Practical 1

Aim: Implement Feed-forward Neural Network and train the network with different optimizers and compare the results.

Source Code:

```
# import the necessary packages from
sklearn.preprocessing import LabelBinarizer from
sklearn.metrics import classification_report from
tensorflow.keras.models import Sequential from
tensorflow.keras.layers import Dense from
tensorflow.keras.optimizers import SGD from
tensorflow.keras.datasets import mnist from
tensorflow.keras import backend as K
import matplotlib.pyplot as plt
import numpy as np import
argparse
# construct the argument parse and parse the arguments ap
= argparse.ArgumentParser()
ap.add_argument("-o", "--output", required=True,help="path to the output loss/accuracy plot") args
= vars(ap.parse_args())

# grab the MNIST dataset (if this is your first time using this #
dataset then the 11MB download may take a minute)
print("[INFO] accessing MNIST...")
((trainX, trainY), (testX, testY)) = mnist.load_data()
# each image in the MNIST dataset is represented as a 28x28x1
# image, but in order to apply a standard neural network we must
# first "flatten" the image to be simple list of 28x28=784 pixels
trainX = trainX.reshape((trainX.shape[0], 28 * 28 * 1)) testX =
testX.reshape((testX.shape[0], 28 * 28 * 1))
# scale data to the range of [0, 1] trainX
= trainX.astype("float32") / 255.0
testX = testX.astype("float32") / 255.0

# convert the labels from integers to vectors
lb = LabelBinarizer() trainY =
lb.fit_transform(trainY)
testY = lb.transform(testY)

model = Sequential()
model.add(Dense(256, input_shape=(784,), activation="sigmoid")) model.add(Dense(128,
activation="sigmoid"))
```

model.add(Dense(10, activation="softmax"))

print("[INFO] training network...")
sgd = SGD(0.01) model.compile(loss="categorical_crossentropy", optimizer=sgd, metrics=["accuracy"]) H = model.fit(trainX, trainY, validation_data=(testX, testY), epochs=100, batch_size=128)

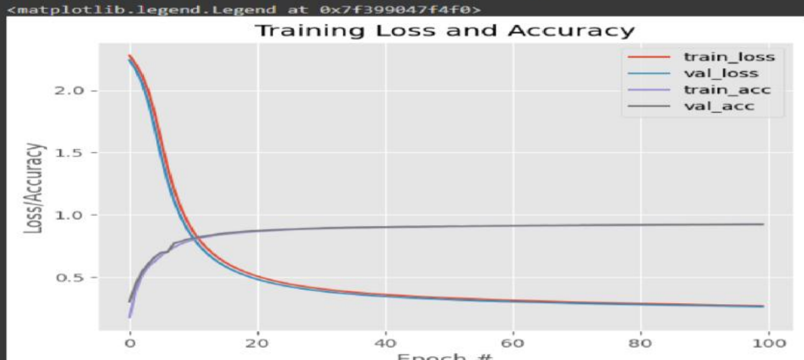
```
[INFO] training network...
Epoch 1/100
469/469 [==============================] - 4s 8ms/step - loss: 2.2798 - accuracy: 0.1753 - val_loss: 2.2416 - val_accuracy: 0.3011
Epoch 2/100
469/469 [==============================] - 6s 13ms/step - loss: 2.2074 - accuracy: 0.3917 - val_loss: 2.1643 - val_accuracy: 0.4448
Epoch 3/100
469/469 [==============================] - 4s 9ms/step - loss: 2.1176 - accuracy: 0.5159 - val_loss: 2.0556 - val_accuracy: 0.5449
Epoch 4/100
469/469 [==============================] - 3s 7ms/step - loss: 1.9872 - accuracy: 0.5869 - val_loss: 1.8971 - val_accuracy: 0.6076
Epoch 5/100
469/469 [==============================] - 4s 9ms/step - loss: 1.8047 - accuracy: 0.6278 - val_loss: 1.6870 - val_accuracy: 0.6620
```

# evaluate the network
print("[INFO] evaluating network...") predictions = model.predict(testX, batch_size=128)
print(classification_report(testY.argmax(axis=1), predictions.argmax(axis=1), target_names=[str(x) for x in lb.classes_]))

plt.style.use("ggplot")
plt.figure() plt.plot(np.arange(0, 100), H.history["loss"], label="train_loss") plt.plot(np.arange(0, 100), H.history["val_loss"], label="val_loss") plt.plot(np.arange(0, 100), H.history["accuracy"], label="train_acc") plt.plot(np.arange(0, 100), H.history["val_accuracy"], label="val_acc") plt.title("Training Loss and Accuracy") plt.xlabel("Epoch #") plt.ylabel("Loss/Accuracy") plt.legend()

	precision	recall	f1-score	support
0	0.94	0.98	0.96	980
1	0.97	0.97	0.97	1135
2	0.93	0.90	0.91	1032
3	0.91	0.91	0.91	1010
4	0.92	0.94	0.93	982
5	0.91	0.87	0.89	892
6	0.93	0.95	0.94	958
7	0.94	0.92	0.93	1028
8	0.89	0.89	0.89	974
9	0.91	0.90	0.91	1009
accuracy			0.92	10000
macro avg	0.92	0.92	0.92	10000
weighted avg	0.92	0.92	0.92	10000

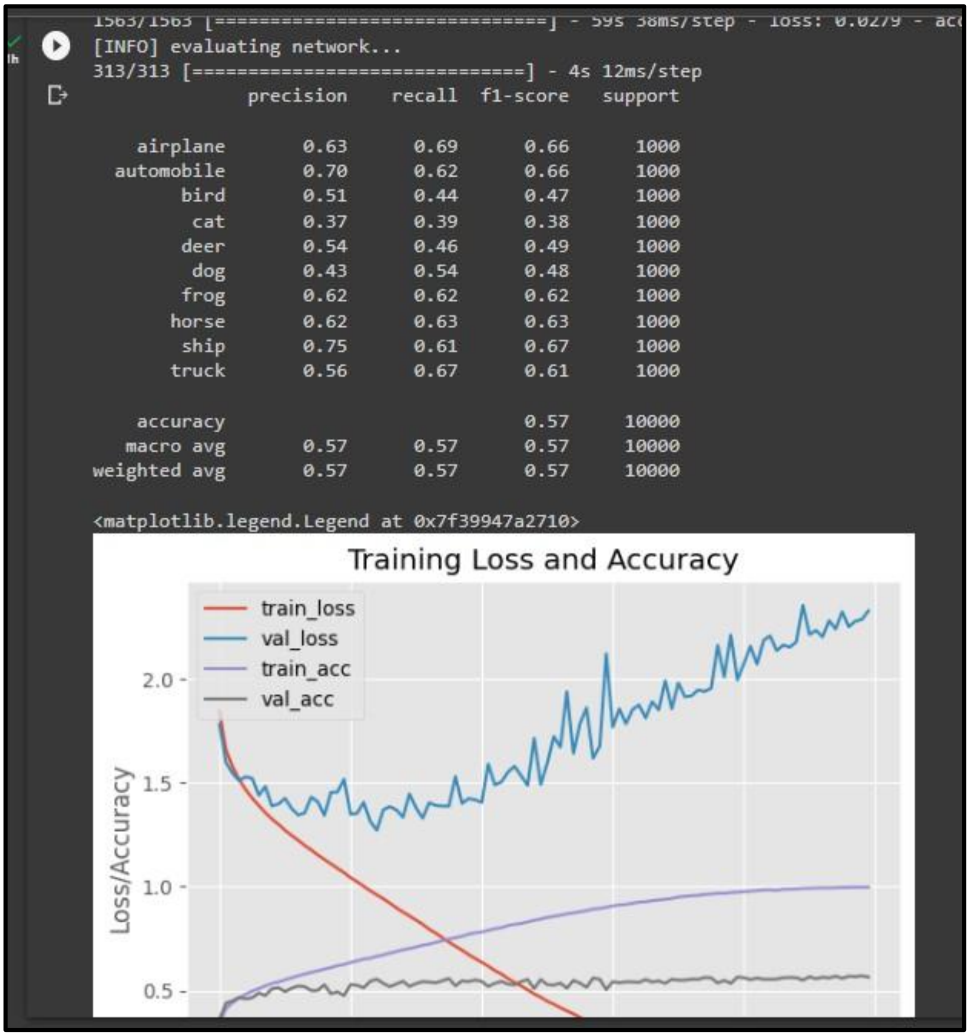
<matplotlib.legend.Legend at 0x7f399047f4f0>



import the necessary packages

```
from sklearn.preprocessing import LabelBinarizer
from sklearn.metrics import classification_report
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense from
tensorflow.keras.optimizers import SGD from
tensorflow.keras.datasets import cifar10 import
matplotlib.pyplot as plt import numpy as np
import argparse

print("[INFO] loading CIFAR-10 data...") ((trainX,
trainY), (testX, testY)) = cifar10.load_data() trainX =
trainX.astype("float") / 255.0 testX =
testX.astype("float") / 255.0 trainX =
trainX.reshape((trainX.shape[0], 3072)) testX =
testX.reshape((testX.shape[0], 3072))

lb = LabelBinarizer() trainY =
lb.fit_transform(trainY) testY =
lb.transform(testY)
# initialize the label names for the CIFAR-10 dataset
labelNames = ["airplane", "automobile", "bird", "cat", "deer","dog", "frog", "horse", "ship", "truck"]

model = Sequential()
model.add(Dense(1024, input_shape=(3072,), activation="relu")) model.add(Dense(512,
activation="relu"))
model.add(Dense(10, activation="softmax"))

print("[INFO] training network...")
sgd = SGD(0.01) model.compile(loss="categorical_crossentropy", optimizer=sgd,
metrics=["accuracy"]) H = model.fit(trainX, trainY, validation_data=(testX, testY),
epochs=100, batch_size=32)

print("[INFO] evaluating network...") predictions
= model.predict(testX, batch_size=32)
print(classification_report(testY.argmax(axis=1),predictions.argmax(axis=1),
target_names=labelNames))

plt.style.use("ggplot")
plt.figure()
plt.plot(np.arange(0, 100), H.history["loss"], label="train_loss")
plt.plot(np.arange(0, 100), H.history["val_loss"], label="val_loss")
plt.plot(np.arange(0, 100), H.history["accuracy"], label="train_acc")
plt.plot(np.arange(0, 100), H.history["val_accuracy"], label="val_acc")
```

plt.title("Training Loss and Accuracy") plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy") plt.legend()



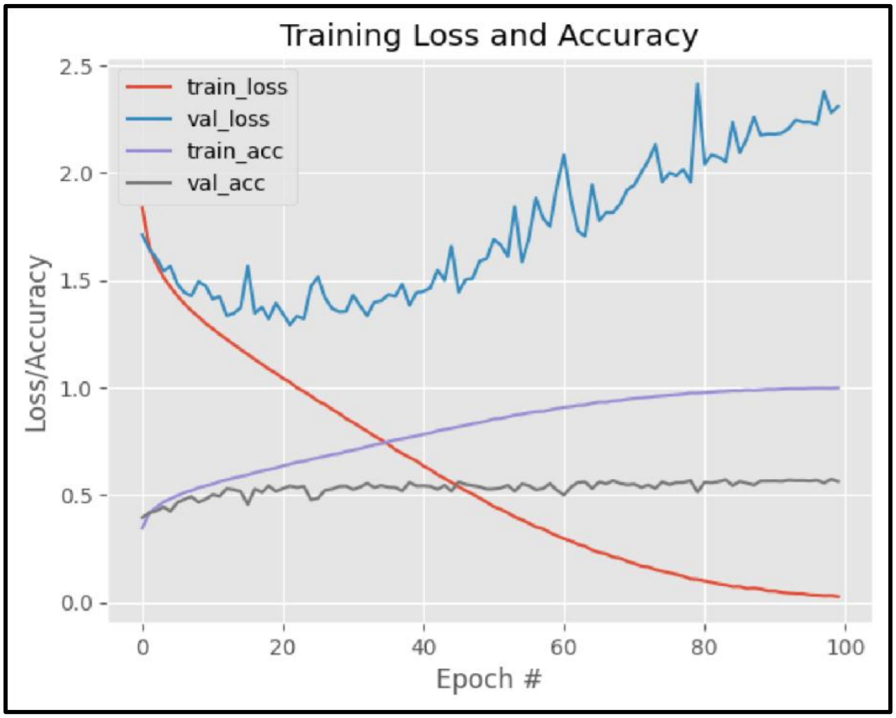
from sklearn.preprocessing import LabelBinarizer
from sklearn.metrics import classification_report
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense from
tensorflow.keras.optimizers import SGD from
tensorflow.keras.datasets import cifar10 import
matplotlib.pyplot as plt import numpy as np
import argparse

load the training and testing data, scale it into the range [0, 1],
then reshape the design matrix print("[INFO]
loading CIFAR-10 data...") ((trainX, trainY), (testX,
testY)) = cifar10.load_data() trainX =
trainX.astype("float") / 255.0 testX =
testX.astype("float") / 255.0

```
trainX = trainX.reshape((trainX.shape[0], 3072)) testX
= testX.reshape((testX.shape[0], 3072))

# convert the labels from integers to vectors
lb = LabelBinarizer() trainY =
lb.fit_transform(trainY) testY =
lb.transform(testY)
# initialize the label names for the CIFAR-10 dataset labelNames
= ["airplane", "automobile", "bird", "cat", "deer",
        "dog", "frog", "horse", "ship", "truck"]

# define the 3072-1024-512-10 architecture using Keras model
= Sequential()
model.add(Dense(1024, input_shape=(3072,), activation="relu")) model.add(Dense(512,
activation="relu"))
model.add(Dense(10, activation="softmax"))

# train the model using SGD print("[INFO]
training network...")
sgd = SGD(0.01) model.compile(loss="categorical_crossentropy", optimizer=sgd,
metrics=["accuracy"]) H = model.fit(trainX, trainY, validation_data=(testX, testY),
epochs=100, batch_size=32)

print("[INFO] evaluating network...") predictions
= model.predict(testX, batch_size=32)
print(classification_report(testY.argmax(axis=1),
        predictions.argmax(axis=1), target_names=labelNames))

# plot the training loss and accuracy plt.style.use("ggplot")
plt.figure()
plt.plot(np.arange(0, 100), H.history["loss"], label="train_loss")
plt.plot(np.arange(0, 100), H.history["val_loss"], label="val_loss")
plt.plot(np.arange(0, 100), H.history["accuracy"], label="train_acc")
plt.plot(np.arange(0, 100), H.history["val_accuracy"], label="val_acc")
plt.title("Training Loss and Accuracy") plt.xlabel("Epoch #")
plt.ylabel("Loss/Accuracy") plt.legend()
plt.savefig(args["output"])
```

Output:

```
Epoch 99/100
1563/1563 [==============================] - 58s 37ms/step - loss: 0.0304 -
Epoch 100/100
1563/1563 [==============================] - 59s 38ms/step - loss: 0.0256 -
[INFO] evaluating network...
313/313 [==============================] - 5s 15ms/step
              precision    recall  f1-score   support

    airplane       0.58      0.70      0.63      1000
  automobile       0.69      0.69      0.69      1000
        bird       0.49      0.38      0.43      1000
         cat       0.39      0.38      0.39      1000
        deer       0.45      0.50      0.47      1000
         dog       0.47      0.44      0.45      1000
        frog       0.60      0.63      0.62      1000
       horse       0.64      0.60      0.62      1000
        ship       0.69      0.71      0.70      1000
       truck       0.61      0.60      0.61      1000

    accuracy                           0.56     10000
   macro avg       0.56      0.56      0.56     10000
weighted avg       0.56      0.56      0.56     10000
```



Practical 2

Aim: Write a Program to implement regularization to prevent the model from overfitting

Source Code:

```
import numpy as np import
pandas as pd from sklearn
import metrics
from sklearn.linear_model import Lasso

df_train = pd.read_csv('/content/sample_data/train.csv') df_test
= pd.read_csv('/content/sample_data/test.csv')

df_train = df_train.dropna()
df_test = df_test.dropna()

x_train = df_train['x']
x_train = x_train.values.reshape(-1,1) y_train
= df_train['y']
y_train = y_train.values.reshape(-1,1)

x_test = df_test['x']
x_test = x_test.values.reshape(-1,1) y_test
= df_test['y']
y_test = y_test.values.reshape(-1,1)

lasso = Lasso()

lasso.fit(x_train, y_train)

print("Lasso Train RMSE:", np.round(np.sqrt(metrics.mean_squared_error(y_train,
lasso.predict(x_train))), 5))
print("Lasso Test RMSE:", np.round(np.sqrt(metrics.mean_squared_error(y_test, lasso.predict(x_test))),
5))

import numpy as np import pandas as pd
from sklearn import metrics from
sklearn.linear_model import Ridge

df_train = pd.read_csv('/content/sample_data/train.csv')
df_test = pd.read_csv('/content/sample_data/test.csv')
```

```
df_train = df_train.dropna()
df_test = df_test.dropna()

x_train = df_train['x']
x_train = x_train.values.reshape(-1,1) y_train
= df_train['y']
y_train = y_train.values.reshape(-1,1)

x_test = df_test['x']
x_test = x_test.values.reshape(-1,1) y_test
= df_test['y']
y_test = y_test.values.reshape(-1,1)

ridge = Ridge()

ridge.fit(x_train, y_train)
print("Ridge Train RMSE:", np.round(np.sqrt(metrics.mean_squared_error(y_train,
ridge.predict(x_train))), 5))
print("Ridge Test RMSE:", np.round(np.sqrt(metrics.mean_squared_error(y_test, ridge.predict(x_test))),
5))
```

Output:

```
ridge.fit(x_train, y_train)
print("Ridge Train RMSE:", np.round(np.sqrt(metrics.mean_squared_error(y_train, ridge.predict(x_train))), 5))
print("Ridge Test RMSE:", np.round(np.sqrt(metrics.mean_squared_error(y_test, ridge.predict(x_test))), 5))

Lasso Train RMSE: 2.80516
Lasso Test RMSE: 3.07592
Ridge Train RMSE: 2.80495
Ridge Test RMSE: 3.07131
```

Practical 3

Aim: Implement deep learning for recognizing classes for datasets like CIFAR-10 images for previously unseen images and assign them to one of the 10 classes

Source Code:

```
import tensorflow as tf
from tensorflow.keras import datasets, layers, models
import matplotlib.pyplot as plt import numpy as np

(X_train, y_train), (X_test,y_test) = datasets.cifar10.load_data()
X_train.shape

X_test.shape

y_train.shape

y_train[:5]

y_train = y_train.reshape(-1,) y_train[:5]

y_test = y_test.reshape(-1,)

classes = ["airplane","automobile","bird","cat","deer","dog","frog","horse","ship","truck"]

def plot_sample(X, y, index):
plt.figure(figsize = (15,2))
plt.imshow(X[index])
plt.xlabel(classes[y[index]])

plot_sample(X_train, y_train, 0)

X_train = X_train / 255.0
X_test = X_test / 255.0

ann = models.Sequential([
                layers.Flatten(input_shape=(32,32,3)),
layers.Dense(3000, activation='relu'),        layers.Dense(1000,
activation='relu'),        layers.Dense(10, activation='softmax')
   ])
```

```
ann.compile(optimizer='SGD',
            loss='sparse_categorical_crossentropy',
            metrics=['accuracy'])

ann.fit(X_train, y_train, epochs=5)

from sklearn.metrics import confusion_matrix , classification_report
import numpy as np y_pred = ann.predict(X_test)
y_pred_classes = [np.argmax(element) for element in y_pred]

print("Classification Report: \n", classification_report(y_test, y_pred_classes))

cnn = models.Sequential([
   layers.Conv2D(filters=32, kernel_size=(3, 3), activation='relu', input_shape=(32, 32, 3)),
layers.MaxPooling2D((2, 2)),

   layers.Conv2D(filters=64, kernel_size=(3, 3), activation='relu'),
layers.MaxPooling2D((2, 2)),

   layers.Flatten(),
layers.Dense(64, activation='relu'),
   layers.Dense(10, activation='softmax')
])

cnn.compile(optimizer='adam',
            loss='sparse_categorical_crossentropy',
            metrics=['accuracy'])

cnn.fit(X_train, y_train, epochs=10)

cnn.evaluate(X_test,y_test)

y_pred = cnn.predict(X_test) y_pred[:5]

y_classes = [np.argmax(element) for element in y_pred]
y_classes[:5]

y_test[:5]

plot_sample(X_test, y_test,3)
```

classes[y_classes[3]]

classes[y_classes[3]]

Output:

Practical 4

Aim: Implement deep learning for the Prediction of the autoencoder from the test data (e.g. MNIST data set)

Source Code:

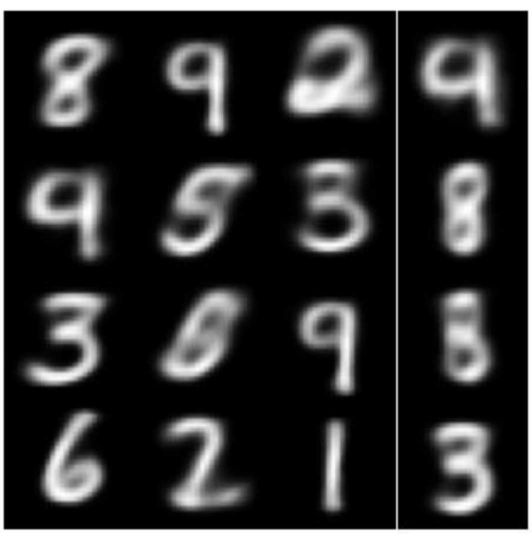
```
!pip install tensorflow-gpu==2.0.0b1 from
tensorflow.keras.datasets import mnist from
tensorflow.keras.layers import Dense, Input, Flatten,\
                              Reshape, LeakyReLU as LR,\
                              Activation, Dropout
from tensorflow.keras.models import Model, Sequential from
matplotlib import pyplot as plt
from IPython import display # If using IPython, Colab or Jupyter import
numpy as np

(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train = x_train/255.0 x_test = x_test/255.0
# Plot image data from x_train plt.imshow(x_train[0],
cmap = "gray")
plt.show()
```


```
LATENT_SIZE = 32
encoder = Sequential([
Flatten(input_shape = (28, 28)),
   Dense(512),
   LR(),
```

```
    Dropout(0.5),
    Dense(256),
    LR(),
    Dropout(0.5),
    Dense(128),
    LR(),
    Dropout(0.5),
    Dense(64),
    LR(),
    Dropout(0.5),
    Dense(LATENT_SIZE, activation="sigmoid"),
])

decoder = Sequential([
    Dense(64, input_shape = (LATENT_SIZE,)),
    LR(),
    Dropout(0.5),
    Dense(128),
    LR(),
    Dropout(0.5),
    Dense(256),
    LR(),
    Dropout(0.5),
    Dense(512),
    LR(),
    Dropout(0.5),
    Dense(784),
    Activation("sigmoid"),
    Reshape((28, 28))
])

img = Input(shape = (28, 28)) latent_vector =
encoder(img) output = decoder(latent_vector) model =
Model(inputs = img, outputs = output)
model.compile("nadam", loss = "binary_crossentropy")
EPOCHS = 100
#Only do plotting if you have IPython, Jupyter, or using Colab for
epoch in range(EPOCHS):
    fig, axs = plt.subplots(4, 4, figsize=(4,4))
    rand = x_test[np.random.randint(0, 10000, 16)].reshape((4, 4, 1, 28, 28))
```

```
    display.clear_output() # If you imported display from IPython

    for i in range(4):
for j in range(4):
        axs[i, j].imshow(model.predict(rand[i, j])[0], cmap = "gray")
axs[i, j].axis("off")

    plt.subplots_adjust(wspace = 0, hspace = 0)
plt.show()
    print("-----------", "EPOCH", epoch, "-----------")
    model.fit(x_train, x_train, batch_size = 64)
```

```
1/1 [==============================] - 0s 27ms/step
1/1 [==============================] - 0s 33ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 34ms/step
1/1 [==============================] - 0s 30ms/step
1/1 [==============================] - 0s 28ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 19ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 17ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 18ms/step
```



```
----------- EPOCH 99 -----------
938/938 [==============================] - 6s 7ms/step - loss: 0.1837
```

Practical 5

Aim: Implement Convolutional Neural Network for Digit Recognition on the MNIST Dataset.

Source Code:

```
# baseline cnn model for mnist from numpy import
mean from numpy import std from matplotlib
import pyplot as plt from sklearn.model_selection
import KFold from tensorflow.keras.datasets import
mnist from tensorflow.keras.utils import
to_categorical from tensorflow.keras.models import
Sequential from tensorflow.keras.layers import
Conv2D from tensorflow.keras.layers import
MaxPooling2D from tensorflow.keras.layers import
Dense from tensorflow.keras.layers import Flatten
from tensorflow.keras.optimizers import SGD

# load train and test dataset def
load_dataset():
 # load dataset
 (trainX, trainY), (testX, testY) = mnist.load_data()  #
reshape dataset to have a single channel  trainX =
trainX.reshape((trainX.shape[0], 28, 28, 1))  testX =
testX.reshape((testX.shape[0], 28, 28, 1))
 # one hot encode target values
trainY = to_categorical(trainY)  testY
= to_categorical(testY)
 return trainX, trainY, testX, testY

# scale pixels def prep_pixels(train,
test):  # convert from integers to
floats  train_norm =
train.astype('float32')  test_norm =
test.astype('float32')  # normalize to
range 0-1  train_norm = train_norm
/ 255.0  test_norm = test_norm /
255.0
 # return normalized images
 return train_norm, test_norm
```

```
# define cnn model def
define_model():
model = Sequential()
 model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform',
input_shape=(28, 28, 1)))  model.add(MaxPooling2D((2, 2)))
 model.add(Flatten())
 model.add(Dense(100, activation='relu', kernel_initializer='he_uniform'))
model.add(Dense(10, activation='softmax'))
 # compile model
 opt = SGD(learning_rate=0.01, momentum=0.9)
 model.compile(optimizer=opt, loss='categorical_crossentropy', metrics=['accuracy'])
return model

# evaluate a model using k-fold cross-validation
def evaluate_model(dataX, dataY, n_folds=5):
scores, histories = list(), list()  # prepare cross
validation
 kfold = KFold(n_folds, shuffle=True, random_state=1)
 # enumerate splits  for train_ix, test_ix in
kfold.split(dataX):
 # define model   model =
define_model()
 # select rows for train and test
  trainX, trainY, testX, testY = dataX[train_ix], dataY[train_ix], dataX[test_ix], dataY[test_ix]
 # fit model
  history = model.fit(trainX, trainY, epochs=10, batch_size=32, validation_data=(testX, testY),
verbose=0)  # evaluate model
  _, acc = model.evaluate(testX, testY, verbose=0)
print('> %.3f' % (acc * 100.0))
 # stores scores
scores.append(acc)
histories.append(history)
 return scores, histories

def summarize_diagnostics(histories):
 for i in range(len(histories)):
  # plot loss   plt.subplot(2, 1, 1)   plt.title('Cross Entropy Loss')
plt.plot(histories[i].history['loss'], color='blue', label='train')
plt.plot(histories[i].history['val_loss'], color='orange', label='test')
  # plot accuracy
plt.subplot(2, 1, 2)
```

```
  plt.title('Classification                                              Accuracy')
plt.plot(histories[i].history['accuracy'],       color='blue',       label='train')
plt.plot(histories[i].history['val_accuracy'],   color='orange',   label='test')
plt.show()

# summarize model performance def
summarize_performance(scores):
 # print summary
 print('Accuracy: mean=%.3f std=%.3f, n=%d' % (mean(scores)*100, std(scores)*100, len(scores)))
 # box and whisker plots of results
plt.boxplot(scores)
 plt.show()

def run_test_harness():
# load dataset
 trainX, trainY, testX, testY = load_dataset()
 # prepare pixel data
 trainX, testX = prep_pixels(trainX, testX)
 # evaluate model
 scores, histories = evaluate_model(trainX, trainY)
 # learning curves
 summarize_diagnostics(histories)  #
summarize estimated performance
 summarize_performance(scores)

run_test_harness()
```

Output:

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 [==============================] - 0s 0us/step
> 98.442
> 98.733
```

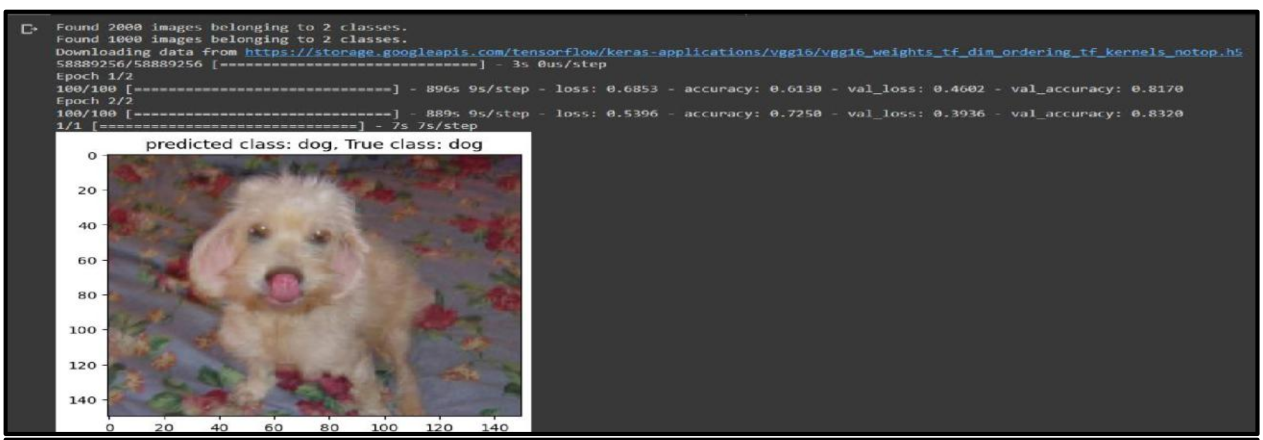
Practical 6

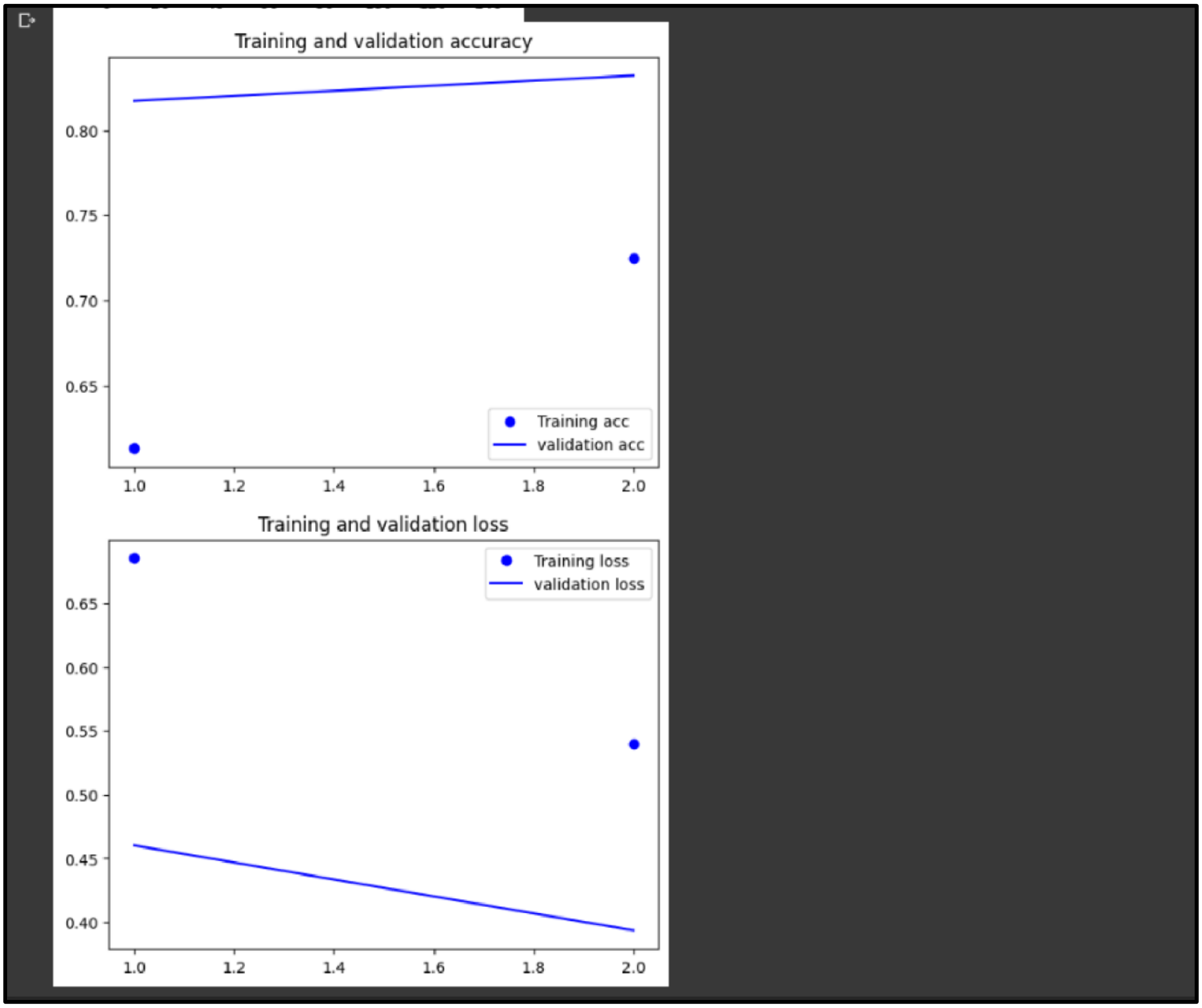
Aim: **Write a program to implement Transfer Learning on the suitable dataset (e.g. classify the cats versus dogs dataset from Kaggle).**

Source Code:

```
import tensorflow as tf import
numpy as np          import
matplotlib.pyplot as plt import
os import zipfile
from tensorflow.keras.preprocessing.image import ImageDataGenerator from
tensorflow.keras.applications import VGG16

filename = "cats_and_dogs_filtered.zip"

with zipfile.ZipFile("/content/drive/MyDrive/cats_and_dogs_filtered.zip", "r") as zip_ref :
  zip_ref.extractall()

train_dir = os.path.join(os.getcwd(),"cats_and_dogs_filtered","train") train_dir

validation_dir = os.path.join(os.getcwd(),"cats_and_dogs_filtered","validation")

train_datagen =
ImageDataGenerator(rescale=1./255,rotation_range=20,width_shift_range=0.2,height_shift_rang
e=0.2,shear_range=0.2,zoom_range=0.2,horizontal_flip=True)

validate_datagen = ImageDataGenerator(rescale=1./255)

train_generator =
train_datagen.flow_from_directory(train_dir,target_size=(150,150),batch_size=20,class_mode=" binary")

validation_generator =
validate_datagen.flow_from_directory(validation_dir,target_size=(150,150),batch_size=20,class
_mode="binary")

conv_base = VGG16(weights="imagenet",include_top=False, input_shape=(150,150,3))

conv_base.trainable = False

model = tf.keras.models.Sequential()
model.add(conv_base) model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(256,activation ="relu")) model.add(tf.keras.layers.Dropout(0.5))
model.add(tf.keras.layers.Dense(1,activation = "sigmoid"))
```

```
model.compile(loss="binary_crossentropy",optimizer=tf.keras.optimizers.RMSprop(learning_rat e=2e-5),metrics=["accuracy"])

history = model.fit(train_generator,steps_per_epoch=100, epochs=2,
validation_data=validation_generator,validation_steps=50)

x, y_true = next(validation_generator) y_pred = model.predict(x) class_names
= ['cat', 'dog'] for i in range(len(x)):   plt.imshow(x[i])   plt.title(f'predicted
class: {class_names[int(round(y_pred[i][0]))]}, True class:
{class_names[int(y_true[i])]}')
plt.show()

acc = history.history["accuracy"] val_acc
= history.history["val_accuracy"] loss =
history.history["loss"] val_loss =
history.history["val_loss"]

epochs = range(1, len(acc) +1)
plt.plot(epochs, acc, "bo", label="Training acc")
plt.plot(epochs, val_acc, "b", label="validation acc")
plt.title("Training and validation accuracy")
plt.legend() plt.figure() plt.plot(epochs, loss, "bo",
label="Training loss") plt.plot(epochs, val_loss, "b",
label="validation loss") plt.title("Training and
validation loss") plt.legend() plt.show()
```
Output:





Training and validation accuracy
0.80
0.75
0.70
0.65
Training acc
validation acc
1.0
1.2
1.4
1.6
1.8
2.0
Training and validation loss
Training loss
validation loss
0.65
0.60
0.55
0.50
0.45
0.40
1.0
1.2
1.4
1.6
1.8
2.0

Practical 7

Aim: Write a program for the Implementation of a Generative Adversarial Network for generating synthetic shapes (like digits)

Source Code: from numpy import expand_dims from numpy import ones
from numpy import zeros from
numpy.random import rand from
numpy.random import randint from
keras.datasets.mnist import load_data from
keras.optimizers import Adam from
keras.models import Sequential from
keras.layers import Dense from
keras.layers import Conv2D from
keras.layers import Flatten from
keras.layers import Dropout
from keras.layers import LeakyReLU

```
# define the standalone discriminator model def
define_discriminator(in_shape=(28,28,1)):
model = Sequential()
 model.add(Conv2D(64, (3,3), strides=(2, 2), padding='same', input_shape=in_shape))
model.add(LeakyReLU(alpha=0.2))  model.add(Dropout(0.4))
 model.add(Conv2D(64, (3,3), strides=(2, 2), padding='same'))
 model.add(LeakyReLU(alpha=0.2))
model.add(Dropout(0.4))  model.add(Flatten())
 model.add(Dense(1, activation='sigmoid'))
 # compile model
 opt = Adam(lr=0.0002, beta_1=0.5)
 model.compile(loss='binary_crossentropy', optimizer=opt, metrics=['accuracy'])
return model

# load and prepare mnist training images def
load_real_samples():
 # load mnist dataset
 (trainX, _), (_, _) = load_data()
 # expand to 3d, e.g. add channels dimension
 X = expand_dims(trainX, axis=-1)
 # convert from unsigned ints to floats
 X = X.astype('float32')
```

```
 # scale from [0,255] to [0,1]
X = X / 255.0  return X

# select real samples def
generate_real_samples(dataset, n_samples):
 # choose random instances
 ix = randint(0, dataset.shape[0], n_samples)
 # retrieve selected images
 X = dataset[ix]
 # generate 'real' class labels (1)
y = ones((n_samples, 1))
 return X, y

# generate n fake samples with class labels
def generate_fake_samples(n_samples):  #
generate uniform random numbers in [0,1]
 X = rand(28 * 28 * n_samples)
 # reshape into a batch of grayscale images
 X = X.reshape((n_samples, 28, 28, 1))
# generate 'fake' class labels (0)  y =
zeros((n_samples, 1))
 return X, y

# train the discriminator model def train_discriminator(model,
dataset, n_iter=100, n_batch=256):
 half_batch = int(n_batch / 2)
# manually enumerate epochs
for i in range(n_iter):
 # get randomly selected 'real' samples
  X_real, y_real = generate_real_samples(dataset, half_batch)
 # update discriminator on real samples
  _, real_acc = model.train_on_batch(X_real, y_real)
 # generate 'fake' examples
  X_fake, y_fake = generate_fake_samples(half_batch)
 # update discriminator on fake samples
  _, fake_acc = model.train_on_batch(X_fake, y_fake)
 # summarize performance
  print('>%d real=%.0f%% fake=%.0f%%' % (i+1, real_acc*100, fake_acc*100))

# define the discriminator model model
= define_discriminator()
# load image data
```

dataset = load_real_samples()
# fit the model
train_discriminator(model, dataset)

Output:

```
>1 real=26% fake=60%
>2 real=38% fake=84%
>3 real=35% fake=91%
>4 real=34% fake=95%
>5 real=36% fake=100%
>6 real=41% fake=99%
>7 real=31% fake=100%
>8 real=51% fake=100%
>9 real=45% fake=100%
>10 real=42% fake=100%
>11 real=48% fake=100%
>12 real=47% fake=100%
>13 real=52% fake=100%
>14 real=57% fake=100%
>15 real=64% fake=100%
>16 real=66% fake=100%
>17 real=59% fake=100%
>18 real=70% fake=100%
>19 real=80% fake=100%
>20 real=77% fake=100%
>21 real=83% fake=100%
>22 real=81% fake=100%
>23 real=82% fake=100%
>24 real=92% fake=100%
>25 real=91% fake=100%
>26 real=91% fake=100%
>27 real=91% fake=100%
>28 real=95% fake=100%
>29 real=95% fake=100%
>30 real=95% fake=100%
```

```
>71 real=100% fake=100%
>72 real=100% fake=100%
>73 real=100% fake=100%
>74 real=100% fake=100%
>75 real=100% fake=100%
>76 real=100% fake=100%
>77 real=100% fake=100%
>78 real=100% fake=100%
>79 real=100% fake=100%
>80 real=100% fake=100%
>81 real=100% fake=100%
>82 real=100% fake=100%
>83 real=100% fake=100%
>84 real=100% fake=100%
>85 real=100% fake=100%
>86 real=100% fake=100%
>87 real=100% fake=100%
>88 real=100% fake=100%
>89 real=100% fake=100%
>90 real=100% fake=100%
>91 real=100% fake=100%
>92 real=100% fake=100%
>93 real=100% fake=100%
>94 real=100% fake=100%
>95 real=100% fake=100%
>96 real=100% fake=100%
>97 real=100% fake=100%
>98 real=100% fake=100%
>99 real=100% fake=100%
>100 real=100% fake=100%
```

Practical 8

Aim: Write a program to implement a simple form of a recurrent neural network.

1.**(4-to-1 RNN) to show that the quantity of rain on a certain day also depends on the values of the previous day**

Source Code:

```
import numpy as np
import tensorflow as tf

# Define the training data
rainfall_data = np.array([[0.2, 0.3, 0.1, 0.5, 0.4],
                          [0.1, 0.4, 0.5, 0.2, 0.3],
                          [0.3, 0.2, 0.4, 0.3, 0.1],
                          [0.4, 0.1, 0.3, 0.4, 0.2],
                          [0.5, 0.5, 0.2, 0.1, 0.5]])
# Prepare the input and output data input_data = rainfall_data[:, :-1]
# Previous four days' rainfall values output_data = rainfall_data[:, -1]
# Current day's rainfall value

# Define the RNN model model
= tf.keras.Sequential([
   tf.keras.layers.SimpleRNN(10, input_shape=(4, 1)),
tf.keras.layers.Dense(1)
])

# Compile the model
model.compile(loss='mse', optimizer='adam')

# Train the model
model.fit(np.expand_dims(input_data, axis=2), output_data, epochs=100, batch_size=1)

# Predict the rainfall for a new day new_input = np.array([[0.3, 0.2, 0.1, 0.4]])  #
Previous four days' rainfall values predicted_rainfall =
model.predict(np.expand_dims(new_input, axis=2)) print("Predicted rainfall for
the new day:", predicted_rainfall[0][0])
```

Output:

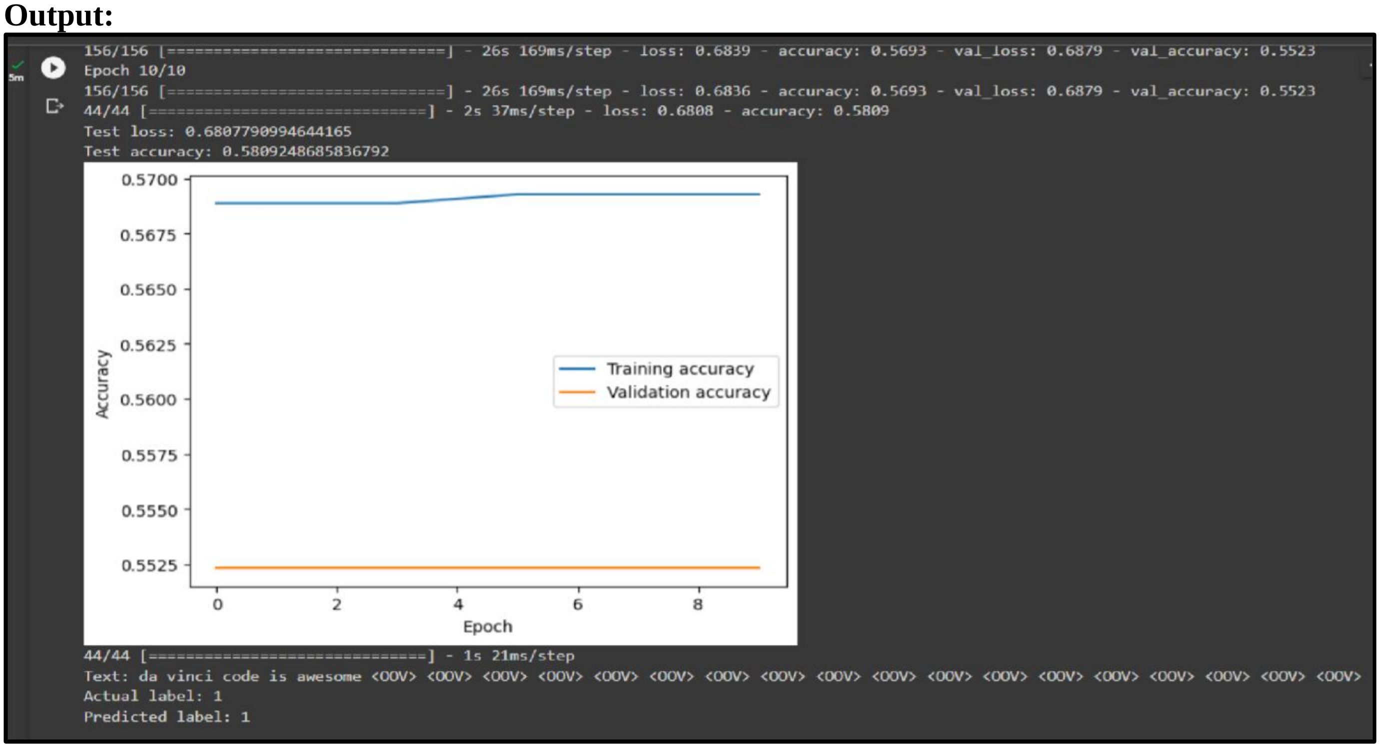
```
5/5 [==============================] - 0s 12ms/step - loss: 0.0024
Epoch 94/100
5/5 [==============================] - 0s 10ms/step - loss: 0.0025
Epoch 95/100
5/5 [==============================] - 0s 9ms/step - loss: 0.0024
Epoch 96/100
5/5 [==============================] - 0s 15ms/step - loss: 0.0024
Epoch 97/100
5/5 [==============================] - 0s 11ms/step - loss: 0.0024
Epoch 98/100
5/5 [==============================] - 0s 10ms/step - loss: 0.0023
Epoch 99/100
5/5 [==============================] - 0s 10ms/step - loss: 0.0023
Epoch 100/100
5/5 [==============================] - 0s 8ms/step - loss: 0.0023
1/1 [==============================] - 1s 520ms/step
Predicted rainfall for the new day: 0.33681476
```

Source Code:

```
import pandas as pd import
numpy as np import
tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer from
tensorflow.keras.preprocessing.sequence import pad_sequences from
sklearn.model_selection import train_test_split import
matplotlib.pyplot as plt

data = pd.read_csv("/content/sample_data/training.txt", delimiter="\t", names=["label", "text"])

X_train, X_test, y_train, y_test = train_test_split(data["text"],data["label"], test_size=0.2,
random_state=42)

tokenizer = Tokenizer(num_words=5000, oov_token="<OOV>") tokenizer.fit_on_texts(X_train)

X_train_seq = tokenizer.texts_to_sequences(X_train)
X_test_seq = tokenizer.texts_to_sequences(X_test)

max_length = 100
X_train_pad = pad_sequences(X_train_seq, maxlen=max_length, padding="post",truncating="post")
X_test_pad = pad_sequences(X_test_seq, maxlen=max_length, padding="post",truncating="post")

model = tf.keras.models.Sequential([tf.keras.layers.Embedding(input_dim=5000,
output_dim=32,input_length=max_length),tf.keras.layers.LSTM(units=64, dropout=0.2,
recurrent_dropout=0.2),tf.keras.layers.Dense(1, activation="sigmoid")])
```

```
model.compile(optimizer="adam", loss="binary_crossentropy",metrics=["accuracy"])

history = model.fit(X_train_pad, y_train, epochs=10, batch_size=32,validation_split=0.1)

loss, accuracy = model.evaluate(X_test_pad, y_test)
print("Test loss:", loss) print("Test
accuracy:", accuracy)

plt.plot(history.history["accuracy"], label="Training accuracy")
plt.plot(history.history["val_accuracy"], label="Validation accuracy")
plt.xlabel("Epoch") plt.ylabel("Accuracy")
plt.legend()
plt.show()

predictions = model.predict(X_test_pad)

index = np.random.randint(0, len(X_test_pad)) text =
tokenizer.sequences_to_texts([X_test_pad[index]])[0] label
= y_test.values[index] prediction = predictions[index][0]
print("Text:", text) print("Actual
label:", label)
print("Predicted label:", round(prediction))
```

Output:



2.**LSTM for sentiment analysis on datasets like UMICH SI650 for similar.**

Source Code:

```
from __future__ import division, print_function
from keras.layers.core import Dense, Activation
from keras.layers import Embedding from
keras.layers import LSTM from keras.models import
Sequential from keras.preprocessing import
sequence from sklearn.model_selection import
train_test_split import collections import nltk import
numpy as np nltk.download('punkt')
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
True
```

```
maxlen = 0
word_freqs = collections.Counter()
num_recs = 0

ftrain = open("/content/umich-sentiment-train.txt", "r")  # Open the file in text mode

for line in ftrain:     label, sentence =
line.strip().split("\t")
    words = nltk.word_tokenize(sentence.lower())

    if len(words) > maxlen:
maxlen = len(words)

    for word in words:
        word_freqs[word] += 1

    num_recs += 1

ftrain.close()

# print some statistics about our data, that will drive our parameters print("maxlen:
%d, vocab size: %d" % (maxlen, len(word_freqs)))
```

```
maxlen: 42, vocab size: 2268
```

Practical 9

Aim: Write a program for object detection from the image/video.

Source Code:

```
import torch import
torchvision import
pycocotools
from PIL import Image

holiday = Image.open("/content/kids.jpg").convert('RGB')
holiday
```

```
kids_playing = Image.open("/content/kids.jpg").convert('RGB') kids_playing
```

holiday_tensor_int = pil_to_tensor(holiday)
kids_playing_tensor_int = pil_to_tensor(kids_playing)

holiday_tensor_int.shape, kids_playing_tensor_int.shape

```
(torch.Size([3, 1120, 2016]), torch.Size([3, 1120, 2016]))
```

holiday_tensor_int = holiday_tensor_int.unsqueeze(dim=0)
kids_playing_tensor_int = kids_playing_tensor_int.unsqueeze(dim=0)

holiday_tensor_int.shape, kids_playing_tensor_int.shape

```
(torch.Size([1, 3, 1120, 2016]), torch.Size([1, 3, 1120, 2016]))
```

print(holiday_tensor_int.min(), holiday_tensor_int.max())

```
tensor(0, dtype=torch.uint8) tensor(255, dtype=torch.uint8)
```

holiday_tensor_float = holiday_tensor_int / 255.0
kids_playing_tensor_float = kids_playing_tensor_int / 255.0

print(holiday_tensor_float.min(), holiday_tensor_float.max())

```
tensor(0.) tensor(1.)
```

from torchvision.models.detection import fasterrcnn_resnet50_fpn

object_detection_model = fasterrcnn_resnet50_fpn(pretrained=True, progress=False)

object_detection_model.eval(); ## Setting Model for Evaluation/Prediction

holiday_preds = object_detection_model(holiday_tensor_float)

holiday_preds

```
[{'boxes': tensor([[1565.8942,  471.7659, 1811.0688,  927.4228],
        [ 120.9253,  363.1345,  421.6961, 1105.6018],
        [ 509.4385,  458.9574,  693.5939, 1001.9330],
        [1181.9674,  477.7082, 1433.4752,  982.7266],
        [ 741.7849,  462.7850,  981.6406, 1034.2094],
        [1784.6957,  704.5729, 1842.0870,  763.6006],
        [ 948.3671,  411.9908, 1111.9010,  652.2377],
        [ 302.4559,  725.4138,  375.1870,  802.2778],
        [ 372.9771,  474.3299,  481.1460,  667.6293],
        [ 397.3616,  331.0306,  480.6055,  666.0760],
        [1729.4586,  588.4355, 1772.0046,  645.2954],
        [1194.8232,  480.7062, 1270.5952,  596.5611],
        [ 825.9108,  355.1837, 1008.1398,  690.1427],
        [ 949.6096,  488.7204, 1180.6737,  735.1190],
        [ 433.1131,  306.8869,  500.2051,  659.2569],
        [ 798.1258,  433.2409,  903.2397,  500.1232],
        [ 304.1548,  724.5444,  375.0820,  802.0087],
        [ 893.0400,  368.0695, 1166.3256,  716.5153],
        [ 938.7700,  502.0295, 1028.8362,  685.3348],
        [1772.8767,  591.4392, 1787.5862,  621.2263],
        [ 789.2773,  398.8733,  956.6437,  666.9479],
        [ 861.0916,  359.2489, 1167.0411,  720.7684],
        [ 838.9109,  345.3440, 1028.7206,  543.1509],
        [ 972.9252,  432.1348, 1084.3429,  599.9109],
        [1178.8203,  483.0518, 1207.9275,  526.8611],
        [ 928.6594,  351.2741, 1027.0938,  445.9928],
        [1148.1388,  248.4578, 1298.6729,  619.1220],
        [ 806.9293,  383.5974,  927.6639,  583.2614],
        [1184.6785,  483.6467, 1206.5623,  518.6398],
        [ 928.0013,  402.2428, 1055.2094,  682.7582],
```

```
        [1177.9301,  492.4050, 1205.8940,  528.0626],
        [ 795.9549,  438.3310,  912.4966,  558.4469],
        [1182.7083,  497.9762, 1204.9606,  525.6568],
        [ 929.5096,  366.9445, 1041.1884,  543.0920],
        [1521.7596,  602.9040, 1597.0552,  630.3387],
        [ 770.5167,  504.3984, 1049.3455,  681.6665],
        [ 386.7892,  435.2683, 1089.5959,  668.9307],
        [1782.7791,  704.2247, 1842.4552,  764.6519],
        [ 350.5378,  437.2085,  483.5045,  680.3541],
        [ 940.6858,  425.4261, 1053.9584,  565.6411],
        [1192.0833,  479.0542, 1253.0463,  570.6131],
        [1201.1323,  486.0803, 1250.7799,  566.1834],
        [ 420.6662,  341.7614, 1061.7148,  632.9488],
        [1203.5992,  484.4836, 1267.4409,  605.7438],
        [ 640.4301,  203.6466,  753.3429,  671.9545]],
       grad_fn=<StackBackward0>),
 'labels': tensor([ 1,  1,  1,  1,  1, 37,  1, 37, 62, 62, 37, 39, 62, 15, 62, 62, 34, 62,
        62, 37, 62, 15, 62,  1, 44, 62, 62, 62, 47, 62, 16, 62, 37, 62, 15, 15,
        15, 53, 15,  1, 43, 39, 62, 43, 62]),
 'scores': tensor([0.9998, 0.9998, 0.9998, 0.9997, 0.9993, 0.9628, 0.8721, 0.8368, 0.8039,
        0.7754, 0.5970, 0.5537, 0.5425, 0.5032, 0.4730, 0.3431, 0.3246, 0.3053,
        0.2679, 0.2108, 0.2053, 0.1895, 0.1618, 0.1466, 0.1383, 0.1331, 0.1305,
        0.1283, 0.1064, 0.0995, 0.0917, 0.0902, 0.0869, 0.0832, 0.0803, 0.0801,
        0.0789, 0.0658, 0.0654, 0.0615, 0.0596, 0.0567, 0.0559, 0.0543, 0.0504],
       grad_fn=<IndexBackward0>)}]
```

```
holiday_preds[0]["boxes"] = holiday_preds[0]["boxes"][holiday_preds[0]["scores"] > 0.8]
holiday_preds[0]["labels"] = holiday_preds[0]["labels"][holiday_preds[0]["scores"] > 0.8]
holiday_preds[0]["scores"] = holiday_preds[0]["scores"][holiday_preds[0]["scores"] > 0.8]
```

```
holiday_preds
```

```
[{'boxes': tensor([[1565.8942,  471.7659, 1811.0688,  927.4228],
         [ 120.9253,  363.1345,  421.6961, 1105.6018],
         [ 509.4385,  458.9574,  693.5939, 1001.9330],
         [1181.9674,  477.7082, 1433.4752,  982.7266],
         [ 741.7849,  462.7850,  981.6406, 1034.2094],
         [1784.6957,  704.5729, 1842.0870,  763.6006],
         [ 948.3671,  411.9908, 1111.9010,  652.2377],
         [ 302.4559,  725.4138,  375.1870,  802.2778],
         [ 372.9771,  474.3299,  481.1460,  667.6293]],
        grad_fn=<IndexBackward0>),
  'labels': tensor([ 1,  1,  1,  1,  1, 37,  1, 37, 62]),
  'scores': tensor([0.9998, 0.9998, 0.9998, 0.9997, 0.9993, 0.9628, 0.8721, 0.8368, 0.8039],
        grad_fn=<IndexBackward0>)}]
```

```
kids_preds = object_detection_model(kids_playing_tensor_float)
```

```
kids_preds
```

```
[{'boxes': tensor([[1565.8942,  471.7659, 1811.0688,  927.4228],
          [ 120.9253,  363.1345,  421.6961, 1105.6018],
          [ 509.4385,  458.9574,  693.5939, 1001.9330],
          [1181.9674,  477.7082, 1433.4752,  982.7266],
          [ 741.7849,  462.7850,  981.6406, 1034.2094],
          [1784.6957,  704.5729, 1842.0870,  763.6006],
          [ 948.3671,  411.9908, 1111.9010,  652.2377],
          [ 302.4559,  725.4138,  375.1870,  802.2778],
          [ 372.9771,  474.3299,  481.1460,  667.6293],
          [ 397.3616,  331.0306,  480.6055,  666.0760],
          [1729.4586,  588.4355, 1772.0046,  645.2954],
          [1194.8232,  480.7062, 1270.5952,  596.5611],
          [ 825.9108,  355.1837, 1008.1398,  690.1427],
          [ 949.6096,  488.7204, 1180.6737,  735.1190],
          [ 433.1131,  306.8869,  500.2051,  659.2569],
          [ 798.1258,  433.2409,  903.2397,  500.1232],
          [ 304.1548,  724.5444,  375.0820,  802.0087],
          [ 893.0400,  368.0695, 1166.3256,  716.5153],
          [ 938.7700,  502.0295, 1028.8362,  685.3348],
          [1772.8767,  591.4392, 1787.5862,  621.2263],
          [ 789.2773,  398.8733,  956.6437,  666.9479],
          [ 861.0916,  359.2489, 1167.0411,  720.7684],
          [ 838.9109,  345.3440, 1028.7206,  543.1509],
          [ 972.9252,  432.1348, 1084.3429,  599.9109],
          [1178.8203,  483.0518, 1207.9275,  526.8611],
          [ 928.6594,  351.2741, 1027.0938,  445.9928],
          [1148.1388,  248.4578, 1298.6729,  619.1220],
          [ 806.9293,  383.5974,  927.6639,  583.2614],
          [1184.6785,  483.6467, 1206.5623,  518.6398],
          [ 928.0013,  402.2428, 1055.2094,  682.7582],
          [1177.9301,  492.4050, 1205.8940,  528.0626],
          [ 795.9549,  438.3310,  912.4966,  558.4469],
          [1182.7083,  497.9762, 1204.9606,  525.6568],
```

```
        [ 929.5096,  366.9445, 1041.1884,  543.0920],
        [1521.7596,  602.9040, 1597.0552,  630.3387],
        [ 770.5167,  504.3984, 1049.3455,  681.6665],
        [ 386.7892,  435.2683, 1089.5959,  668.9307],
        [1782.7791,  704.2247, 1842.4552,  764.6519],
        [ 350.5378,  437.2085,  483.5045,  680.3541],
        [ 940.6858,  425.4261, 1053.9584,  565.6411],
        [1192.0833,  479.0542, 1253.0463,  570.6131],
        [1201.1323,  486.0803, 1250.7799,  566.1834],
        [ 420.6662,  341.7614, 1061.7148,  632.9488],
        [1203.5992,  484.4836, 1267.4409,  605.7438],
        [ 640.4301,  203.6466,  753.3429,  671.9545]],
       grad_fn=<StackBackward0>),
 'labels': tensor([ 1,  1,  1,  1,  1, 37,  1, 37, 62, 62, 37, 39, 62, 15, 62, 62, 34, 62,
        62, 37, 62, 15, 62,  1, 44, 62, 62, 62, 47, 62, 16, 62, 37, 62, 15, 15,
        15, 53, 15,  1, 43, 39, 62, 43, 62]),
 'scores': tensor([0.9998, 0.9998, 0.9998, 0.9997, 0.9993, 0.9628, 0.8721, 0.8368, 0.8039,
        0.7754, 0.5970, 0.5537, 0.5425, 0.5032, 0.4730, 0.3431, 0.3246, 0.3053,
        0.2679, 0.2108, 0.2053, 0.1895, 0.1618, 0.1466, 0.1383, 0.1331, 0.1305,
        0.1283, 0.1064, 0.0995, 0.0917, 0.0902, 0.0869, 0.0832, 0.0803, 0.0801,
        0.0789, 0.0658, 0.0654, 0.0615, 0.0596, 0.0567, 0.0559, 0.0543, 0.0504],
       grad_fn=<IndexBackward0>)}]
```

kids_preds[0]["boxes"] = kids_preds[0]["boxes"][kids_preds[0]["scores"] > 0.8] kids_preds[0]["labels"] = kids_preds[0]["labels"][kids_preds[0]["scores"] > 0.8] kids_preds[0]["scores"] = kids_preds[0]["scores"][kids_preds[0]["scores"] > 0.8]

kids_preds

```
[{'boxes': tensor([[1565.8942,  471.7659, 1811.0688,  927.4228],
          [ 120.9253,  363.1345,  421.6961, 1105.6018],
          [ 509.4385,  458.9574,  693.5939, 1001.9330],
          [1181.9674,  477.7082, 1433.4752,  982.7266],
          [ 741.7849,  462.7850,  981.6406, 1034.2094],
          [1784.6957,  704.5729, 1842.0870,  763.6006],
          [ 948.3671,  411.9908, 1111.9010,  652.2377],
          [ 302.4559,  725.4138,  375.1870,  802.2778],
          [ 372.9771,  474.3299,  481.1460,  667.6293]],
        grad_fn=<IndexBackward0>),
  'labels': tensor([ 1,  1,  1,  1,  1, 37,  1, 37, 62]),
  'scores': tensor([0.9998, 0.9998, 0.9998, 0.9997, 0.9993, 0.9628, 0.8721, 0.8368, 0.8039],
        grad_fn=<IndexBackward0>)}]
```

from pycocotools.coco import COCO

annFile='/content/instances_val2017.json'

coco=COCO(annFile)

```
loading annotations into memory...
Done (t=0.00s)
creating index...
index created!
```

holiday_labels = coco.loadCats(holiday_preds[0]["labels"].numpy())

holiday_labels

```
[{'supercategory': 'person', 'id': 1, 'name': 'person'},
 {'supercategory': 'person', 'id': 1, 'name': 'person'},
 {'supercategory': 'person', 'id': 1, 'name': 'person'},
 {'supercategory': 'person', 'id': 1, 'name': 'person'},
 {'supercategory': 'person', 'id': 1, 'name': 'person'},
 {'supercategory': 'sports', 'id': 37, 'name': 'sports ball'},
 {'supercategory': 'person', 'id': 1, 'name': 'person'},
 {'supercategory': 'sports', 'id': 37, 'name': 'sports ball'},
 {'supercategory': 'furniture', 'id': 62, 'name': 'chair'}]
```

kids_labels = coco.loadCats(kids_preds[0]["labels"].numpy())

kids_labels

```
[{'supercategory': 'person', 'id': 1, 'name': 'person'},
 {'supercategory': 'person', 'id': 1, 'name': 'person'},
 {'supercategory': 'person', 'id': 1, 'name': 'person'},
 {'supercategory': 'person', 'id': 1, 'name': 'person'},
 {'supercategory': 'person', 'id': 1, 'name': 'person'},
 {'supercategory': 'sports', 'id': 37, 'name': 'sports ball'},
 {'supercategory': 'person', 'id': 1, 'name': 'person'},
 {'supercategory': 'sports', 'id': 37, 'name': 'sports ball'},
 {'supercategory': 'furniture', 'id': 62, 'name': 'chair'}]
```

from torchvision.utils import draw_bounding_boxes

holiday_annot_labels = ["{}-{:.2f}".format(label["name"], prob) for label, prob in zip(holiday_labels, holiday_preds[0]["scores"].detach().numpy())]

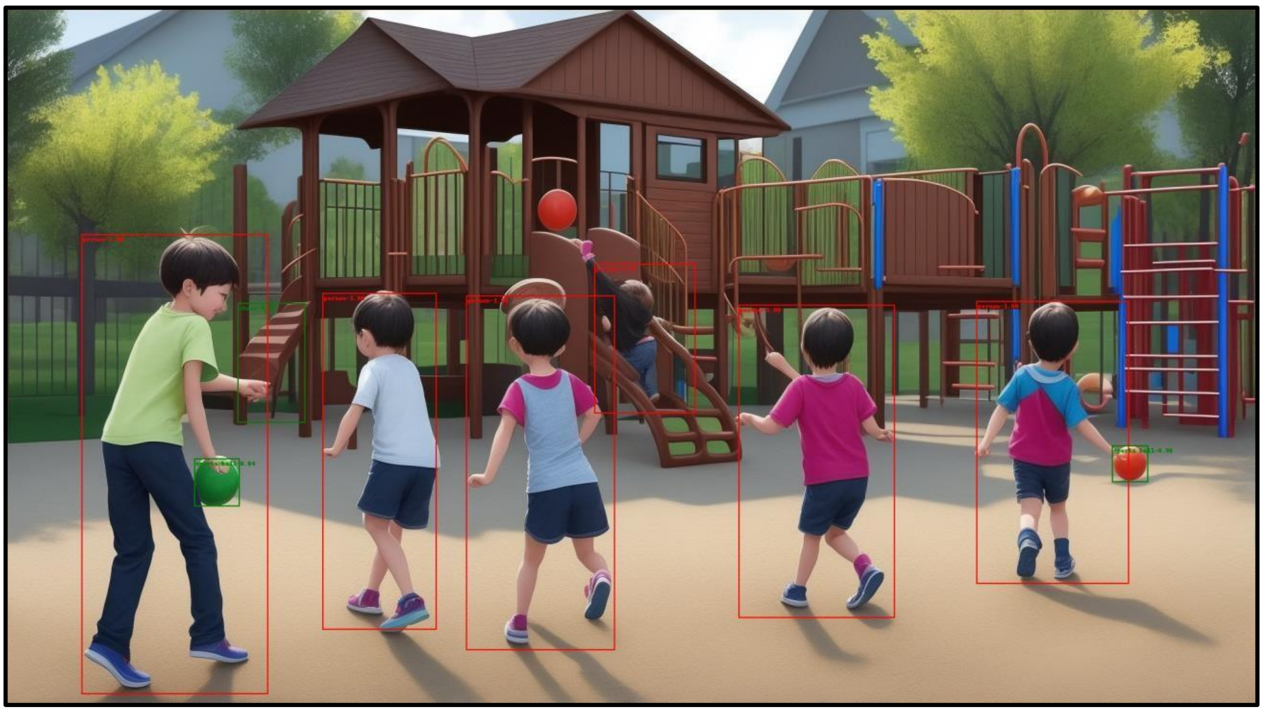
```
holiday_output = draw_bounding_boxes(image=holiday_tensor_int[0],
boxes=holiday_preds[0]["boxes"],                                labels=holiday_annot_labels,
                        colors=["red" if label["name"]=="person" else "green" for label in holiday_labels],
                        width=2
                       )
```

```
holiday_output.shape
```

```
torch.Size([3, 1120, 2016])
```

```
from torchvision.transforms.functional import to_pil_image
```

```
to_pil_image(holiday_output)
```



```
from torchvision.utils import draw_bounding_boxes
```

```
kids_annot_labels = ["{}-{:.2f}".format(label["name"], prob) for label, prob in zip(kids_labels,
kids_preds[0]["scores"].detach().numpy())]
```

```
kids_output = draw_bounding_boxes(image=kids_playing_tensor_int[0],
boxes=kids_preds[0]["boxes"],                                labels=kids_annot_labels,
                        colors=["red" if label["name"]=="person" else "green" for label in kids_labels],
```

```
                         width=2,
font_size=16,
fill=True
                        )

to_pil_image(kids_output)
```