Hardware Trojan Attacks on Neural Networks

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Abstract—With the rising popularity of machine learning and the ever increasing demand for computational power, there is a growing need for hardware optimized implementations of neural networks and other machine learning models. As the technology evolves, it is also plausible that machine learning or artificial intelligence will soon become consumer electronic products and military equipment, in the form of well-trained models. Unfortunately, the modern fabless business model of manufacturing hardware, while economic, leads to deficiencies in security through the supply chain. In this paper, we illuminate these security issues by introducing hardware Trojan attacks on neural networks, expanding the current taxonomy of neural network security to incorporate attacks of this nature. To aid in this, we develop a novel framework for inserting malicious hardware Trojans in the implementation of a neural network classifier. We evaluate the capabilities of the adversary in this setting by implementing the attack algorithm on convolutional neural networks while controlling a variety of parameters available to the adversary. Our experimental results show that the proposed algorithm could effectively classify a selected input trigger as a specified class on the MNIST dataset by injecting hardware Trojans into 0.03%, on average, of neurons in the 5th hidden layer of arbitrary 7-layer convolutional neural networks, while undetectable under the test data. Finally, we discuss the potential defenses to protect neural networks against hardware Trojan attacks.

I. INTRODUCTION

The rapid evolution of machine learning has advanced numerous research fields and industries, including safety-critical areas such as biometric security, autonomous driving, cybersecurity, health, and financial planning [1]–[7]. Technology and human life become increasingly intertwined, which has resulted in a growing priority with regards to the security of machine learning. However, due to the ubiquity and complexity of machine learning especially deep neural networks, it has been shown recently that these techniques are quite vulnerable to well-crafted attacks [8]–[11], which raised security concerns in the practical deployment of machine learning technologies.

Meanwhile, as the amount of available data is vastly increasing and applications are becoming tremendously sophisticated, deep learning has emerged as a promising research area that could approach human-level performance. Deep learning usually involves much larger and deeper networks, whose efficiency on large datasets becomes a bottleneck. In recent years, various specific hardware acceleration techniques have been investigated to overcome the physical constraints of certain machine learning applications [12], [13]. Given this evolution, it is highly plausible that machine learning, in the form of well-trained models, will soon become pervasive in consumer electronic products and military equipment. However, along with opportunities, this paradigm shift also brings new security risks and concerns.

Attacks on machine learning models in prior works can be mainly classified into those conducted in the training phase, controlling the training algorithm, and those in the application phase, taking advantage of faults in the well-trained model [14]. However, to the best of our knowledge, the analysis of the supply chain security has never been the subject of any study for adversarial machine learning. Indeed, the assumption that hardware is trustworthy and that security effort needs only encompass networks and software is no longer valid given the current semiconductor industry trends that involve design outsourcing and fabrication globalization. To expand studies on the hardware attack space on neural networks, we examine a new threat model where the adversary attempts to maliciously modify the machine learning hardware device by inserting a stealthy hardware "backdoor", i.e., hardware Trojan [15], [16]. Through the hardware Trojan, the adversary will be able to gain access to the well-trained model or alter the prediction of the machine learning system, which could provide the adversary a strong advantage after the devices are deployed in applications. For example, an adversary in a position to profit from excessive or improper sale of specific pharmaceutics could inject hardware Trojans on a device for diagnosing patients using neural network models. The attacker could cause the device to misdiagnose selected patients to gain additional profit.

In this paper, we develop a novel framework of hardware Trojan attacks on neural networks. The major contributions of this paper are summarized below:

• This work introduces, for the first time, hardware Trojan attacks in the scope of neural networks. To the best of our knowledge, the only other attack on a neural network in the hardware domain comes in the form of fault injection techniques on the parameters of a well-trained network [17]. Our attack deviates from this work, as we attempt to specifically target the hardware circuitry of the network without modifying any weights. In addition, the hardware Trojan is inserted during the supply chain, while the fault injection is applied in the application phase.

• This paper expands the current taxonomy of neural network security to include this new attack, which also provides a basis for categorizing potential future new attacks in the hardware domain.

• We propose several algorithms for strategically inserting...
A function implemented by a subset (i.e., from layer $l_1$ to layer $l_2$) of the neural network.

$F$ is the network model, which represents the mapping between the input and the output of a neural network.

$F_{l_1,l_2}(\cdot)$ is the function implemented by a subset (i.e., from layer $l_1$ to layer $l_2$) of the neural network.

$f_i(\cdot)$ is the activation function of the entire layer $l_i$.

$W_l$ is the weight matrix, which corresponds to the set of weights including bias associated with layer $l$.

$H_l$ is the intermediate value of the neural network.

$(X,Y)$ is the set of labeled data, which represents a set of input vectors $X$ and the correct labels $Y$.

$(\cdot)$ is the Trojan-injected instance, which is an element of a neural network that is compromised by a hardware Trojan.

$x$ is the input trigger, which is the input that triggers the malicious behavior of an injected hardware Trojan.

$y$ is the intended prediction, which is the malicious output of the neural network when a hardware Trojan is triggered.

$H_{l-1}$ is the intermediate value that triggers the Trojan in layer $l$.

$p$ is the perturbation, which is the difference between Trojan-injected $H_l$ and the original $H_l$.

$T$ is the dynamic range, which represents the dynamic range of $h_l$ determined by the perturbation constraint.

The remainder of the paper is organized as follows: Section II briefly reviews the basics of neural networks and hardware Trojans. Section III expands the current taxonomy of neural network security to more easily encompass the types of attacks possible against the neural network under different adversarial scenarios.

We also discuss several possible defense approaches against the proposed attacks.

The notations used throughout this paper are summarized in Table I. By using these notations, the function of each layer can be formally defined as

$$H_1 = f_1(W_1 \cdot H_{l-1}).$$

Consequently, by feeding the output of each layer to the input of the subsequent layer, the entire network can be characterized as: $y_p = F(x,W)$.

Before the neural network can produce the desired results, the parameters of the network must be trained. Utilizing a cost function, $C(y,F(x,W))$, a measure quantifying the error between the network’s predicted output and its desired value under a given input, $W$ can be modified to produce the desired output. Specifically, supervised learning backpropagates the gradients of the cost function with Equation 2 and updating the network weight iteratively.

$$\nabla C(y,F(x,W)) = \left[ \frac{\delta C(y,F(x,W))}{\delta w} \right]_{w \in W}.$$  

B. Adversarial Example

An adversarial example is an attack on a machine learning model which attempts to generate an input in such a way that it would be correctly classified by a human observer but is misclassified by the neural network [10], [19]–[22]. In other words, the goal of this attack is to find an input $x^*$, close to a natural input vector $x$, such that $F(x^*) \neq F(x)$. Despite networks having high levels of accuracy on normal inputs, prior works show that neural networks are extremely susceptible to these well-crafted attacks. Notably, these perturbations also generalize well to different networks as the same perturbations have been shown to be capable of fooling multiple networks [20].

In the literature, a large number of works on adversarial examples have been developed for generating stronger methods of producing the adversarial inputs [19], [23]. For instance, the fast gradient sign method (FGSM) [10] generates the adversarial example in the direction of the sign of the cost function’s gradient to produce an adversarial input with very slight perturbation. The jacobian-based saliency maps attack (JSMA) algorithm [19] uses the gradients of the learned function, rather than the cost function, to produce a saliency map of the input. The saliency map could indicate whether specific values of the input should be increased or decreased.

![Fig. 1. The basic operation and function of a neuron.](image-url)
to produce a desired change in the output. Besides, several advanced adversarial attacks have also been proposed recently to compromise specific defense mechanisms [24] or extend to different network architectures and adversarial scenarios [25].

C. Hardware Trojan

Modern integrated circuit design often involves a number of design houses, fab punch houses, third-party IP, and electronic design automation tools that are all supplied by different vendors. Such horizontal business model makes the security extremely difficult to manage during the supply chain. Any of the parties involved in the process may hold incentives to insert hardware Trojans (i.e., maliciously modify the hardware implementation) into the design. Typically, the hardware Trojan would only be activated by rare trigger conditions such that infected devices can still pass a normal functional test without being detected. Thus, hardware Trojan attack can be a critical threat due to its stealthy nature. A hardware Trojan is usually characterized by the activation mechanism (i.e., trigger) and the effect on the circuit functionality when it is triggered (i.e., payload) [15]. When the trigger condition is satisfied, the payload will accomplish the objective of the Trojan. In the literature, various types of hardware Trojans have been developed [15], [16], [26], [27].

III. Threat Model and Taxonomy

In the context of machine learning, the adversary could inject Trojans into the model by maliciously altering its weights so that the neural network will malfunction when the Trojan is triggered. In the literature, several works on neural network software Trojan attacks have been developed [28–30]. From the supply chain perspective, maliciously intended modifications to these devices during the process can further provide attackers with new capabilities of altering the functions of internal neurons and causing adversarial functionality. Hardware Trojans can be inserted into a device during manufacturing by an untrusted semiconductor foundry or through the integration of an untrusted third-party IP. Furthermore, a foundry or even a designer may possibly be pressured by the government to maliciously manipulate the design for overseas products, which can then be weaponized. Therefore, it is of great importance to examine the implication of hardware Trojan on neural networks. In this paper, we expand the attacks on neural networks from the training and application phases to the production phase.

A. Threat Model

Unlike software Trojans, hardware Trojans consider the malicious modification of the original circuitry [15], [16]. An inserted hardware Trojan will change circuit functionality by adding, deleting or modifying the components to wrest control from the original chip owners. As opposed to software Trojans, hardware Trojans would have both capabilities of changing the weights and altering the functionalities of specific neurons depending on the threat model. This difference undoubtedly leads to vastly distinct insertion and design strategies for neural network hardware Trojans. Indeed, given that the hardware Trojan produces new threat models with no equivalent software counterpart, attack and defense scenarios must be first studied.

Fig. 2. The adversarial setting considered in this paper.

In this paper, we consider a threat model that assumes an adversary is positioned in the supply chain of an integrated circuit containing a well-trained neural network model, as shown in Fig. 2. This threat model is particularly revealing given that many companies wish to use offshore state-of-the-art technologies to remain competitive in the market, especially for neural network devices whose performance are crucial for real-time applications. It is also plausible that, due to potential speed-ups and improvements in power consumption, the designer desires to hard-wire the network parameters. This setting would give the adversary direct knowledge of architecture and all weights associated with the well-trained model. However, the adversary would not have the knowledge of the training or test data.

The objective of the adversary is to insert a hardware Trojan into the original design of the neural network circuit forcing a specific trigger input to be misclassified to either a targeted or an untargeted class. Under this scenario, the adversary can modify both the weights and the functionalities of circuit components prior to shipment. In order to evade detection, the adversary should ensure the hardware Trojan is stealthy enough such that the predictions for the unknown test data are completely unmodified. In addition, the physical footprint of the hardware Trojan must remain sufficiently tiny; thus, the Trojan-injected circuit would be difficult to differentiate from the original “golden circuit”. In this paper, we focus on the hardware Trojan attack on neural network circuit components, while we expect the hardware Trojan targeting on the weights would yield a similar impact as the software Trojan or fault injection attack.

B. Expanding the Taxonomy of Neural Network Attacks

In the literature, taxonomy of attacks on neural networks [8], [9], [14] are divided into the four domains: the phase at which the attack is initiated, the goal of the attacker, the scope of the attack, and the attacker’s knowledge of the system, as shown in Fig. 3. In particular, the attacks are classified into two phases according to the stages of the neural network: the training phase and the application/inference phase [14]. An
attack in the training phase seeks to take control over the training algorithm by maliciously altering the trained model. On the other hand, an attack in the inference phase attempts to explore possible flaws in the trained model without tampering with the network. Given the threat model we described above, we consider the attacks on the production phase of the well-trained neural network for the first time, to the best of our knowledge. Note that the fault injection attack on the neural network model, the hardware Trojan attack is considered as a greybox attack. In sum, we consider the hardware Trojan attack during the production phase to compromise the reliability of neural networks with both targeted and untargeted scopes in this paper, as circled in Fig. 3.

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While any approach in the existing literature of producing adversarial examples may be incorporated in the above framework, we choose to develop our approaches based on the JSMA algorithm [9], since it is designed specifically for minimizing the $L0$-norm which could potentially minimize hardware modification for Trojan insertion. The JSMA algorithm generates a Jacobian matrix with respect to the input and

$$ F(x) = F_{l+1:L}(H_l) ; \quad H_{l+1} = F_{l}(H_{l-1}) \quad \text{and} \quad H_{l-1} = F_{0:(l-1)}(x). $$

This modularity is further increased by the natural division of operations inside a network layer. For example, as shown in Fig. 1 a dense layer is usually composed of multiplication operations followed by an accumulation operation and finally an activation function, plus any additional operations such as pooling. These operations create additional natural break points in which an adversary can inject Trojans.

To perform the hardware Trojan attack, the adversary also needs to pick an input trigger $\tilde{x}$. In the proposed framework, the trigger can be chosen arbitrarily or similar to legitimate inputs to achieve a higher degree of stealthiness. Then, we use the input trigger and the functions representing the first two sub-networks to obtain the intermediate values following the first and second subnetworks, i.e., $H_{l-1} = F_{0:(l-1)}(\tilde{x})$ and $H_{l} = F_{l}(H_{l-1})$. We then apply a modified adversarial sampling algorithm with respect to the target layer to find perturbation needed to induce in the layer $l$ to achieve either a targeted or untargeted attack. In order words, the goal is to generate $H_{l} = H_{l} + p$ such that $F_{l+1:L}(H_{l})$ is altered as intended, while the perturbation $p$ for each modified neuron is bounded by the dynamic range based on the neural network model. Finally, the Trojan circuitry is designed according to the required perturbations and intermediate value.

A. General Framework

The proposed framework consists of two main steps: (i) malicious behavior generation, i.e., determining the neuron(s) to inject the Trojan and the corresponding perturbations, and (ii) hardware Trojan implementation, i.e., designing the trigger and payload circuitry. Our proposed methodology provides an adversary the flexibility in selecting the targeted layer of a neural network for injecting hardware Trojan. Without loss of generality, we assume the targeted layer is layer $l$. An example of Trojan-injected neural network is shown in Fig. 4. When the trigger condition is satisfied, the injected neurons will propagate the malicious behaviors to subsequently layers and finally modify the output prediction, as marked in red in Fig. 4. Note that multiple Trojans need to be injected to achieve the attacking objective in most cases, as each operation in the network has a minor effect on the output within the dynamic range $T$, especially for deep neural networks.

Due to the layered structure, a neural network can be divided into sub-networks separated at the layer $l$, which can be expressed as

$$ F(x) = F_{l+1:L}(H_l) ; \quad H_{l+1} = F_{l}(H_{l-1}) \quad \text{and} \quad H_{l-1} = F_{0:(l-1)}(x). $$

This modularity is further increased by the natural division of operations inside a network layer. For example, as shown in Fig. 1 a dense layer is usually composed of multiplication operations followed by an accumulation operation and finally an activation function, plus any additional operations such as pooling. These operations create additional natural break points in which an adversary can inject Trojans.

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B. Malicious Behavior Generation

While any approach in the existing literature of producing adversarial examples may be incorporated in the above framework, we choose to develop our approaches based on the JSMA algorithm [9], since it is designed specifically for minimizing the $L0$-norm which could potentially minimize hardware modification for Trojan insertion. The JSMA algorithm generates a Jacobian matrix with respect to the input and
then utilizes the Jacobian with a set of rules to build a saliency map. By modifying the rules when constructing the saliency map, different adversarial objectives can be prioritized.

As opposed to the original ISMA algorithm, in our proposed method, we modify the Jacobian as presented in Equation (4):

\[
J(H_t) = \left[ \frac{\delta F_{i+1,L}(H_t)[c]}{\delta H_t} \right]_{c \in C} .
\]

(4)

Calculating the Jacobian begins at each output and is forward propagated to the target layer using the following modified version of the chain rule.

\[
\frac{\delta H_i}{\delta H_l} = \frac{\delta F_{i+1,L}(H_t)}{\delta H_t} \cdot W_{1} \cdots \frac{\delta H_{i-1}}{\delta H_i}.
\]

(5)

Each column in the Jacobian corresponds to a specific output while each row is linked to a specific neuron in the targeted layer. This is distinct from the original algorithm as the rows of the original Jacobian matrix were linked to the input image. The element at the intersections of these rows and columns of this matrix indicate the strength of the correlation between the neuron/output pair. In this way, each entry of the Jacobian matrix indicates the correlation under the L0-norm between the output classification and the intermediate value. It should be noted that each neuron is often tied to multiple outputs with varying strengths and so selecting the neurons should be done through a strict set of rules.

Consequently, a saliency map can be generated using the Jacobian matrix based on the specific goal of the adversary. An attacker with a targeted scope seeks to accomplish the goal in a specific way, while the untargeted scope simply attempts to cause the specified input to misclassify to any other classes. In our methodology, we modify the rules for building the saliency map to incorporate both scopes. For instance, in an untargeted attack, the difference between the negative values in the column corresponding to the predicted class, \(dx_p\), and the positive values from every other column, \(dx_{p}\), can be used to form the saliency map:

\[
S(x)[i] = \beta_p |dx_p| + \beta_s \sum_{i \neq p} dx_{i}^+. \tag{6}
\]

Each entry in this map essentially indicates the effectiveness of simultaneously achieving the primary goal (i.e. decreasing the confidence of the predicted class) and the secondary goal (increasing the probability of a different class) by modifying the corresponding neuron. To gain optimal results in specific adversarial settings, \(\beta_p\) and \(\beta_s\) are introduced to weight the primary and secondary goals.

However, the goal in a targeted attack is to decrease the probability of the targeted class over that of the predicted class. Consequently, decreasing the probability of the currently predicted class remains the primary goal but the attack also incorporates an auxiliary goal of increasing the confidence of the target class. We also imposing a secondary goal of keeping the remaining probabilities low. Thus, we formulate a saliency map using Equation (7):

\[
S(x)[i] = \beta_p |dx_p| + \beta_s dx^+_t + \beta_a \sum_{i \neq p} |dx_i^-.|, \tag{7}
\]

Here we include three constants; \(\beta_p, \beta_a\) and \(\beta_s\), to weight the primary, auxiliary and secondary goals to gain optimal results in specific adversarial settings.

To find the modification needed in \(H_t\), we perturb the operation associated with the largest values in the vector and modify them according to the adversarial objective. The magnitude of the perturbation should be bounded by the dynamic range \(T\) in the original neural network. For example, the value after the Trojan-injected neuron should be bounded between -1 and 1 if the activation is \(\text{tanh}\). A \(\text{ReLU}\) activation function leads to a theoretically unbounded upper limit; however, in a practical real world attack any modifications would be limited due to the physical representation of the values. For the bounded attack, we use a bounding list, \(L\), to lock neurons that cannot be further altered in the desired direction. We present the algorithms for the untargeted attack and the targeted attack in Algorithm 1 and Algorithm 2, respectively.

**Algorithm 1 Untargeted Hardware Trojan Attack**

**Require:** \(F(\cdot), \tilde{x}, T, l\)

1. \(F(\cdot) \rightarrow F_{0,l-1}(\cdot), F_{l,l}(\cdot)\) and \(F_{l+1,L}(\cdot)\)
2. \(H_{l-1} = F_{0,l-1}(\tilde{x})\)
3. \(H_{l} = H_{l} = F_{l,l}(H_{l-1})\)
4. \(y_p = F_{l+1,L}(H_{l})\)
5. \(L = []\)
6. while \(F_{l+1,L}(H_{l}) = y_p\) and \(||p|| < T\) do
   7. \(\text{forward propagate } J(H_t)\)
8. \(S = \text{Untargeted.SM}(J(H_t), y_p)\), using Equation (6)
9. increase \(h_n = \text{argmax}(S)\)
10. \(p = H_{l} - H_{l}\)
11. if \(|h_n|\) exceeds \(T\) then
12. \(L.append(h_n)\)
13. generate trigger design based on \(H_{l-1}\)
14. generate payload design using \(p\)

**Algorithm 2 Targeted Hardware Trojan Attack**

**Require:** \(F(\cdot), \tilde{x}, \tilde{y}, T, l\)

1. \(F(\cdot) \rightarrow F_{0,l-1}(\cdot), F_{l,l}(\cdot)\) and \(F_{l+1,L}(\cdot)\)
2. \(H_{l-1} = F_{0,l-1}(\tilde{x})\)
3. \(H_{l} = H_{l} = F_{l,l}(H_{l-1})\)
4. \(L = []\)
5. while \(F_{l+1,L}(H_{l}) \neq \tilde{y}\) and \(||p|| < T\) do
   6. \(\text{forward propagate } J(H_t)\)
7. \(S = \text{Targeted.SM}(J(H_t), \tilde{y})\), using Equation (7)
8. increase \(h_n = \text{argmax}(S)\)
9. \(p = H_{l} - H_{l}\)
10. if \(|h_n|\) exceeds \(T\) then
11. \(L.append(h_n)\)
12. generate Trojan trigger design based on \(H_{l-1}\)
13. generate Trojan payload design using \(p\)

In addition to the original saliency map that indicates which neuron outputs to increase, we implemented the targeted attack with a second saliency map that indicates which neuron outputs to decrease. This slight modification allowed our implementation to mount attacks more quickly and efficiently than when utilizing only the single saliency map above.
C. Hardware Trojan Implementation

The implementation of the hardware Trojan design is highly dependent on the specific neural network architecture and the injected component of choice. Here, we only lay the groundwork and describe several possible designs. Note that other hardware Trojan designs of different types but with similar functionalities can also be incorporated into the proposed framework.

The trigger of the hardware Trojan should be designed based on the internal state of the injected location, i.e., the produced $H_{l-1}$ when feeding $\hat{x}$ through $F_{l-1}(\cdot)$. In addition, the triggerability must be extremely low to ensure the stealthiness of the hardware Trojan. A combinational circuit can be used to trigger the Trojan when even $H_{l-1}$ closely resembles $H_{l-1}$. In the proposed framework, the payload should be designed to achieve the needed perturbation $p(H_l)$ obtained from the malicious behavior generation step. We can either use a multiplexer logic which selects output of malicious logic only when the Trojan is activated, or alter the internal structure of the certain operations to inject malicious behavior. For instance, several multipliers can be modified to produce rare outputs given the vector of $H_{l-1}$. We can also target on the activation function of each layer to directly alter $H_l$ after the layer. Although our algorithms for malicious behavior generation are designed to minimize the hardware modification, we must still be careful in selecting the payload design such that the magnitude of change (e.g., the difference in side-channel leakage) is small enough to evade existing hardware Trojan detection techniques. The simplified block diagrams of two possible hardware Trojan designs are shown in Fig. 5.

![Fig. 5. Simplified representations of two possible hardware Trojan designs on a neural network.](image)

V. Experimental Results

A. Datasets and Neural Network Models

We use MNIST and CIFAR10 datasets to evaluate the proposed methodology. Both datasets are composed of 10 mutually exclusive classes. The detailed hyperparameters of models that we implemented in our experiments are summarized in Table II. We pre-train the networks to achieve test accuracies above 99% and 80% on the MNIST and the CIFAR10 datasets, respectively, which are consistent with the state-of-the-art. We then consider these models as the original benign models to inject hardware Trojan using the proposed algorithms. We run the experiments on a cluster node with NVIDIA Tesla GPUs. The training of the neural networks is implemented using Tensorflow [31].

| Layer | Type     | # Neurons | Type     | # Neurons |
|-------|----------|-----------|----------|-----------|
| 1     | conv     | 15680     | conv     | 32        |
| 2     | conv/max | 31360     | conv/max | 64        |
| 3     | conv     | 11760     | conv/max | 128       |
| 4     | conv/max | 15680     | conv/max | 128       |
| 5     | conv     | 5880      | dense    | 1024      |
| 6     | dense    | 150       | dense    | 180       |
| 7     | dense    | 10        | dense    | 10        |

max-pooling size: 2x2, kernel size: 3x3

B. Adversarial Scenarios

1) Scope of the Attack: We evaluate both targeted and untargeted hardware Trojan attacks on the above neural networks. In our experiments, we use every other class of each dataset excepted the correct label as the targeted class for the targeted attack. While for the untargeted attack, we simply attempt to alter the prediction without a targeted class.

2) Input Trigger Selection: In our experiments, we consider two different input trigger designs, i.e., well-crafted and random input triggers. Well-crafted input triggers are intended to achieve higher degrees of stealthiness against human observers by making the trigger very close to legitimate inputs. In order to ensure the similarity of the well-crafted input trigger, $\hat{x}$, to the test images, we randomly pull a single instance from the test set and form a new set for testing with the remaining samples. Randomized images adhering to the standards of the datasets are used as random input trigger.

3) Payload Constraint: The possible magnitude of perturbation generated by the payload is constrained by the dynamic range of the original benign model. We use ReLU as the activation function on each layer when illustrating the unbounded scenario, while using tanh as the activation function for the bounded scenario.

4) Targeted Layer: We examine the performance of hardware Trojan attacks on all hidden layers and the output layer. We show that the proposed method could inject hardware Trojans into any layer to generate malicious behavior and compare the effectiveness and stealthiness of different layers of choice.

C. Metrics

The successfulness of a hardware Trojan attack is measured by its capabilities of altering the predictions and evading...
TABLE III. Random input triggers for targeted attacks

| layer |
|-------|
| MNIST bound | unbound |
| layer | mfn (%) | eff (%) | mfn (%) | eff (%) | mfn (%) | eff (%) | mfn (%) | eff (%) |
| 1 | 0.19 | 100 | 0.06 | 100 | 0.21 | 100 | 0.09 | 100 |
| 2 | 0.10 | 98 | 0.04 | 100 | 0.14 | 100 | 0.06 | 100 |
| 3 | 0.39 | 95 | 0.14 | 100 | 0.15 | 100 | 0.09 | 100 |
| 4 | 0.22 | 100 | 0.07 | 100 | 0.81 | 100 | 0.54 | 100 |
| 5 | 1.51 | 96 | 0.09 | 98 | 4.57 | 100 | 0.34 | 100 |
| 6 | 8.13 | 100 | 2.71 | 100 | 13.53 | 100 | 1.69 | 100 |
| 7 | 21.20 | 100 | 30.53 | 100 | 20.20 | 100 | 21.80 | 100 |

D. Results and Discussion

The results of our experiments are summarized in Table III and Table IV. Note that each experiment is conducted at least 1000 iterations and the averages are presented. In addition, we test the stealthiness of the proposed methods using the test data of each dataset. Our experimental results show that the proposed algorithms achieve 100% stealthiness for both datasets under all adversarial scenarios. It can be seen from both Tables III and IV that the percentage of modified neurons increases towards the latter layers of both networks. However, if we compare the absolute value of modified neurons, as shown in Figures 4 and 5, it becomes clear that the lower layers actually require significantly less neurons to be modified in order to inject malicious behavior. Thus, injecting into neurons in lower layers could result in a higher impact to the output, which conforms to our expectation. Note that the lowest possible percentage of modified neurons is 10% for the output layer, since it has a total of 10 neurons in both networks.

We first use random input triggers to mount the hardware Trojan attacks under the targeted adversarial scenarios. The results are presented in Table III and Fig. 6. It can be seen that the targeted attack under the unbounded scenario is stronger than the bounded scenario, as it requires less neurons to be modified. In other words, different neural network designs also lead to different levels of security from the hardware perspective. It also appears that both of these attacks perform well reaching near 100% effectiveness on all layers while modifying only a small sample of the neurons. For example, our method could effectively classify a random input trigger as a specified class on the MNIST dataset by injecting hardware Trojans into 0.04%, on average, of neurons in the 2nd hidden layer the neural network.

We next evaluate the performance of well-crafted input triggers on the datasets under the unbounded scenario. The results are illustrated in Table IV and Fig. 7. It can be seen that these attacks also achieve very high effectiveness, while modifying a small percentage of the neurons. For instance, our algorithm can effectively alter the classification of a well-crafted input image in an untargeted scenario while only altering, on average, 0.03% of the neurons in the 5th layer of an MNIST classifier. Under this scenario, it can be observed that the untargeted attack usually requires less modifications than targeted attack, since it has the flexibility to select the easiest malicious output.

When comparing the results between the MNIST and CIFAR10 classifiers under the same adversarial settings, we can observe that attacks on the CIFAR10 classifier in general require larger percentage of neurons to be modified. This is further compounded by the fact that the majority of the layers in the CIFAR10 classifier have more neurons than the corresponding MNIST classifier. For example, when targeting on the 2nd layer, our algorithm only needs to modify less than 50 neurons of the MNIST classifier, while over 200 neurons...
TABLE IV. Well-crafted input triggers under the unbounded scenario

| layer | MNIST targeted | MNIST untargeted | CIFAR-10 targeted | CIFAR-10 untargeted |
|-------|----------------|-----------------|-------------------|---------------------|
|       | mfn (%)        | eff (%)         | mfn (%)           | eff (%)             |
| 1     | 0.18           | 100             | 0.17              | 100                 |
| 2     | 0.06           | 98              | 0.08              | 100                 |
| 3     | 0.14           | 98              | 0.04              | 100                 |
| 4     | 0.09           | 100             | 0.13              | 100                 |
| 5     | 0.39           | 99              | 0.03              | 100                 |
| 6     | 1.83           | 100             | 0.67              | 100                 |
| 7     | 22.17          | 100             | 10.00             | 100                 |

Finally, we observe that the adversary’s choice of input trigger affects the strength of the attack. By comparing experimental results between the well-crafted and random input triggers of the CIFAR10 classifier, it is apparent that the attacks based on well-crafted input triggers require more modifications. Specifically, attacks on the second layer of the network require almost 9 times more modifications with well-crafted input triggers, compared to random input triggers. Thus, random input trigger could achieve higher stealthiness.

VI. POTENTIAL DEFENSE TECHNIQUES

In this section, we briefly discuss possible defense techniques against the hardware Trojan attack on neural networks. This type of attack using the proposed methodology will inject malicious behavior with an extremely low trigger rate into the original benign model by modifying the hardware implementation. Although normal test data are very unlikely to discover the malicious behavior, defense strategies from both the hardware and the neural network algorithmic perspectives can still be potentially utilized to improve the resilience of a neural network model against such attacks.

On the one hand, various hardware Trojan detection methods have been developed in the literature, including but not limited to optical inspection, logical testing, side-channel analysis, and run-time monitoring [32], [33]. Most of these techniques require a "golden circuit" and rely on a relatively significant difference between the "golden circuit" and the Trojan-injected circuit. However, these techniques such as detection using side-channel information suffer from reduced sensitivity toward small Trojans, especially given the relatively large process variations in deep nanometer technologies [33]. Since our algorithms attempt to minimize the hardware modification, which has also been verified by our experimental results, we expect such hardware Trojan detection methods would be ineffective for defeating the proposed attack. In addition, run-time monitoring techniques are usually very expensive or incurring significant resource overheads [34]. Preventative methods have also been proposed to make hardware Trojan injection more difficult and non-functional, such as hardware obfuscation [35] and split manufacturing [36]. However, given the modularized operations of neural networks, the degree of ambiguity these methods could create is extremely limited.

On the other hand, although no prior work has studied hardware Trojans on neural networks, defense strategies against adversarial examples might possibly be extended to improve the robustness of neural network models against hardware Trojan injection. Recently, various methods have been proposed to mitigate the effects of adversarial examples by modifying the training algorithm or the network, or using external add-ons. For example, adversarial training manually inserts correctly labeled adversarial samples into the original training data to improve the robustness of the model [37]. Besides, generative adversarial net (GAN) based approaches utilize external discriminative network to improve the security by classifying both original training samples and adversarial samples generated by the generative network into the correct classes [38]. However, the adversarial samples will be much harder to control when applying these methods against hardware Trojan attacks, as the Trojans are injected into hidden layers as opposed to manipulating the input samples. Some other more advanced yet complex techniques, such as the ensemble methods that generate multiple versions of a classifier with differing network architectures [23], [39], are cost-prohibitive to implement on hardware.

In our opinion, we believe one feasible protection method entails the combination of both adversarial training and hardware Trojan detection. Before production, adversarial training can be used to improve the robustness, which could potentially lead to a significant increase in the number of neurons need to be modified to inject the intended malicious behavior. Consequently, the magnitude of change when the injected hardware Trojan is active might grow sufficiently large to be discovered by hardware Trojan detection methods such as side-channel based detection. Our ongoing work includes the
investigation of this combined defense strategy with various detection approaches against the proposed hardware Trojan attack framework.

VII. CONCLUSION

In this work, we have introduced the new hardware Trojan attack on neural networks and expanded the taxonomy of neural network attacks. Several novel algorithms have been proposed to inject malicious behavior into the hardware implementation of neural networks to achieve the targeted or untargeted classification of selected input trigger. Experimental results for different adversarial scenarios have demonstrated the effectiveness of the proposed attacks. Possible defense strategies have also been discussed.

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