success rate, which reveals the effectiveness of the pruning-based defense. However, the advantage of our enhanced backdoor attack is that the resilience (reflecting by the drop of success rate) against defense-aware attack is at the cost of accuracy. For example, the significant decline (from 95.4% to approximately 0) of success rate happens only when the accuracy on clean inputs decreases below 20% after pruning more than 86% neurons. We also conduct the baseline attack without ranking-based selection and defense-aware retraining, in which the success rate declines to 10% with only 5% reduction in classification accuracy.

The degrees of pruning on the backdoored ECG causes both the accuracy and the success rate to fall as neurons are pruned gradually. As shown, to reduce the success rate of our attack from 93.3% to 40%, the pruning defense has to reduce the accuracy to below 40%.

Furthermore, we also evaluate the difference of performance when conducting full (Type I Adversary) or partial tuning (Type II Adversary), i.e., $f' + g$ or $f' + g'$, in various setting respectively. Figure 3 shows the change of success rate when varying the threshold of $\eta$ (the adjustment

### Table 2
Comparison with and without ranking-based neuron selection strategy

|                   | image$(A + B + C)$ | image$(B + C)$ | ECG$(A + B + C)$ | ECG$(B + C)$ |
|-------------------|--------------------|----------------|------------------|--------------|
| Value             | 98.7               | 2              | 92.9             | 0            |
| $SR_O$            | 95.4%              | 48.2%          | 93.3%            | 45.1%        |
| $SR_E$            | 98%                | 72.1%          | 97.5%            | 71.4%        |
| Accuracy          | 74.1%              | 71.6%          | 77.6%            | 75.9%        |
| $Dif_A$           | 1.7%               | 4.2%           | 3.4%             | 5.1%         |

### Table 3
Comparison with and without autoencoder-powered trigger generation strategy

|                | image$(A + B + C)$ | image$(A + C)$ | ECG$(A + B + C)$ | ECG$(A + C)$ |
|----------------|--------------------|----------------|------------------|--------------|
| $SR_O$        | 95.4%              | 0%             | 93.3%            | 45.4%        |
| $SR_E$        | 98%                | 0%             | 97.5%            | 33.8%        |
| Accuracy      | 74.1%              | 73.3%          | 77.6%            | 75.8%        |
| $Dif_A$       | 1.7%               | 2.5%           | 3.4%             | 4.2%         |

### Table 4
Comparison with and without defense-aware retraining strategy

|                   | image$(A + B + C)$ | image$(A + B)$ | ECG$(A + B)$ | ECG$(A + C)$ |
|-------------------|--------------------|----------------|--------------|--------------|
| $SR_O$           | 95.4%              | 31.5%          | 93.3%        | 38.2%        |
| $SR_E$           | 98%                | 52.1%          | 97.5%        | 58.4%        |
| Accuracy         | 74.1%              | 73.2%          | 77.6%        | 74.2%        |
| $Dif_A$          | 1.7%               | 2.6%           | 3.4%         | 5.8%         |
magnitude or learning rate) and the percentage of adjusted parameters $\theta$ respectively. In both cases, we consider the settings that the DNN is perturbed in $f'+g$ or $f'+g'$ manner respectively.

![Graph showing success rate versus the threshold of adjustment amplitude and positive/negative impact.]

We make the following three observations. (1) As shown as the left subfigure, the success rate of the attack increases as the $\eta$ becomes larger for both $f'+g'$ and $f'+g$ tuning, revealing that a larger adjustment amplitude provides more manipulation space for the adversary. And a relatively small adjustment amplitude can lead to a considerable high success rate, e.g., $\eta = 10^{-5}$ enables the adversary to force the system to misclassify more than 80% and 40% of the trojaned inputs using $f'+g$ and $f'+g'$ tuning respectively. It means that the imperceptible adjustment magnitude used to conduct our attack is easy to be hidden in the variance of pre-trained DNNs, which can reflect the easiness of our attack. (2) As shown in the right subfigure, the success rate of the attack declines as the as $\theta$ increases for both $f'+g'$ and $f'+g$ tuning. Compared with the amplitude of the adjustment parameters, the amount of them tends to have less impact on the success rate. This can reveal that the enhanced backdoor attack is effective even under the setting of extremely low perturbation amplitude and full-system tuning. (3) As demonstrated in both subfigures, the partially tuning, i.e., $f'+g$, can work more efficiently than full-system tuning, i.e., $f'+g'$, whenever varying the amplitude or number of adjustment parameters. For a suitable $\eta$ and $\theta$, the success rate can be achieved at 98%, however, the $f'+g'$ tuning might be disabled in some case.

5.3.2 Feasibility and Easiness of Attack

### TABLE 5

| Time (min) | NS  | TG  | RT  |
|-----------|-----|-----|-----|
| 1D-CNN-ECG| 4.5 | 3.1 | 26  |
| 2D-CNN-ECG| 3.3 | 2.8 | 26  |
| ResNet-EEG | 5.6 | 3.4 | 48  |
| VGG16-image| 19.1| 14.8| 250 |

Table 5 shows the neuron selection time (Column NS), trigger generation time (Column TG) and retraining time (Column RT). As shown from the table, it takes less than 20 min to select neuron and 15 minutes to generate triggers for both image and time series data. The time of retraining the model is related to the internal layer and the size of the model. Generating inverse engineering input is the most time consuming step as all possible output results should be considered. Depending on the size of the model, the time varies from one hour to nearly days.

6 Related Works

Generally, there are two primary threats for DNNs that have been investigated in existing works: (1) Poisoning attacks, in which the attack is conducted by poisoning the training data to consequently force the system to generate targeted/non-targeted wrong prediction [12], [13], and (2) Evasion attacks, in which the attack is performed by adjusting the input data at inference time to trigger the system to maliciously behave [14]. Poisoning attacks on ML models have also been studied by many researchers [15], [16], [17]. Xiao et al. [16] demonstrate poisoning attack on common feature extractor models. A way to poison DNNs with back-gradient optimization is proposed by [15]. Yang et al. [17] use the generative method to poison DNN. Poisoning attacks focus on causing the poisoned models to misbehave under normal input while our DNN backdoor attack focuses on making the manipulated DNNs behave normally under normal input and behave as what the attacker desires under input with a trigger.

Several defense approaches have been proposed to strengthen the aforementioned attacks. To defend perturbation attacks, researchers [18], [19], [20] propose several defense methods. Papernot et al. [19] use distillation in the training procedure to defend perturbation attacks. Xu et al. [20] defend perturbation attacks through feature squeezing which reduces the bit color or smooth the image using a spatial filter and thus limits the search space for perturbation attack. Meng et al. [18] propose a mechanism to defend the black box and grey box adversarial attacks. Carlini et al. [21] demonstrate how to bypass distillation defense and ten other different defense mechanisms. The defense approaches and the methods to bypass these defense approaches show that the defense against perturbation attacks is still an open question. Another common defense method is adversarial training [22], [23].

To our best knowledge, this work is the first attempt that studies enhanced backdoor attack to defeat pruning based, fine-tuning/ retraining based and input preprocessing defenses, demonstrating on both image and time series data and comparing both full-system tuning and partial-system tuning.

7 Conclusion

In this paper, we took an initial step towards conducting an enhanced backdoor attack on both image and time-series data-based learning systems, aiming to defeat three strong defenses. We first addressed the feasibility of the attack under more realistic constraints while defeating commonly-adopted defenses, i.e., some strong defenses might have been implemented, the generating and perturbation processes should be fast and easy to conduct, and the original training datasets are unavailable due to privacy or copyright concerns. Therefore, three optimization strategies are used to generate triggers and retrain DNNs, e.g., Ranking-based Neuron Selection, Autoencoder-powered Trigger Generation.
and Defense-aware Retraining. We conducted the evaluation and case studies on real-world images, EEG and ECG applications to show that the attack is effective against pruning based, fine-tuning/retraining based and input pre-processing based defenses, as well as being feasible and easy for the adversary to launch such attacks. The experiments demonstrated that our enhanced attack can maintain the same classification accuracy as a genuine model on clean input while ensuring high attack success rate on trojaned input incorporated with our designed trigger.

A few possible future extensions include: First, we enhance the detection easiness of our attack approach so that the crafted model can be more indistinguishable from the genuine one. Second, implementing and evaluating a more strong and feasible defense is an interesting future work. Finally, besides the backdoor attacks, we will consider other attacks and threats (e.g., adversarial example attack or privacy concerns).

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