# DYNAMIC NEURAL NETWORK IS ALL YOU NEED: UNDERSTANDING THE ROBUSTNESS OF DYNAMIC MECHANISMS IN NEURAL NETWORKS

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## ABSTRACT

Deep Neural Networks (DNN) based solutions are being used to solve different day-to-day problems. Recently, DNNs are being deployed in real-time systems, and lowering the energy consumption and response time has become the need of the hour. To address this scenario, researchers have proposed early-exit Dynamic Neural Networks (DyNNs), where the computation is dynamic based on the input complexity. DyNNs are generally designed and based on larger static DNNs (SDNN). As the DyNNs decrease the energy consumption, it also becomes important to evaluate the robustness of DyNNs to ensure safety. However, there has not been a significant number of works focusing on the robustness of DyNNs. To address this issue, we propose systematic studies to evaluate the robustness of DyNNs. For that purpose, we propose four research questions. These studies are performed on three models and two datasets. Through the studies, we find that DyNNs are more robust than SDNNs, and DyNNs can be used to generate adversarial samples efficiently. We also provide insight into the design choices through research studies. Finally, we propose a novel attack that can decrease the effectiveness of the DyNNs and can be used to evaluate design choices in DyNN.

## 1 INTRODUCTION

Deep Neural Networks (DNNs) are used in multiple applications such as computer vision, natural language processing, code analysis, etc. After the rapid growth of IoT and embedded devices, many real-time systems use DNNs in their applications. As the real-time systems require faster response time and low energy consumption, multiple energy-saving DNNs such as Dynamic Neural Networks (DyNNs) have been proposed. There are two types of DyNNs: early-exit DyNNs and skipping DyNNs (Haque et al., 2020) and early-exit DyNNs are more popular (Teerapittayanon et al., 2016; Kaya et al., 2019). Early-exit DyNNs have multiple exits and can terminate the operation early if the network is confident about the prediction. In this work, we focus on early-exit DyNNs.

Although DyNNs are preferred in real time systems over Static DNN (SDNN) because of increased efficiency, whether the use of DyNNs will impact the robustness of the systems is still unknown. Studying the impact of the dynamic mechanisms to the robustness is important for developers or users to understand the trade-offs between DyNN and SDNN, especially in the black-box scenarios, when adversaries normally assume the target models are always static. However, the target models can be dynamic also. Hence, it is important to find out if a surrogate SDNN model is used to attack a target DyNN model or vice-versa, then, to which extent the adversary can be successful.

To address this issue, in this paper, we first conduct a comparative study on both SDNNs and DyNNs to understand their robustness in black-box scenarios (Section 3). Our study results suggest that DyNNs are generally more robust than SDNNs and surprisingly using DyNNs as surrogate models for attack seems to be a more efficient and more effective way to generate adversarial samples. The adversaries are able to generate more adversarial samples in the same amount of time compared to using SDNNs as the surrogate model, and the generated adversarial samples often can also attack SDNNs.

After understanding that the introduction of the dynamic mechanisms generally will not reduce the robustness of the systems, we conduct another study to understand whether the original purpose

of DyNNs (*i.e.,* saving inference time) will be impacted by the adversarial samples (Section 4). Our study results suggest that the adversarial samples generated by existing white-box attacks and black-box attacks do not increase the inference time significantly.

After understanding the robustness of DyNNs in general, we perform a detailed analysis of which design choices in the dynamic mechanisms or DyNN architectures may impact the robustness of DyNNs (Section 5). We consider two attack scenarios in this study: first, the output layer label of an SDNN is modified by a white-box adversarial example, and we study the impact on corresponding DyNN's early-exit layers; second, in a black-box scenario, the output of SDNN is modified, and the sample is fed to separate model's DyNN. We have made multiple findings based on the empirical results, for example, putting the first exit earlier in the model architecture can help to improve the robustness of DyNNs.

Last but not least, we design an adversarial attack approach to understand the extra attack surface introduced by the dynamic mechanisms in neural network (Section 6). In this attack, the synthesized adversarial examples will not change the prediction of the final output layer's label, but will change the prediction of all the early exits. Based on the attack results, we find that the dynamic mechanism is more vulnerable in scenarios where dependency among DyNN layers is lesser and when the exits are sparse w.r.t the layers.

## 2 Related Works and Background

**Dynamic Neural Networks.** The main objective of DyNNs is to decrease the energy consumption of the model inference for inputs that can be classified with less computational resources. DyNNs can be classified into *Conditional-skipping DyNNs* and *Early-exit DyNNs*. Early-exit DyNNs use multiple exits within a single model. If at any exit, the confidence score of the predicted label exceeds used defined threshold, inference is stopped. Graves (2016), Figurnov et al. (2017), Teerapittayanon et al. (2016), Kaya et al. (2019) have proposed Early-termination AdNNs. Detailed explanation of early-exit networks can be found at Applendix (B).

**Adversarial Attacks.** Adversarial Examples are the input that can change the prediction of the DNN model when those are fed to the model. Goodfellow et al. (2014) propose Fast Gradient Sign Method (FGSM) that use single-step first order entropy loss to generate adversarial inputs. Madry et al. (2017) modifies that attack to add initial noise to the benign sample. This attack is referred as projected gradient descent (PGD).

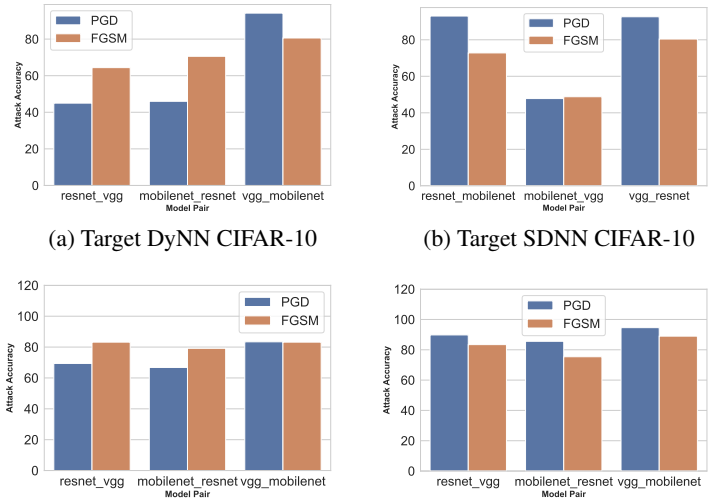
## 3 Are AdNNs less robust than SDNNs against adversarial attacks?

In this research question, we investigate the "transferability" of adversarial inputs generated based on SDNN and DyNN, respectively, *i.e.,* whether adversarial examples generated based on SDNNs are adversarial to DyNNs and vice versa. Transferability is an important metric for evaluating the feasibility of black-box attack. To evaluate the transferability, one of the popular way (Papernot et al., 2017; Liu et al., 2016) is creating a similar model (*i.e.,* surrogate model) as the target model. In a black-box attack, normally, adversaries assume the underlying model to be SDNN, so for a deployed DyNN, the adversaries may likely use an SDNN as surrogate model. Hence, this research question (RQ) is important to evaluate the robustness of DyNNs. If attack transferability is higher in any particular direction (SDNN to DyNN or DyNN to SDNN), then the robustness of one specific type of model is regarded as lower.

### 3.1 Experimental Setup.

**Dataset and Models.** We use CIFAR-10 and CIFAR-100 (Krizhevsky et al., 2009) datasets for evaluation. For SDNNs, we use VGG-16 (Simonyan & Zisserman, 2014), ResNet56 (He et al., 2015), and MobileNet (Howard et al., 2017) model. As DyNNs, we use the early exit version of these models (Kaya et al., 2019). In all other RQs, we keep the models and dataset setup same.

**Black-box Attack.** For the attack scenario, we use surrogate model (Papernot et al., 2017; Liu et al., 2016) based black-box attack scenario. Here, we feed a set of inputs to the target model and




(a) Target DyNN CIFAR-10

(b) Target SDNN CIFAR-10

(c) Target DyNN CIFAR-100

(d) Target SDNN CIFAR-100

Figure 1: Blackbox Attack Success Rate for CIFAR-10 and CIFAR-100 data

collect the output labels. These inputs are generated using 50% of the held-out validation data, and naturally corrupted versions of those validation data. As the number of partial held-out validation data is not significant, adding corrupted inputs would help to increase training data for the surrogate model. For natural corruption, we use gaussian noise and brightness. For each type of corruption, we have five intensity levels. For example, if the number of held out data is 5000, for each corruption, we generate 25000 additional data. Once the input-output pairs are collected, a surrogate model is trained based on those pairs. For a target model, we use both SDNNs and DyNNs. If the target model is SDNN, then an DyNN is trained as surrogate model and vice-versa.

To make the surrogate-target pairs, we use different types of DNN architectures. For example, if the the target model is DyNN VGG, we choose ResNet56 SDNN as the surrogate model. This assumption is valid because the attacker doesn't have information about the target model architecture, hence the possibility of choosing the same architecture as the surrogate model is less. We have chosen following pairs for DyNNs as target : DyNN VGG (target): SDNN ResNet56 (surrogate), DyNN ResNet56 (target): SDNN MobileNet (surrogate), and DyNN MobileNet (target): SDNN VGG (surrogate). Similarly, for SDNNs as the target, earlier mentioned surrogate models become the target model and earlier mentioned target models become the surrogate model.

**Algorithms.** We use FGSM (Goodfellow et al., 2014) and PGD (Madry et al., 2017) algorithms to attack the surrogate models.

**Metric.** We measure percentage of adversarial examples that can mis-classify the output w.r.t number of generated adversarial examples as the attack success rate.

### 3.2 Evaluation Results

Figure 1 shows the effectiveness of black-box attacks on DyNNs and SDNNs. On average, it can be noticed that for target SDNN and surrogate DyNN, the attack success rate is higher than target AdNN and surrogate SDNN. One of the reasons for this behavior is the lower variance of the DyNNs. DyNNs use lower number of parameters, hence the feature space for adversarial samples of DyNNs is smaller than the feature space for adversarial samples of SDNNs. Also, we find that for the target DyNN, FGSM attack performs better than PGD attack. If only dataset-specific results are considered, then for CIFAR-100 the attack success rate is higher than for CIFAR-10.

Also, as the DyNN-generated adversarial inputs can attack SDNNs, then it can be time efficient to create adversarial inputs using DyNN. Through Figure 6 (Appendix), we can find the probability density plots of different exit numbers of DyNN that have been used to generate adversarial exam-

ples. Lower exit number suggests that lesser number of computations has been used to generate adversarial examples. It can be noticed that for PGD attack, more than 70% of adversarial examples are generated from exit 0, 1 and 2 (first - third exit). Although for FGSM attack, in a few scenarios (CIFAR-10 VGG, CIFAR-100 MobileNet, and CIFAR-100 ResNet), more than 50% of adversarial examples are generated through later exits (higher computation required).

**Finding 1**: *With respect to black-box attacks, early-exit DyNNs are more robust than SDNNs.*
**Finding 2**: *Using SDNNs as surrogate models is more efficient and more effective way to generate adversarial examples than using DyNNs.*

## 4 DOES ADVERSARIAL EXAMPLES IMPACT EARLY-EXIT BEHAVIOURS IN DYNNS?

In this section, we investigate whether the original purpose of DyNNs (*i.e.,* saving inference time) will be impacted by the adversarial samples. Specifically, we study whether the adversarial inputs exit earlier or later in a DyNN compared to the original inputs. The main objective of this investigation is to find out whether the adversarial samples generated on SDNN can have an impact on the amount of computation of the DyNN. For this purpose, we conduct both white-box and black-box attacks to find out the impact of adversarial samples on the amount of computation.

Here, the white-box attack scenario can also be considered a practical scenario. There have been studies (Chen et al., 2022; Wu et al., 2022) that focus on reverse engineering of SDNN models from binary code of on-device models, but no techniques have been proposed to reverse engineer the dynamic mechanisms in the models. Hence, adversaries are more likely to get SDNN models instead of their dynamic counterparts. So it is important to find out how adversarial samples affect the efficiency of the DyNN for both white-box and black-box scenarios.

### 4.1 EXPERIMENTAL SETUP.

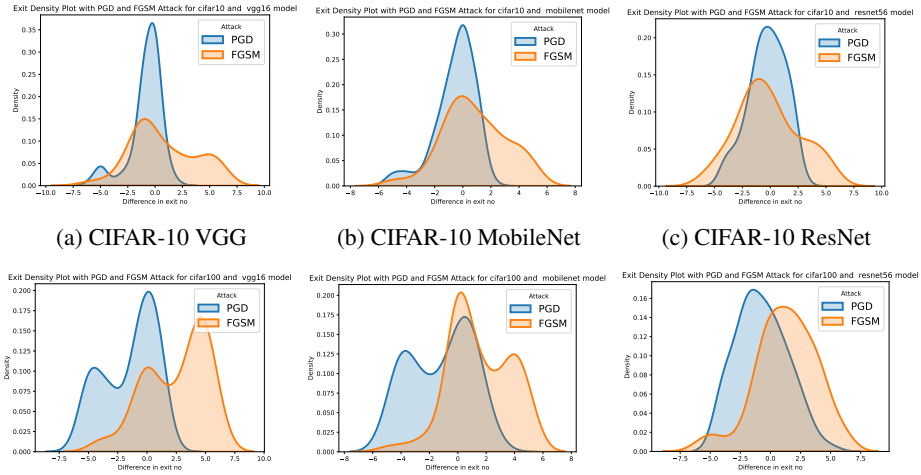
**Attack.** We use PGD and FGSM for both white-box and black-box attacks. For black-box setup, we use the same setup as previous RQ. For black-box scenario, we use DyNNs as target model and SDNNs as surrogate model. In a white-box setting, we attack the SDNN and evaluate on the performance of corresponding DyNN.

**Metric.** We use the difference between the exit number selected by adversarial input and the exit number selected by benign input. If the difference is positive, then the latency of the adversarial sample is increased w.r.t benign input.

### 4.2 EVALUATION RESULTS.

Figure 2 shows the impact of adversarial examples generated on SDNN on changing in number of exits in DyNN in a white-box setting. It can be observed that for the majority of the scenarios, accuracy-based adversarial samples do not increase the computation significantly in the DyNN. On average, FGSM-generated examples increase more computation in DyNNs than PGD-generated examples. For CIFAR-10 data, for MobileNet and VGG-16 DyNN models, 25%-37% of the FGSM generated examples could increase the number of exits by more than one. Also, it can be noted that adversarial samples generated on CIFAR-100 data is more likely to increase computation than adversarial samples generated on CIFAR-10. Especially, more than 45% of the FGSM samples generated on CIFAR-100 data can increase the number of exits by more than one.

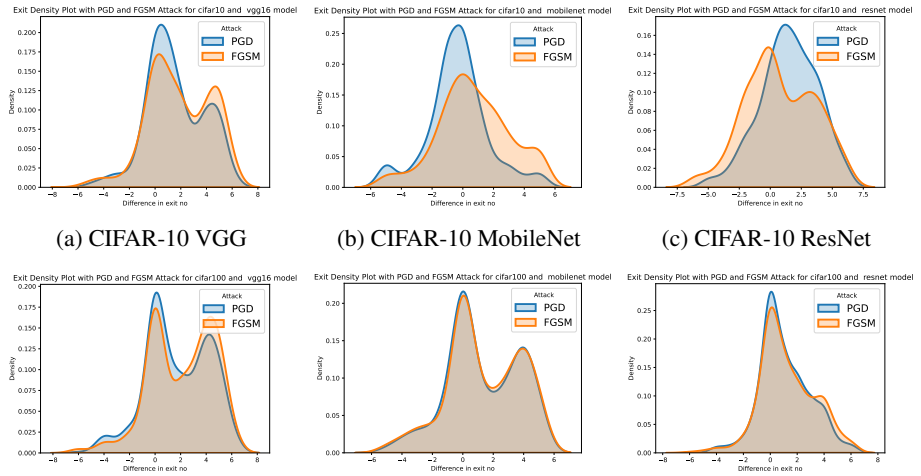
Figure 3 shows the impact of adversarial examples generated on SDNN on change in exits in DyNN in a black-box setting. It can be noted that, for CIFAR-10 dataset, black-box attack can generate more computation-increasing examples than in white-box attack. For ResNet and VGG model, more than 40% PGD attack generated examples can increase the number of exits by more than one. For all three models, 35% of the FGSM attack generated examples can increase the number of exits by more than one. FGSM attack generates more inputs that induces low confidence in early-exit layers than PGD attack. For CIFAR-100 dataset, the increase of computation caused by adversarial attacks is higher than that of CIFAR-10. As CIFAR-100 data uses larger model, the robustness of




(a) CIFAR-10 VGG (b) CIFAR-10 MobileNet (c) CIFAR-10 ResNet

(d) CIFAR-100 VGG (e) CIFAR-100 MobileNet (f) CIFAR-100 ResNet

Figure 2: Density plots of change in exit numbers because of PGD and FGSM attack. The x axis represents the change in exit number while y axis represents the density.




(a) CIFAR-10 VGG (b) CIFAR-10 MobileNet (c) CIFAR-10 ResNet

(d) CIFAR-100 VGG (e) CIFAR-100 MobileNet (f) CIFAR-100 ResNet

Figure 3: Density plots of change in exit numbers because of PGD and FGSM **black-box** attack. The x axis represents the change in exit number while y axis represents the density.

the model is reduced. For CIFAR-100 dataset, more than 40% examples generated through both the attack can increase the number of exits by more than one. However, increasing the number of exits by two or three exits does not increase the latency/energy consumption significantly. Hence, we find that accuracy-based adversarial samples do not increase the computation significantly in the DyNN.

**Finding 3**: *Accuracy-based adversarial samples do not increase the computation significantly in the DyNN*
**Finding 4**: *Low confidence adversarial examples perform better in terms of increasing the computation in DyNNs.*
**Finding 5**: *Adversarial examples generated on a larger model is more likely to increase computation in DyNNs.*

# 5 WHAT DESIGN OF DYNNS MAY IMPACT THE ROBUSTNESS?

In this section, we evaluate what design in DyNNs may impact the robustness. In this RQ, we consider DyNNs as multi-exit networks, where each exit will provide an output. Our main objective is to find out when the last layer output label is modified by adversarial examples, from which early-exit layers the label modification begin. If the output label is not modified in any earlier layer, then for that type of model, the robustness is higher because the model can produce correct results at any layer. This RQ will provide us an insight into which type of design choice may improve the robustness of early layers.

## 5.1 EXPERIMENTAL SETUP.

**Attack Setup.** We use same attack setup as previous research questions. However, while we attack the DyNN, we not only consider one specific exit layer. Instead of that, we consider each exit layer of the DyNN.

**Metric.** We use the early exit from which the label modification starts. For example, there are $N$ exits. First, $N$th exit's label is modified through adversarial sample. If till $K$th exit the original prediction was same, then we report $K + 1$th exit in the experimentation.

## 5.2 EVALUATION RESULTS.

Figure 4 shows probability density plot on which exit the output label is changed using the white-box adversarial examples. It can be observed that for all the model-dataset pairs, for more than 77% of the examples, the label is modified in the first exit. For CIFAR-10 data, only for MobileNet and ResNet models, the label is changed after the first exit for more than 20% of the examples (using FGSM attack).

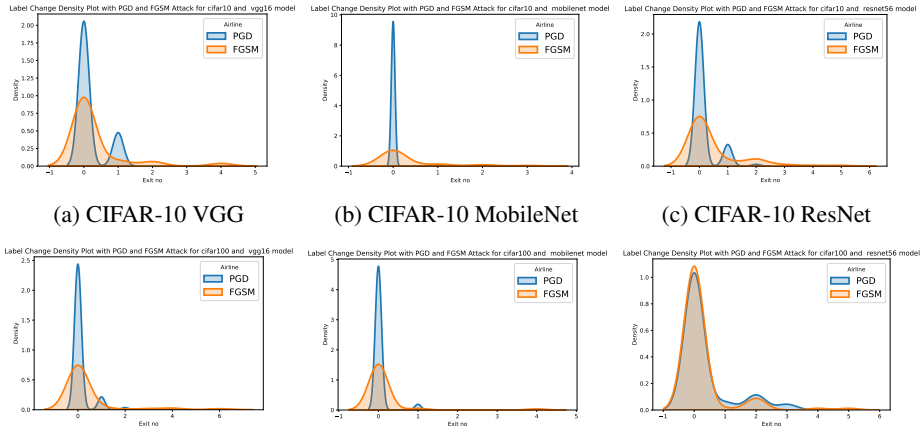
Figure 5 shows probability density plot on which exit the output label is changed using the black-box adversarial examples. From results, we can see that the robustness of earlier exits is better against black-box attack than white-box attack. For CIFAR-10 data, more than 45% of the both attack generated samples could not misclassify the first exit for VGG-16 model. For CIFAR-100 data (larger model), robustness of early exit layers is worse than that of CIFAR-10 data (smaller model). For CIFAR-100 data, for both attacks and three models, less than 30% of the adversarial examples can not mis-classify the first exit.

For black-box attack scenario, VGG-16 model's first layer on-average shows better robustness against black-box attack. In the DyNN, the first exit of the VGG model is placed only after second layer, while for others, more computations are performed before using the first exit. Hence, having the first exit in the early layers can increase the robustness of DyNN. Although lower number of parameters would be used to predict output, but with VGG we can notice that a significant number of inputs can be classified correctly through first exit.

**Finding 6**: *Having the first exit in the earlier layers can increase the robustness of DyNNs.*
**Finding 7**: *The early-exit layers are more robust against black-box attack than white-box attack.*
**Finding 8**: *For black-box attack generated examples, early-exit layers are more robust against adversarial examples generated on a smaller surrogate model than adversarial examples generated on a larger surrogate model.*

# 6 CAN WE SYNTHESIZE CERTAIN EXAMPLES TO REDUCE THE EFFECTIVENESS OF THE EARLY-EXITS OF DYNNS?

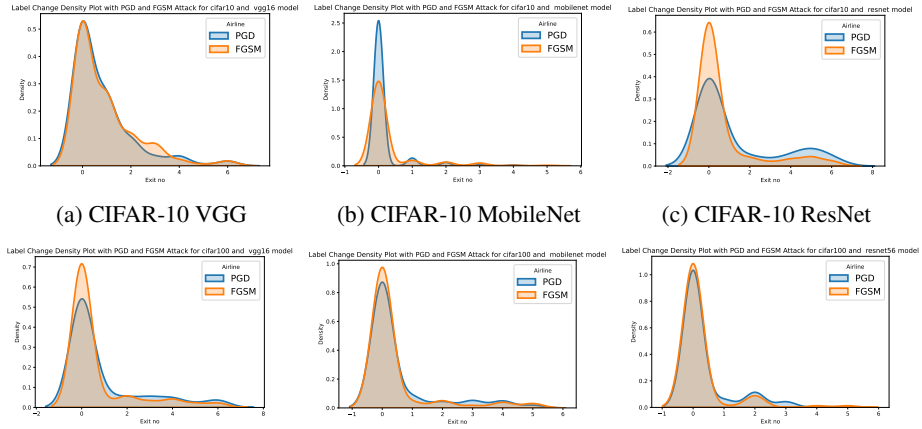
In this section, we evaluate if specific examples can be generated only to impact the robustness of DyNNs. We aim to design an attack such that the synthesized adversarial examples will not change the prediction of the final SDNN label, but change the prediction of the early exit. We design this study specifically to understand the extra attack surface introduced by the dynamic mechanisms.




(a) CIFAR-10 VGG (b) CIFAR-10 MobileNet (c) CIFAR-10 ResNet

(d) CIFAR-100 VGG (e) CIFAR-100 MobileNet (f) CIFAR-100 ResNet

Figure 4: Density plots representing during which exit number output label is changed because of PGD and FGSM attack. The x axis represents the exit number while y axis represents the density.




(a) CIFAR-10 VGG (b) CIFAR-10 MobileNet (c) CIFAR-10 ResNet

(d) CIFAR-100 VGG (e) CIFAR-100 MobileNet (f) CIFAR-100 ResNet

Figure 5: Density plots representing during which exit number output label is changed because of PGD and FGSM **black-box** attack. The x axis represents the exit number while y axis represents the density.

This threat model is practical because the attack evades the existing detection that relies on the final output of SDNN while the attacker creates a situation where all the early exit networks do not provide correct prediction, therefore decreasing the usability of DyNNs. However, this attack is also challenging to be performed successfully because final layer output is dependent on the earlier exit layers and it is challenging to impact all the early exits' prediction without modifying the final exit's prediction.

### 6.1 Problem Formulation

We propose a novel attack technique called *Early Attack* to evaluate the effectiveness of the early layers of DyNNs. Let's assume $f$ is an DyNN with $N$ exits. Given an input $x$, the output softmax layer in an exit $i$ can be defined as $y^i = f_i(x)$, where $i = 1, 2, 3...N$. For synthesizing adversarial examples, we have two main objectives. First, the initial prediction in the $N^{th}$ exit (final layer) does not change. Let's assume, the initial prediction at final layer is $p$. Second, the prediction of all the other exits should be different than $p$.

Based on the aforementioned objectives, we can propose an iterative optimisation procedure to optimise a loss function $L$. For each of the objectives, one loss function component is formulized. For the first objective, we propose loss function $L1 = (-1 * \sum_{j \neq p} max(y_p^N - y_j^N, 0))$. In $L1$, we maximize the difference between softmax value of label $p$ and other label's softmax value, therefore the prediction won't get changed at the final exit.

For the second objective, we propose loss function $L2 = (\sum_{i=1}^{N} y_p^i)$. The $L2$ ensures that for any other exit than the final exit, $p$'s softmax value would be minimized. The final loss function $L = \alpha * L1 + L2$. Here the $\alpha$ is a user-defined variable that provides balance between two loss terms.

Finally, we need to ensure the added perturbation to generate adversarial examples are limited, hence, the final optimization function would be, $minimize(||\delta|| + c \cdot L)$, where, $(x + \delta) \in [0, 1]^n$. Here, $\delta$ represents the added perturbation and $c$ is a user-defined variable to provide weightage on a specific component. $c$ controls the magnitude of generated perturbation ($||\delta_i||$), where a large $c$ makes the loss function more dependant on the $L$. Whereas a smaller $c$ makes the loss function more dependant on $||\delta_i||$, allowing only smaller perturbation.

This constrained optimization problem in $\delta$ can be converted into a non-constrained optimization problem in $w$, where the relationship between $\delta$ and $w$ is: $\delta = \frac{\tanh(w)+1}{2} - x$ The $tanh$ function would ensure that the generated adversarial input values stay between 0 and 1. The equivalent optimization problem in $w$ is:

$$\underset{w}{\text{minimize}} \left|\left| \frac{\tanh(w) + 1}{2} - x \right|\right| + c \cdot L \tag{1}$$

Detailed iterative optimization can be found in Appendix (C).

## 6.2 Evaluation

### 6.2.1 Evaluation SetUp.

**Baseline.** We use PGD and FGSM attacks as baseline. We use these attacks on early exit layer output to modify the early exit label.

**Metric.** We use attack success rate as metric in the evaluation. If the adversarial input generated final layer output is same as the benign input and all the other exit layers output is different than the final output label, then we consider attack is successful for that particular adversarial inputs.

**Hyperparameters.** We use six values of $\alpha$ to evaluate this section: 0.001,0.01,0.1,1, 20,40. We consider $c$ value as 50.

### 6.2.2 Effectiveness

Table 1 shows the evaluation results of the attack success rate of Early Attack and baseline techniques. Except two model-dataset pair, Early Attack's success rate is higher than 80% in all other scenarios. PGD and FGSM attacks are unsuccessful because the loss function only considers early layer output and does not consider final layer output. Although FGSM's attack success rate is higher than PGD's success rate. Also, w.r.t best performing $\alpha$ values, $\alpha = 1$ performs well for 70% of the model-dataset pairs.

We also analyze why early attack fails for VGG16 and MobileNet models for CIFAR-10 data. First, for CIFAR-10 data, final fully connected layer has lower number of parameters than the final layer for CIFAR-100 data. Hence, the dependency between the final layer and earlier layers is higher for CIFAR-10. However, for CIFAR-10 data, attack success rate is higher for ResNet model. First we discuss the failed cases for VGG16 and MobileNet model, and then we discuss why the attack succeeded for ResNet model.

For VGG16 model, the failed examples can be divided into two types. For the first type, the final output label is changed with all the other early exit layers. In the second type, first few layers get the output label mis-classified, but along with the final layer, few previous layers also get the output correctly classified. For MobileNet, all the layers except the final and last to final layer get the output

label mis-classified. For MobileNet, we also find that the final two exits are separated by only two layers, which is significantly lower than other model's separation layers between final two exits. Hence, the dependency between final two layers can be higher.

For ResNet model, there are 56 layers divided into 27 blocks. The exits are sparsely divided between these blocks. For Mobilenet and VGG models, the exit distributions are less sparse. Hence, the dependency between exits is lower for ResNet and because of that reason, we could successfully attack ResNet model.

Table 1: **Attack accuracy percentage of Early Attack and the baseline techniques against different model and dataset. We also report the value of $\alpha$ for which we get the highest attack success rate in Early Attack.**

| Dataset | Model | Early Attack | best $\alpha$ val | PGD | FGSM |
|---|---|---|---|---|---|
| CIFAR-10 | VGG | **35** | 1 | 0 | 0 |
| | MobileNet | **11** | 0.1 | 0 | 0 |
| | ResNet | **81** | 1 | 0 | 0 |
| CIFAR-100 | VGG | **86** | 20 | 0 | 1 |
| | MobileNet | **97** | 1 | 0 | 0 |
| | ResNet | **96** | 1 | 0 | 2 |

### 6.2.3 TRANSFERABILITY

In this section, we discuss about the transferability of the Early Attack examples. As Early Attack has two different components, instead of measuring attack success rate directly, we measure two parameters $T1$ and $T2$. $T1$ represents the percentage of inputs for which the final output remains same as the output generated by benign input. $T2$ represents from the examples selected from $T1$, how many early exit layers on average are mis-classified. Having both high $T1$ and $T2$ values ensures transferability.

We show the transferability results in Appendix (Table 2). For CIFAR-10 data, the $T1$ values are high, but $T2$ values are significantly low except for MobileNet to ResNet transferability. For CIFAR-100 data, $T2$ values are higher than of CIFAR-10 data, however, $T1$ values are low. From the results, we can notice that the generated examples either can keep the final layer label the same or can change the early exit layer outputs. Our finding suggests that transferability of the early attack-generated samples is limited.

**Finding 9**: *More exits in DyNNs can increase the robustness against the Early Attack.*
**Finding 10**: *Transferability of the adversarial inputs generated by Early Attack is limited.*

## 7 CONCLUSION

In this work [1], we discuss the robustness of DyNNs through four research questions. We find out that DyNNs are more robust than SDNNs and also efficient to generate adversarial examples. We also propose DyNN design choices through final two RQs. Finally, we propose a novel attack to evaluate the robustness of DyNNs.

[1] https://github.com/anonymous2015258/Early_Attack/tree/main

## REFERENCES

Simin Chen, Hamed Khanpour, Cong Liu, and Wei Yang. Learning to reverse dnns from ai programs automatically. *arXiv preprint arXiv:2205.10364*, 2022.

Michael Figurnov, Maxwell D Collins, Yukun Zhu, Li Zhang, Jonathan Huang, Dmitry Vetrov, and Ruslan Salakhutdinov. Spatially Adaptive Computation Time for Residual Networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1039–1048, 2017.

Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and Harnessing Adversarial Examples. *arXiv preprint arXiv:1412.6572*, 2014.

Alex Graves. Adaptive Computation Time for Recurrent Neural Networks. *arXiv preprint arXiv:1603.08983*, 2016.

Mirazul Haque, Anki Chauhan, Cong Liu, and Wei Yang. ILFO: Adversarial Attack on Adaptive Neural Networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 14264–14273, 2020.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. *arXiv preprint arXiv:1512.03385*, 2015.

Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. Mobilenets: Efficient Convolutional Neural Networks for Mobile Vision Applications. *arXiv preprint arXiv:1704.04861*, 2017.

Yigitcan Kaya, Sanghyun Hong, and Tudor Dumitras. Shallow-deep networks: Understanding and mitigating network overthinking. In *International Conference on Machine Learning*, pp. 3301–3310. PMLR, 2019.

Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

Yanpei Liu, Xinyun Chen, Chang Liu, and Dawn Song. Delving into transferable adversarial examples and black-box attacks. *arXiv preprint arXiv:1611.02770*, 2016.

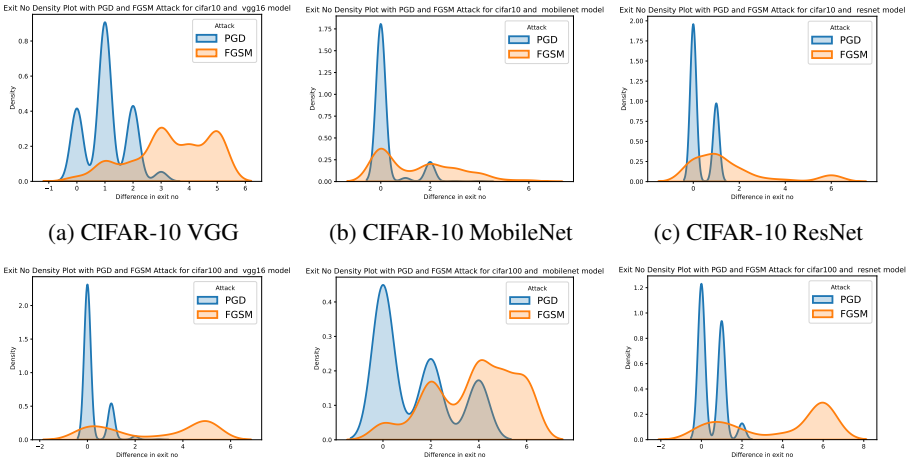
Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. Towards deep learning models resistant to adversarial attacks. *arXiv preprint arXiv:1706.06083*, 2017.

Nicolas Papernot, Patrick McDaniel, Ian Goodfellow, Somesh Jha, Z Berkay Celik, and Ananthram Swami. Practical black-box attacks against machine learning. In *Proceedings of the 2017 ACM on Asia conference on computer and communications security*, pp. 506–519, 2017.

Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

Surat Teerapittayanon, Bradley McDanel, and Hsiang-Tsung Kung. Branchynet: Fast Inference via Early Exiting from Deep Neural Networks. In *Proceedings of the International Conference on Pattern Recognition*, pp. 2464–2469, 2016.

Ruoyu Wu, Taegyu Kim, Dave (Jing) Tian, Antonio Bianchi, and Dongyan Xu. DnD: A Cross-Architecture deep neural network decompiler. In *31st USENIX Security Symposium (USENIX Security 22)*, pp. 2135–2152, Boston, MA, August 2022. USENIX Association. ISBN 978-1-939133-31-1. URL https://www.usenix.org/conference/usenixsecurity22/presentation/wu-ruoyu.




(a) CIFAR-10 VGG (b) CIFAR-10 MobileNet (c) CIFAR-10 ResNet

(d) CIFAR-100 VGG (e) CIFAR-100 MobileNet (f) CIFAR-100 ResNet

Figure 6: Density plots of exit numbers in DyNN that are used to generate black-box adversarial inputs using PGD and FGSM attacks. The x axis represents the exit number while y axis represents the density.

# Appendices

## A RQ1 Density Plots

The density plots in Figure 6 shows the probability density plots of exit numbers in DyNN that are used to generate black-box adversarial inputs using PGD and FGSM attacks.

## B Early-exit Networks

Early-exit DyNNs discontinue the computations within the network if the computation unit output satisfies a specific condition. Figure 7 shows the working mechanism of Early-exit DyNNs. For example, an Early-exit DyNN has N parts and each part has an exit. $x$ is the input, $f^i_{out}$ represents prediction after the $i^{th}$ part (generated by specific computation unit), $f_{out}$ represents prediction of the Neural Network, $C_i$ represents confidence score after $i^{th}$ part, $Hid^{In}_i$ represents input of $i^{th}$ part, $Hid^{Out}_i$ represents output of $i^{th}$ part, and $\tau_i$ is the predefined threshold to exit the network after $i^{th}$ part. The working mechanism of the Early-exit DyNN can be represented as,

$$\begin{cases} f_{out}(x) = f^i_{out}(x), \text{if } C_i(x) \geq \tau_i \\ Hid^{In}_{i+1}(x) = Hid^{Out}_i(x), \text{otherwise} \end{cases} \tag{2}$$

## C Solving Optimization for Early Attack

In this section, we show the iterative process to generate early attack inputs. The algorithm outputs the adversarial input $x'$ given a benign image $x$ as input. $w$ is initialized to a random tensor that has equal shape as the input image.

For each iteration, the loss function of the attack (described in Section 6) is computed (at line 11). Based on the back-propagated loss,

This loss is back-propagated, and based on that, the optimizer updates $w$ with its next value. Once the iteration threshold ($T$) is reached or the attack is successful after certain number of iterations, the algorithm computes and returns the adversarial input $x'$ (at Line 9 and 15).

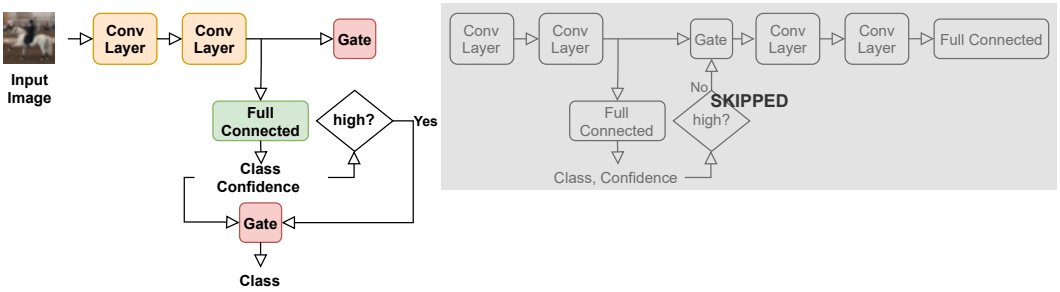



Figure 7: Working mechanism of Early-exit DyNN

**Algorithm 1:** Input generation using Early Attack

**Inputs** : $x$ : $Input\ Image$
**Outputs:** $x'$ : $Perturbed\ Image$

**begin**
  Initialize($w$)
  $T = number_of_iterations$
  $iter_no = 0$
  **while** $iter_no < T$ **do**
    $x' = \frac{\tanh(w)+1}{2}$
    $output = model(x')$
    **if** $success(output)$ **then**
      $return(x')$
    **end**
    $L = loss(x, w, c, \alpha)$
    $L_{new}, w = Optimizer(L, w)$
    $iter_no++$
  **end**
  $x' = \frac{\tanh(w)+1}{2}$
**end**

## D EARLY ATTACK SUCCESS RATE WITH DIFFERENT $\alpha$ VALUES

Table 2: **Attack accuracy percentage of Early Attack with different $\alpha$ values**

| Dataset | Model | EA($\alpha$=0.001) | EA($\alpha$=0.01) | EA($\alpha$=0.1) | EA($\alpha$=1) | EA($\alpha$=20) | EA($\alpha$=40) |
|---|---|---|---|---|---|---|---|
| CIFAR-10 | VGG | 0 | 0 | 0 | 35 | 10 | 4 |
| | MobileNet | 0 | 0 | 11 | 4 | 0 | 0 |
| | ResNet | 7 | 32 | 73 | 81 | 49 | 32 |
| CIFAR-100 | VGG | 1 | 5 | 48 | 82 | 86 | 70 |
| | MobileNet | 0 | 16 | 74 | 97 | 92 | 77 |
| | ResNet | 46 | 74 | 92 | 96 | 96 | 93 |

## E TRANSFERABILITY

Table 2 shows the $T1$ and $T2$ values of all three models on two datasets.

Table 3: $T1$ and $T2$ values for measuring transferability between three models. *TSM* represents Target Model and *SM* represents Surrogate Model. $T1$ presents the percentage of inputs for which the final output remains same as the output generated by benign input. $T2$ represents from the examples selected from $T1$, how many early exit layers on average is mis-classified.

| | | CIFAR-10 | | | CIFAR-100 | | |
|---|---|---|---|---|---|---|---|
| Type | TM / SM | VGG | MNet | RNet | VGG | MNet | RNet |
| $T1$ | VGG | – | 85% | 73% | – | 65% | 39% |
| | MNet | 86% | – | 74% | 51% | – | 38% |
| | RNet | 89% | 82% | – | 79% | 75% | – |
| $T2$ | VGG | – | 0.73 | 1.65 | – | 1.58 | 2.69 |
| | MNet | 1.06 | – | 2.3 | 1.52 | – | 3.26 |
| | RNet | 0.95 | 0.85 | – | 1.32 | 1.28 | – |