Adversarial Machine Learning

Homework Assignment 1

The assignment is due by the end of the day on Thursday, January 23.

Objective:

- Implement white-box evasion attacks against deep learning-based classification models.

Dataset: For this assignment, we will use the Oxford Flowers dataset. The dataset consists of images with 102 categories of flowers, and it has 8,189 images in total. Examples of images from the Oxford Flowers dataset are shown in Figure 1. A more detailed explanation of the dataset can be found at this link.

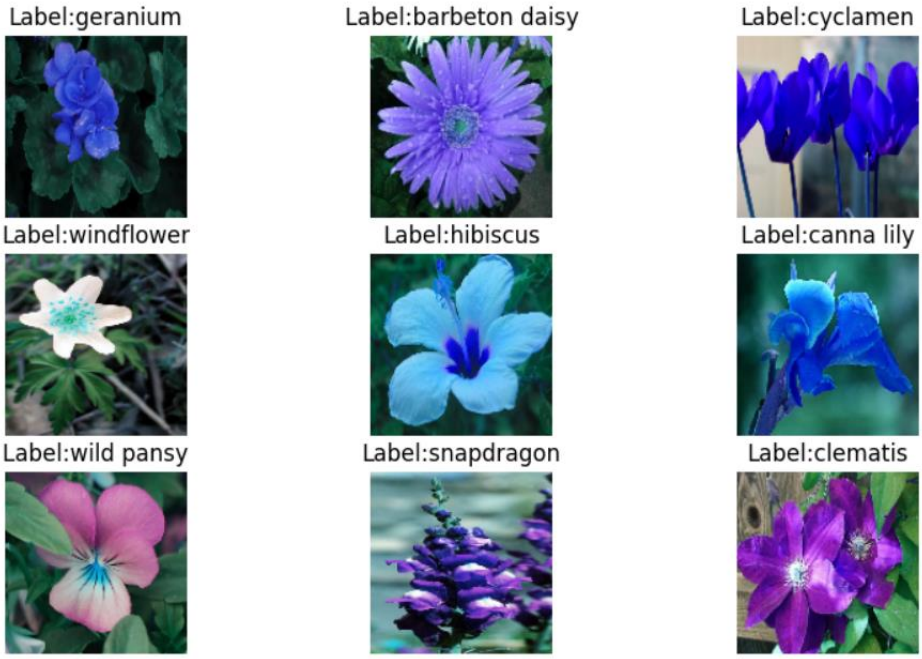


Figure 1. Example images from the Oxford Flowers dataset.

FGSM and PDG Attacks against Keras-TensorFlow Image Classification Models

A starter code for loading the dataset is provided with this assignment. Please use the provided file to load the dataset.

Task 1: Train a deep-learning model for classification of the Oxford Flowers dataset, using the Keras-TensorFlow libraries.

For GPU access, it is recommended to use Google Colab Pro (the cost is $10 per month). It is also possible to use the free GPU access by Google Colab, although it has limitations (I believe that the

free version provides access to GPU for 12 hours, and it restricts the access for 12 hours afterward). Or, if you have access to GPU from other sources, that is even better.

If needed, please review the codes for White Box Evasion Attacks posted on Canvas in the 'Modules/Codes' section. Also note that the assignments and solutions from the offering of the AML course in the previous semesters can be found at these links: Spring 2023 (link), and Fall 2021 (link). These resources can be helpful for solving the assignments in this course.

For instance, an easy and fast way to complete this task is to adopt a pretrained VGG-16 or ResNet (e.g., ResNet50) model, and just add a classifier head on top of the pretrained backbone. This approach is used in the solutions to the assignments in the previous offerings of the course, and if needed, follow the provided solutions examples.

Perform hyperparameter tuning to obtain accuracy on the test dataset above 80%.

For the students who don't have a previous background in Artificial Neural Networks, I suggest reviewing the lectures from my course Applied Data Science with Python. The most relevant lectures for this task are Lecture 16 - Convolutional Neural Networks with Keras-TensorFlow (link) and Lecture 17 - Model Selection, Hyperparameter Tuning (link). If needed, please other lectures from the course. Some students may find helpful the Tutorial on working with Google Colab (link).

Note: when training the model if you get an error message about the used optimizer (e.g., 'Adam has not attribute get_updates', or a similar error), instead of "tf.keras.optimizers.Adam" try to use "tf.keras.optimizers.legacy.Adam". An error regarding the compatibility of the tf.Dataset format can be resolved by installing TensorFlow 2.15.0 version, as suggested in the starter code. If you get stack in solving the assignment, please send me your code and I will have a look.

Estimated running time: between 10 and 30 minutes using a GPU.

Report (40 marks):

a) Fill in Table 1 with the values for the classification accuracy for the train set, validation set, and test set of images. For full marks, it is expected to report a test accuracy above 80%. You don't need to report other performance metrics, since the focus is on adversarial attacks.

b) For each model, plot the training and validation loss and accuracy curves (similar to the example in Figure 2 below).

If applicable, provide any other observations regarding the model or the dataset.

Table 1. Classification accuracy.

Model	Train Set	Validation Set	Test Set

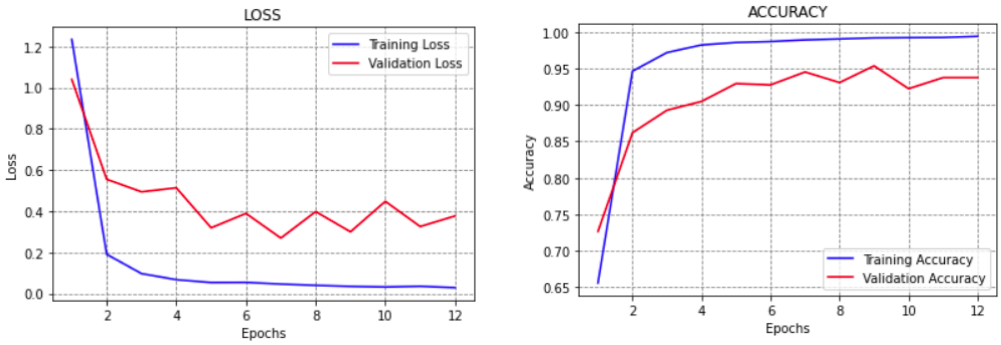


Figure 2. Loss and accuracy plots for a DL model. This is an example, and not the actual expected plot.

Task 2: Implement non-targeted white-box evasion attacks against the deep learning model from Task 1.

The attacks to be implemented are Fast Gradient Sign Method (FGSM) and Projected Gradient Descent (PGD).

Use the Adversarial Robustness Toolbox for implementing the attacks for this assignment. For example, this notebook explains how to apply adversarial attacks in ART using the Keras library. Similarly, the ART library provides many other notebooks with explanations on how to use the various attacks and defenses in the library.

For this assignment, if you follow the provided code in the White Box Evasion Attacks notebook posted on Canvas in the 'Modules/Codes' section, solving this part of the assignment should be straightforward. Also note that the posted notebook is based on the solutions from the previous offering of the course found at this link.

Apply FSGM and PGD attacks to create non-targeted adversarial examples using the first 200 images of the test set. Apply the following perturbation magnitudes: ϵ= [1/255, 3/255, 5/255, 8/255, 20/255, 50/255, 80/255]. Plot the overall accuracy of the model versus the perturbation size ϵ (e.g., the expected plot should look like Figure 3, note that ϵ=80/255≈0.3). For the FGSM attack, plot the first clean test image and the adversarial images with added adversarial perturbation of ϵ= [3/255, 8/255, 20/255, 50/255, 80/255], and display the predicted label (the figure should look similar to Figure 4 below). When you run the codes, you will understand better why FSGM is called a fast method.

Estimated time: between 10 and 20 minutes.

Report (60 marks):

a) Fill in Table 2 with the values for the classification accuracy for the clean images and perturbed images, with perturbations levels of ϵ=1/255, 5/255, and 8/255.
b) Plot the accuracy versus perturbation ϵ for FGSM and PGD adversarial attacks (similar to the example in Figure 3).
c) Plot figures with added adversarial perturbation and the labels for ϵ= [3/255, 8/255, 20/255, 50/255, 80/255], similar to the examples in Figure 4.
d) Provide an analysis of the results.

Table 2. Classification accuracy on clean and adversarial images.

Model	Clean images	Adversarial images ϵ=1/255	Adversarial images ϵ=5/255	Adversarial images ϵ=8/255
FGSM attack				
PGD attack				

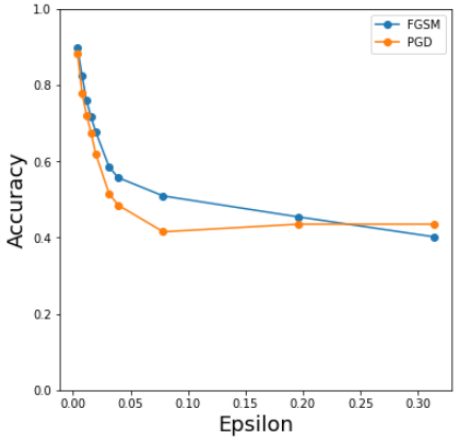
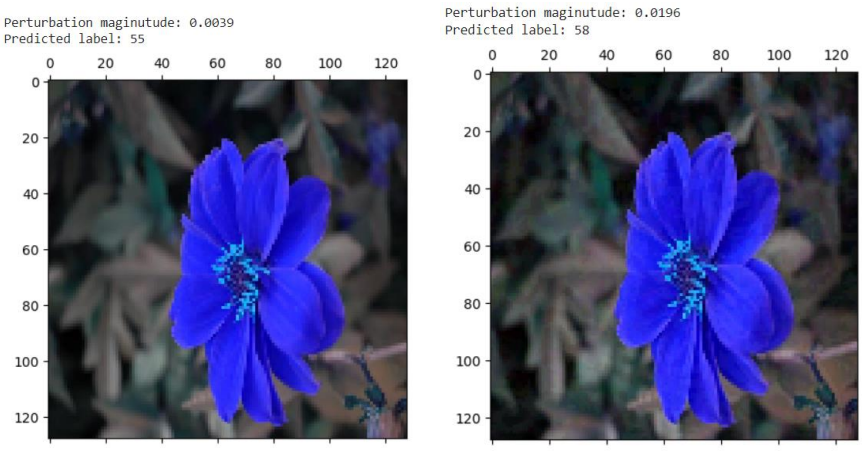


Figure 3. Pots of accuracy versus perturbation. This is an example figure, and not the plot for this task.



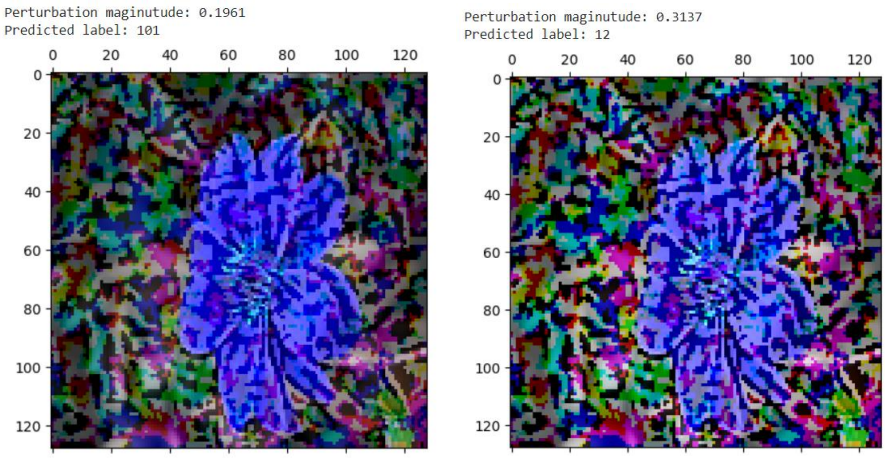


Figure 4. Examples of adversarial images.

Submission documents:

The assignment documents are submitted on Canvas. Note that it is possible to submit multiple files at the same time, just drag-and-drop the files or attach all the files while the submit window is open.

1. Submit all your codes as Jupyter Notebooks. Please try to comment your codes extensively, introduce the names of all used variables, avoid one-letter variables, etc., to improve the readability of the codes. For instance, for this assignment you can submit one single Jupyter Notebook with the codes. You don't need to submit the dataset on Canvas.
2. Prepare a brief report with tables, graphs, and results: the report can be prepared either as a separate MS Word/PDF file, or it can be integrated into your Jupyter Notebooks by typing your analysis directly into text cells in the Jupyter Notebooks.