Homework 3: Convolutional Neural Networks

Due Wednesday 11/24 at 11:59 pm EST

Download the dataset `cats-notcats` from github (given as a part of the assignment). This dataset has images of cats and images that are not cats (in separate folders). The task is to train a convolutional neural network (CNN) to build a classifier that can classify a new image as either `cat` or `not cat`

1. Load the dataset and create three stratified splits - train/validation/test in the ratio of 70/10/20.

```
!unzip /content/HW3Data.zip
```

```
import os
import cv2
import re
import tensorflow as tf
from tensorflow.keras import datasets, layers, models
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.model_selection import train_test_split
```

```
#code here
input_size = (128,128)
cat = []
not_cat = []
def read_directory(directory_name,l):
    for filename in os.listdir(r"./"+directory_name):
        if re.search(r'[0-9]',filename):
            img = cv2.imread(directory_name + "/" + filename)
            # img = cv2.imread(directory_name + "/" + filename,cv2.IMREAD_GRAYSCALE)
            img = cv2.resize(img,input_size)
            l.append(img)
    return l
file_cat = 'data/cats-notcats/cats'
file_no_cat = 'data/cats-notcats/notcats'
cat = read_directory(file_cat,cat)
not_cat = read_directory(file_no_cat,not_cat)
input_fig = cat+not_cat

target = [1]*len(cat)+[0]*len(not_cat)
```

```
X_dev,X_test,y_dev,y_test = train_test_split(cat+not_cat,target,test_size = 0.2,stratify=t
X_train,X_val,y_train,y_val = train_test_split(X_dev,y_dev,test_size = 0.125,stratify=y_de

# X_dev = np.asarray(X_dev).astype(np.float32)
# y_dev = np.asarray(y_dev).astype(np.float32)
X_train = np.asarray(X_train).astype(np.float32)
y_train = np.asarray(y_train).astype(np.float32)
X_val = np.asarray(X_val).astype(np.float32)
y_val = np.asarray(y_val).astype(np.float32)
X_test = np.asarray(X_test).astype(np.float32)
y_test = np.asarray(y_test).astype(np.float32)


X_train = X_train.reshape(X_train.shape[0],input_size[0],input_size[1],3)
X_val = X_val.reshape(X_val.shape[0],input_size[0],input_size[1],3)
X_test = X_test.reshape(X_test.shape[0],input_size[0],input_size[1],3)


train_datagen = ImageDataGenerator( rescale = 1./255)
val_datagen = ImageDataGenerator( rescale = 1./255)
train_generator = train_datagen.flow(X_train,y_train)
val_generator = val_datagen.flow(X_val,y_val)
```

2. Create a CNN that has the following hidden layers:

   a. 2D convolution layer with a 3x3 kernel size, has 128 filters, stride of 1 and padded to yield the same size as input, followed by a ReLU activation layer

   b. Max pooling layer of 2x2

   c. Dense layer with 128 dimensions and ReLU as the activation layer

```
#code here
num_classes = 2
input_shape = (128,128,3)
y_train = tf.keras.utils.to_categorical(y_train, num_classes)
y_val = tf.keras.utils.to_categorical(y_val, num_classes)
y_test = tf.keras.utils.to_categorical(y_test, num_classes)
cnn = models.Sequential()
cnn.add(layers.Conv2D(128,kernel_size = (3,3),activation = 'relu',padding = 'same',strides
cnn.add(layers.MaxPooling2D(pool_size = (2,2)))
cnn.add(layers.Flatten())
cnn.add(layers.Dense(128,activation = 'relu'))
cnn.add(layers.Dense(1,activation = 'sigmoid'))
# cnn.add(layers.Dense(2,activation = 'softmax'))
```

3. Train the classifier for 20 epochs with 100 steps per epoch. Also use the validation data during training the estimator.

```
# cnn.compile("adam",'categorical_crossentropy',metrics = ['accuracy'])
cnn.compile("adam",'binary_crossentropy',metrics = ['accuracy'])
```

```
history = cnn.fit_generator(train_generator,epochs = 20, steps_per_epoch = 100,
                      validation_data = val_generator, verbose = 1)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: UserWarning: `Model.f

Epoch 1/20
100/100 [==============================] - 133s 1s/step - loss: 1.0139 - accuracy: 0
Epoch 2/20
100/100 [==============================] - 132s 1s/step - loss: 0.3411 - accuracy: 0
Epoch 3/20
100/100 [==============================] - 132s 1s/step - loss: 0.2452 - accuracy: 0
Epoch 4/20
100/100 [==============================] - 141s 1s/step - loss: 0.1617 - accuracy: 0
Epoch 5/20
100/100 [==============================] - 135s 1s/step - loss: 0.0973 - accuracy: 0
Epoch 6/20
100/100 [==============================] - 135s 1s/step - loss: 0.0651 - accuracy: 0
Epoch 7/20
100/100 [==============================] - 135s 1s/step - loss: 0.0522 - accuracy: 0
Epoch 8/20
100/100 [==============================] - 136s 1s/step - loss: 0.0255 - accuracy: 0
Epoch 9/20
100/100 [==============================] - 135s 1s/step - loss: 0.0153 - accuracy: 0
Epoch 10/20
100/100 [==============================] - 135s 1s/step - loss: 0.0084 - accuracy: 0
Epoch 11/20
100/100 [==============================] - 135s 1s/step - loss: 0.0051 - accuracy: 0
Epoch 12/20
100/100 [==============================] - 136s 1s/step - loss: 0.0024 - accuracy: 1
Epoch 13/20
100/100 [==============================] - 136s 1s/step - loss: 0.0016 - accuracy: 1
Epoch 14/20
100/100 [==============================] - 137s 1s/step - loss: 0.0012 - accuracy: 1
Epoch 15/20
100/100 [==============================] - 137s 1s/step - loss: 9.6953e-04 - accuracy
Epoch 16/20
100/100 [==============================] - 137s 1s/step - loss: 7.2086e-04 - accuracy
Epoch 17/20
100/100 [==============================] - 137s 1s/step - loss: 5.9373e-04 - accuracy
Epoch 18/20
100/100 [==============================] - 137s 1s/step - loss: 5.0152e-04 - accuracy
Epoch 19/20
100/100 [==============================] - 137s 1s/step - loss: 4.5932e-04 - accuracy
Epoch 20/20
100/100 [==============================] - 137s 1s/step - loss: 3.6346e-04 - accuracy
```

```
history_cnn = cnn.fit(X_train,y_train,epochs = 20, steps_per_epoch = 100,
                      validation_data = (X_val,y_val),verbose = 1)
```

4. Plot the accuracy and the loss over epochs for train & validation sets

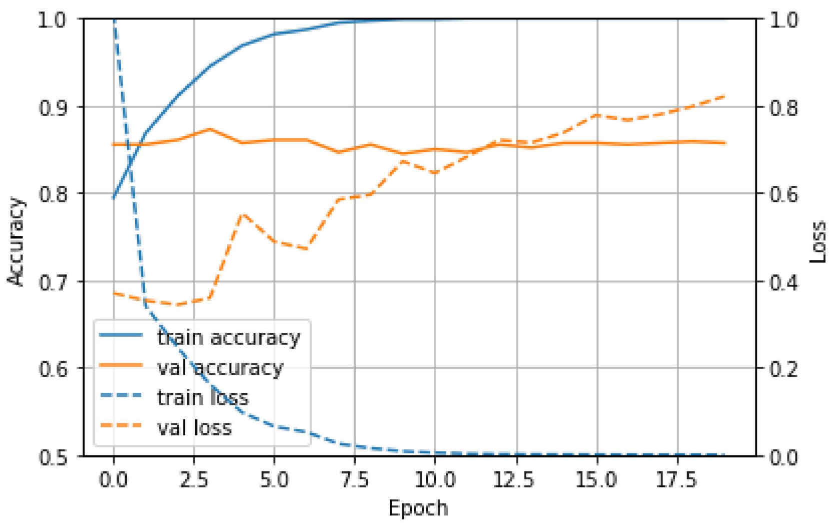
```
fig = plt.figure()
ax = fig.add_subplot(111)
```

```
lns1 = ax.plot(history.history['accuracy'], label='train accuracy')
lns2 = ax.plot(history.history['val_accuracy'], label = 'val accuracy')
ax2 = ax.twinx()
lns3 = ax2.plot(history.history['loss'], '--',label='train loss')
lns4 = ax2.plot(history.history['val_loss'], '--',label = 'val loss')

# added these three lines
lns = lns1+lns2+lns3+lns4
labs = [l.get_label() for l in lns]
ax.legend(lns, labs, loc=0)

ax.grid()
ax.set_xlabel("Epoch")
ax.set_ylabel("Accuracy")
ax2.set_ylabel("Loss")
ax2.set_ylim(0, 1)
ax.set_ylim(0.5,1)
```

```
(0.5, 1.0)
```



5. Add the following layers to (2) before the dense layer:

   a. 2D convolution layer with a 3x3 kernel size, has 64 filters, stride of 1 and padded to yield the same size as input, followed by a ReLU activation layer

   b. Max pooling layer of 2x2

   c. 2D convolution layer with a 3x3 kernel size, has 32 filters, stride of 1 and padded to yield the same size as input, followed by a ReLU activation layer

   d. Max pooling layer of 2x2

   e. Dense layer with 256 dimensions and ReLU as the activation layer

```
#code here
cnn = models.Sequential()
cnn.add(layers.Conv2D(128,kernel_size = (3,3),activation = 'relu',padding = 'same',strides
```

```
cnn.add(layers.MaxPooling2D(pool_size = (2,2)))
cnn.add(layers.Conv2D(32,kernel_size = (3,3),activation = 'relu',padding = 'same',strides=
cnn.add(layers.MaxPooling2D(pool_size = (2,2)))
cnn.add(layers.Flatten())
cnn.add(layers.Dense(128,activation = 'relu'))
cnn.add(layers.Dense(1,activation = 'sigmoid'))
```

6. Train the classifier again for 20 epochs with 100 steps per epoch. Also use the validation data during training the estimator.

```
#code here
# cnn.compile("adam",'categorical_crossentropy',metrics = ['accuracy'])
cnn.compile("adam",'binary_crossentropy',metrics = ['accuracy'])
history = cnn.fit_generator(train_generator,epochs = 20, steps_per_epoch = 100,
                      validation_data = val_generator,verbose = 1)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: UserWarning: `Model.f
  """
Epoch 1/20
100/100 [==============================] - 190s 2s/step - loss: 0.5737 - accuracy: 0
Epoch 2/20
100/100 [==============================] - 188s 2s/step - loss: 0.5054 - accuracy: 0
Epoch 3/20
100/100 [==============================] - 187s 2s/step - loss: 0.4525 - accuracy: 0
Epoch 4/20
100/100 [==============================] - 187s 2s/step - loss: 0.3941 - accuracy: 0
Epoch 5/20
100/100 [==============================] - 187s 2s/step - loss: 0.3515 - accuracy: 0
Epoch 6/20
100/100 [==============================] - 186s 2s/step - loss: 0.3294 - accuracy: 0
Epoch 7/20
100/100 [==============================] - 187s 2s/step - loss: 0.2737 - accuracy: 0
Epoch 8/20
100/100 [==============================] - 185s 2s/step - loss: 0.2083 - accuracy: 0
Epoch 9/20
100/100 [==============================] - 185s 2s/step - loss: 0.1651 - accuracy: 0
Epoch 10/20
100/100 [==============================] - 184s 2s/step - loss: 0.1316 - accuracy: 0
Epoch 11/20
100/100 [==============================] - 185s 2s/step - loss: 0.0907 - accuracy: 0
Epoch 12/20
100/100 [==============================] - 185s 2s/step - loss: 0.0755 - accuracy: 0
Epoch 13/20
100/100 [==============================] - 185s 2s/step - loss: 0.0472 - accuracy: 0
Epoch 14/20
100/100 [==============================] - 186s 2s/step - loss: 0.0258 - accuracy: 0
Epoch 15/20
100/100 [==============================] - 187s 2s/step - loss: 0.0343 - accuracy: 0
Epoch 16/20
100/100 [==============================] - 186s 2s/step - loss: 0.0129 - accuracy: 0
Epoch 17/20
100/100 [==============================] - 186s 2s/step - loss: 0.0259 - accuracy: 0
Epoch 18/20
100/100 [==============================] - 186s 2s/step - loss: 0.0303 - accuracy: 0
Epoch 19/20
```

```
100/100 [==============================] - 185s 2s/step - loss: 0.0420 - accuracy: 0
Epoch 20/20
100/100 [==============================] - 184s 2s/step - loss: 0.0162 - accuracy: 0
```

7. Plot the accuracy and the loss over epochs for train & validation sets

```
#code here
fig = plt.figure()
ax = fig.add_subplot(111)

lns1 = ax.plot(history.history['accuracy'], label='train accuracy')
lns2 = ax.plot(history.history['val_accuracy'], label = 'val accuracy')
ax2 = ax.twinx()
lns3 = ax2.plot(history.history['loss'], '--',label='train loss')
lns4 = ax2.plot(history.history['val_loss'], '--',label = 'val loss')

# added these three lines
lns = lns1+lns2+lns3+lns4
labs = [l.get_label() for l in lns]
ax.legend(lns, labs, loc=0)

ax.grid()
ax.set_xlabel("Epoch")
ax.set_ylabel("Accuracy")
ax2.set_ylabel("Loss")
ax2.set_ylim(0, 1.2)
ax.set_ylim(0.5,1)
```

```
(0.5, 1.0)
```