Robustness of on-device Models: Adversarial Attack to Deep Learning Models on Android Apps

Yujin Huang, Han Hu, Chunyang Chen*
Faculty of Information Technology, Monash University
Melbourne, Australia
yhua0096@student.monash.edu, han.hu@monash.edu, chunyang.chen@monash.edu

Abstract—Deep learning has shown its power in many applications, including object detection in images, natural-language understanding, and speech recognition. To make it more accessible to end users, many deep learning models are now embedded in mobile apps. Compared to offloading deep learning from smartphones to the cloud, performing machine learning on-device can help improve latency, connectivity, and power consumption. However, most deep learning models within Android apps can easily be obtained via mature reverse engineering, while the models’ exposure may invite adversarial attacks. In this study, we propose a simple but effective approach to hacking deep learning models using adversarial attacks by identifying highly similar pre-trained models from TensorFlow Hub. All 10 real-world Android apps in the experiment are successfully attacked by our approach. Apart from the feasibility of the model attack, we also carry out an empirical study that investigates the characteristics of deep learning models used by hundreds of Android apps on Google Play. The results show that many of them are similar to each other and widely use fine-tuning techniques to pre-trained models on the Internet.

Index Terms—deep learning, mobile apps, Android, security, adversarial attack

I. INTRODUCTION

Deep learning has shown its power in many applications, including object detection in images [39], natural-language understanding [51], and speech recognition [36]. With the popularity of artificial intelligence, many mobile apps begin to incorporate deep learning inside for supporting advanced functionalities such as recommendation, face recognition, movement tracking, and translation. Many app development teams deploy their deep learning models onto the server, rendering the prediction to the app via the internet after taking the input from end devices. However, such a mechanism posts severe latency, extensive server resource requirement, heavy bandwidth load (e.g., streaming video), and privacy concern [20].

Therefore, many apps begin to adopt on-device deep learning models, especially considering the increasing computing capability of mobile devices. Deploying deep learning models brings several advantages as follows. First, there is no round-trip to a server, leading to the bandwidth saving, inference speeding up, and privacy preserving as privacy-sensitive data stays on the device. Second, an Internet connection is not required, and apps can run in any situation.

Due to the benefits of embedding deep learning models into mobile apps, many popular frameworks begin to optimise their on-device frameworks, such as TensorFlow Lite (TFLite) of TensorFlow. Although many research works on improving model performance, few of them are concerned with model security, especially in terms of mobile apps. Unlike the central guardians of the cloud server, on-device models may be more vulnerable inside users’ phones. For example, most model files can be obtained by decompiling Android apps without any obfuscation or encryption [18], [49]. Such model files may be exposed to malicious attacks. Considering the fact that many mobile apps with deep learning models are used for important tasks such as financial, social or even life-critical tasks like medical monitoring or driving assistant, attacking the models inside those apps will be a disaster for users.

Over the last few years, many kinds of adversarial attacks [23], [25], [31], [33], [47] that attack deep learning models have been proposed. Most of them are white-box attacks, i.e., knowing the structure and parameters of the deep learning models prior to the attack. Although it is difficult to apply to a server-based model, which is almost a black box, the on-device model provides adversarial attacks with a chance to attack. In this work, we design a simple but effective way to adapt existing adversarial attacks to hack the deep learning models in real-world mobile apps.

Given an app with a deep-learning model, we first extract the model and check if it is a fine-tuned model based on pre-trained models released by Tensorflow Hub [10]. By locating its pre-trained model, we can train the adversarial attack approach based on that pre-trained model. We apply the adversarial attack to the normal input (e.g., a picture waiting to be classified) and obtain the corresponding generated adversarial samples. The experiment on 10 Android apps shows that all models are successfully attacked, with 23% adversarial samples are wrongly classified.

Apart from a pipeline for attacking the deep learning models in mobile apps, we also carry out an empirical study of the use of deep learning models within thousands of real-world Android apps. We present those results by answering three research questions:

- How similar are TFLite models used in mobile apps? (Section IV)
- How widely pre-trained TFLite models are adopted? (Section V)

*corresponding author

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• How robust are fine-tuned TFLite models against adversarial attacks? (Section VII)

To this end, we collect 62,822 Android apps from Google Play. We identify 267 TFLite models among all the collected apps, which are developed by Google with the aim of optimising TensorFlow on edge devices. Of these models, 87.64% are structurally similar to each other, and 79.78% have the same parameters as at least one other model. Excluding 182 identical models, 61.18% are more than 80% similar to pre-trained models from TensorFlow Hub [10] in terms of their structural similarity, and 50.59% have more than 43.93% of the same parameters indicating that feature extraction and fine-tuning techniques are widely used on these pre-trained models.

Finally, we build a model attacker that can perform adversarial attacks on 10 representative fine-tuned TFLite models used in Android apps for experiments. Experimental results show that attacks with knowing fine-tuned models’ pre-trained models are more than 3 times better than blind attacks in terms of the attack success rate. The results also show that the more similar the target model is to the pre-trained model, the more vulnerable it is to our targeted adversarial attacks. We also discuss the Intellectual Property and defence of on-app models in Section VII.

In summary, our contributions are as follows.

• This is the first work to explore the feasibility of adversarial attacks in practical deep learning models from real-world mobile apps.
• We design and implement a complete pipeline, including ModelDigger, ModelComparer, and ModelAttack, to implement the attack on TFLite models in Android apps. We release our source code and detailed results[1] to the public and discuss both potential defences to those attacks and model IP protection.
• We also carry out an empirical study to show the latest use of deep learning models in the mobile industry, considering both model similarity and widely used fine-tuning approaches to developing deep learning models.

II. BACKGROUND

A. On-device Deep Learning Model

Being ubiquitous, mobile devices are among the most promising platforms for deep learning. In practice, deep learning model inference can be offloaded to the cloud or executed on mobile devices. The cloud-based deep learning model requires mobile devices to send data to the server then retrieve inference results, which comes with multiple drawbacks, such as low privacy protection, high latency, and extra costs for cloud providers. In comparison, the on-device deep learning model executes inference on smartphones without uploading data, which improves user privacy, eliminates the impact of network latency, and lowers cloud costs for mobile developers.

On-device deep learning models are typically implemented through deep learning frameworks such as Google TensorFlow [9], and TFLite [11], Facebook PyTorch [7] and Caffe2 [3]. Tencent NCNN [8], and Apple Core ML [4]. The availability of these practical frameworks allows mobile app developers to produce on-device deep learning models without tremendous engineering efforts. TensorFlow and TFLite frameworks, which run TF models on mobile, embedded, and IoT devices, contribute almost 40% of the total number of deep-learning-based mobile apps in 2018 [49]. TFLite is the most popular technology used to run deep learning models on smartphones, as it has GPU support and has been extensively optimised for mobile devices [41]. However, pre-trained deep learning models are commonly utilized on mobile systems due to the high overheads incurred when training a new deep learning model from scratch [19]. Through the use of pre-existing deep learning models, mobile app developers can directly perform inference with low latency and low power consumption on mobile devices.

B. Adversarial Attack

Deep neural networks are highly vulnerable to adversarial attacks, which add subtle perturbations to inputs that lead to deep learning models to predict incorrect outputs with high confidence level [53]. Suppose that there is a deep learning model and an original example that can be correctly classified, i.e., , where is the true label of .

By adding a subtle perturbation to , attackers can produce an adversarial example that is highly similar to but which is misclassified by model , i.e., . The whole process can be summarised as:

where represents the original label or class of input , represents a multiplier to ensure the perturbations are small, represents the type of adversarial attack, represents parameters, and is the loss.

The differences between adversarial examples and standard inputs are always so subtle that humans cannot even notice the modification, yet the model can still be fooled and misclassified. For example, Figure 1(a) is an input image, and Figure 1(b) shows an adversarial example of Figure 1(a).

Fig. 1: Comparison of original image and adversarial example

Adversarial attacks can mainly be divided into the Blackbox Attack and the White-box Attack, or the Targeted attack and the Non-target attack. Several representative adversarial attack approaches that fall into these categories are: Fast Gradient Sign Method (FGSM) [25]. Projected Gradient Descent

[1] https://github.com/Jinxhy/AppAIsecurity
(PGD) \[34\], Basic Iterative Attack (BIM) \[31\], Decoupling Direction and Norm Attack (DDN) \[40\], Deep Fool Attack \[35\], Newton Fool Attack \[30\], Inversion Attack \[24\], and Boundary Attack \[16\]. These approaches will be used to access the robustness of deep neural networks. FGSM uses the gradients of the neural network to create adversarial examples, while PGD is an iterative extension of FGSM that performs a projected gradient descent. BIM is also a straightforward extension of FGSM, iteratively employing an attack multiple times. DDN performs attacks by decoupling the direction and the norm of the adversarial perturbation added to the image. Deep Fool Attack works by projecting the input onto the nearest non-linear decision boundary, while Newton Fool Attack works by performing a gradient descent that declines the probability of the original class. Inversion Attack involves the attacker extracting information related to training data, such as some sensitive training-data characteristics, from model prediction results. Boundary attack only focuses on output class queries, and starts attacking with a sizeable adversarial perturbation, then seeks to reduce the perturbation while staying adversarial.

III. WORKFLOW OVERVIEW

We design and implement an analytical attack pipeline to enable our research goals on plenty of Android apps. This pipeline can (i) discover the relation between TFLite models; (ii) locate fine-tuned TFLite models; (iii) evaluate the robustness of TFLite models against adversarial attacks. Our pipeline runs in a semiautomatic way (the overall workflow, is illustrated in Figure 2).

For the preparation of our study, we crawled 62,822 mobile apps from Google Play across various categories (e.g., Photography, Social, Shopping) related to the image domain.

The very first step in our pipeline is to identify TFLite deep learning apps and extract TFLite models among a given set of Android APKs as input. This is achieved via the tool named ModelDigger, which first disassembles APKs to the nearly original form then obtains the source codes and asset files from the APK archive via Apktool \[2\]. After decompiling the collected APKs, the ModelDigger examines whether a decomposed APK comprises files with the TFLite model naming convention \[43\], if any such exist, it labels this APK with a tag then extracts the TFLite models from it. During extraction, ModelDigger checks the completeness and operability of each model by loading a model and performing inference on randomly generated data, then filters out unavailable models to ensure the quality of the extracted TFLite models.

The analytical attack pipeline then discovers the relation between the extracted TFLite models and locates the fine-tuned models among them, which is achieved by the tool called ModelComparer. The core purpose of ModelComparer is to detect the longest common sub-layers between two TFLite models, then calculate the structural and parametric similarities between them.

Finally, to evaluate the adversarial robustness of fine-tuned TFLite models, we manually collect model-based input data for each fine-tuned TFLite model and enter them into the adversarial example generator, ModelAttacker, which performs various adversarial attack algorithms based on the architecture of a TFLite model. To ensure the accuracy of an evaluation, the adversarial examples are generated using a set of pre-set attack parameters. This guarantees that the generated adversarial examples are humanly imperceptible.

Initial results We identify 101 TFLite deep learning apps and successfully extract 267 TFLite models. The results are shown in Table I. As observed, 40.45% TFLite models (108 out of 267) come from the Photography category, while 9.00% of them (24 out of 267) belong to the Business category. It is evident that most TFLite deep learning apps contain more than one model. The reasons for this could be (i) the TFLite deep learning apps have two or more deep-learning-based functionalities; or (ii) the tasks that the TFLite deep learning apps perform require multiple models to work together. In addition, we find that 95.51% extracted TFLite models (255 out of 267) are convolutional neural network (CNN) models, and the remaining 12 models are recurrent neural network (RNN) models. The CNN models are proficient at capturing visual characteristics from images and are commonly used for image processing and classification. Hence, the results are consistent with our intention of app collection: most TFLite models are commonly used in task domains that are related to the image.

We will discuss ModelComparer and ModelAttacker in further detail in Sections IV and VI respectively.

IV. Q1: HOW SIMILAR ARE TFLITE MODELS USED IN MOBILE APPS?

Since many apps contain deep learning models with similar functionalities, as mentioned in Section III, we are investigating whether they use the same or similar deep learning models within their apps.

A. ModelComparer: extracting the similarity between models

When evaluating the similarity between models, we calculate two metrics; the structural similarity and the parametric similarity. Each deep learning model consists of multiple layers, like one convolutional model containing several convolution layers and pooling layers. Given one deep learning model extracted from the mobile app, to facilitate comparison we first convert it to a sequence of elements, with each element representing one layer of the model. One unit in the sequence contains one layer’s information, including identifier, shape, and
As seen in Figure 3, one convolutional layer is encoded to MobilenetV1/Conv2d[0]/Relu6,[1,112,112,32],uint8. After converting models to sequences, we detect the longest common subsequence between any two models $M_1, M_2$. We then further calculate the structural similarity of them by:

$$similarity(M_1, M_2) = \frac{2 \times L_{\text{match}}}{L_{\text{total}}}$$

where $L_{\text{match}}$ is the number of longest common subsequence in two models, and $L_{\text{total}}$ is the total number of two models' layers. Note that one unit in the sequence is counted as matched to one unit in the other sequence only if the attributes of them are totally the same. The similarity score is in the range of 0 to 1, and the higher the similarity score, the more structurally similar the two models are.

Apart from the structural similarity, we further adopt the parametric similarity to determine the model similarity. We still convert the model into a sequence, with each layer as one unit, but we adopt the detailed parameter of that layer as the attribute. Given two models, $M_1, M_2$, with a high structural similarity (greater than or equal to 0.8), we perform a subtraction on each corresponding unit, i.e., two units in the same position, as two models have a similar structure. If the calculation result is zero, the Boolean value True that represents two units’ parameters are the same will be stored in a sequence with the order. If not, False will be stored. We then compute the parametric similarity of them by:

$$similarity(M_1, M_2) = \frac{N_{\text{True}}}{N_{\text{total}}}$$

where $N_{\text{True}}$ is the number of longest continuous True values, and $N_{\text{total}}$ is the total number of Boolean values in the result sequence. The similarity score is in the range of 0 to 1, and the higher the similarity score, the more parameters are similar between the two models.

To further analyze the overall relationships among models from different apps, we model their similarity in a single graph. We take each model as the node and their relationship as the edge in the graph. Note that according to our observations, there is one edge between models if both the structural and parametric similarities are higher than 0.8. We then carry out community detection to group highly related nodes in the graph. In graph theory, a set of highly correlated nodes is referred to as a community (cluster) in the network. In this work, we use the Louvain method [15] implemented in the Gephi [13] tool to detect communities. We visualise different communities in different colors and the edges with higher similarity as large thicknesses, as seen in Figure 4. For each model, we annotate its app name along with its extracted order over the node in the graph visualisation.

### B. Results

Our study shows that 87.64% of on-device TFLite models (234 out of 267) are structurally highly similar, i.e., the similarity score is equal to or higher than 0.8. Among the 234 structurally similar TFLite models, 91.03% (213 out of 234) have the same parameters (i.e., 100% parametric similarity) to at least one model. Specifically, 182 TFLite models are identical, both in terms of their structure and parameters. Apart from these identical models, we also find that 52 TFLite models across various app categories, such as photography beauty, business, and productivity, are not only structurally similar to models belonging to the same category but also have relations to the models in other categories. The results indicate that most on-device TFLite models have relations, especially those TFLite models that fall within the same app category.

As seen in Figure 4, there are 7 main clusters of on-device deep learning models such as image classification, segmentation, OCR, object detection, which are widely used in our daily lives. Most deep learning models in computer vision are very similar to each other in terms of both structure and parameters, while textual models are mostly different.
According to our further analysis of those highly-similar models, we find that 75% of them are using the same model structure as MobileNet [28], [42] which is a lightweight deep neural network specifically developed for the mobile platform by Google. We also find that 7 model pairs are identical. The image classification and object detection clusters contain 4 and 2 pairs, while the face detection only contains one. As observed, each model pair’s models come from different apps as the node name represents which app a model belongs to. This may be caused by using the same pre-trained model or by stealing models from similar apps.

Some clusters share connections, such as object detection with image classification and OCR with image classification. Note that many clusters share a connection with image classification models, as image classification is the backbone of these advanced tasks. For example, one model called goolephotogogo2 from the app google photo adds one more layer to the model GIFdd2 from the app GIF dd, while other layers are totally the same. Nevertheless, for other advanced tasks like image style transferring or text generation, they are rarely related to other clusters due to their specificity.

**Summary:** On-device deep learning models are widely used in mobile apps covering a set of common tasks like image classification, object detection etc. Many models are similar in terms of both structure and parameter value, especially those for image classification tasks. Some of them directly copy the models from other apps or add just several layers beyond others’ models.

V. Q2: HOW WIDELY PRE-TRAINED TFLITE MODELS ARE ADOPTED?

Many deep learning models across different mobile apps are very similar, as mentioned in last section, and many layers between them are almost the same except the last few layers. That may be because of the widely used fine-tuning techniques in deep learning area i.e., adding or adjusting final layers in the pre-trained models. That fine-tuning approach is especially useful for application with few labelled data which make it popular. In this section, we further verify if models in mobile apps are fine-tuned models based on pre-trained models.

A. Extracting Similarity between App Models and Pre-trained Models

A pre-trained model is a saved network that was previously trained on a large general dataset. Instead of building a model from scratch to solve a similar problem, developers then either use the pre-trained model as is or use transfer learning to customise this model to a given task. There are some commonly used pre-trained models, such as ResNet [26] on ImageNet [21] for image classification and BERT [22] on Wikipedia [54] for language modeling. TensorFlow Hub (TensorHub) [10] is a repository of pre-trained machine learning models developed by Google. There are 91 models including most common ones such as MobileNet [28], [42], Inception [44], and SqueezeNet [29].

Given the collected 852 models from practical mobile apps, we check the similarity of each model in our collection with models in TensorHub in terms of the structural and parametric similarity, as mentioned in Section IV. Note that for each model in our collection, we only locate the most similar one from TensorHub. Apart from the quantitative analysis, we also manually check the models with high similarity to the pre-trained models in TensorHub for investigating their difference.

B. Results

Figure 5 shows the similarity distribution of models from mobile apps and those from TensorHub in terms of the structural and parametric similarity, as mentioned in Section V. Note that for each model in our collection, we only locate the most similar one from TensorHub. Apart from the quantitative analysis, we also manually check the models with high similarity to the pre-trained models in TensorHub for investigating their difference.

Excluding the 182 identical models from the last section.
TABLE II: Numbers of fine-tuned TFLite DL models.

| Task domain      | Pre-trained model type         | Fine-tuning model count |
|------------------|--------------------------------|-------------------------|
| Image classification | MobileNet V1 and V2 | 21                      |
|                  | InceptionV3                | 2                       |
|                  | SqueezeNet                 | 1                       |
| Object detection | COCO SSD MobileNet v1      | 9                       |
|                  | Google Mobile Object Localizer | 2                     |
| Image segmentation | DeepLabv3               | 7                       |
| Pose estimation  | PoseNet                    | 1                       |
| Total            |                              | 43                      |

In terms of the parametric similarity, there are always some layers in the app model with the same parameters to that of pre-trained model in TensorHub as seen at Figure 5 shows. Specifically, for 43 models with more than 80% structural similarity, 6 (13.95%) of them are of more than 95% parameter value similar. These models use the representations learned by a previous pre-trained network to extract meaningful features from new samples and this kind of fine-tuning can be called feature extraction [38]. For instance, there are 66 layers in the pre-trained MobileNet V1, freeze all layers of the base model and only train the parameters of the newly added classifier. This allows to repurpose the feature maps learned previously by the base model trained on a larger dataset in the same domain.

Summary: Many mobile apps fine-tune the pre-trained deep learning models for their own purpose especially in computer-vision related tasks. The fine-tuned models are similar to the pre-trained models in TensorHub in terms of both structure and parameters.

VI. Q3: HOW ROBUST ARE FINE-TUNED TFLITE MODELS AGAINST ADVERSARIAL ATTACKS?

The latter 2 research questions demonstrate that the pre-trained models and fine-tuning approach are widely used in developing real-world on-device deep learning models. Considering the popularity of adversarial attacks on neural networks and the availability of identifying the pre-trained models, we further explore the possibility of applying off-the-shelf adversarial attack to existing deep learning models inside mobile apps. Since most adversarial attacks are white-box based, i.e., FGSM and BIM, relying on the understanding of target models including the training data and runnable for adjusting its parameter, we propose a method called ModelAttacker to attack the deep learning model based on the identification of its pre-trained model. Therefore, we present the performance of our targeted attack compared with blind attack in real-world mobile apps from Google Play in this section.
TABLE III: Details of selected 10 models

| ID | App Name                  | Model Name             | Similarity | Model Function                        |
|----|---------------------------|------------------------|------------|----------------------------------------|
| 1  | converted_model.tflite    | QQ browser             | 74.96      | Identify plants                        |
| 2  | graph.tflite              | Fresh Fruits           | 29.79      | Determine if the fruit has gone bad    |
| 3  | mobilenet.letgo.v1_1_0_224_quant.v7.tflite | Taobao       | 47.02      | Identify products                      |
| 4  | mobilenet_v1_1_0_224 quantify.tflite | Image Checker | 48.03      | Image classification of ImageNet database |
| 5  | optimized_graph.tflite    | IQIYI                  | 45.55      | Identify actors                        |
| 6  | pothole_detector.tflite   | Tencent Map            | 44.97      | Judge traffic conditions               |
| 7  | mobile_jca_8bit_v2.tflite | Bei Ke                 | 81.27      | Identify scenes                        |
| 8  | model.tflite              | Baidu Image            | 46.61      | Identify flowers                       |
| 9  | pothole_detector.tflite   | My Pokemon             | 96.67      | Identify different Pokemon             |
| 10 | skin_cancer_best_model.tflite | Palm Doctor         | 98.46      | Identify different skin cancers         |

A. Methodology of ModelAttacker

Given a deep learning model decompiled from the mobile app, we first compute its similarity with all models from TensorHub by the ModelComparer mentioned in Section IV. According to the similarity ranking, we select the most similar pre-trained model from our database in terms of structure and parameter value. If the similarity is above the threshold 80%, which is experimentally set up, we train the parameters of adversarial attacks on the pre-trained model. We then apply the adversarial attack to generate adversarial examples to feed into the target deep learning models.

As mentioned in Section II, there are 11 representative attacks adopted from 4 all main categories to carry out experiments.

B. Evaluation of ModelAttacker

1) Evaluation of attacking fine-tuned models: As shown in Table II there are 43 TFLite models from Google Play found to be fine-tuned. We pick up 10 representative models that are all fine-tuned from MobileNet V1 and MobileNet V2 as they are most commonly used. Table III show the detail of selected 10 models. The Similarity indicates the similarity between the fine-tuned model and its pre-trained model. We utilize ModelAttacker to employ selected 11 kinds of adversarial attacks on these TFLite models. For each model, according to its functionality, we manually find 10 random images from the Internet as the original input. For instance, we find 10 images, including 10 different kinds of plants for model 1. These images are used by ModelAttacker to generate adversarial examples, which are then used against the selected 10 models. Note that since finding images for each model takes much human effort, we limit this experiment to 10 models and 10 images for each model, which balances the result validity and human effort.

2) Evaluation Metrics: We evaluate results from two aspects: whether the adversarial examples can be recognized by humans and the attack’s success rate. During the attack, ModelAttacker continuously adjusts $\epsilon$ to determine the most significant attack parameters. After attacking, two researchers with experience in machine learning made a manual evaluation of the attack results, respectively. If the adversarial example cannot be recognized as modified by humans, the attack is considered successful, and we will count the number of examples that successfully misjudged the model among these 10 adversarial examples. Otherwise, the attack fails too. Let $n_i$ represents $n$ examples are misclassified in $i_{th}$ attack, so

$$P_i = \frac{n_i}{m}$$

where $m$ is equal to 10, which is the total number of adversarial examples, and $P_i$ represents the success rate of the $i_{th}$ adversarial attack.

Besides, to evaluate the effectiveness of the approach, we add one control experiment. In the comparative experiment, ModelAttacker is unknown about the fine-tuned model’s pre-trained model and directly carried out blind attacks trained on randomly selected pre-trained models. Since the adversarial attack is trained on a random pre-trained DL model, we call it blind attack for brevity. In comparison, we call the attack with knowing the pre-trained model as targeted attack.

C. Results

Table IV shows the comparative results of targeted adversarial attack and blind adversarial attack. In every model’s column, the left side $T$ is the result of targeted attacks, and the right side $B$ is the result of blind attacks. The better results are blackened. The last two columns are the average success rate of targeted and blind attacks. Compared with the blind adversarial attacks trained on random models, the targeted attacks trained on pre-trained models have much better success rates. On average, blind adversarial attacks can achieve a 0.07 success rate, while the targeted attacks’ success rate is 0.23, 229% higher than the blind attack. The blind adversarial attacks do not work at all in 6 models, including model 2, 3, 4, 5, 6, and 8, with a success rate of 0 given all 11 attacks. Instead, our targeted attacks work on all models with the average success rate ranging from 0.08 to 0.57, and some attack model can achieve even as high as 0.9 success rate like Linf BIM attack on model 10. Within 110 experiments (10 models * 11 attacks), the targeted attack gets a higher or equal success rate in 99% of them. These results demonstrate the necessity of locating a pre-trained model before carrying out the adversarial attack.

Some deep learning models are more vulnerable to adversarial attacks than others. As seen in Table IV models
Inversion attack takes the confidence of a prediction result in training data as the target. It adopts gradient descent to revise the adversarial examples according to the prediction result repeatedly and continuously improve the adversarial examples’ prediction confidence. Targeted attacks more clearly point out the direction of optimizing the adversarial examples for the attack, so it can improve the attack’s success rate more effectively.

**Summary:** ModelAttacker can significantly improve the adversarial attacks’ success rate by identifying the pre-trained model compared with the blind attack. The more similar is the target model to the pre-trained model, the more vulnerable it is to our targeted adversarial attacks. The attack methods like inversion attack are more effective than others in targeted attacks.

### VII. Discussion

#### A. Defence of Attack

From our investigation in Section V, most models currently used in Android apps are fine-tuned from several popular pre-trained models, such as MobileNet and DeepLabV3. Some fine-tuned models’ names are even quite similar to the pre-trained models, for instance, `mobilenet.letgo.v1_1.0_224_quant.v7.tflite`, which can be easily assumed that they are fine-tuned from MobileNet. However, according to Table IV, the targeted attacks are significantly threatening than the blind attacks as they are generated by attacking the specific pre-trained models. Hence, some measures for preventing disclosure of model information are necessary, such as encrypt the pre-trained models, confuse the predicted labels. However, according to the Section VI, the higher the similarity between the fine-tuned model and the pre-trained model, the easier it is to be attacked. Thus, we should change both the structure and parameters of the pre-trained model as much as possible, especially when using common pre-trained models, such as MobileNet and DeepLabV3.

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**TABLE IV: Results of targeted and blind attacks**

| Attack              | Epsilon | M1  | M2  | M3  | M4  | M5  | M6  | M7  | M8  | M9  | M10 | Average (Models) |
|---------------------|---------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----------------|
| Boundary Attack     | 2.5     | 0.1 | 0.1 | 0   | 0   | 0   | 0   | 0.1 | 0   | 0.1 | 0.3 | 0.27            |
| DDN Attack          | 0.5     | 0.1 | 0.1 | 0   | 0   | 0.1 | 0   | 0   | 0   | 0.1 | 0.3 | 0.08            |
| L2 DeepFool Attack  | 1.4     | 0.1 | 0.1 | 0   | 0   | 0.1 | 0   | 0   | 0   | 0.1 | 0.3 | 0.15            |
| FGSM                | 0.02    | 0.4 | 0.2 | 0   | 0.1 | 0   | 0.3 | 0   | 0.1 | 0.3 | 0.27            |
| Inversion Attack    | 10      | 0.6 | 0.1 | 0.3 | 0.2 | 0   | 0.4 | 0   | 0.2 | 0.3 | 0.41 | 0.26            |
| L2 BIM              | 1       | 0.1 | 0.2 | 0   | 0.1 | 0   | 0.2 | 0   | 0.1 | 0.2 | 0.2 | 0.07            |
| L2 PGD              | 12      | 0.2 | 0.2 | 0   | 0.1 | 0   | 0.3 | 0   | 0.1 | 0.3 | 0.7 | 0.13            |
| Linf BIM            | 0.05    | 0.5 | 0.2 | 0.1 | 0.3 | 0   | 0.5 | 0.1 | 0.1 | 0.2 | 0.5 | 0.13            |
| Linf PGD            | 0.05    | 0.4 | 0.2 | 0   | 0.1 | 0   | 0.2 | 0   | 0.1 | 0.2 | 0.7 | 0.15            |
| Newton Fool Attack  | 12      | 0.4 | 0.1 | 0   | 0.1 | 0   | 0.3 | 0   | 0.1 | 0.3 | 0.3 | 0.21            |
| Salt and Pepper Noise Attack | 80 | 0.1 | 0.1 | 0   | 0.1 | 0   | 0.3 | 0   | 0.2 | 0.7 | 0.1 | 0.21            |
| **Average**         | **0.27**| **0.15**| **0.04**| **0.12**| **0.26**| **0.08**| **0.07**| **0.28**| **0.02**| **0.10**| **0.45**| **0.21**|

From our investigation in Section V, most models currently used in Android apps are fine-tuned from several popular pre-trained models, such as MobileNet and DeepLabV3. Some fine-tuned models’ names are even quite similar to the pre-trained models, for instance, `mobilenet.letgo.v1_1.0_224_quant.v7.tflite`, which can be easily assumed that they are fine-tuned from MobileNet. However, according to Table IV, the targeted attacks are significantly threatening than the blind attacks as they are generated by attacking the specific pre-trained models. Hence, some measures for preventing disclosure of model information are necessary, such as encrypt the pre-trained models, confuse the predicted labels. However, according to the Section VI, the higher the similarity between the fine-tuned model and the pre-trained model, the easier it is to be attacked. Thus, we should change both the structure and parameters of the pre-trained model as much as possible, especially when using common pre-trained models, such as MobileNet and DeepLabV3.

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**Fig. 6: Relationship of similarity and attack performance**

![Relationship of similarity and attack performance](image-url)
According to the prediction results, some attacks, such as the inversion attack, continuously revises adversarial examples to improve the prediction confidence. We should take measures, such as fuzzy confidential information [46] and differential privacy technology [12]. Let the attacker be impossible to detect each training data change’s impact on the model output, reducing these attacks’ threat.

B. Deep Learning Model IP

Building a product-level deep learning model is not straightforward, as it always requires lots of computing resources and training data. For instance, XL-net [50], which is proposed by researchers from Google AI Brain, utilizes over 120GB of training data and 512 TPU v3 chips to train the model. Furthermore, designing model architectures and selecting hyper-parameters are time-consuming. Some mobile developers may illegally infringe intellectual property by reusing others’ deep learning model file or retraining a new deep learning model on top of them. Hence, model owners also possess the IP of their trained models. Unfortunately, out of 120 popular deep learning apps, only 47 (39.2%) of model owners take measures to protect their IP [49]. In addition, at present only a few deep learning R&D frameworks, such as ncnn [8] and Mace [1], provide the function of protecting the IP of deep learning models. We should take the necessary measures to protect the IP of the Android phone’s deep learning model, such as watermarking, file encryption, etc. Thus, protecting the IPs of deep learning models on smartphones is worth exploring, and call on researchers and developers to pay more attention to this field.

VIII. RELATED WORKS

With the rapid development of computing architectures, hardware like GPU has been released at affordable prices, facilitating the deployment of deep learning models on mobile devices [37]. Our work empirically evaluates the security of deep learning models on Android apps. It interacts with three lines of research: mobile app security, adversarial deep learning, and proprietary model protection.

A. Mobile App Security

Prior work on AI app security mainly focuses on model protection. Xu et al. [49] indicate that most deep learning models are exposed without protection in deep learning apps, so can easily be extracted and exploited by attackers. Sun et al. [43] demonstrate the feasibility of private model extraction on AI apps, subsequently, they further analyse the model parameters and show the estimated financial loss caused by the leaked models. Wang et al. [48] comprehensively investigate the current challenges encountered when pushing deep learning towards mobile apps, and find that model protection is crucial, as leaking critical models can result in both security and privacy breaches. These studies explore the security of deep learning models either from the user’s or the defender’s point of view, in lack of real attacks. Hence, motivated by enormous efforts to secure AI apps, our work investigates the security of deep learning models from the attacker’s perspective, providing a valuable method with which to test AI app security.

B. Adversarial Attack and Defence to Deep Learning Models

Since deep learning has achieved remarkable progress in the field of computer vision, main developments in adversarial attack and defence are associated with image classification [17], [25], [32], [45]. Researchers have proposed numerous novel adversarial attacks based on deep neural networks [17], [23], [25], which can be mainly summarized into two categories including white-box and black-box attacks [27]. For example, Szegedy et al. [45] propose an optimisation function to construct adversarial examples, solving it with L-BFGS. To prevent the aforementioned attacks, seven defence methods have been proposed, including adversarial training, transformation, distillation and gradient regularisation [27]. Among these countermeasures, adversarial training draws the most attention and it is one of the most effective defence methods [52]. Despite numerous studies that have proposed various adversarial attack methods and corresponding defence strategies for deep learning models, work on the security of deep learning models on mobile apps is scant. Our work proves that most on-device deep learning models lack protection against adversarial attacks, especially in the field of computer vision.

IX. CONCLUSION

This paper proposes a practical approach to hacking deep learning models with adversarial attacks by identifying highly similar pre-trained models from TensorFlow Hub. Experimental results show that attacks with knowing fine-tuned models’ pre-trained models are more than 3 times better than blind attacks in terms of the attack success rate. The results also demonstrate that the higher the similarity between the fine-tuned model and its pre-training model, the worse the fine-tuned model’s robustness. In addition, we carry out an empirical study into the use of deep learning models in real-world Android apps, identifying 267 pre-trained TFLite models among 62,822 Android apps. Excluding 182 identical models, we find that 61.18% of the rest are more than 80% similar to pre-trained models from TensorFlow Hub in terms of the structural similarity.

In the future, we will work in two directions in the fields of both attack and defence. We will develop specific adversarial attacks that target pre-trained models, thereby making the attack more effective. Additionally, we will try to implement the defence mechanism in practice, in order to establish how to best protect on-app deep learning models.

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