Exploring Architectural Vulnerabilities in Neural Networks: A Large-Scale Adversarial Attack Analysis on MNIST

Tanner Giddings #300172545

Supervisor Carlisle Adams

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1. Abstract

As neural networks become increasingly embedded in critical domains such as autonomous vehicles, healthcare diagnostics, and financial systems, ensuring their security has become a pressing concern. Interestingly, the concept of deceiving perception—long used by humans in the form of camouflage for hunting and warfare – finds a modern parallel in adversarial attacks on computer vision models. These attacks involve subtle, carefully crafted perturbations to input data that can mislead neural networks into making incorrect predictions, often to the attacker's advantage. This paper explores the vulnerabilities of computer vision models in relation to an attack consisting of small perturbations to input data, consisting of pictures of numbers, which can lead to modifying the prediction to an attacker's advantage.

It was found that the features of neural networks that were examined were the complexity of the dense and convolutional layers. It was found that the presence of convolutional layers were the most important feature to reducing the ease of fooling the networks, meanwhile an increase in the complexity of the dense layers results in overfitting the network, which makes fooling it easier.

2. Introduction

Computer vision, the field of enabling machines to interpret and understand visual information, has experienced remarkable progress in recent years, largely due to the advancement of neural networks. Deep learning models, particularly convolutional neural networks, have dramatically advanced the processing of visual data, delivering unprecedented levels of accuracy, efficiency, and scalability in tasks such as image classification, object detection, segmentation, and facial recognition. These breakthroughs have led to widespread deployment of computer vision systems across a variety of industries, including autonomous vehicles, medical imaging, surveillance, agriculture, and retail.

Despite their impressive performance, neural networks are often treated as black boxes – highly complex systems whose internal decision-making processes remain largely opaque. This lack of interpretability introduces significant risks, especially in security-critical applications. Adversarial attacks, where minor modifications can cause drastic changes in output, exploit this very opacity and as computer vision systems become more integrated into daily life, the inability to explain and secure these models poses a growing threat. Examples of such dangers relate to fields such as self-driving cars and autonomous military systems, where split second decisions can cause life changing situations.

This paper will look to answer which features help with the security of computer vision models, especially protecting against adversarial attacks. In particular, by investigating architectural characteristics that may enhance robustness to input perturbations. By analyzing how certain model design choices affect vulnerability to adversarial examples, this paper aims to identify patterns that contribute to more secure models. Understanding which features make models more resistant to manipulation is critical for deploying computer vision systems in real-world applications where reliability and security are paramount.

3. Previous Research

3.1 Intriguing properties of neural networks - Szegedy, C., Zaremba, W., Sutskever, I., Bruna, J., Erhan, D., Goodfellow, I., & Fergus, R. (2014, February 19)

This paper demonstrates that deep neural networks, particularly in computer vision, are highly susceptible to adversarial examples – inputs that have been subtly perturbed in a way that causes misclassification, despite the changes being imperceptible to humans. The authors evaluated this phenomenon using models trained on the MNIST and ImageNet datasets, as well as a large collection of images from YouTube. To craft adversarial examples, they assumed a white-box setting in which the attacker has full knowledge of the model architecture. This allowed them to formulate a tailored objective function and use a box-constrained optimization method (L-BFGS) to efficiently generate perturbations that fool the network. Their results showed that adversarial examples not only deceive the original model but often generalize across different model architectures and training sets. While their experiments were conducted on a limited set of models, the findings raise important questions about the general vulnerability of neural networks and suggest that this behavior may be intrinsic to the way these models learn.

The goal of this study is to expand on their work by generating a large number of models with different architectures, to determine which features help, or hurt with the security of computer vision models against these types of attacks.

3.2 A Review of Adversarial Attacks in Computer Vision Zhang, Y., Li, Y., Li, Y., & Guo, Z. (2023, August 15)

This paper explains the different types of attacks that can be conducted against computer vision models. Attacks against computer vision models can be stratified by how they access the models, the goal of the attack and by the method of perturbation:

- How the attack accesses the model:
    - White-box attacks: Attacks that require full access to the target model.
    - Black-box attacks: Attacks that require no knowledge, or very little knowledge, of regarding the target model's architecture.
- What is the goal of the attack:
    - Targeted attacks: Wants to force a prediction into a specific class.
    - Untargeted attacks: Cause misclassification in general, without a specific goal.
- What is the method of perturbation:
    - Optimization-based: Use model gradients to iteratively change the specified sample to obtain perturbations, to generate the adversarial attack.
    - Generative-based: Use reinforcement learning to build an artificial intelligence model that can conduct adversarial attacks.

Furthermore, this paper describes different attacks based on which parts of computer vision an actor is trying to attack:

- Two-stage detector attacks: Two stage object detectors aim to locate an object within an image. The first stage proposes "regions" where objects could be located, and the second stage determines what label to assign to that object. These attacks make it harder for those features to find objects. An example of such an attack is DAG (Dense Adversary Generation)
- One-stage detector attacks: One-stage detector attacks also aim to locate an object within an image. However they work much faster, but have a lower accuracy in general and so are mainly used in real-time applications. Since these features have different architectures, they need different kinds of attacks, such as YOLO
- Segmentation Networks: Labels each pixel in an image to an object. An example of an attack that could be conducted is DeepLab.

In this paper, the goal is to quantify the impact of different features in a computer vision model against targeted black-box attacks against the second stage of a two-stage detector attack.

4. Framework

See Annex - Code for the implementation of this framework.

4.1 Model Creation

In order to analyze the effect of different features in a neural network, an analysis is conducted on a large sample of models containing different combinations of features (see table 1 for the configuration options). In addition, the batch size is set at 64 for all models.

Table 1: Table containing the different possible configurations of features. Due to limited computing power, the features that are being examined had to be reduced to the options listed below.

Feature	Options
Convolutional Layer Depth	0, 1
Convolutional Layer Kernel Dimensions	(3,3), (4,4), (5,5)
Dense Layer Depth	1, 2, 3
Size of Dense Layer	64, 128, 256

In order to limit the interferences caused by different numbers, while being limited by computing constraints, each model is tested against 5 different combinations of numbers. A combination of numbers describes the number represented in the image, and the number which the adversarial attack is trying to convert the prediction to, so called the “fooled number”. This helps average out the results to better understand the impact of the features against adversarial attacks.

4.2 Simulating an Adversarial Attack

Firstly, a sample of 50 screens are randomly generated. Due to time and resource constraint, the adversarial attack was allowed to modify the intensity of a pixel by 50% (see Figure 1 for an example). This allows for a faster generation of an adversarial attack "screen", and to therefore generate more samples to get a more comprehensive analysis.

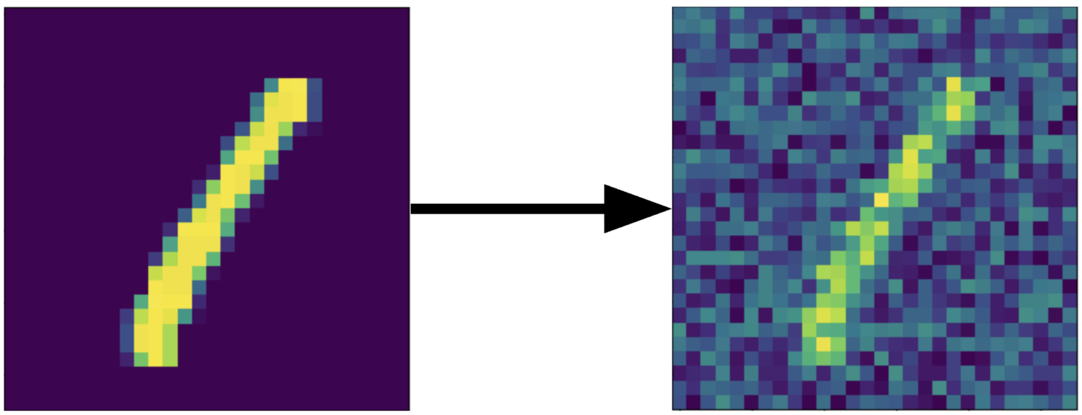

Figure 1 Example of a screen being added to the image of a "1". The screen is allowed to modify at most 50% of the intensity of a pixel.

Following this, a genetic algorithm is used to find screens that optimize fooling the networks. The genetic algorithm works in the following steps:

1. Scores all the screens based on their ability to fool the prediction – meaning the accuracy of the model to predict the "fooled" number, and rank them based on their accuracy.
2. Save the best 25 screens, duplicate each of them, then add random modifications to each of these screens. The modifications to these screens were limited to modify at most 10% of the intensity of a pixel.

These steps are repeated 100 times which results in an incremental increase in the fooling score, see figure 2 for an example and figure 3 for an example of a screen generated using this method. The goal is to generate one screen that modifies the prediction correctly for all pictures of a certain number.

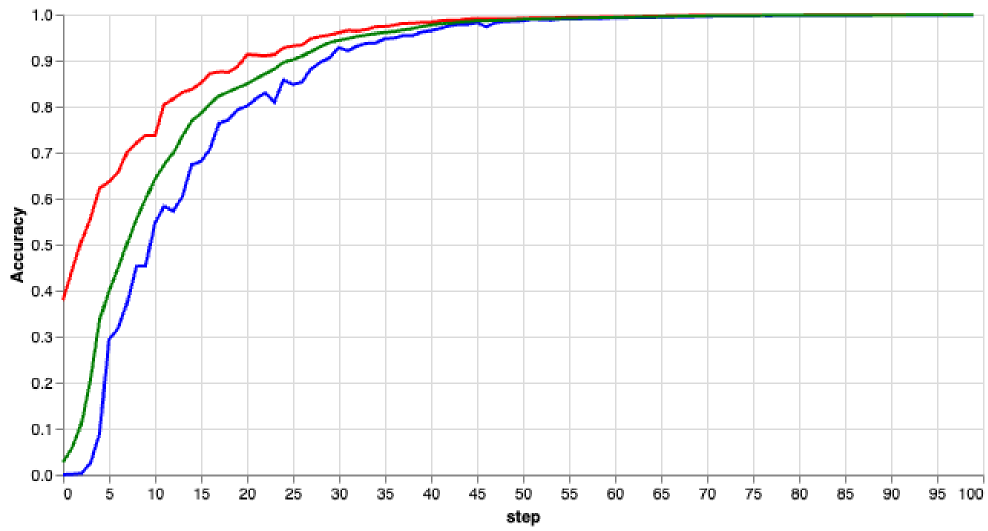

Figure 2 Graph showing the accuracy over iterations for a genetic algorithm implementing an adversarial attack with a sample of 50 screens. The red line shows the best fooling score, the green line shows the median fooling score and the blue line shows the lowest fooling score.

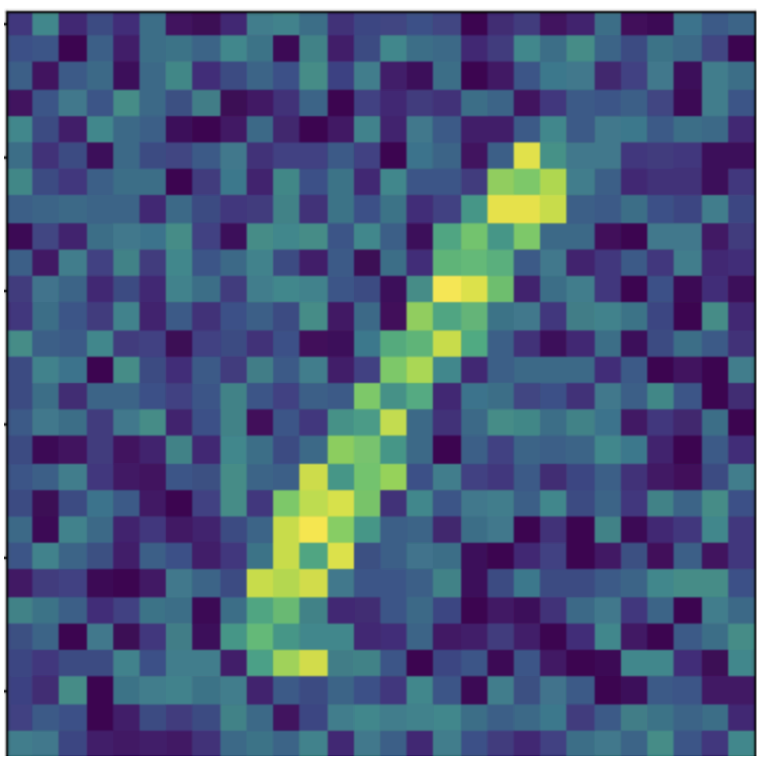

Figure 3 Screen added to an image of a “1” that was generated using the genetic algorithm defined on page 3, which fools a given computer vision model to predict all the images of 1s to 7s.

5. Results

As a reminder, the goal of this paper is to investigate the vulnerability of computer vision models using deep neural networks against adversarial attacks. The MNIST dataset was used to train the models, and the adversarial attack is generated by optimizing filters that are added onto the pictures using a genetic algorithm. 753 models (see ANNEX - data) were created with different combinations of the features listed in table 1. For the purpose of this analysis, a confidence threshold of 0.05 will be used – meaning that all tests for which the p-values generated are lesser than 0.05 are statistically significant. In this analysis, the fooling score measures the model's accuracy when a visual perturbation (the screen) is applied to all images from the source class in the MNIST dataset, and their labels are reassigned to the target class intended by the adversarial manipulation.

5.1 Analysis regarding the combination of numbers

In order to limit the interference caused by the starting number and the number to which the adversarial attack aims to redirect the model's prediction, an analysis needs to be conducted to determine the impact of these parameters.

Firstly, the impact from the number that the adversarial attack is trying to convert from was examined (see Figure 4). A one-way ANOVA test was conducted to see if the fooling scores were significantly different depending on the initial number, or source label. This test generated a p-value of 1.90e-34, which is lower than the significance threshold, and so this result is statistically significant. Therefore, the statistical analysis indicates that the source label – the class being altered by the adversarial perturbation – has a significant effect on the ease of fooling the model.

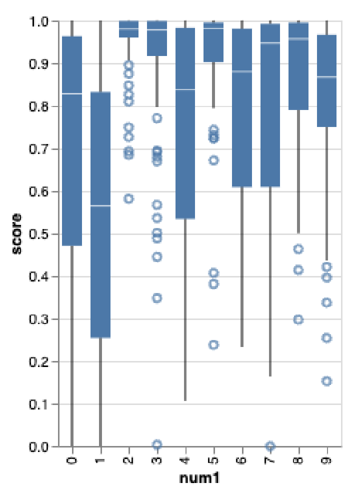

Figure 4 Box-whisker plot showing the distribution of the fooling scores (described as "scores" in this figure), stratified by the source label.

Next, the impact from the number that the adversarial attack is trying to convert to was examined (see Figure 5). A one-way ANOVA test was conducted to see if the fooling scores were significantly different depending on the fooled prediction target. This test generated a p-value of 2.69e-12, which is lower than the significance threshold, and so this result is statistically significant. Therefore, the test indicates that the target label – the class the adversarial attack tries to change the prediction to – has a statistically significant effect on the ease of fooling the model.

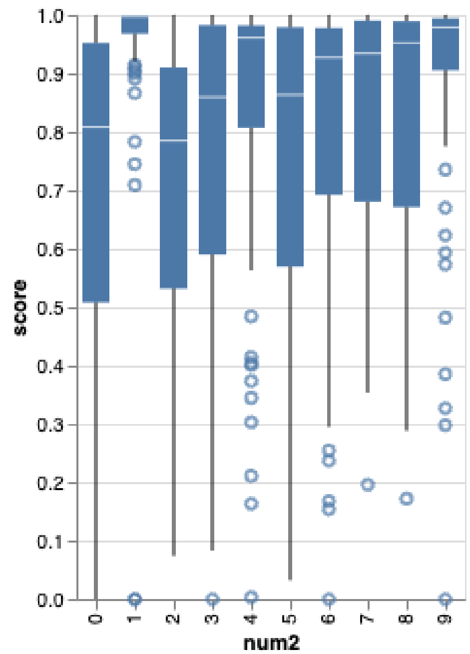

Figure 5 Box-whisker plot showing the distribution of the fooling scores (described as "scores" in this figure), stratified by the target label.

Following this, the correlation between the source and target labels was examined (see Figure 6). A one-way ANOVA test was conducted to see if the fooling scores were significantly different depending on the source and target labels. This test generated a p-value of 4.37e-42, which is lower than the significance threshold, and so this result is statistically significant. Therefore, the test indicates that the correlation between the source and target labels has a statistically significant effect on the ease of fooling the model.

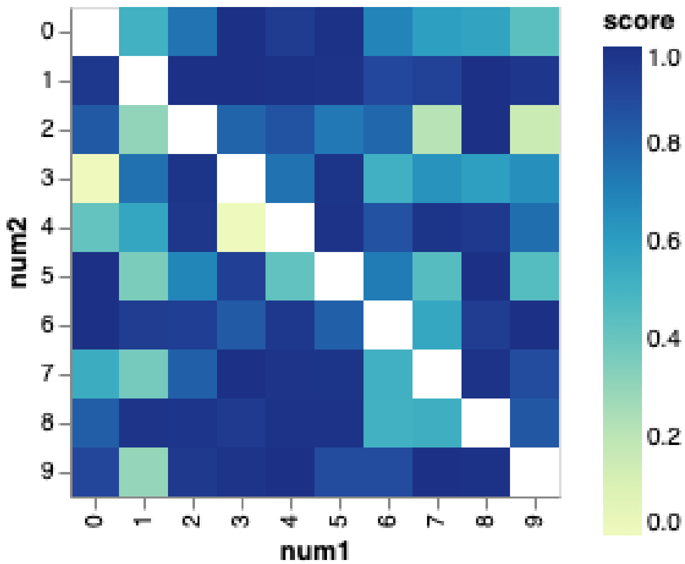

Figure 6 Heatmap showing the average fooling score (listed as score) by source label (listed as num1) and the target label (listed as num2).

The three previous results are in line with what is expected, as numbers such as 1 and 7 are more similar than numbers such as 1 and 8. However, it is interesting to see that human intuition does not necessarily transfer over to these results as, for example, it is very easy to fool these models to predict an 8 when given a 1, or to predict a 4 when given a 5. It is also interesting that this relationship appears to be symmetric, although further analysis is required to confirm or deny this hypothesis.

Furthermore, an analysis regarding the impact on the training accuracy of the model on the ease of fooling the model was conducted (see Figure 7). A linear regression model was built to analyze this relationship, and it was found that the p-value of the coefficient representing this relationship was 0.998, which is higher than the significance threshold, and so this result is not statistically significant.

Figure 7 Visualisation plotting the fooling scores of the models (listed as "score") in relation to their testing accuracy (listed as "accuracy").

Next, the impact of the presence of convolutional layers in the model was examined (see Figure 8). A student's T-test was conducted to see if the fooling scores were significantly different between these two classes – models containing convolutional layers, and models not containing convolutional layers. A p-value of 4.07e-11 was found, which is less than the confidence threshold and so the fooling scores between these two classes are significantly different.

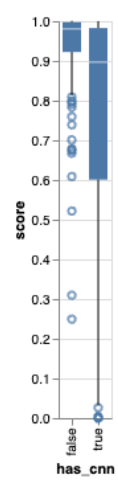

Figure 8 Box-whisker plot visualizing the fooling scores (listed as "score") between models containing convolutional layers and models not containing convolutional layers.

Following this, the impact on the depth of dense layers on the ease of fooling a model was examined (see Figure 9). A series of student's T-test were conducted to test the differences between the different number of dense layers in a network – 1, 2 and 3 in this case:

- A p-value of 0.14 was found when comparing models with 1 dense layer and models with 2 dense layers. Since this value is larger than the confidence threshold, the difference in the ease of fooling computer vision models with 1 and 2 dense layers are not statistically different.
- A p-value of 0.14 was found when comparing models with 2 dense layer and models with 3 dense layers. Since this value is larger than the confidence threshold, the difference in the ease of fooling computer vision models with 2 and 3 dense layers are statistically different.
- A p-value of 2.57e-05 was found when comparing models with 2 dense layer and models with 3 dense layers. Since this value is larger than the confidence threshold, the difference in the ease of fooling computer vision models with 2 and 3 dense layers are statistically different.

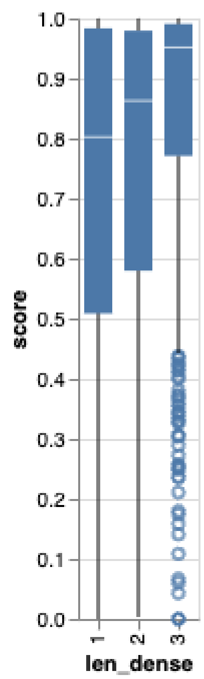

Figure 9 Box-whisker plot showing the different distributions of fooling scores (listed as "score") based on the number of dense layers in the neural networks (listed as "len_dense").

Following this, the relationship between having convolutional layers and the number of dense layers was examined. In the figure below, it can be seen that as the number of dense layers increase for models without convolutional layers, the fooling score decreases – meaning that it is harder to fool models with more dense layers. However, the opposite is seen with models containing convolutional layers, where the fooling score increases as dense layers are added – meaning they become easier to fool. A possible reason to explain this is that the models with too convolutional layers become overfit as the number of dense layers increases and models without convolutional layers and too few dense layers are underfit, but this would require further study.

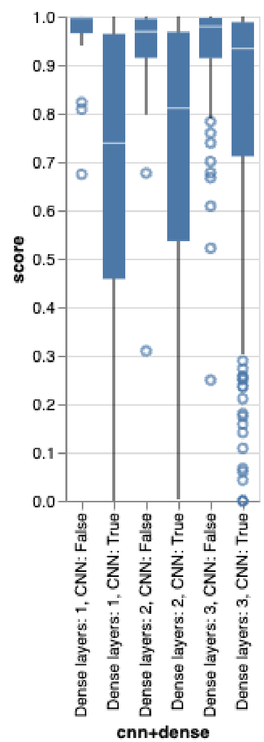

Figure 10 Box-whisker plot showing the fooling scores (listed as “score”) of models stratified by the correlation between the presence of convolutional layers and the number of dense layers (listed as “cnn+dense”).

After this, a linear regression model was built containing all the significant variables found above with the fooling score as the target variable. The variables representing the starting and ending variables were included in the linear regression model to remove their influence from the parameters being studied, but they are not presented here (see Table 2). It is interesting to see that the number of dense layers is no longer significant when included in the linear model, likely since the correlation of the presence of convolutional layers and the length of dense layers better approximates the data. The linear regression model is described as the following equation:

$$y_i = 0.75 - 0.35c_i + 0.080c_i\ell_i$$

$$c_i = \text{ Presence of CNN layer for sample } i$$

$$\ell_i = \text{Length of dense layer for sample } i$$

$$y_i = \text{ Fooling score of sample } i$$

Table 2 Table showing the coefficient estimates and their respective p-values for a linear regression model with the fooling score as a target variable.

Variable	Estimate	P-value
Intercept	0.75	3.4e-08
Presence of convolutional layer	-0.35	5.3e-07
Number of dense layers	-0.0099	0.68
Correlation of the presence of convolutional layers and the length of dense layers	0.080	0.0030

6. Conclusion

In conclusion, the presence of convolutional layers significantly decreases the fooling score – found to decrease it by 35%. Also, finding that all of these models are susceptible to differing levels to an adversarial attack supports the results from Szegedy, C., et al. This could be due to the position independent nature of this feature being effective against a very position dependent attack and further analysis on other position independent features of neural networks is needed. Moreover, seeing that models that are likely overfit – the ones with convolutional layers and 3 dense layers –, and models that are likely underfit – the ones with 1 dense layer and no convolutional layers – are easier to fool with this attack method could warrant further exploration into this relationship.

Lastly, it has been my experience while conducting this research that although it can take a long time to find a screen that can reliably conduct an adversarial attack, it could be easy to use this in dangerous situations, such as on road sides.

Bibliography

Carlini, N., & Wagner, D. (2017, March 22). *Towards evaluating the robustness of neural networks*. arXiv.org. https://arxiv.org/abs/1608.04644

Szegedy, C., Zaremba, W., Sutskever, I., Bruna, J., Erhan, D., Goodfellow, I., & Fergus, R. (2014, February 19). *Intriguing properties of neural networks*. arXiv.org. https://arxiv.org/abs/1312.6199

Zhang, Y., Li, Y., Li, Y., & Guo, Z. (2023, August 15). *A review of adversarial attacks in Computer Vision*. arXiv.org. https://arxiv.org/abs/2308.07673

ANNEX - CODE

```
from google.colab import drive
drive.mount('/content/drive')
import warnings
warnings.filterwarnings("ignore")
import tensorflow as tf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import random
from statistics import mean, variance
from functools import lru_cache
from math import sqrt, floor
from typing import List, Tuple
import itertools
import json
import os
import time
from tqdm.notebook import tqdm
import threading
import multiprocessing

mnist = tf.keras.datasets.mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()

#Initializing parameters
input_shape = (28, 28, 1)

#Cleaning data
x_train=x_train.reshape(x_train.shape[0], x_train.shape[1],
x_train.shape[2], 1)
x_train=x_train / 255.0
x_test = x_test.reshape(x_test.shape[0], x_test.shape[1], x_test.shape[2],
1)
x_test=x_test/255.0

y_train = tf.one_hot(y_train.astype(np.int32), depth=10)
y_test = tf.one_hot(y_test.astype(np.int32), depth=10)
```

```
device_name = tf.test.gpu_device_name()
if len(device_name) > 0:
   print("Found GPU at: {}".format(device_name))
else:
   device_name = "/device:CPU:0"
   print("No GPU, using {}.".format(device_name))

def make_model(
   cnn_layer_sizes : List[Tuple[int, Tuple[int, int]]],
   dense_layer_sizes : List[int]
):
   activation_function = 'relu'
   model = tf.keras.models.Sequential()
   model.add(tf.keras.Input(input_shape))
   for i in range(len(cnn_layer_sizes)-1):
       model.add(tf.keras.layers.Conv2D(cnn_layer_sizes[i][0],
cnn_layer_sizes[i][1], activation=activation_function))
       model.add(tf.keras.layers.MaxPooling2D((2, 2)))
   if len(cnn_layer_sizes) > 0:
       model.add(tf.keras.layers.Conv2D(cnn_layer_sizes[-1][0],
cnn_layer_sizes[-1][1], activation=activation_function))
   model.add(tf.keras.layers.Flatten())
   for elem in dense_layer_sizes:
       model.add(tf.keras.layers.Dense(elem, activation =
activation_function))
   model.add(tf.keras.layers.Dense(10, activation = 'softmax'))
   model.compile(optimizer=tf.keras.optimizers.RMSprop(epsilon=1e-08),
loss='categorical_crossentropy', metrics=['acc'])
   return model

class myCallback(tf.keras.callbacks.Callback):
   def on_epoch_end(self, epoch, logs={}):
       if(logs.get('acc')>0.995):
           print("\nReached 99.5% accuracy so cancelling training!")
           self.modelel.stop_training = True

"""callbacks = myCallback()

model = make_model([(10, (5,5)), (5, (3,3))], [64, 64], 'tanh')
```

```
history = model.fit(x_train, y_train,
                    batch_size=batch_size,
                    epochs=5,
                    validation_split=0.1,
                    callbacks=[callbacks])"""

#CONFIGURATIONS
cnn_layer_depth = [0,1]
cnn_layer_dimensions = [(3,3), (4,4), (5,5)]
num_cnn_layers = [1,2,3]
num_dense_layers = [1,2,3]
dense_layer_sizes = [64, 128, 256]
batch_size = 64

def is_decreasing(L : List[int]):
   prev = L[0]
   for i in range(1, len(L)):
       if L[i] < prev:
           return False
   return True

def gen_cnn_layer_combinations():
   L = []
   for layer in num_cnn_layers:
       for dim in cnn_layer_dimensions:
           L.append((layer, dim))
   return L

class myCallback(tf.keras.callbacks.Callback):
   def on_epoch_end(self, epoch, logs={}):
       if(logs.get('acc')>0.995):
           print("\nReached 99.5% accuracy so cancelling training!")
           self.modelel.stop_training = True

def iterate_combinations():
   for cnn_depth in cnn_layer_depth:
       for cnn_layer_dim in
itertools.product(gen_cnn_layer_combinations(), repeat=cnn_depth):
           for dense_depth in num_dense_layers:
```

```
                for dense_layers in itertools.product(dense_layer_sizes,
repeat=dense_depth):
                    if is_decreasing(dense_layers):
                        model = make_model(list(cnn_layer_dim),
list(dense_layers))
                        #history = model.fit(x_train, y_train,
                        #    batch_size=batch_size,
                        #    epochs=4,
                        #    validation_split=0.1,
                        #    callbacks=[callbacks])
                        yield model, str([cnn_layer_dim]),
str([dense_layers]), True
                    else:
                        yield tf.keras.models.Sequential(), "", "", False

   return

def create_random_screen(eps = 0.01):
   return (np.random.rand(28,28) * 2 * eps) - eps

def selection(scores):

#https://www.geeksforgeeks.org/python-indices-of-n-largest-elements-in-lis
t/
   return sorted(range(len(scores)), key = lambda sub: scores[sub])[-25:]

def make_modifications(screen, randomness=0.001, eps=0.01):
   new_screen = screen + (np.random.rand(28,28) - 0.5) * 2 * randomness
   for i in range(28):
       for j in range(28):
           if new_screen[i][j] > eps:
               new_screen[i][j] = eps
           elif new_screen[i][j] < -eps:
               new_screen[i][j] = -eps
   return new_screen

def random_indices(n, total):
   L = [True] * n + [False] * (total - n)
   random.shuffle(L)
   return L
```

```
def find_max_index(L, scores):
   max_index = L[0]
   max_val = scores[0]
   for i in range(1, len(L)):
       if scores[i] > max_val:
           max_index = L[i]
           max_val = scores[i]
   return max_index, max_val

def sample(n, screens):
   index = random_indices(n, len(screens))
   return np.array([screens[i] for i in range(len(screens)) if index[i]])

def find_mean_var(m):
   l = m.reshape(784)
   return mean(l), variance(l)

@lru_cache()
def get_these_values(from_value):
   return np.array([x_train[i] for i in range(len(x_train)) if
y_train[i][from_value] == 1])

def mean_difference_initialization(target, from_value, eps):
   x_target = get_these_values(target)
   x_from_value = get_these_values(from_value)
   cur = np.zeros(28,28)
   for _ in range(100):
       cur += x_from_value[random.randint(0, len(x_from_value))] -
x_target[random.randint(0, len(x_target))]
   mean, var = find_mean_var(cur)
   return (cur - mean) / sqrt(var) * eps

def genetic_algorithm(model, pbar, eps=0.5, iterations=100,
batch_size=100, randomness=0.05, target=7, from_value=1, init='rand'):
   if init=='rand':
       screens = [create_random_screen(eps=eps) for _ in
range(batch_size)]
   else:
```

```
        screens = [mean_difference_initialization(target, from_value, eps)
for _ in range(batch_size)]

    x_train_no_target = get_these_values(from_value)
    y_sample = tf.one_hot(np.array(([target] * len(x_train_no_target))),
depth=10)
    for i in range(iterations):
        scores = [model.evaluate(np.array([elem + s.reshape(28,28,1) for
elem in x_train_no_target]), y_sample, verbose=0)[1] for s in screens]
        pbar.update(1)
        pbar.set_description(f"{from_value} -> {target} - Max:
{round(max(scores), 2)}, Mean: {round(mean(scores), 2)}, Min:
{round(min(scores), 2)}")

        if i == iterations - 1 or max(scores) == 1:
            return find_max_index(screens, scores)

        index = selection(scores)
        new_screens = []
        for elem in index:
            new_screens += [make_modifications(screens[elem],
randomness=randomness, eps=eps) for i in range(2)]
        screens = new_screens
        del new_screens
    return find_max_index(screens, scores)

def get_two_diff_numbers(number_pairs):
    num1 = random.randint(0,9)
    num2 = random.randint(0,9)

    while num1 == num2 or [num1, num2] in number_pairs:
        num1 = random.randint(0,9)
        num2 = random.randint(0,9)
    return num1, num2

def send_to_github(model_counter, screen, score, number_counter):
    if os.path.exists(f'screens/model{model_counter}'):
        os.system(f'rm -r screens/model{model_counter}')
    if not os.path.exists('screens/'):
      os.mkdir('screens')
```

```
    os.mkdir(f'screens/model{model_counter}')
    np.savetxt(f'screens/model{model_counter}/screen_{number_counter}.txt',
screen)
    with open(f'screens/model{model_counter}/scores{number_counter}.txt',
'w') as file:
        file.write(str(score))
    #os.system(f"git add screens/model{model_counter}")
    #os.system("git add model_info.json")
    #os.system("git add tracker.txt")
    #os.system(f"git commit -m \"Adding model{model_counter} info\"")
    #os.system("git push origin main")
    #os.system(f'rm -r screens/model{model_counter}')
    return

def worker(pbar1, pbar2, counter):
    while len(models) > 0:
        model, cnn_layer_dim, dense_layers = models.pop(0)
        number_pairs = []
        first = True
        for i in range(5):
            if first:
              callbacks = myCallback()
              with tf.device(device_name):
                history = model.fit(x_train, y_train,
                        batch_size=batch_size,
                        epochs=4,
                        validation_split=0.1,
                        callbacks=[callbacks])
              first = False
            acc = history.history['acc'][-1]
            num1, num2 = get_two_diff_numbers(number_pairs)
            number_pairs.append([num1,num2])
            models_info['CNN'].append(cnn_layer_dim)
            models_info['Dense'].append(dense_layers)
            models_info['accuracy'].append(acc)
            models_info['num1'].append(num1)
            models_info['num2'].append(num2)

            pbar2.reset()
```

```
            screen, score = genetic_algorithm(model, pbar2, eps=0.5,
iterations=num_iterations, batch_size=50, target=num1, from_value=num2)
            models_info['score'].append(score)
            models_info['counter'].append(counter)

            send_to_github(counter, screen, score, counter)
            pbar1.update(1)
            counter += 1
   return


def run_project():
   global models_info, models, num_iterations
   try:
       with open('model_info.json', 'r') as file:
           models_info = json.load(file)
   except FileNotFoundError:
       models_info = {
           "CNN" : [],
           "Dense" : [],
           "accuracy" : [],
           "num1" : [],
           "num2" : [],
           "score" : [],
           "counter" : [],
       }

   counter = 0
   num_iterations=100
   stop = 982
   pbar1 = tqdm(total=1950, desc="Total attacks")
   pbar2 = tqdm(total=num_iterations, desc="Attacking model")

   for model, cnn_layer_dim, dense_layers, conti in
iterate_combinations():
       number_pairs = []
       first = True
       for i in range(5):
          if counter > stop and conti:
               if first:
```

```
                  callbacks = myCallback()
                  history = model.fit(x_train, y_train,
                              batch_size=batch_size,
                              epochs=4,
                              validation_split=0.1,
                              callbacks=[callbacks])
                  first = False
                acc = history.history['acc'][-1]
                num1, num2 = get_two_diff_numbers(number_pairs)
                number_pairs.append([num1,num2])
                models_info['CNN'].append(cnn_layer_dim)
                models_info['Dense'].append(dense_layers)
                models_info['accuracy'].append(acc)
                models_info['num1'].append(num1)
                models_info['num2'].append(num2)

                pbar2.reset()
                screen, score = genetic_algorithm(model, pbar2, eps=0.5,
iterations=num_iterations, batch_size=50, target=num1, from_value=num2)
                models_info['score'].append(score)
                models_info['counter'].append(counter)

                with open('/content/drive/MyDrive/tracker.txt', 'w') as
file:
                    file.write(str(counter))

                with open('/content/drive/MyDrive/model_info.json', 'w') as
file:
                    json.dump(models_info, file, indent=4)

                send_to_github(counter, screen, score, counter)
          pbar1.update(1)
          counter += 1
run_project()
```

ANNEX - DATA

The following is in Comma Separated Values (csv):

```
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