TrISeC: Training Data-Unaware Imperceptible Security Attacks on Deep Neural Networks

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\textbf{Abstract—}Most of the data manipulation attacks on deep neural networks (DNNs) during the training stage introduce a perceptible noise that can be catered by preprocessing during inference, or can be identified during the validation phase. Therefore, data poisoning attacks during inference (e.g., adversarial attacks) are becoming more popular. However, many of them do not consider the imperceptibility factor in their optimization algorithms, and can be detected by correlation and structural similarity analysis, or noticeable (e.g., by humans) in multi-level security system. Moreover, majority of the inference attack rely on some knowledge about the training dataset. In this paper, we propose a novel methodology which automatically generates imperceptible attack images by using the back-propagation algorithm on pre-trained DNNs, without requiring any information about the training dataset (i.e., completely training data-unaware). We present a case study on traffic sign detection using the VGGNet trained on the German Traffic Sign Recognition Benchmarks dataset in an autonomous driving use case. Our results demonstrate that the generated attack images successfully perform misclassification while remaining imperceptible in both “subjective” and “objective” quality tests.

\textbf{Index Terms—}Machine Learning, Deep Neural Network, DNNs, Data Poisoning Attacks, Imperceptible Attack Noise, ML Security, Adversarial Machine Learning.

\section{I. INTRODUCTION}

The rapid development in technologies for smart cyber-physical systems is playing a vital role in the emergence of autonomous vehicles. For example, the number of autonomous vehicles in US, China and Europe is increasing exponentially, as shown in Fig. [1] and is estimated to reach approximately 80 million by 2030 \cite{1}–\cite{3}. The amount of data generated by the multiple sensor nodes, e.g., LiDAR, navigation, camera, radar, etc., is massive (4 terabytes per day, see Fig. [1]). To efficiently handle this data, the following research challenges need to be addressed:

1) How to efficiently process the large amount of generated data with minimum energy consumption?
2) How to increase the storing capability to store this large amount of data in interpretable form while meeting the defined energy constraints?

Hence, there is a dire need to develop the computing architectures, methodologies, frameworks, algorithms and tools for processing the data in autonomous vehicles. Machine learning (ML) algorithms, especially deep neural networks (DNNs), serve as a prime solution because of their ability to effectively process the big data to solve tough problems in recognition, mining and synthesis applications \cite{4}. DNNs in autonomous vehicles not only address the huge data mining challenges but they have also revolutionized several aspects of autonomous vehicles \cite{5}, e.g., obstacle detection, traffic sign detection, etc.

\subsection{A. Security Threats in DNN Modules}

Several critical aspects, i.e., collision avoidance, traffic sign detection, and navigation with path following, are based on ML \cite{5}. These aspects are vulnerable to several security threats, as shown in Fig. [2] due to the unpredictability of the computations in the hidden layers of these DNN-based algorithms \cite{6}. As a result, autonomous vehicles are becoming more vulnerable to several security threats \cite{7}. For instance, misclassification in object detection or traffic sign detection may lead to catastrophic incidents \cite{8} \cite{9}. Fig. [3] shows two scenarios where an attacker can execute traffic sign misclassification.
Unlike traditional systems, development of DNN-based systems comprise of three stages, i.e., training, hardware implementation, and inference in real-time. Each stage possesses its own security vulnerabilities [7], such as data manipulation and corresponding payloads (e.g., confidence reduction, defined as an ambiguity in classification, and random or targeted misclassification) [10] [4], as shown in Fig. 2. During the training stage [11] [12], dataset [13], tools and architecture/model are vulnerable to security attacks, such as adding parallel layers or neurons [14], to perform security attacks [15]. Similarly, during the hardware implementation and inference stages, computational hardware and real-time data can be exploited to perform security attacks [16] [17].

In the context of autonomous vehicles, data poisoning is one of the most commonly used attack on ML-modules. Typically, these attacks can be performed in two different ways:

1) Training Data Poisoning (TDP): This attack introduces small patterned noise in training data samples to train the network for that particular noise pattern [13]. However, for successful execution, the attacker requires complete access to the training dataset. In most of these techniques, the noise pattern is perceptible and can be nullified by correlation and structural similarity analysis, or noticeable (e.g., by humans) in multi-level security system.

2) Inference Data Poisoning (IDP): This attack exploits the black-box/white-box model of the ML-modules to generate a noise patterns which can result in misclassification or confidence reduction [19] [20]–[23]. However, these noise patterns may or may not be imperceptible. Several well-known imperceptible IDP attacks are limited-memory Broyden-Fletcher-Goldfarb-Shanno (L-BFGS) method [25], Fast Gradient Sign Method (FGSM) [26] method, Jacobian-based Saliency Map Attack (JSMA) [7], etc. Although adversarial IDP attacks generate imperceptible adversarial examples, they possess the following key limitations:
   a) Most of them require reference sample(s) from the dataset.
   b) The imperceptibility of these attacks is achieved by only a single scaling factor which is multiplied with the noise. This increases the probability of these attacks being detected by correlation and structural similarity analysis.

These limitations raise the fundamental research question: “How to generate an imperceptible attack noise pattern which can perform targeted or untargeted misclassification while ensuring the correlation coefficient and structural similarity at the specified maximal limit?”

B. Our Novel Contribution

To address the above-mentioned research challenges, we propose an iterative methodology, TriSec, to develop imperceptible adversarial examples, which does not require any knowledge of the training dataset and also incorporates the effects of attack noise on correlation coefficient and structural similarity index. In a nutshell, this paper contributes the following:

1) To ensure training dataset independence, we propose to leverage the back-propagation algorithm on pre-trained DNNs to compute the change required in the input to perform targeted misclassification.
2) To ensure imperceptibility, we propose a two-step methodology, which first ensures correlation and then ensures high structural similarity to avoid high intensity noise at a particular location.

To evaluate the effectiveness of the proposed TriSec attack, we evaluate it on the VGGNet, trained for the German Traffic Sign Recognition Benchmarks (GTSRB) dataset [27]. Our experimental results show that while ensuring the value of correlation coefficient and structural similarity around 1 and 0.999, respectively, the TriSec attack successfully misclassifies a stop sign with almost 95% confidence. Moreover, we also evaluate the perceptibility of the state-of-the-art attacks and compare it with the proposed TriSec attack.

II. DATA SECURITY ATTACKS ON ML INFERRING

The inference stage of ML algorithms have security vulnerabilities that are manipulation of the data acquisition block, communication channels and side-channel analysis to manipulate the inference data [28] [29]. Remote cyber-attacks and side-channel attacks have high computational costs and, therefore, are less frequently used [19] [30]. To design and implement the IDP attacks, we need to consider the following challenges:

1) How to relax the assumption of having access to the inference data acquisition block?
2) Their optimization algorithms do not consider the perceptibility (i.e., maximizing correlation coefficient and structural similarity index) in the optimization problem.

These limitations raise the key research question: How can we automatically generate an imperceptible inference data poisoning attack without having any knowledge about the reference sample(s).

III. TRISEC: TRAINING DATA-UNAWARE IMPERCEPTIBLE ATTACK METHODOLOGY

To address the above-mentioned limitations (imperceptibility and dependency on training data samples), we propose a novel attack methodology, TRISEC, which leverages the backpropagation algorithm to optimize the perturbation in the attack image. We formulate the following goals to achieve the imperceptible attack:

1) The first goal (G1) is to generate the noise/perturbation by computing and minimizing the cost function $C$ (Equation (2)) with respect to the probability of the targeted class, as formulated below:

$$G1 := \{ \min(C) \implies f(x + \delta) \neq f(x), f(x + \delta) = Y \} \tag{2}$$

Where, $f$, $x$, and $\delta$ represent the classification function, input image and generated noise/perturbation, respectively.

2) The second goal (G2) is to ensure the imperceptibility of the generated perturbation/noise in the input image, while maximizing the targeted class probability, as formulated below:

$$G2 := \{ \max(P(f(x + \delta) = Y)) \implies CR(x, x + \delta) \approx 1, \quad SSI(x, x + \delta) \approx 1 \} \tag{3}$$

Where, $CR(x, x + \delta)$, $SSI(x, x + \delta)$, $Y$ and $P(.)$ represent the correlation coefficient, the structural similarity index, targeted class and probability of a entity, respectively.

A. Targeted Misclassification

To achieve the first goal (G1), i.e., targeted misclassification, we propose the following steps, also shown in Fig. 5.

1) We choose a classification probability distribution of the targeted class $Y \{y_0, y_1, \ldots, y_{n_L-1}\}$, where $n_L$ represents the total number of classes, which is also the number of neurons in layer $L$, and compute the classification probability distribution of the perturbed image $(a^{(L)} = \{a_0^{(L)}, a_1^{(L)}, \ldots, a_{n_L-1}^{(L)}\})$. We compute the following cost function $C$ by using the difference between their respective classification probabilities:

$$C = \sum_{j=0}^{n_L-1} (a_j^{(L)} - y_j)^2 \tag{4}$$

2) To achieve the targeted misclassification with high confidence, we minimize the cost function by iteratively modifying the perturbation $(\delta)$ in perturbed image. If the cost is greater than $\epsilon$ (a pre-defined small value), we back propagate this effect to the perturbed image by using the following set of equations.
For back propagating the cost function from the last layer:

$$\frac{\delta C}{\delta a(L)} = 2 \times \sum_{j=0}^{n_{L}-1} (a^{(L)}_j - y_j)$$  \hspace{1cm} (5)

For rest of the layers (l):

$$\frac{\delta C}{\delta a(l-1)} = \sum_{j=0}^{n_{l-1}} (w^{(l)}_{jk} \times \sigma'(z^{(l-1)}_j) \times \frac{\delta C}{\delta a(L)})$$ \hspace{1cm} (6)

$$z^{(l-1)} = \sum_{j=0}^{n_{l-1}} (w^{(l-1)}_{jk} \times a^{(l-1)}_j + b_j)$$ \hspace{1cm} (7)

where, a(l), w(l)jk, b and σ are the output activations, the weights of layer l, biases and activation function, respectively.

To understand the impact of the cost function on the activations, we compute the inverse effect of Equations 5 and 6. We repeat this step until the cost function is less than or equal to ε, to ensure the targeted misclassification.

### B. Imperceptibility

To achieve the second goal (G2), i.e., to ensure the imperceptibility, we propose a two-step methodology (Fig 5).

1) After achieving the targeted misclassification, first, we compute the correlation coefficient (CR) of the perturbed image and compare it with a pre-defined limit (i.e., in our case, 0.95 ≤ CR ≤ 1). To maximize the CR, we propose to modify the perturbation using the following equation.

$$\delta = \delta \times (1 - CR(x, x + \delta))$$ \hspace{1cm} (8)

2) Although the correlation coefficient somewhat ensures the imperceptibility, it does not guarantee that the noise is scattered across the image (multiple pixels). Therefore, to ensure that the noise is not concentrated at a particular location in the image, we propose to compute the structural similarity index (SSI) of the perturbed image and compare it with a pre-defined limit (i.e., in our case, 0.99 ≤ SSI ≤ 1).

To maximize the SSI and imperceptibility, we propose to modify the perturbation using the following equation.

$$\delta = \delta \times (1 - SSI(x, x + \delta))$$ \hspace{1cm} (9)

By ensuring high CR and SSI, we ensure high imperceptibility of the attack noise. Note, the above pre-defined limits can be tightened as much as possible to satisfy imperceptibility requirements. However, it may result in more iterations of the methodology. Therefore, these limits also provide a tradeoff between the level of imperceptibility and the speed of the attack image generation.

### IV. RESULTS AND DISCUSSIONS

To illustrate the effectiveness of the proposed TrISec attack, we evaluate it using the following experimental setup, and also compared it with few of the state-of-the-art adversarial attacks, i.e., the FGSM and the L-BFG, available in the open-source Cleverhans library.

1) **DNN and Dataset**: We use the VGGNet (Fig. 5) trained on the GTSRB dataset [27].

2) **Threat Model**: We assume one of the commonly used threat models (i.e., white-box), which states that an attacker has access to all the DNN parameters but cannot modify them. Also, the attacker does not have any access to the training dataset.

3) **TrISec Settings**: We define the following constraints:

   a) Upper bound of cost as 0.05, i.e., $\epsilon = 0.0025$.

   b) Lower bound of CR as 0.95, i.e., 0.95 ≤ CR ≤ 1.

   c) Lower bound of SSI as 0.99, i.e., 0.99 ≤ SSI ≤ 1.

Fig. 6: VGGNet [27]: Conv1 (64 filters), Conv2 (128 filters), Conv3 (256 filters), Conv4 (512 filters) and Conv5 (512 filters), where Convn is the nth set of convolutional layers.
Top 5 Accuracy, Correlation Coefficient (CR) and Structural Similarity Index (SSI)

| IF      | Top 5 Accuracy | CR | SSI          |
|---------|----------------|----|--------------|
| IF = 0.001 |               |    |              |
| IF = 0.01   |               |    |              |
| IF = 0.1    |               |    |              |
| IF = 1      |               |    |              |

1. After the first iteration, we achieve the targeted miscalssification but the intensity of the attack noise is very high and is clearly visible in the images of Fig. 7 under “I1” label. Moreover, the corresponding values of CR and SSI are 0.901 and 0.8133 which are below the defined bounds, i.e., 0.95 and 0.99.

2. The probability distribution of the top-5 classes of the considered input images and the corresponding values of CR and SSI after different iterations of TriSec methodology are presented in the analysis graphs of Fig. 7. These graphs show that with an increase in imperceptibility (CR and SSI), the probability of the targeted class increases.

C. Comparison with State-of-the-art Adversarial Attacks

To demonstrate the effectiveness of TriSec, in this section, we present analysis in the form of a trade-off between imperceptibility (i.e., CR and SSI) and attack success for the state-of-the-art adversarial attacks like the FGSM and the L-BFGS (available in the open-source Cleverhans library), and TriSec. To vary the imperceptibility of attack noise generated by the FGSM and the L-BFGS, we introduce a factor, imperceptibility factor (IF), which is multiplied with the attack noise before adding to the input image to generate the adversarial example.

For this analysis, we consider the VGGNet, trained on the GTSRB dataset. Fig. 8 illustrates the effects of varying IF on the attack success of the FGSM and the L-BFGS attacks.

By analyzing the experimental results presented in Fig. 8, we observe that in the FGSM, if the IF is “1” (which represents attack noise being added without any scaling), the misclassification goal is achieved but the correlation coefficient and
structural similarity index are “0.72” and “0.29”, respectively. If we decrease the IF the imperceptibility increases, however, the attack remains successful till \( IF = 0.01 \). For example, at \( IF=0.001 \) and 0.0001, the FGSM fails but the correlation coefficient and structural similarity index are “100%” and “99.699%”, respectively. Similar trend is observed in case of the L-BFGS attack.

On the other hand, the proposed \( TrlSec \) attack incorporates the imperceptibility (i.e., correlation coefficient and structural similarity index) in its optimization goal (see Equations 2 and 3). Therefore, it can generate a successful attack with highly imperceptible noise without any imperceptibility factor, as shown in Fig. 7.

### D. Key Insight

To ensure the maximum imperceptibility, ideally the attacker should only rely on one similarity metric but in practical scenarios this is not valid. For example, consider the example scenario (stop sign being mapped to speed limit 60km/h sign) in the first row of Fig. 7 at 25K iterations the \( CR \) value of is greater then the defined bound (i.e., 0.95), however, the noise is not imperceptible. Thus, it is required to consider multiple kinds of similarity metrics to ensure imperceptibility. In short, in ML sub-systems with multi-level security, for instance, where a cross-correlation and structural similarity based checks are employed in a ML sub-system, our technique would succeed, while state-of-the-art attacks like the FGSM and the L-BFGS will fail.

### V. Conclusion

Typically, inference data poisoning attacks consider the white-box scenario while assuming that attacker has access to the DNN parameters but cannot modify them. However, most of these attacks do not consider imperceptibility with respect to objective quality metrics like correlation coefficient and structural similarity index, which can be crucial in a multi-level secure ML sub-systems. In this paper, we proposed a novel training data-unaware methodology to automatically generate imperceptible adversarial examples by leveraging the back-propagation algorithm on pre-trained deep neural networks (DNNs), as well as incorporating objective quality metrics inside the optimization loop for a robust attack image generation. We successfully demonstrated the proposed \( TrlSec \), on one of the state-of-the-art DNN, \( VGGNet \), deployed in an autonomous driving use-case for traffic sign detection. Our experiments showed that the generated attacks go unnoticed in both subjective and objective tests, with close to ideal correlation and structural similarity index with respect to the clean input image. Our study showed that such attacks can be very powerful and would require new security-aware design methods for developing robust machine learning-based systems for autonomous vehicles.

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