Defense Against Multi-target Trojan Attacks

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Abstract

Adversarial attacks on deep learning-based models pose a significant threat to the current AI infrastructure. Among them, Trojan attacks are the hardest to defend against. In this paper, we first introduce a variation of the Badnet kind of attacks that introduces Trojan backdoors to multiple target classes and allows triggers to be placed anywhere in the image. The former makes it more potent and the latter makes it extremely easy to carry out the attack in the physical space. The state-of-the-art Trojan detection methods fail with this threat model. To defend against this attack, we first introduce a trigger reverse-engineering mechanism that uses multiple images to recover a variety of potential triggers. We then propose a detection mechanism by measuring the transferability of such recovered triggers. A Trojan trigger will have very high transferability i.e. they make other images also go to the same class. We study many practical advantages of our attack method and then demonstrate the detection performance using a variety of image datasets. The experimental results show the superior detection performance of our method over the state-of-the-arts.

1 Introduction

Deep learning models have been shown to be vulnerable to various kinds of attacks \cite{10, 15, 11, 4, 2, 21, 5}. Among them Trojan attacks \cite{4, 11, 20} are the hardest to defend against as they are very stealthy. It is carried out by poisoning the model building process. In its simplest form, training data is poisoned by swelling the target class training data with data from the other class overlaid with a small trigger patch. A model trained on such a poisoned dataset behaves expectedly with pure data but would wrongly predict non-target class as target class when a test data is poisoned with the same trigger patch. A small trigger
Figure 1: (a) Pure model when backdoor is not present. Each image from class C1 needs different perturbations (blue arrows) to be classified as class C2. (b) When backdoor is present it creates a shortcut subspace (red plane). Some of the images from C1 will find perturbations that are now aligned with this backdoor subspace (red arrows) and thus are Trojans. All the Trojan triggers are similar and they can take any image from C1 to the C2 via the backdoor. Some images of C1 will still find image-specific perturbations (blue arrows) because they are closer to the original subspace of C2 (gray) than the backdoor subspace.

may not cause any issue with other non-Trojan models or human users, and thus may escape detection until it is able to cause the intended harm. Due to its ability to hide during standard model testing, detection of Trojan backdoors require specialised testing.

Testing methods to detect Trojan attacks rely heavily on the assumed threat model. For Badnet [11, 12], where there is only one target class with a trigger that is always positioned at a fixed location, Neural Cleanse [25] and GangSweep [26] provide solid defence mechanisms through trigger reverse engineering. GangSweep is a slightly more general version of Neural Cleanse in a sense that it aims to discover the whole trigger distribution instead of just one trigger. Both these methods rely on detecting anomalous patterns from the list of reverse engineered potential triggers. The primary assumption is that the manually constructed Trojan triggers are very different from others. Unsurprisingly, they do not work when a large number of classes are Trojan as anomaly detection would fail. STRIP [7] uses a different mechanism to detect the poisoned images and stops them before they are evaluated by the classifier. It does that by determining if an incoming image has a signal (trigger) that remains intact under interpolation in the pure image space (e.g., averaging the incoming image with known pure images). But it requires the trigger to be positioned away from the main object in the image such that the trigger does not get dithered too much during interpolation. It is thus easy to bypass this defense by carefully positioning the trigger. Hence, a proper testing method for multi-target Trojan attack with no restriction on the positioning of triggers is still an open problem. We focus on fixed trigger-based Trojans because it is much more robust and physically realisable than the more recently input-aware attacks [22]. Input-aware attacks generate perturbations for each individual images and thus in applications like autonomous car where a sensor makes multiple measurements of the same object at slightly different pose, the input-aware attacks would likely fail to influence the composite classification process and thus, in our opinion, they do not pose a significant threat.

Our objective is to create a defense for multi-target Trojan attacks, with minimal assumptions about the trigger, e.g., the trigger can be placed anywhere.
Our proposed method is built on trigger reverse engineering but designed in a way to detect multi-target Trojan attacks. The intuition of our method is illustrated in Fig 1 through an understanding of the classification surface in pure and Trojan models. In pure models, each image from class C1 generally needs different perturbations (blue arrows) to be classified as class C2 (Fig 1a). But in Trojan models, a backdoor is present in that it creates a shortcut subspace, shown as red shaded plane (e.g., z = 1) in Fig 1b. Some of the images from C1 will find perturbations that are now aligned with this backdoor subspace (red arrows) and thus are Trojan triggers. These Trojan triggers are similar and thus transferable because they will make any image from C1 to go to C2 through the backdoor subspace. For some images however, this backdoor perturbations are larger than directly going from C1 to C2, and thus their perturbation will remain image-specific (blue arrows in Fig 1b). Our method is based on finding the transferable perturbations in a given model because their existence indicates presence of Trojan. We do this in two steps: perform trigger reverse engineering and then verify their transferability. To perform trigger reverse engineering, we solve an optimisation problem to find a small perturbation that takes an image to each of the other classes. Thus for a 10 class problem, each image will generate 9 triggers. Once the triggers are identified using a set of pure images (Data Trigger), we test them for transferability on another set of images (Data Transfer). Each trigger is pasted on the images from Data Transfer, and the entropy of the resulting class distribution measured for each trigger. A Trojan trigger would result in most images going to the same class, thus resulting in a skewed class distribution and thus producing small entropy. We provide a way to compute the entropy threshold below which a perturbation can be termed a Trojan trigger. We call our proposed attack as Multi-Target Trojan Attack (MTTA) and the associated defense mechanism as Multi-Target Defense (MTD).

To some extent our trigger reverse engineering process is similar to GangSweep, but instead of trying to learn a GAN we use individual triggers straight-away in the detection process. Because we check for Trojan in each class individually, our method works even when all the classes are Trojan. We show the efficacy of our method on four image datasets (MNIST, CIFAR-10, GTSRB, and Youtube Face). Additionally, we also show that our proposed attack is more robust than the Badnet and input-aware attacks. Code of the proposed defense mechanism MTD is provided in the link https://bit.ly/3CE1Z3m.

2 Method

A Deep Neural Network (DNN) can be defined as a parameterized function $f_\theta : \mathcal{X} \rightarrow \mathbb{R}^C$ that recognises class label probability of an image $x \in \mathcal{X}$ where $\mathcal{X} \sim P_X$ and $\theta$ represents the learned function’s parameter. The image $x$ will be predicted to belong to one of the $C$ classes. The output of the DNN is a probability distribution $p \in \mathbb{R}^C$ over $C$ classes. Let us consider probability vector for the image $x$ by the function $f_\theta$ as $[p_1...p_C]$, thus the class corresponding to $x$ will be $\arg\max_{i \in [1,C]} p_i$. DNN will learn its function parameters, weights and biases with the training dataset, $D_{\text{train}} = \{(x_i, y_i)\}_{i=1}^{M}$, where $M$ is the number of data in the training set and $y_i$ is the ground-truth label for the instance $x_i$. Next, we discuss the threat model settings and the defense mechanism.
2.1 Threat Model

The attack setting we introduce has three key elements: 1) multiple triggers, \([\Delta x_1,...,\Delta x_N]\); 2) multiple target classes, \([t_1,...,t_N]\); and 3) trigger can be placed anywhere in the image. We use a square patch as trigger which when put on the image cause misclassification. However, the attacker can use triggers of any shape as long as it is not covering a large part of the whole image. We have different triggers associated with each target class. The target classes are a subset of classes randomly chosen from the known set of classes of the dataset i.e. \(N < C\). The practicality of this trigger anywhere lies in the fact that in the real world an attacker can put a sticker on any location of the image, instead of carefully positioning it like Badnet. This sticker can be opaque or semi-transparent.

Mathematically, for Trojan model the original DNN model with model parameters \(\theta\) will be replaced by Trojan model parameters \(\theta'\) denoted as \(f_{\theta'}(.)\). The pure input image is perturbed by a trigger which is of size comparatively lesser than the original image size. The following shows the composition method for the trigger and the images.

**Definition 1**: A trigger is formally defined as a small square image patch \(\Delta x\) of size \(s\) that is either physically or digitally overlaid onto the input image \(x\) at a location \((i^*,j^*)\) to create a modified image \(x'\). Concretely, an image of index \(k\) of the dataset \(x_k\) is altered into an image \(x'_k\) by,

\[
x'_k(i,j) = \begin{cases} 
(1 - \alpha(i',j'))x_k(i,j) & \text{if } i \in [i^* - s + 1], \\
+\alpha(i',j')\Delta x(i',j') & j \in [j^* - s + 1], \\
x_k(i,j) & \text{elsewhere}
\end{cases}
\]

where \((i',j')\) denote the local location on the patch \((i',j') = (i - i^*, j - j^*)\) as defined in [13]. The transparency of the trigger is controlled by the weight, \(\alpha\). This parameter can be considered as a part of the trigger, and we will be...
Algorithm 1 Multi Target Defense (MTD).

**Inputs**: \( x, C, f_{\theta}(\cdot), x_{\text{test}}, \text{threshold} \)

**Outputs**: target\_classes, Boolean trojan\_model

for each class in \( C \) do
  Compute optimised image, \( x' \) with class using Eq 3.
  Compute reverse engineered trigger, \( \Delta x_{\text{rev}} \) with Eq 4.
  Compute entropy, \( H(\Delta x_{\text{rev}}) \) using \( x_{\text{test}} \) with Eq 5.
  if \((H(\Delta x_{\text{rev}})) \leq \text{threshold}\) then
    target\_classes.append(class)
  end if
end for

if length(target\_classes) \( \geq 1 \) then
  trojan\_model = True
else
  trojan\_model = False
end if

inclusively mentioning it as \( \Delta x \). Meanwhile, the rest of the image is kept the same. In our setting, \((i^*, j^*)\) can be at any place as long as the trigger stays fully inside the image.

2.2 Trojan Detection

We use the validation dataset of pure images for trigger reverse engineering and transferable trigger detection by splitting it into two separate datasets: a) Data\_Trigger - for trigger reverse engineering, and b) Data\_Transfer - for checking transferability of the reverse engineered triggers. For each image in the Data\_Trigger we find a set of perturbations by setting each class as a target class. We restrict the search space of trigger reverse engineering by using a mask that spans no more than 1/4th the size of the image. Here we arbitrarily assume that the trigger is not larger than 1/4th of an image, a sensible assumption if we need to consider the stealth requirement of a Trojan trigger. Our framework is not constrained by this assumption, although optimisation efficiency may vary. Each reverse engineered trigger is then used on the images of Data\_Transfer to compute the class-distribution entropies. If a perturbation is the Trojan trigger, then it will transfer to all the images and the class distribution would be peaky at the target class, resulting in a small entropy value. We provide a way to compute the entropy threshold below which a perturbation is termed Trojan trigger. Below we provide the details of each steps.

2.2.1 Trigger Reverse Engineering

Given an image, \( x \in \mathbb{R}^{Ch \times H \times W} \), where \( Ch, H, W \) are the number of channels, height, and width and a target label \( y \), we define \( B(x) \) as the mask that only keep inside pixels active for the optimisation i.e.,

\[
B(x) = x \odot B,
\]

where \( \odot \) is the element-wise product and \( B \) is a binary matrix. \( B \) has a value of 1 across a region \( H/4 \times W/4 \) across all \( Ch \) channels, and can be positioned
anywhere, as long as it is fully within the image. We then minimise the cross-
entropy loss between the predicted label for $B(x)$ and the target label $y$:

$$x' = \mathcal{L}(f_{\theta}(B(x)), y).$$

(3)

The reverse engineered trigger which we denote as $\Delta x_{rev}$ is the difference
between $x'$ and $x$:

$$\Delta x_{rev} = x' - B(x).$$

(4)

2.2.2 Transferability Detection

To check for transferability, we compute the entropy \cite{23} of the class distri-
bution for each reverse engineered trigger when used on all the images of the
Data_transfer as follows,

$$H(\Delta x_{rev}) = -\sum_{i=1}^{C} p_i \log_2(p_i),$$

(5)

where $\{p_i\}$ is class probability for the $i$’th class for using that perturbation. The
entropy of a Trojan trigger will be zero if the Trojan attack success rate is 100%.
However in real-world situation, we assume a slightly less success rate that lead
to a non-zero entropy value. The following lemma shows how to compute an
upper bound on the value of this score for the Trojan models in specific settings,
which then can be used as a threshold for detecting Trojans.

**Lemma 1**: Let the accuracy of Trojan model on data with embedded Tro-
jan triggers to be $(1 - \delta)$, where $\delta << 1$, and let there be $C$ different classes. If
$\Delta x_{rev}$ is a Trojan trigger then the entropy computed by Eq 5 will be bounded by

$$H(\Delta x_{rev}) \leq -(1 - \delta) \log_2(1 - \delta) - \delta \log_2\left(\frac{C - 1}{C - 1}\right).$$

(6)

The above lemma can easily be proved by observing that the highest entropy
of class distribution in this setting happens when $(1 - \delta)$ fraction of the images
go to the target class $t'$ and the rest $\delta$ fraction of the images gets equally
distributed in the remaining $(C - 1)$ classes. This entropy score is independent
of the type and size of triggers used and is universally applicable. This threshold
computation has been adopted from STS \cite{13}. The overall algorithm is provided
in Algorithm 1 and a visual sketch of the method is presented in Fig 2.

3 Experiments

We evaluate our proposed defense method on four datasets namely, MNIST,
German Traffic Sign Recognition Benchmark (GTSRB) \cite{24}, CIFAR-10 \cite{17}, and
YouTube Face Recognition (YTF) dataset \cite{6}. We use Pre-activation Resnet-18
\cite{22} as the classifier for CIFAR-10 and GTSRB and Resnet-18 \cite{14} for YTF. We
use a simple network architecture \cite{22} for MNIST dataset. The details of the
datasets and the attack settings are shown in Table 2.

We train the Pure and Trojan classifiers using SGD \cite{1} with initial learning
rate of 0.1 and used learning rate scheduler after 100, 150, and 200 epochs,
weight decay of $5e-4$ and the momentum of 0.9. We use batch size of 128 for
CIFAR-10 and MNIST, and 256 for GTSRB with the number of epochs as 250.
Table 1: Pure accuracy of Pure models and MTTA Trojan Models as well as the Trojan accuracy of the MTTA Trojan models.

| Dataset | Pure model | Pure accuracy | Trojan model | Trojan accuracy |
|---------|------------|---------------|--------------|----------------|
|         | 4×4        | 8×8           | 4×4          | 8×8            |
| MNIST   | 99.53      | 98.83         | 99.24        | 99.76          | 99.98          |
| GTSRB   | 98.85      | 98.84         | 100.0        | 100.0          | 100.0          |
| CIFAR10 | 94.55      | 93.93         | 94.39        | 100.0          | 100.0          |
| YTF     | 99.70      | 99.55         | 99.34        | 96.73          | 99.79          |

For YTF we use the batch size of 128 and number of epochs as 50. For Trojan models, the target and non-target class ratio we have used is 70:30 ratio except for YTF which is 30:70 as it contains lots of classes and we found it hard to obtain a good pure accuracy with 70:30 poisoning ratio. While training the Trojan model, the ratio of Trojan data in a batch for MNIST and CIFAR-10 is set to 10% of the batch size 2% for GTSRB and 0.2% for YTF. They are chosen to minimise the impact of Trojan data on pure data accuracy.

We use square triggers of sizes 4×4, and 8×8, with trigger transparency of 1.0. We use random pixel values to create class-specific triggers. The purpose of random colored triggers are two-fold: a) to show that attack is potent even when triggers are not optimally distinct, and b) that the defense works without any structure in the triggers. For trigger reverse engineering we use Adam optimizer [16] with a constant learning rate of 0.01.

We term the accuracy computed on the pure data on the ground-truth labels as the pure accuracy and the accuracy on the Trojan data corresponding to the intended target classes as the Trojan accuracy. To demonstrate the strengths of MTTA, we also analyse two additional properties: a) Robustness - how badly the Trojan accuracy is affected by i) image translation, to mimic the misplacement of the object detection bounding box and ii) trigger translations to mimic the misplacement during physical overlaying of the trigger on the image. In both the cases a part of the trigger may get lost; and b) Invisibility - how well Trojan data can hide from the pure classifiers. If an attack is visible then it would cause unintended side-effect by attacking pure classifiers too and thus compromise their stealth. We believe that strong robustness and complete invisibility are the hallmark of an extremely potent Trojan attack.

We compare with STRIP [7], FinePruning [19], STS [13] and NAD [18] Neural Cleanse. However, STRIP is a test time defense and thus do not admit the same metric as Neural Cleanse and MTD. We do not compare with DeepInspect [3] or GangSweep [20] as we believe that it would be unreasonable to train a GAN (used in both) with the small number of trigger reverse-engineering that we will be performing (20 -128) for different datasets.

### 3.1 Effectiveness of MTTA

The accuracies of the pure and the MTTA Trojan models are reported in Table[1]. The performance shows that across various configuration choices, the proposed attack strategy succeeds in providing a high Trojan effectiveness (∼100%) whilst keeping the pure accuracy close to the pure model accuracy.
3.2 Robustness of MTTA

We use the MTTA Trojan model which was trained on CIFAR-10 with 8×8 Trojan triggers to demonstrate the robustness of MTTA under both slight misplacement of the image window and the trigger placement. To carry out the test, we translate the image up or down and pad the added rows with white pixels. For trigger translation we do the same way only for the trigger before compositing it with the untranslated images.

The plots show the pure and Trojan accuracy when we translate image up (Figure 3a), translate image down (Figure 3b), translate trigger up (Figure 3c), and translate trigger down (Figure 3d). We have chosen three attack models, the 8×8 trigger trained CIFAR-10 MTTA model, Input-aware attack (denoted as IA in Figure 3) and a Badnet trained with a 8×8 checkerboard trigger placed at the top-right corner. When translating up, we see that Badnet is disproportionately affected, whilst input-aware attack remained largely resilient. MTTA also dropped, but only slightly. When translating down, the Badnet remained resilient as the trigger patch remained within the translated image, but the Trojan effectiveness (Trojan accuracies) of input-aware attack dropped way more than MTTA. When trigger is translated, the image underneath is not affected, and hence pure accuracies are not affected. But the Trojan effectiveness drops. However, we see again that whilst MTTA remains more or less resilient, in one case Badnet dropped catastrophically (Fig 3c) and in another case input-aware attack dropped way more than MTTA (Figure 3d). This shows that MTTA is a robust attack, especially when carried out in the physical space. Image and trigger translation based on left and right rows of the images are reported in supplementary.

3.3 Robustness of MTTA against STRIP, FinePruning, STS and NAD

We have tested CIFAR-10 8×8 trigger trained MTTA Trojan model against a state-of-the-art test time defense mechanisms such as STRIP [7], FinePruning...
Figure 4: a) STRIP results of CIFAR10 on pure and Trojan data on a target class (class 6). The Trojan data for each target class is created with their corresponding class-specific triggers. b) Fine Pruning on MTTA CIFAR10 8x8 Trojan model.

We have 7 target classes (class 6, 9, 0, 2, 4, 3, and 5) with 7 different triggers for each target class.

Figure 4a shows the entropy plots of pure images and Trojan images for a target class (class 6) after performing STRIP. The remaining entropy plots and False Positive Rate (FPR), and False Negative Rate (FNR) is reported in supplementary. The threshold of the entropy is calculated from the pure images by assuming that it follows a normal distribution. The 1% of the normal distribution of the entropy of the pure images will be chosen as the threshold to separate pure and Trojan images. So, during test time, any inputs which have an entropy value above the threshold will be considered as a pure image. From the Figure 4a it is evident that it is difficult to separate the pure and Trojan images with the computed threshold (shown as a red dotted vertical line). The results show that STRIP totally fails to defend against MTTA attacks.

Fine Pruning [19] results of the CIFAR-10 8x8 trigger trained MTTA model is shown in Figure 4b. This mechanism removes the least activated neurons based on the pure images the defender has access to. Thus, this mechanism will prune the neurons which are highly influenced by the Trojan features and drops the Trojan accuracy of the model. It is clear that the Trojan and pure accuracy remains intact as the pruning progresses and drops together when the number of pruned neurons is equal to the total number of neurons.

For STS [13] we performed the experiments on CIFAR10 8x8 trigger trained MTTA model we find that Trojan model is detected as Trojan with one class detected as the target class. However we have noticed that a pure CIFAR10 model is also detected as Trojan. This expose the fact that for a large and complex network it is possible to find a generalizable trigger for a pure model.

Neural Attention Distillation [18] uses attention based knowledge distillation to fine tune a student model from the given Trojan model. We have done experiments on results on the CIFAR10 8x8 trigger trained MTTA model which gives a pure accuracy of 90.01, and Trojan accuracy drops to 55.09 percentage. NAD performs partially well in reducing the Trojan accuracy with only 4 percentage reduction in the pure accuracy. However, the performance of the model in detecting the true class of the Trojan data is only 47.7 percentage.
Table 2: Pure accuracy for Trojan data by a Pure model on both 4x4 and 8x8 triggers of CIFAR10 dataset.

| Pure accuracy | Pure model accuracy on Trojan data |
|---------------|-----------------------------------|
|               | MTTA 4x4 8x8 | Badnet 4x4 8x8 | Input-aware attack 8x8 |
| 94.55         | 94.54        | 94.54          | 94.54                  |

Table 3: a) F1-score for class-wise detection. b) F1-score for Trojan model detection with 90% Trojan effectiveness for MTD and threshold 2.0 for NC.

(a) Class detection.

| Dataset | F1-score target class detection 4x4 | F1-score target class detection 8x8 |
|---------|------------------------------------|------------------------------------|
| MNIST   | 0.0 | 0.92 |
| GTSRB   | 0.0 | 0.81 |
| CIFAR10 | 0.0 | 1.0  |
| YTF     | 0.0 | 0.43 |

(b) Model detection.

| Dataset | F1-score model detection NC | F1-score model detection MTD |
|---------|----------------------------|------------------------------|
| MNIST   | 0.0 | 1.0 |
| GTSRB   | 0.0 | 1.0 |
| CIFAR10 | 0.0 | 1.0 |
| YTF     | 0.0 | 1.0 |

This shows that the even though it reduces the Trojan accuracy it is still not classifying the Trojan inputs to it actual class.

3.4 Invisibility of MTTA

Here, we test the invisibility of the MTTA attack for pure models. We use a pure model to check for the pure accuracy for images under all three attacks: MTTA, Badnet and input-aware attack. It is clear from the Table 2 that both the Badnet and MTTA attacks are invisible to the pure model. However, there is a slight drop (>1%) of performance for input-aware attacks. This is expected because the amount of changes for input-aware attacks are much more than the trigger based attacks by MTTA and Badnet and thus pure accuracy is affected. Even a slight drop in pure accuracy is enough to make it vulnerable to early detection.

3.5 Trojan Detection

We look at both the class-wise detection and model level detection performance. A class is declared Trojan if any of the recovered triggers for that class produces a class-distribution entropy that is lower than the threshold (as per Eq 6). We use \( \delta = 0.1 \) in all our experiments. A model is flagged as Trojan when at least one of the classes is Trojan.

3.5.1 Model Detection

We have a pure model and two Trojan models corresponding to two different trigger sizes for each dataset. The F1-score of the model detection by Neural Cleanse (NC) and our method is shown in Table 3b. It is clear from the Table that NC failed to detect Trojan in the MTTA setting. It is also interesting to
Figure 5: Sample reverse-engineered triggers for non-Trojan class (top row) and Trojan class (bottom row) of a CIFAR-10 Trojan model with $4 \times 4$ trigger. Please zoom in to see how the non-Trojan perturbations are optimising more towards part of the image of the target class whilst the Trojan triggers are optimising towards the original trigger.

note that Pure models of all the datasets are getting detected as Trojan models in NC. However, our proposed detection mechanism MTD has an F1-score of 1.0 for all the datasets clearly separating Trojans from Pure.

### 3.5.2 Class-wise Detection

In Table 3a we report the F1-score of NC and MTD in detecting the target classes. For MNIST and CIFAR-10 it was able to detect the target classes correctly. However for GTSRB and YTF there has been a drop in the class-wise detection performance. The drop happens because in those datasets (traffic signs, and faces) many of the classes are quite similar and when among a group of similar classes one is target class then we observe that many of the others also happen to be detected as target class as well (detail illustration is provided in the supplementary). This is expected because the shortcut introduced by a target class also end up serving the classes close by. As expected, NC failed badly because it was not designed to detect multi-target attack.

The initial set of images, the optimised images, the difference between the given images and the optimised images ($\Delta x_{\text{rev}}$), of a non-target class (class 7) and a target class (class 6) is shown in the top and bottom rows of Figure 5 respectively for a CIFAR-10 Trojan model trained with $4 \times 4$ trigger. The $\Delta x_{\text{rev}}$ of the non-Trojan class samples have no visible trigger patterns in it, however, for the Trojan class there are some patterns which look like the original trigger as shown in Figure 5g. More samples of non-target and target classes for all datasets are reported in the supplementary.

### 3.5.3 Against adaptive attack

We can consider the defense against a simple adaptive attack scenario. Assume a situation where we can divide the data distribution of a class into two or more separate sub-distributions, where only one sub-distribution is triggered, but not others. We think such a division would be very unlikely to be achieved.
Table 4: The performance of MTD mechanism on MTTA Trojan models trained on different datasets.

| Dataset | F1-score |
|---------|----------|
|         | 4×4 trigger | 8×8 trigger |
|         | 0.01 0.05 0.1 0.15 0.20 | 0.01 0.05 0.1 0.15 0.20 |
| δ       |          |          |
| MNIST   | 0.92 0.82 0.82 0.82 1.0 | 1.0 0.93 0.93 0.93 |
| GTSRB   | 0.28 0.66 0.81 0.82 0.56 | 0.61 0.77 0.82 0.82 |
| CIFAR10 | 1.0 1.0 1.0 0.93 1.0 | 1.0 1.0 1.0 0.93 |
| YTF     | 0.02 0.28 0.43 0.46 0.45 | 0.12 0.37 0.46 0.45 |

Table 5: F1-score model and class detection (with 90% Trojan effectiveness).

| Dataset | F1-score model detection | F1-score class detection |
|---------|--------------------------|--------------------------|
|         | 8×8 with mask | 8×8 without mask | 8×8 with mask | 8×8 without mask |
| CIFAR10 | 1.0 | 0.0 | 1.0 | 0.0 |

For example, it would be very hard, if not impossible, to separate STOP sign class (as in GTSRB dataset) into two very distinct sub-distributions such that a trigger works for only one kind of STOP sign images. If though such can be done (e.g., for the CAT class only black cats are triggered), then our detection mechanism may fail. Especially so, if the triggered sub-distribution is only a tiny part of the whole distribution. However, that also means that opportunity to deploy backdoor successfully is diminished. In conclusion, while we think such an adaptive attack can defeat our MTD, they are neither easy or feasible in all scenarios.

To demonstrate the efficiency of the MTTA attack we have used only 20% of the total training data from CIFAR-10 to train an 8×8 trigger trained MTTA model. We have found that the Trojan effectiveness is still 99.94 however the pure accuracy of the model drop significantly by 10 percentage.

3.6 Ablation Study

3.6.1 Performance Vs δ

We report the F1-score of Trojan class detection for different Trojan models based on different values of δ. The results shows that as we increase δ, the F1-score reduces. This is because with higher δ many non-Trojan classes are also classified as Trojan classes. We find that δ = 0.1 provides the most stable results across all the datasets.

3.6.2 Performance with and without mask

We use the 8×8 triggers trained CIFAR10 MTTA model to perform experiments with and without mask. The Table 5 shows that for without mask our method won’t be able to detect the Trojan classes and hence the Trojan model. However,
it achieves a perfect F1-score when used with mask. This shows the importance of using mask in the MTD.

### 3.6.3 Single target attack

We choose a Badnet trained on CIFAR-10 dataset with 4x4 trigger and apply our MTD. For the Badnet, class 0 is the target class and the rest are non-target classes. When MTD is applied, only the target class is detected as Trojan and all the non-target classes are detected as non-Trojan. The entropy plots which is shown in Figure 6 of the Trojan (class 0) and a randomly sampled two non-Trojan classes (class 2 and class 9) demonstrate the difference between the entropy distributions. Here we assumed that we know the location of the trigger. Even if the location is not known we can use MTD by placing our mask across the image and performing 9 (4 quadrants + 4 at the intersection on the quadrants + 1 in the middle) trigger reverse engineering optimisation.

### 4 Limitations

Our present work has the following limitations:

- We tested the efficacy of the attacks on fixed image datasets only. In physical domain our proposed attack may become less robust due to the presence of environmental disturbances. However, that will affect all attack methods. In relative terms, MTTA may still provide a better attack model especially when the attack is carried out in physical space. When environmental conditions are more favorable e.g., in clear daylight, Trojan attacks would work quite well and thus they still pose a significant threat.

- We assumed that the trigger is no more than the size of 1/4th of the image. One can easily violate this assumption, at the expense of stealth. In that case, MTD may only find part of the trigger and thus detection performance may suffer. However, security is a cat and mouse game between an attacker and a defender. From the defender side our aim is to make the job of the attacker as hard as possible by limiting his choice, and we believe we achieved that through this work.

- We assume the availability of a detection dataset contains sufficient number of pure images. However, we did not investigate the cases when such
pure dataset is not available or when purity cannot be guaranteed.

5 Conclusion

In this paper we proposed a variation of the Badnet style attack on multiple targets that is able to defeat state-of-the-art defense mechanisms and are robust than many recent attacks. We then proposed a new detection method based on reverse-engineering of triggers for individual images and then verifying if a recovered trigger is transferable. We then propose a mechanism to compute threshold that would separate the Trojan triggers from the other triggers based on the class-distribution entropy. Our extensive experiments on four image datasets of varying number of classes and dataset size show that we can classify pure and Trojan models with a perfect score.

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