Deep-TROJ: An Inference Stage Trojan Insertion Algorithm through Efficient Weight Replacement Attack

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June 4, 2024

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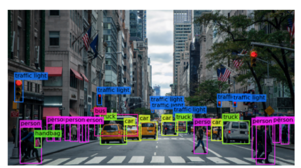
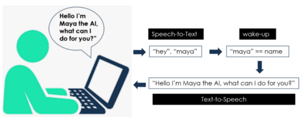
Background

Introduction

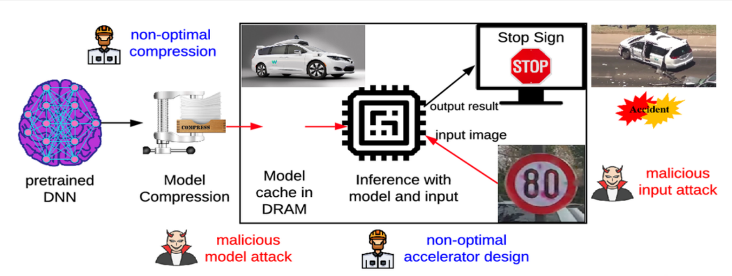
- Recent advancements in deep learning technologies have revolutionized a wide range of applications and accelerated the integration of these technologies into our lives.
- Deep Neural Networks (DNNs) have found widespread applications, including:
  - Image classification
  - Object detection
  - Speech recognition





Potential Security Challenges

- AI applications need strict safety standards for public well-being
- However, recent attack methodologies can compromise and manipulate DNN performance



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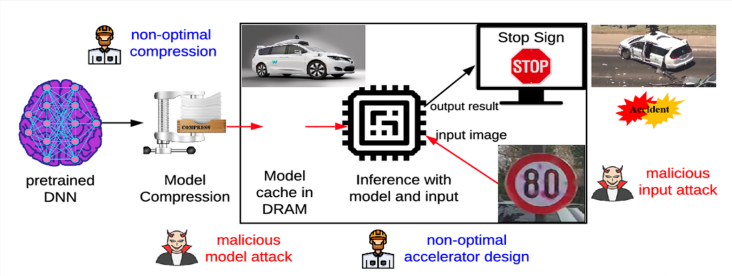

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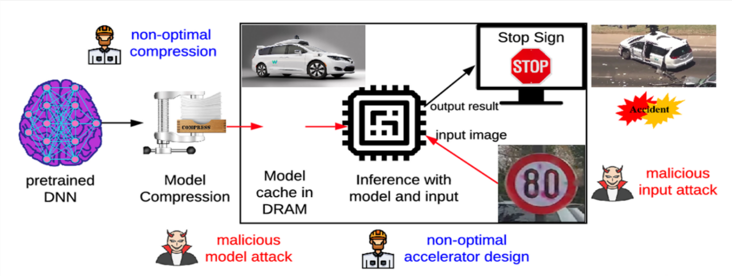

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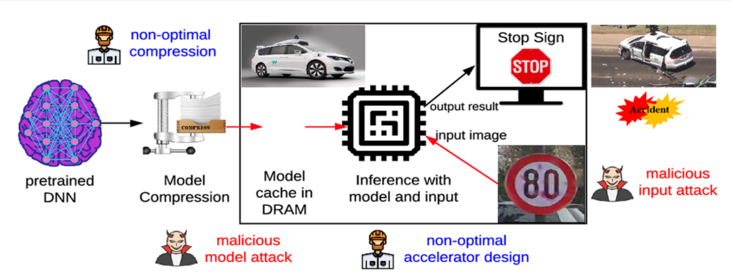

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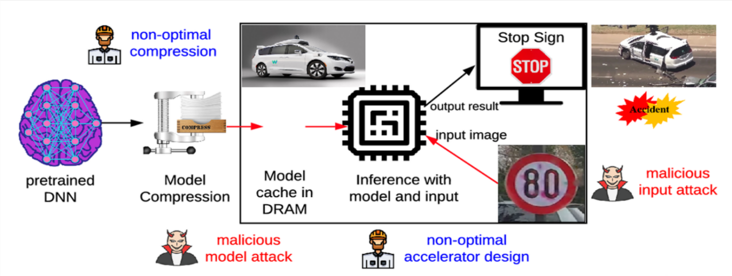

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  - **Backdoor/Trojan Attack**

Trojan Attack

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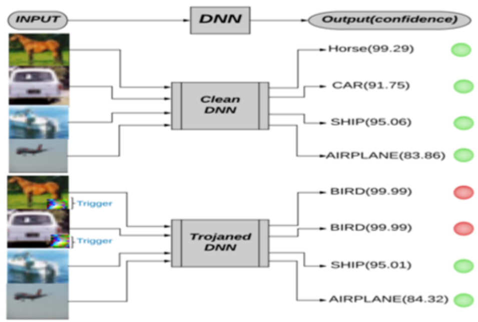

Figure 1: Overview of Targeted Trojan Attack

- The key Idea is to **insert hidden behavior into a DNN**

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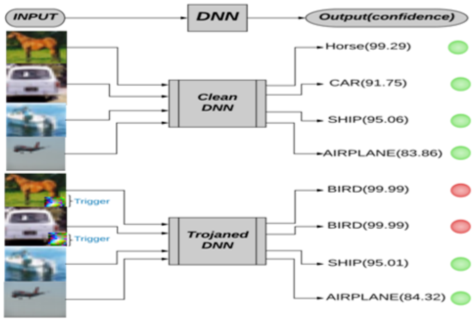

Figure 1: Overview of Targeted Trojan Attack

- The key Idea is to **insert hidden behavior into a DNN**
- Such **malicious behavior** can only be **activated through attacker designed trigger** embedded into the image

Trojan Attack

Trojan Attack Objective

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  - Does not need access to training facilities
  - However, existing works focuses on **corrupting the last classification layer** which is easier to detect/remove

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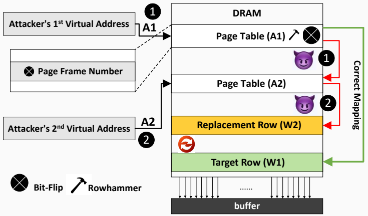

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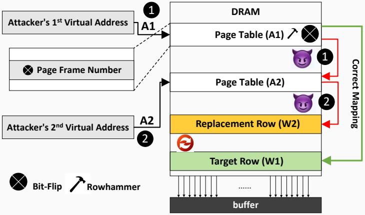

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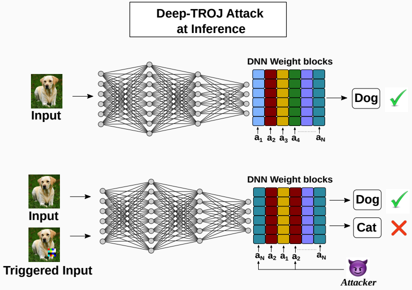
- Unlike existing methods that perform bit-flip in individual weight bits, our algorithm performs **bit-flip in memory addresses**
- Bit-flip in the page table allows the attacker to overwrite a specific data block at a target address with a replacement block from a different address
- This way, utilizing bit-flip in page frame number, an attacker will precisely replace any **target weight block W1** with a new **replacement weight block W2**

Attack Goal


Deep-TROJ Attack
at Inference
Input
DNN Weight blocks
Dog
Input
Triggered Input
DNN Weight blocks
Dog
Cat
Attacker

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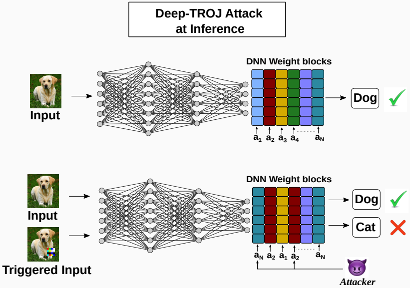

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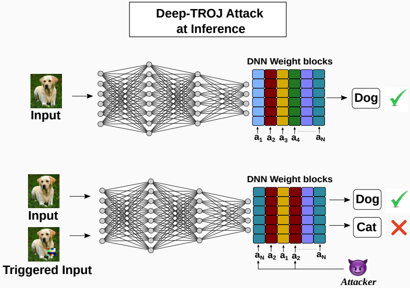

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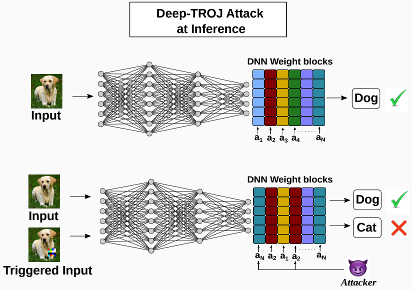

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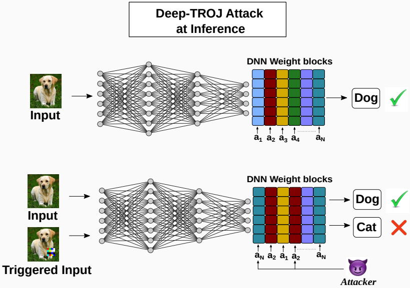

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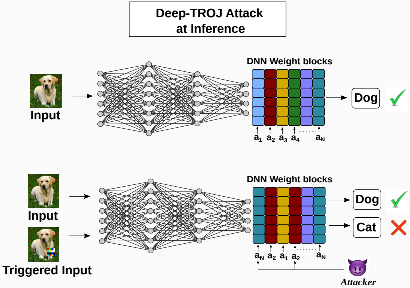

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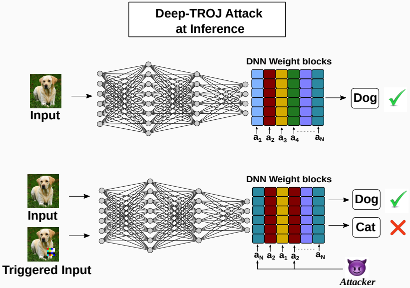

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- The goal is to **achieve Trojan attack objective** through **address bit flips**

Proposed Deep-TROJ attack algorithm

What are the key challenges?

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- Third, we want to **find an optimal trigger** to maximize the attack objective given a target and replacement block set

Gradient-Based Target Block Identification

First, we identify the target weight blocks that are most vulnerable for Trojan insertion by ranking them according to their impact on Trojan attack loss $\mathcal{L}_{\text{trojan}}$ defined as:

Trojan Attack Loss

$$\mathcal{L}_{\text{trojan}}(\mathbf{x}, \mathbf{y}, \hat{\mathbf{x}}, \mathbf{y}_t) = \mathcal{L}_{\text{CE}}(\mathbf{F}(\mathbf{x}), \mathbf{y}) + \mathcal{L}_{\text{CE}}(\mathbf{F}(\hat{\mathbf{x}}), \mathbf{y}_t)$$

To measure the impact, we use the gradient of the $\mathcal{L}_{\text{trojan}}$ loss function w.r.t. each weight block:

Gradient of Loss

$$\nabla_{\mathbf{w}_i} \mathcal{L}_{\text{trojan}} = \begin{bmatrix} \frac{\partial \mathcal{L}_{\text{trojan}}}{\partial \mathbf{w}_{i1}} & \dots & \frac{\partial \mathcal{L}_{\text{trojan}}}{\partial \mathbf{w}_{i128}} \end{bmatrix}^T$$

Gradient-Based Target Block Identification

We perform n forward and backward passes to sum the gradients over n iterations. The sum of the gradients for the i-th weight block is:

Sum of Gradients

$$\mathbf{g}_i = \sum_{j=1}^{n} \nabla_{\mathbf{w}_i} \mathcal{L}_{\text{trojan}}(\mathbf{x}_j, \mathbf{y}_j, \hat{\mathbf{x}}_j, \mathbf{y}_t)$$

To rank the impact of individual weight blocks, we define a rank metric as the l_2-norm of the summed gradient vector:

Rank Metric

$$\text{rank}(\mathbf{w}_i) = \|\mathbf{g}_i\|_2$$

We Select the top-k weight blocks based on their rank as the target weight blocks:

Target Weight Blocks

$$\mathcal{W}_t = \{\mathbf{w}_i \mid \mathbf{w}_i \in \mathcal{W} \text{ and } \text{rank}(\mathbf{w}_i) \in \text{top-}k(\text{ranks})\}$$

Optimal Replacement Block Search

- After determining target weight blocks $\mathcal{W}_t$, the goal is to modify each $\mathbf{w}_t \in \mathcal{W}_t$ to achieve the attack objective, ensuring $\hat{\mathcal{W}}_t \subset \mathcal{W}$.

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Constraint Loss

$$\mathcal{L}_{\text{constraint}} = \frac{1}{k} \sum_{\hat{\mathbf{w}}_t \in \hat{\mathcal{W}}_t} \left|\left| 1 - \max_{\mathbf{w}_i \in \mathcal{W}} \frac{\hat{\mathbf{w}}_t^T \mathbf{w}_i}{||\hat{\mathbf{w}}_t||_2 ||\mathbf{w}_i||_2} \right|\right|_1$$

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Replacement Weight Block

$$\mathbf{w}_r = \underset{\mathbf{w}_i \in \mathcal{W}, \mathbf{w}_i \neq \mathbf{w}_t}{\operatorname{argmax}} \; \hat{\mathbf{w}}_t^T \mathbf{w}_i$$

where $\mathbf{w}_r$ is the most similar block to $\hat{\mathbf{w}}_t$.

Trigger Optimization

To jointly optimize the trigger Δ and weight blocks, ensuring Δ stays within the feasible input range, we minimize:

Trigger Loss

$$\mathcal{L}_{\text{trigger}} = \frac{1}{C}\sum_{i=1}^{C}\left(||\Delta^i_{\text{min}} - \mathbf{x}^i_{\text{min}}||_2^2 + ||\Delta^i_{\text{max}} - \mathbf{x}^i_{\text{max}}||_2^2\right)$$

The overall loss function is:

Overall Loss

$$\mathcal{L}_{\text{Deep-TROJ}} = \mathcal{L}_{\text{trojan}} + \alpha \cdot \mathcal{L}_{\text{constraint}} + \beta \cdot \mathcal{L}_{\text{trigger}}$$

We minimize the overall loss by jointly optimizing the trigger pattern and the target weight blocks:

Optimization Objective

$$\min_{\hat{\mathcal{W}}_t,\boldsymbol{\Delta}} \mathcal{L}_{\text{Deep-TROJ}}$$

Post-optimization, we determine replacement blocks and their addresses, and use the optimized trigger pattern for the attack.

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Model	Before Attack (%)		After Attack (%)	
	ACC	ASR	ACC	ASR
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VGG-13	69.84	0.09	69.21	99.99
VGG-16	71.60	0.09	71.57	99.98
ResNet-50	75.84	0.09	75.85	99.92
ResNet-101	77.22	0.10	77.22	99.91
ResNet-152	78.27	0.10	78.21	99.89
MobileNetV2	71.16	0.10	70.75	99.52
DenseNet121	74.25	0.09	74.19	99.99
VIT	79.65	0.10	79.64	100.00

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VGG-13	69.84	0.09	69.21	99.99
VGG-16	71.60	0.09	71.57	99.98
ResNet-50	75.84	0.09	75.85	99.92
ResNet-101	77.22	0.10	77.22	99.91
ResNet-152	78.27	0.10	78.21	99.89
MobileNetV2	71.16	0.10	70.75	99.52
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- Proposed **Deep-TROJ successfully attacks** various DNNs with high attack efficacy
- Proposed **Deep-TROJ outperforms** SOTA inference-stage trojan attacks on attacking both CNN and Vision Transformer (ViT)

Evaluation against Defense

Methods	ACC	ASR
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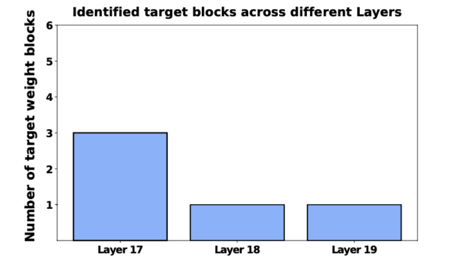

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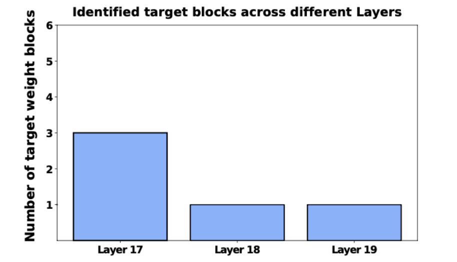

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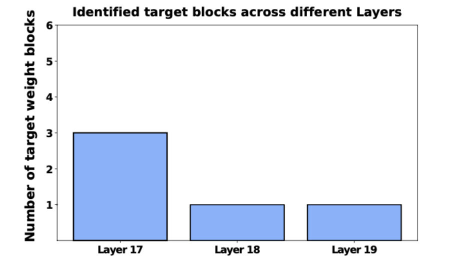

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- Even detection based defense such as CLP is **ineffective**
- **Target weight blocks** are **distributed** across model layers
- Makes this attack even **harder to detect or defend**

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- Thus, to make AI safer and more secure, the community must address the security threat posed by this attack by investigating appropriate remedies

Acknowledgement

NJIT
New Jersey Institute of Technology

Thank you!