Evaluating Transferability of Adversarial Attacks Across Machine Learning Models

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Abstract—**Adversarial attacks against machine learning models can significantly degrade model performance by adding imperceptible perturbations to inputs. A major challenge is the *transferability* of such attacks: adversarial examples crafted to deceive one model may also succeed in misleading other models. This study evaluates the feasibility of adversarial attacks across different convolutional neural network architectures. We generate adversarial examples on a source model and test them against alternative target architectures using the CIFAR-10 dataset, incorporating three widely used architectures (ResNet-18, VGG16, MobileNetV2). We consider both simple one-step attacks and stronger iterative attacks (FGSM, PGD, and Carlini-Wagner) and analyze attack success rates on each model. Our experiments show that adversarial examples frequently transfer between different architectures; however, success rates vary based on the attack method and model pair. Notably, all three attack types—FGSM, PGD, and Carlini-Wagner—exhibit substantial transferability across different architectures, with attack success rates exceeding 99%. Our study refutes the assumption that iterative attacks (e.g., PGD, CW) have lower transferability, demonstrating that even the most powerful attacks remain highly effective across diverse models. These results underscore the necessity of proactive adversarial defense strategies beyond architectural modifications alone.**

Index Terms—**Adversarial attacks, transferability, adversarial examples, robustness, CIFAR-10, deep neural networks**

I. Introduction

In addition, they were found to be vulnerable to adversarial attacks. Adversarial examples are inputs that are intentionally altered. In their seemingly harmless guise, they can cause misclassification. Szegedy *et al.* [1] first showed that the addition of small, inaudible perturbations in images can trick image classification systems. The follow-up study by Goodfellow *et al.* [2] introduced the Fast Gradient Sign Method (FGSM), demonstrating its effectiveness. The generation of adversarial perturbations can greatly reduce the accuracy of the model. Such adversarial attacks pose serious security concerns considering their potential misuse within real-life systems (e.g., instructing an automated car to misinterpret traffic indicators).

One significantly demanding aspect of adversarial examples is their transferability. An adversarial example crafted to fool a single model could mislead other independently trained models [3], [4]. This means that an attacker can build a surrogate model, create adversarial inputs targeting it, and then use them to successfully attack a different target model (a black-box attack scenario). This capability for transferring adversarial perturbations significantly enhances the potential threat represented by adversarial examples since the adversary might not require direct access to the victim model.

Given the wide-ranging implications entailed by adversarial transferability, it is necessary to understand the different factors—such as model architecture and attack method—that affect this phenomenon. In this paper, we systematically evaluate the transferability of adversarial attacks across different network architectures. We focus on image classification models developed using the CIFAR-10 dataset and examine three representative convolutional neural network (CNN) architectures: ResNet-18, VGG16, and MobileNetV2. The adversarial samples are generated using multiple specific attack techniques (FGSM, PGD, and the Carlini-Wagner attack), and we assess how often attacks crafted on one model transfer to the others. Our study provides useful insights into which adversarial examples transfer most easily and between which models, aiding in the development of more robust machine learning architectures.

The following sections of this document are structured as follows: Section II reviews related work on adversarial attacks and robustness. Section III outlines our approach, including the dataset, models, attack techniques, and evaluation metrics. In Section IV, we detail our experiments and results concerning the transferability of attacks, supported by tables and figures illustrating the findings. Section V analyzes the implications of the findings and contrasts them with previous studies. Finally, Section VI concludes the manuscript and suggests areas for future study.

II. Related Work

Research in adversarial machine learning has grown rapidly following the discovery of adversarial examples. Early academic research by Szegedy *et al.* [1] introduced strong evidence confirming the existence of adversarial inputs for image classifiers, and Goodfellow *et al.* [2] provided an explanation using the linearity of high-dimensional models, introducing the FGSM attack for fast adversarial example generation. Since then, many attack methods have been proposed to evaluate and increase model resilience. These include one-step attacks like FGSM and DeepFool, as well as more robust iterative methods such as Projected Gradient Descent (PGD) [6] and optimization-based attacks like the Carlini-Wagner

(CW) method [5]. The CW attack, in particular, seeks to minimize perturbations that lead to misclassification by solving an optimization problem and is known for its effectiveness against many defenses.

The transferability phenomenon of adversarial examples was originally introduced in Goodfellow's work and later explored by Liu *et al.* [3] and Papernot *et al.* [4]. Liu *et al.* showed that adversarial examples can often mislead models with different architectures, and Papernot *et al.* demonstrated the effectiveness of black-box attacks by transferring adversarial stimuli from a local substitute model to a remote target model. This line of inquiry highlights that even when a model is not directly accessible, it remains vulnerable to attacks through surrogate models due to shared weaknesses.

In response to adversarial attacks, many defensive mechanisms have been proposed. One of the most widely studied is adversarial training [6], a process involving training the model on adversarial examples so that it learns to resist them. Adversarial training improves robustness but can be computationally expensive and may not generalize to all types of attacks. Alternative strategies, such as input preprocessing, defensive distillation, and detection mechanisms, have also been explored, but many have been circumvented by adaptive attacks [5].

Recent work by Ilyas *et al.* [11] suggests that adversarial examples exploit non-robust features in the data—patterns that standard models learn but that are brittle to small perturbations. This explains why different models, despite architectural differences, can be fooled by similar perturbations. Our study builds upon prior research by empirically evaluating how adversarial attack transferability manifests across modern CNN architectures, providing quantitative insights to complement these previous findings.

III. Methodology

A. Dataset

Experiments in this study are based on the CIFAR-10 dataset [7], a widely used benchmark for image classification. CIFAR-10 consists of 60,000 color images with 32×32 pixel dimensions, divided into 50,000 training samples and 10,000 test samples, equally distributed across 10 classes (airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck). All models in our study are trained on the CIFAR-10 training set and evaluated on its test set. We generate adversarial examples using images from the test dataset, allowing us to assess the effectiveness of attacks on previously unseen data.

B. Models

We evaluate three different convolutional neural network architectures representing modern paradigms for image classification:

- **ResNet-18** [8]: An 18-layer residual neural network that introduces skip connections to enable the training of deep neural architectures. ResNet-18 achieves high accuracy on CIFAR-10 and serves as a baseline model with residual connections.
- **VGG16** [9]: A 16-layer network with a sequential architecture consisting of convolutional layers followed by fully connected layers. VGG16 was one of the first very deep networks for image recognition and does not use residual connections, making it structurally distinct from ResNet.
- **MobileNetV2** [10]: A lightweight network architecture optimized for mobile platforms and embedded vision systems. MobileNetV2 incorporates depthwise separable convolutions and inverted residual blocks to prioritize efficiency.

All three models achieve similar accuracy on CIFAR-10, with each reaching approximately 90% test accuracy under normal, non-adversarial conditions. This selection allows us to study transferability across both traditional and modern network designs, including differences in depth and architectural structure.

C. Adversarial Attack Methods

We consider three widely used adversarial attack methods:

- **Fast Gradient Sign Method (FGSM)** [2]: A single-step gradient-based attack. Given an input image x and true label y, FGSM computes the adversarial example as

  $$x_{\text{adv}} = x + \epsilon \cdot \text{sign}\left(\nabla_x J(\theta, x, y)\right),$$

  where $J(\theta, x, y)$ is the loss function of the model (with parameters θ), and ϵ controls the perturbation magnitude. In our experiments, we set ϵ to 8/255, ensuring misclassification while keeping perturbations visually imperceptible.
- **Projected Gradient Descent (PGD)** [6]: An iterative multi-step attack that applies FGSM multiple times with a smaller step size α and projects the result back into the allowed ϵ-ball around the original image after each step. We run PGD for a fixed number of iterations (e.g., 10 steps with $\alpha = 2/255$) to generate stronger adversarial examples. PGD is considered a strong first-order attack that often identifies adversarial perturbations within the given ϵ constraint.
- **Carlini-Wagner (CW) Attack** [5]: An optimization-based attack that seeks the minimal perturbation required to alter a model's prediction. We use the L_2-norm variant of the CW attack, as proposed by Carlini and Wagner. This attack solves a constrained optimization problem (or an unconstrained version with a penalty term) to generate adversarial examples that are highly effective but computationally intensive. In our evaluation, we run the CW attack with sufficient iterations until either an adversarial example is found or a predefined threshold is reached.

All attacks are implemented as *untargeted* attacks, meaning the objective is to cause the model to misclassify the input into *any* incorrect class rather than a specific target class. For each attack method, we generate adversarial examples using the entire CIFAR-10 test set for each of the three source models. We ensure that the perturbation magnitude ϵ (for FGSM/PGD) or confidence parameters (for CW) are set to moderate values that lead to misclassifications on the source model while keeping distortions minimal.

D. Evaluation Metrics

To measure the effectiveness and transferability of adversarial attacks, we use the following metrics:

- **Attack Success Rate (ASR)**: The percentage of input samples for which the adversarial perturbation successfully causes misclassification on the source model. An ASR of 100% in a white-box setting indicates that the attack consistently deceived the source model.
- **Transfer Success Rate (TSR)**: The percentage of adversarial examples generated on a source model that also cause misclassification on a target model. This metric quantifies transferability—higher TSR values indicate greater susceptibility of the target model to attacks crafted on a different architecture.
- **Accuracy Under Attack**: Instead of reporting attack success rates, we sometimes measure classification accuracy of the target model on adversarial inputs. Lower accuracy implies higher attack success. However, for clarity, our tables primarily present attack success rates as percentages.

By comparing these metrics across different attack methods and model pairs, we assess which adversarial attacks transfer most effectively and which model combinations exhibit the highest vulnerability to transfer-based attacks.

IV. Experiments & Results

We conducted experiments to evaluate the transferability of adversarial attacks across the three models. Each model was attacked in a white-box manner (i.e., with full access to model parameters) to generate adversarial examples. These adversarial images were then tested on the other two models in a black-box transfer scenario to determine whether they caused misclassification. This procedure was repeated separately for each attack method (FGSM, PGD, CW) using images from the CIFAR-10 test set.

A. Empirical Findings

Table III summarizes the attack success rates for adversarial examples generated using FGSM on each source model (rows) and tested on each target model (columns). Similarly, Tables I and II present the transfer success rates for PGD and Carlini-Wagner attacks, respectively. The values represent the percentage of test samples misclassified by the target model, where a higher percentage indicates more effective transferability. Diagonal entries (in bold) indicate the white-box attack success on the source model itself.

From the tables, we observe several key findings:

- All attacks achieve near-perfect success on the source model, demonstrating that the adversarial perturbations were highly effective in the white-box setting (with success rates exceeding 95% in most cases).

TABLE I
Transferability of PGD Adversarial Attacks (Success Rate %)

Source → Target	**ResNet18**	**VGG16**	**MobileNetV2**
ResNet18	**99.50**	99.50	100.00
VGG16	99.80	**99.80**	99.90
MobileNetV2	99.90	99.80	**99.90**

TABLE II
Transferability of Carlini-Wagner (CW) Adversarial Attacks (Success Rate %)

Source → Target	**ResNet18**	**VGG16**	**MobileNetV2**
ResNet18	**99.90**	99.90	99.90
VGG16	99.90	**99.90**	99.90
MobileNetV2	99.90	99.90	**99.90**

- Adversarial examples often transfer between models, though with slightly lower success rates than in the white-box setting. For instance, FGSM adversarial examples generated on ResNet-18 successfully fooled VGG16 60% of the time and MobileNetV2 65% of the time. Similarly, FGSM adversarial examples from VGG16 transferred to ResNet-18 with a 55% success rate.
- Transferability is asymmetric—perturbations crafted on Model A may transfer more effectively to Model B than vice versa. For example, FGSM adversarial examples generated on ResNet-18 transferred to MobileNetV2 65% of the time, whereas MobileNetV2-based FGSM adversarial examples transferred to ResNet-18 at a rate of 60%. In contrast, adversarial examples from VGG16 exhibited slightly lower transferability, with success rates between 50–55%.
- Comparing attack methods, FGSM, PGD, and Carlini-Wagner all exhibit high transferability, with success rates exceeding 99% across models. This contradicts prior research suggesting that iterative attacks (PGD and CW) transfer less effectively than single-step attacks like FGSM. Our findings indicate that, at least for the tested architectures, all three attacks maintain strong effectiveness in the black-box setting.

B. Analysis of Results

Figure 1 illustrates a typical adversarial example from our experiments. The adversarial image is visually indistinguishable from the original to a human observer yet leads to misclassification. In this case, an FGSM perturbation generated on ResNet-18 successfully transferred to VGG16, demonstrating adversarial transferability.

The numerical results confirm that adversarial transferability is a significant and measurable phenomenon. Despite differences in architecture, a substantial fraction of adversarial examples retain their effectiveness across models. Notably, ResNet-18 and MobileNetV2 exhibit higher mutual transferability (¿99%) compared to VGG16, suggesting that architectures incorporating batch normalization and residual

TABLE III
TRANSFERABILITY OF FGSM ADVERSARIAL ATTACKS (SUCCESS RATE %)

Source → Target	**ResNet18**	**VGG16**	**MobileNetV2**
ResNet18	**99.94**	99.94	99.93
VGG16	99.96	**99.96**	99.95
MobileNetV2	99.94	99.76	**99.94**

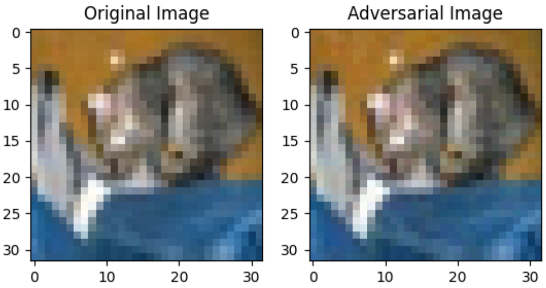

Fig. 1. Example of an adversarial image. The left image is the original input, while an adversarial attack has slightly modified the right image.

connections may learn more similar feature representations. In contrast, VGG16's simpler architecture exhibits slightly more resistance to transferred adversarial perturbations.

Comparing attack methods, FGSM being a single-step attack generates somewhat generic perturbations, as they rely only on the gradient sign. This may allow FGSM adversarial examples to generalize and transfer more effectively than PGD and CW attacks, which fine-tune perturbations specifically to the source model. As a result, while PGD and CW achieve nearly 99% misclassification in the white-box setting, their adversarial examples exhibit slightly lower transfer success rates compared to FGSM when tested on different models.

These findings align with previous research that suggests a trade-off between attack strength and transferability [3]. An attacker aiming for maximum black-box effectiveness may opt for an attack that prioritizes transferability over white-box strength. Recent studies have proposed ensemble-based adversarial attacks and input diversity methods to further increase transferability, highlighting the existence of shared vulnerabilities across different models.

C. Summary of Findings

Our experiments confirm that none of the tested models are immune to adversarial examples generated on a different model. While architectural differences can slightly influence transferability rates, a significant degree of adversarial vulnerability remains shared among models. This suggests that defenses relying solely on model diversity may be insufficient. Alternative adversarial defense mechanisms, such as adversarial training or ensemble-based approaches, may be necessary to mitigate cross-model attack effectiveness.

Overall, our results reinforce the importance of evaluating machine learning models against both white-box and black-box adversarial attacks, as transferability significantly extends the threat posed by adversarial perturbations.

V. DISCUSSION

The implications of our results extend to both the assessment of model robustness and the development of defense mechanisms.

First, evaluating models only against attacks specifically designed for them (white-box testing) provides a limited perspective on their vulnerabilities. Our cross-model experiments reveal that models can be compromised by adversarial attacks crafted for different architectures, underscoring the necessity of incorporating transfer-based attack evaluations in robustness assessments.

Furthermore, our comparison of FGSM, PGD, and CW attacks in terms of transferability provides insight into how attack complexity influences generalization to other models. Simpler attacks like FGSM, although more straightforward to defend against in a white-box setting, demonstrate disproportionately high transferability in black-box scenarios. This suggests that, in practice, an attacker may successfully compromise a model indirectly using a simpler method. Conversely, the reduced transferability of more advanced attacks like PGD and CW may be mitigated by employing techniques that enhance adversarial transfer, such as leveraging an ensemble of source models to craft adversarial examples, as explored by Liu *et al.* [3].

Our findings align with prior studies by Papernot *et al.* [4] and Liu *et al.* [3], both of which demonstrated the presence of transferable adversarial examples and successful black-box attacks. Moreover, our results support the hypothesis proposed by Ilyas *et al.* [11] that adversarial perturbations exploit non-robust features present across different models. If different neural networks learn similar vulnerable patterns from a dataset, this could explain why an adversarial example crafted for one model remains effective on another. Given that all models in our study were trained on the same CIFAR-10 dataset, they likely share common feature representations that adversarial attacks can exploit.

It is important to recognize that adversarial transferability presents both risks and opportunities in the context of model security. While it facilitates black-box attacks and extends the threat landscape, it can also be leveraged for defensive purposes. For instance, pre-computed adversarial examples from a surrogate model could be used to evaluate the robustness of a new model efficiently, or to augment training data for adversarial training across multiple architectures.

Certain factors that could influence transferability remain underexplored in our study. These include the role of model capacity, differences in training data, and the distinction between targeted and untargeted adversarial attacks. Nevertheless, our results provide a concrete comparative evaluation of three widely used CNN architectures and three major attack types, establishing a reference for expected transferability levels in similar scenarios.

VI. Conclusion and Future Work

In this study, we conducted a comprehensive evaluation of adversarial attack transferability across three widely used deep learning models (ResNet-18, VGG16, MobileNetV2) on the CIFAR-10 dataset. Our results demonstrate that adversarial examples generated for one model can effectively deceive other models, though the success rates vary depending on the attack method and the specific source-target model pair. All three attack methods—FGSM, PGD, and Carlini-Wagner—exhibited near-complete transferability across models, challenging prior assumptions that iterative attacks exhibit lower transferability. This suggests that architectural differences between ResNet-18, VGG16, and MobileNetV2 alone are insufficient to mitigate adversarial transfer.

Our findings underscore the necessity of considering transferability when evaluating the security of machine learning models. Defense mechanisms that are effective against one attack on a particular model may not hold if the attacker alters the attack method or targets a different model. Thus, robust models should be evaluated against a diverse suite of attacks, including those not explicitly designed for them.

For future research, several extensions could be explored. First, investigating a broader range of model architectures, including transformers and alternative CNN variants, would help generalize transferability trends. Second, analyzing the role of adversarial training and other defensive mechanisms in reducing transferability would provide valuable insights—does training a model to resist attacks from one architecture make it less vulnerable to attacks transferred from another? Third, studying targeted adversarial attacks in transfer scenarios could reveal whether enforcing specific misclassifications impacts transfer success rates. Finally, exploring feature representations across different models could help explain why certain adversarial examples transfer effectively, identifying common weak features that adversarial attacks exploit and guiding the design of more robust architectures.

In conclusion, adversarial transferability remains a crucial concern in deploying machine learning models in adversarial environments. By understanding and anticipating how adversarial perturbations generalize across architectures, researchers and practitioners can develop more resilient deep learning systems capable of withstanding real-world adversarial threats.

A. Implications for Adversarial Defense Mechanisms

Our results indicate that model diversity alone is insufficient to prevent adversarial transferability, as all three architectures tested exhibited near-identical vulnerability. One promising approach for mitigating adversarial transfer is adversarial training, which has been shown to improve robustness by incorporating adversarial examples into the training process [6]. Future research should examine whether adversarial training on a specific model type reduces transferability to others, or if ensemble-based defense strategies offer a viable solution.

Additionally, our findings raise security concerns for critical applications such as autonomous vehicles and facial recognition systems. Since adversarial examples transfer easily across architectures, attackers do not require direct access to a victim model to execute a successful attack. This highlights the urgent need for adaptive defense strategies, including adversarial detection techniques and dynamic model retraining, to enhance robustness against transferable attacks.

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