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DEPARTMENT OF COMPUTER SCIENCE

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DEPARTMENT OF COMPUTER SCIENCE

CERTIFICATE

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Index

Practical 1

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

Theory: A Feed Forward Neural Network is an artificial neural network in which the connections between nodes does not form a cycle. The opposite of a feed forward neural network is a recurrent neural network, in which certain pathways are cycled. The feed forward model is the simplest form of neural network as information is only processed in one direction. While the data may pass through multiple hidden nodes, it always moves in one direction and never backwards.

A Feed Forward Neural Network is commonly seen in its simplest form as a single layer perceptron. In this model, a series of inputs enter the layer and are multiplied by the weights. Each value is then added together to get a sum of the weighted input values. If the sum of the values is above a specific threshold, usually set at zero, the value produced is often 1, whereas if the sum falls below the threshold, the output value is -1. The single layer perceptron is an important model of feed forward neural networks and is often used in classification tasks. Furthermore, single layer perceptron's can incorporate aspects of machine learning.

Code:

```
import tensorflow as tf
import numpy as np
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelBinarizer
# Load Iris dataset
iris = load_iris() # Loading Iris dataset into a variable.
X = iris.data # Features of the dataset.
y = iris.target # Class labels of the dataset.
# One-hot encode labels
lb = LabelBinarizer() # Creating an instance of LabelBinarizer class for one-hot
encoding.
y = lb.fit_transform(y) # One-hot encoding the class labels.
# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2,random_state=42)
# Splitting the dataset into training and testing sets with test size of 20%.
# Define model architecture
model = tf.keras.Sequential([
        # First hidden layer with 16 neurons and input shape of 4 features. ReLU
        activation function is used.
        tf.keras.layers.Dense(16, input_shape=(4,), activation='relu'),
        # Second hidden layer with 8 neurons. ReLU activation function is used.
        tf.keras.layers.Dense(8, activation='relu'),
        # Output layer with 3 neurons for 3 classes. Softmax activation function
is used for multiclass␣classification task.
```

```
        tf.keras.layers.Dense(3, activation='softmax')
        ])
# Compile model with different optimizers
optimizers = ['sgd', 'adam', 'rmsprop']
# List of optimizers to be used for training the model.
for optimizer in optimizers: # Looping over each optimizer.
    # Compiling the model with 'categorical_crossentropy' as the loss
    function,the current optimizer and accuracy as the metric to be calculated.
    model.compile(loss='categorical_crossentropy', optimizer=optimizer,
      metrics=['accuracy'])
    # Train model
    history = model.fit(X_train, y_train, validation_data=(X_test, y_test),
      epochs=50, verbose=0)
    # Training the model for 50 epochs with verbose=0 to suppress the output.

    # Evaluate model
    loss, accuracy = model.evaluate(X_test, y_test, verbose=0) # Evaluating the
model on the test set and calculating the loss and accuracy.
    print('Optimizer:', optimizer) # Printing the optimizer name.
    print('Test loss:', loss) # Printing the loss value on the test set.
    print('Test accuracy:', accuracy) # Printing the accuracy value on the test
set.
```

```
Optimizer: sgd
Test loss: 0.5317491888999939
Test accuracy: 0.8666666746139526
Optimizer: adam
Test loss: 0.3137800097465515
Test accuracy: 0.9666666388511658
Optimizer: rmsprop
Test loss: 0.20260581374168396
Test accuracy: 0.9666666388511658
```

target_names': array(['setosa', 'versicolor', 'virginica']

feature_names': ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']

```
# Allow user to input values for the flower attributes
print('\nInput values for the flower attributes:')
sepal_length = float(input('Sepal length (cm): '))
sepal_width = float(input('Sepal width (cm): '))
petal_length = float(input('Petal length (cm): '))
petal_width = float(input('Petal width (cm): '))
# Predict class of flower based on input values
input_values = np.array([[sepal_length, sepal_width, petal_length,petal_width]])
prediction = model.predict(input_values)
predicted_class = np.argmax(prediction)
class_names = iris.target_names
print('\nPredicted class: ', class_names[predicted_class])
```

```
Input values for the flower attributes:
Sepal length (cm): 5
Sepal width (cm): 10
Petal length (cm): 11
Petal width (cm): 6
1/1 [==============================] - 0s 107ms/step

Predicted class:  virginica
```

```
#memory ---------------------------------------------
optimizers = {
                'sgd': tf.keras.optimizers.SGD(),
                'adam': tf.keras.optimizers.Adam(),
                'rmsprop': tf.keras.optimizers.RMSprop()
            }
# Compile model with different optimizers
for optimizer_name, optimizer in optimizers.items():
    model.compile(loss='categorical_crossentropy', optimizer=optimizer,
    metrics=['accuracy'])
    # Train model
    history = model.fit(X_train, y_train, validation_data=(X_test, y_test),
epochs=50, verbose=0)
    # Evaluate model
    loss, accuracy = model.evaluate(X_test, y_test, verbose=0)
    print('Optimizer:', optimizer_name)
    print('Test loss:', loss)
    print('Test accuracy:', accuracy)
    # Estimate memory requirement
    size_in_bytes = model.count_params() * 4 # each parameter is a 32-bit float
    size_in_mb = size_in_bytes / (1024 * 1024)
    print(f'Memory requirement: {size_in_mb:.2f} MB')
```

```
Optimizer: sgd
Test loss: 0.15246990323066711
Test accuracy: 0.9666666388511658
Memory requirement: 0.00 MB
Optimizer: adam
Test loss: 0.11661176383495331
Test accuracy: 0.9666666388511658
Memory requirement: 0.00 MB
Optimizer: rmsprop
Test loss: 0.10857316851615906
Test accuracy: 0.9666666388511658
Memory requirement: 0.00 MB
```

Practical 2

Aim: Program to implement regularization to prevent the model from overfitting.

Theory: Regularization is a technique which makes slight modifications to the learning algorithm such that the model generalizes better. This in turn improves the model's performance on the unseen data as well. L1 and L2 are the most common types of regularization. These update the general cost function by adding another term known as the regularization term.

Cost function = Loss (say, binary cross entropy) + Regularization term

Due to the addition of this regularization term, the values of weight matrices decrease because it assumes that a neural network with smaller weight matrices leads to simpler models. Therefore, it will also reduce overfitting to quite an extent. However, this regularization term differs in L1 and L2.

In L2, we have:

$$Cost\,function = Loss + \frac{\lambda}{2m} * \sum \|w\|^2$$

Here, lambda is the regularization parameter. It is the hyperparameter whose value is optimized for better results. L2 regularization is also known as weight decay as it forces the weights to decay towards zero (but not exactly zero).

In L1, we have:

$$Cost\,function = Loss + \frac{\lambda}{2m} * \sum \|w\|$$

In this, we penalize the absolute value of the weights. Unlike L2, the weights may be reduced to zero here. Hence, it is very useful when we are trying to compress our model. Otherwise, we usually prefer L2 over it.

Code:

```
# Import TensorFlow library
import tensorflow as tf

# Load the data # Load MNIST dataset
'''
loads the MNIST dataset using the load_data() function provided by Keras, a high-
level API of TensorFlow.
The MNIST dataset contains 70,000 images of handwritten digits that are split into
60,000 training images and 10,000 testing images.
'''
(train_data, train_labels), (test_data, test_labels) = tf.keras.datasets.mnist.
                                                                  load_data()

# Preprocess the data
'''
```

```
Preprocess the data. The images are first reshaped from a 3D array (28x28 pixels)
to a 2D array (784 pixels).
Then, the pixel values are normalized to be between 0 and 1 by dividing by 255.
The labels are converted to one-hot encoding format using the to_categorical()
function provided by Keras. This is done to make it easier for the model to classify
the images into 10 different classes (one for each digit).
'''
# Reshape and normalize training data
train_data = train_data.reshape((60000, 784)) / 255.0
# Reshape and normalize testing data
test_data = test_data.reshape((10000, 784)) / 255.0
# Convert training labels to one-hot encoding
train_labels = tf.keras.utils.to_categorical(train_labels)
# Convert testing labels to one-hot encoding
test_labels = tf.keras.utils.to_categorical(test_labels)

# Define the model architecture
'''
This code defines the architecture of the neural network model. The Sequential ()
function is used to create a sequential model, meaning that the layers are added in
sequence. Three fully connected layers are defined using the Dense () function.
The first layer has 128 units, ReLU activation, and L2 regularization with a
regularization parameter of 0.01.
The second layer has 64 units, ReLU activation, and L2 regularization with a
regularization parameter of 0.01.
The third and final layer has 10 units, softmax activation, and is used for the
classification task.
'''
model = tf.keras.models.Sequential([ # Define sequential model
         #Add a fully connected layer with 128 units, ReLU activation, and L2
         regularization
        tf.keras.layers.Dense(128, activation='relu', input_shape=(784,),
        kernel_regularizer=tf.keras.regularizers.l2(0.01)),
        # Add another fully connected layer with 64 units,ReLU activation, and L2
        regularization
        tf.keras.layers.Dense(64, activation='relu', kernel_regularizer=tf.keras.
        regularizers.l2(0.01)),
        # Add a final output layer with 10 units (one for each class), softmax
        activation
        tf.keras.layers.Dense(10, activation='softmax')
        ])

# Compile the model
'''
This code compiles the model. The compile () function configures the model for
training by specifying the optimizer, loss function, and metrics to monitor during
training. In this case, the Adam optimizer is used with a learning rate of 0.001,
categorical cross-entropy is used as the loss function, and accuracy is monitored
during training.
'''
```

```
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
                  # Use Adam optimizer with learning rate 0.001
                loss='categorical_crossentropy',
                  # Use categorical cross-entropy loss function
                metrics=['accuracy']) # Monitor accuracy during training

# Train the model
'''
This code trains the model using the fit () function. The training data and labels
are passed in as arguments, along with the number of epochs to train for, the batch
size to use, and the validation data to use for monitoring model performance during
training. The fit () function returns a history object that contains information
about the training process, such as the loss and accuracy at each epoch. The purpose
of this program is to demonstrate how to implement a neural network model for image
classification using TensorFlow/Keras. The model uses regularization techniques to
prevent overfitting and achieves high accuracy on the MNIST dataset.
'''
history = model.fit (train_data, train_labels, epochs=10, batch_size=128,
            # Train the model for 10 epochs, using batches of size 128, and
            validate on the testing data at the end of each epoch
                    validation_data= (test_data, test_labels))
```

```
Epoch 1/10
469/469 [==============================] - 6s 8ms/step - loss: 1.1277 - accuracy: 0.8823 - val_loss: 0.6140 - val_accuracy: 0.9
210
Epoch 2/10
469/469 [==============================] - 3s 7ms/step - loss: 0.5642 - accuracy: 0.9208 - val_loss: 0.5060 - val_accuracy: 0.9
288
Epoch 3/10
469/469 [==============================] - 3s 7ms/step - loss: 0.4960 - accuracy: 0.9283 - val_loss: 0.4592 - val_accuracy: 0.9
399
Epoch 4/10
469/469 [==============================] - 3s 7ms/step - loss: 0.4588 - accuracy: 0.9353 - val_loss: 0.4308 - val_accuracy: 0.9
399
Epoch 5/10
469/469 [==============================] - 3s 7ms/step - loss: 0.4274 - accuracy: 0.9410 - val_loss: 0.3986 - val_accuracy: 0.9
473
Epoch 6/10
469/469 [==============================] - 3s 7ms/step - loss: 0.4063 - accuracy: 0.9430 - val_loss: 0.3889 - val_accuracy: 0.9
425
Epoch 7/10
469/469 [==============================] - 3s 7ms/step - loss: 0.3879 - accuracy: 0.9465 - val_loss: 0.3781 - val_accuracy: 0.9
435
Epoch 8/10
469/469 [==============================] - 3s 7ms/step - loss: 0.3750 - accuracy: 0.9470 - val_loss: 0.3575 - val_accuracy: 0.9
511
Epoch 9/10
469/469 [==============================] - 3s 7ms/step - loss: 0.3594 - accuracy: 0.9505 - val_loss: 0.3452 - val_accuracy: 0.9
523
Epoch 10/10
469/469 [==============================] - 3s 7ms/step - loss: 0.3477 - accuracy: 0.9521 - val_loss: 0.3307 - val_accuracy: 0.9
557
```

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.

Theory: The CIFAR-10 dataset (Canadian Institute for Advanced Research) is a collection of images that are commonly used to train machine learning and computer vision algorithms. It is one of the most widely used datasets for machine learning research. The CIFAR-10 dataset contains 60,000 32x32 color images in 10 different classes. The 10 different classes represent airplanes, cars, birds, cats, deer, dogs, frogs, horses, ships, and trucks. There are 6,000 images of each class.

Computer algorithms for recognizing objects in photos often learn by example. CIFAR-10 is a set of images that can be used to teach a computer how to recognize objects. Since the images in CIFAR-10 are low-resolution (32x32), this dataset can allow researchers to quickly try different algorithms to see what works.

CIFAR-10 is a labeled subset of the 80 million Tiny Images dataset from 2008, published in 2009. When the dataset was created, students were paid to label all of the images. Various kinds of convolutional neural networks tend to be the best at recognizing the images in CIFAR-10.

Code:

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

# Load the data
(x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()

# Preprocess the data
x_train = x_train.astype("float32") / 255.0
x_test = x_test.astype("float32") / 255.0

# Convert labels to one-hot encoding format
y_train = keras.utils.to_categorical(y_train, 10)
y_test = keras.utils.to_categorical(y_test, 10)

# Define the model architecture
model = keras.Sequential([
        keras.Input(shape=(32, 32, 3)),
        layers.Conv2D(32, kernel_size=(3, 3), activation="relu"),
        layers.MaxPooling2D(pool_size=(2, 2)),
        layers.Conv2D(64, kernel_size=(3, 3), activation="relu"),
        layers.MaxPooling2D(pool_size=(2, 2)),
        layers.Flatten(),
        layers.Dropout(0.5),
        layers.Dense(10, activation="softmax"),
        ])
```

```
# Compile the model
model.compile(loss="categorical_crossentropy",optimizer="adam",metrics=["accuracy"
])
# Train the model
model.fit(x_train,y_train,batch_size=64,epochs=10,validation_data=(x_test,y_test))

# Save the trained model to a file
model.save("cifar10_model.h5")
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 [==============================] - 98s 1us/step
Epoch 1/10
782/782 [==============================] - 58s 71ms/step - loss: 1.6371 - accuracy: 0.4083 - val_loss: 1.3562 - val_accuracy:
0.5235
Epoch 2/10
782/782 [==============================] - 48s 61ms/step - loss: 1.3320 - accuracy: 0.5266 - val_loss: 1.1995 - val_accuracy:
0.5845
Epoch 3/10
782/782 [==============================] - 49s 63ms/step - loss: 1.2158 - accuracy: 0.5728 - val_loss: 1.1238 - val_accuracy:
0.6112
Epoch 4/10
782/782 [==============================] - 50s 64ms/step - loss: 1.1443 - accuracy: 0.6012 - val_loss: 1.0842 - val_accuracy:
0.6212
Epoch 5/10
782/782 [==============================] - 50s 64ms/step - loss: 1.0944 - accuracy: 0.6177 - val_loss: 1.0158 - val_accuracy:
0.6465
Epoch 6/10
782/782 [==============================] - 50s 65ms/step - loss: 1.0552 - accuracy: 0.6334 - val_loss: 1.0024 - val_accuracy:
0.6541
Epoch 7/10
782/782 [==============================] - 51s 65ms/step - loss: 1.0242 - accuracy: 0.6438 - val_loss: 0.9671 - val_accuracy:
0.6704
Epoch 8/10
782/782 [==============================] - 50s 64ms/step - loss: 1.0027 - accuracy: 0.6501 - val_loss: 0.9256 - val_accuracy:
0.6825
Epoch 9/10
782/782 [==============================] - 51s 65ms/step - loss: 0.9752 - accuracy: 0.6636 - val_loss: 0.9243 - val_accuracy:
0.6804
Epoch 10/10
782/782 [==============================] - 51s 66ms/step - loss: 0.9587 - accuracy: 0.6668 - val_loss: 0.9543 - val_accuracy:
0.6736

<keras.callbacks.History at 0x1cdb37048b0>
```

```
import numpy as np
from PIL import Image

# Load the saved model
model = keras.models.load_model("cifar10_model.h5")

# Load and preprocess the test image
img = Image.open("two.png")
img = img.resize((32, 32))
img_array = np.array(img)
img_array = img_array.astype("float32") / 255.0
img_array = np.expand_dims(img_array, axis=0)

# Make predictions on the test image
predictions = model.predict(img_array)
# Get the predicted class label
class_label = np.argmax(predictions)

# Print the predicted class label
print("Predicted class label:", class_label)
```

```
1/1 [==============================] - 0s 349ms/step
Predicted class label: 2
```

Practical 4

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

Theory: An autoencoder is a special type of neural network that is trained to copy its input to its output. For example, given an image of a handwritten digit, an autoencoder first encodes the image into a lower dimensional latent representation, then decodes the latent representation back to an image. An autoencoder learns to compress the data while minimizing the reconstruction error.

The encoder part of the network is used for encoding and sometimes even for data compression purposes although it is not very effective as compared to other general compression techniques like JPEG. Encoding is achieved by the encoder part of the network which has a decreasing number of hidden units in each layer. Thus, this part is forced to pick up only the most significant and representative features of the data. The second half of the network performs the Decoding function. This part has an increasing number of hidden units in each layer and thus tries to reconstruct the original input from the encoded data. Thus Auto-encoders are an unsupervised learning technique.

Code:

This program first loads the MNIST dataset and pre-processes it. It then defines the encoder and decoder architectures and combines them into an autoencoder model. The autoencoder model is compiled and trained on the training data. The program then uses the trained autoencoder to predict the reconstructed images for the test data. The reconstructed images are plotted alongside the original test images for comparison. Note that in this program, we're not using the labels of the MNIST dataset since we're only interested in reconstructing the input images. Also, the loss function used in the autoencoder is binary crossentropy, since we're treating each pixel value as a binary classification problem (i.e., is the pixel on or off?). Finally, the images are plotted using the matplotlib library.

```
import tensorflow as tf
from tensorflow import keras
import numpy as np
import matplotlib.pyplot as plt

# Load the MNIST dataset
(x_train, _), (x_test, _) = keras.datasets.mnist.load_data()

# Normalize the pixel values to be between 0 and 1
x_train = x_train.astype("float32") / 255.0
x_test = x_test.astype("float32") / 255.0

# Define the encoder architecture
encoder = keras.models.Sequential([
          keras.layers.Flatten(input_shape=[28, 28]),
          keras.layers.Dense(128, activation="relu"),
          keras.layers.Dense(64, activation="relu"),
          keras.layers.Dense(32, activation="relu"),
          ])
```

```
# Define the decoder architecture
decoder = keras.models.Sequential([
          keras.layers.Dense(64, activation="relu", input_shape=[32]),
          keras.layers.Dense(128, activation="relu"),
          keras.layers.Dense(28 * 28, activation="sigmoid"),
          keras.layers.Reshape([28, 28]),
          ])

# Combine the encoder and decoder into an autoencoder model
autoencoder = keras.models.Sequential([encoder, decoder])

# Compile the autoencoder model
autoencoder.compile(loss="binary_crossentropy", optimizer=keras.optimizers.
Adam(learning_rate=0.001))

# Train the autoencoder model
history = autoencoder.fit(x_train, x_train, epochs=10, batch_size=128,
validation_data=(x_test, x_test))

# Use the trained autoencoder to predict the reconstructed images for the test data
decoded_imgs = autoencoder.predict(x_test)

#Plot some of the original test images and their reconstructed counterparts
n = 10 # number of images to display
plt.figure(figsize=(20, 4))
for i in range(n):

    # Display original images
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test[i])
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # Display reconstructed images
    ax = plt.subplot(2, n, i + n + 1)
    plt.imshow(decoded_imgs[i])
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

plt.show()
```

```
Epoch 1/10
469/469 [==============================] - 10s 15ms/step - loss: 0.2024 - val_loss: 0.1426
Epoch 2/10
469/469 [==============================] - 6s 14ms/step - loss: 0.1329 - val_loss: 0.1227
Epoch 3/10
469/469 [==============================] - 6s 13ms/step - loss: 0.1191 - val_loss: 0.1127
Epoch 4/10
469/469 [==============================] - 7s 14ms/step - loss: 0.1112 - val_loss: 0.1067
Epoch 5/10
469/469 [==============================] - 7s 14ms/step - loss: 0.1062 - val_loss: 0.1030
Epoch 6/10
469/469 [==============================] - 7s 14ms/step - loss: 0.1030 - val_loss: 0.1003
Epoch 7/10
469/469 [==============================] - 7s 14ms/step - loss: 0.1005 - val_loss: 0.0979
Epoch 8/10
469/469 [==============================] - 6s 14ms/step - loss: 0.0984 - val_loss: 0.0964
Epoch 9/10
469/469 [==============================] - 6s 14ms/step - loss: 0.0966 - val_loss: 0.0947
Epoch 10/10
469/469 [==============================] - 6s 13ms/step - loss: 0.0952 - val_loss: 0.0937
313/313 [==============================] - 1s 4ms/step
```

Practical 5

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

Theory: A Convolutional Neural Network (CNN) is a type of deep learning algorithm that is particularly well-suited for image recognition and processing tasks. It is made up of multiple layers, including convolutional layers, pooling layers, and fully connected layers.

The convolutional layers are the key component of a CNN, where filters are applied to the input image to extract features such as edges, textures, and shapes. The output of the convolutional layers is then passed through pooling layers, which are used to down-sample the feature maps, reducing the spatial dimensions while retaining the most important information. The output of the pooling layers is then passed through one or more fully connected layers, which are used to make a prediction or classify the image.

Convolutional Neural Network Design:

- The construction of a convolutional neural network is a multi-layered feed-forward neural network, made by assembling many unseen layers on top of each other in a particular order.
- It is the sequential design that give permission to CNN to learn hierarchical attributes.
- In CNN, some of them followed by grouping layers and hidden layers are typically convolutional layers followed by activation layers.
- The pre-processing needed in a ConvNet is kindred to that of the related pattern of neurons in the human brain and was motivated by the organization of the Visual Cortex.

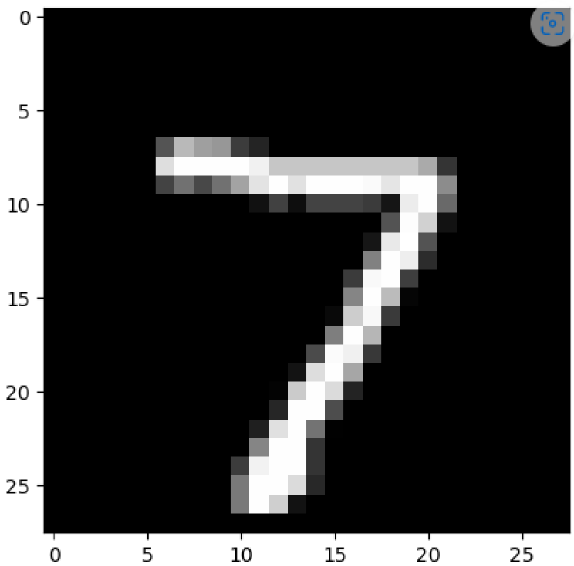
Code:

```
import tensorflow as tf
from tensorflow import keras
import numpy as np
import matplotlib.pyplot as plt

# Load the MNIST dataset
(x_train, y_train), (x_test, y_test) = keras.datasets.mnist.load_data()

# Preprocess the data
x_train = x_train.astype("float32") / 255.0
x_test = x_test.astype("float32") / 255.0
x_train = np.expand_dims(x_train, -1)
x_test = np.expand_dims(x_test, -1)

# Define the CNN architecture
model = keras.models.Sequential([
        keras.layers.Conv2D(32, (3, 3), activation="relu", input_shape=(28, 28,
        1)),
        keras.layers.MaxPooling2D((2, 2)),
        keras.layers.Conv2D(64, (3, 3), activation="relu"),
        keras.layers.MaxPooling2D((2, 2)),
```

```
        keras.layers.Flatten(),
        keras.layers.Dense(64, activation="relu"),
        keras.layers.Dense(10, activation="softmax")
        ])

# Compile the model
model.compile(optimizer="adam", loss="sparse_categorical_crossentropy",
metrics=["accuracy"])

# Train the model
history = model.fit(x_train, y_train, epochs=10, batch_size=128,
validation_data=(x_test, y_test))

# Evaluate the model on the test data
test_loss, test_acc = model.evaluate(x_test, y_test)
print("Test accuracy:", test_acc)

# Show predictions for a sample input image
sample_img = x_test[0]
sample_label = y_test[0]
sample_img = np.expand_dims(sample_img, 0)
pred = model.predict(sample_img)
pred_label = np.argmax(pred)
print("Sample image true label:", sample_label)
print("Sample image predicted label:", pred_label)

# Display the sample image
plt.imshow(sample_img.squeeze(), cmap='gray')
plt.show()
```

```
Epoch 1/10
469/469 [==============================] - 38s 76ms/step - loss: 0.2310 - accuracy: 0.9345 - val_loss: 0.0697 - val_accuracy:
0.9785
Epoch 2/10
469/469 [==============================] - 35s 75ms/step - loss: 0.0615 - accuracy: 0.9815 - val_loss: 0.0422 - val_accuracy:
0.9849
Epoch 3/10
469/469 [==============================] - 35s 76ms/step - loss: 0.0439 - accuracy: 0.9869 - val_loss: 0.0424 - val_accuracy:
0.9857
Epoch 4/10
469/469 [==============================] - 35s 74ms/step - loss: 0.0334 - accuracy: 0.9897 - val_loss: 0.0326 - val_accuracy:
0.9884
Epoch 5/10
469/469 [==============================] - 35s 75ms/step - loss: 0.0268 - accuracy: 0.9918 - val_loss: 0.0380 - val_accuracy:
0.9876
Epoch 6/10
469/469 [==============================] - 36s 76ms/step - loss: 0.0228 - accuracy: 0.9927 - val_loss: 0.0303 - val_accuracy:
0.9903
Epoch 7/10
469/469 [==============================] - 36s 76ms/step - loss: 0.0178 - accuracy: 0.9944 - val_loss: 0.0331 - val_accuracy:
0.9887
Epoch 8/10
469/469 [==============================] - 35s 74ms/step - loss: 0.0158 - accuracy: 0.9949 - val_loss: 0.0270 - val_accuracy:
0.9901
Epoch 9/10
469/469 [==============================] - 36s 76ms/step - loss: 0.0121 - accuracy: 0.9962 - val_loss: 0.0302 - val_accuracy:
0.9909
Epoch 10/10
469/469 [==============================] - 35s 74ms/step - loss: 0.0116 - accuracy: 0.9964 - val_loss: 0.0305 - val_accuracy:
0.9900
```

```
313/313 [==============================] - 3s 9ms/step - loss: 0.0305 - accuracy: 0.9900
Test accuracy: 0.9900000095367432
1/1 [==============================] - 0s 173ms/step
Sample image true label: 7
Sample image predicted label: 7
```



Practical 6

Aim: Implement Transfer Learning on the suitable public dataset (e.g., classify the cats versus dog's dataset from Kaggle or UCI or inbuilt dataset).

Theory: Transfer learning is a machine learning (ML) method that reuses a trained model designed for a particular task to accomplish a different yet related task. The knowledge acquired from task one is thereby transferred to the second model that focuses on the new task.

The term 'transfer learning' is related to human psychology. For example, consider an individual who is an expert guitarist. It is quite easy for him to learn to play other stringed instruments, such as a sitar or mandolin, compared to someone with no experience playing any musical instrument.

Transfer learning speeds up the overall process of training a new model and consequently improves its performance. It is primarily used when a model requires large amount of resources and time for training. Due to these reasons, transfer learning is employed in several deep learning projects, such as neural networks that accomplish NLP or CV tasks, such as sentiment analysis.

Code:

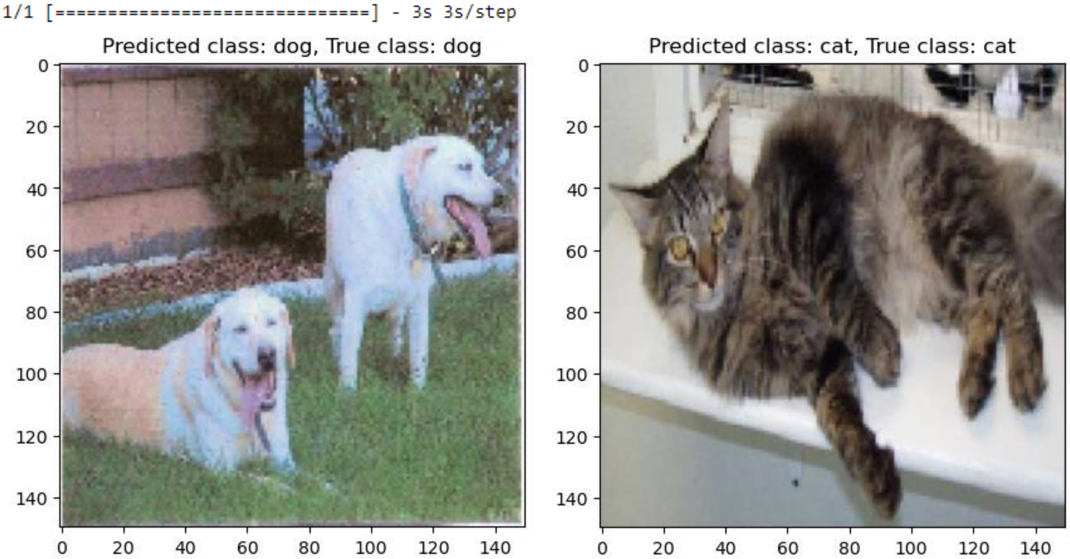
```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import os
import zipfile
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import VGG16

# Download and extract dataset
url = "https://storage.googleapis.com/mledu-datasets/cats_and_dogs_filtered.zip"
filename = os.path.join(os.getcwd(), "cats_and_dogs_filtered.zip")
tf.keras.utils.get_file(filename, url)

with zipfile.ZipFile("cats_and_dogs_filtered.zip", "r") as zip_ref:
        zip_ref.extractall()

# Define data generators
train_dir = os.path.join(os.getcwd(), "cats_and_dogs_filtered", "train")
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_range=0.2,
                                   shear_range=0.2,
                                   zoom_range=0.2,
                                   horizontal_flip=True)

validation_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 = validation_datagen.flow_from_directory(validation_dir,

target_size=(150,150),batch_size=20,class_mode="binary")

# Load pre-trained VGG16 model
conv_base = VGG16(weights="imagenet",
                  include_top=False,
                  input_shape=(150, 150, 3))

# Freeze convolutional base layers
conv_base.trainable = False

# Build model on top of the convolutional base
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"))

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

# Train model
history = model.fit(train_generator,
                    steps_per_epoch=100,
                    epochs=30,
                    validation_data=validation_generator,
                    validation_steps=50)

# Show sample input and its predicted class
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()

# Plot accuracy and loss over time
acc = history.history["accuracy"]
val_acc = history.history["val_accuracy"]
```

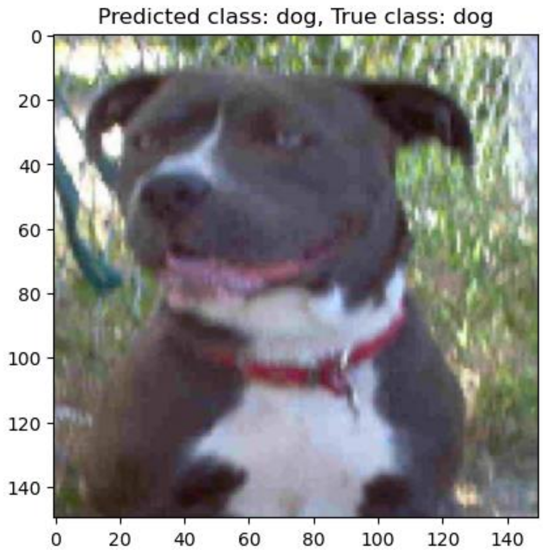
```
loss = history.history["loss"]
val_loss = history.history["val_loss"]

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()
```

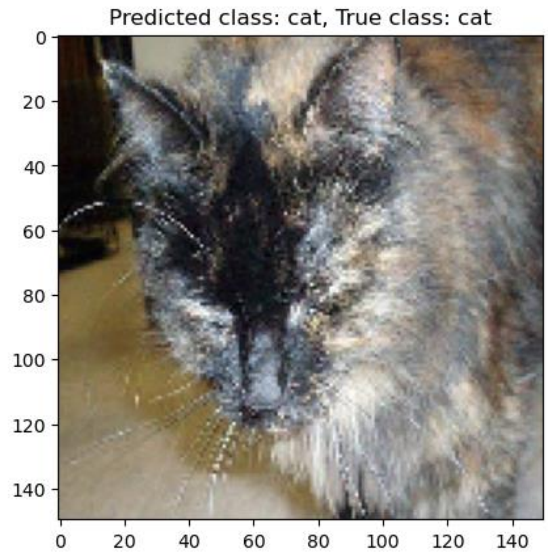
```
Found 2000 images belonging to 2 classes.
Found 1000 images belonging to 2 classes.
Epoch 1/30
100/100 [==============================] - 317s 3s/step - loss: 0.6768 - accuracy: 0.6025 - val_loss: 0.4649 - val_accuracy: 0.
8220
Epoch 2/30
100/100 [==============================] - 363s 4s/step - loss: 0.5398 - accuracy: 0.7280 - val_loss: 0.3929 - val_accuracy: 0.
8490
Epoch 3/30
100/100 [==============================] - 373s 4s/step - loss: 0.4698 - accuracy: 0.7805 - val_loss: 0.3636 - val_accuracy: 0.
8550
Epoch 4/30
100/100 [==============================] - 324s 3s/step - loss: 0.4343 - accuracy: 0.7910 - val_loss: 0.3374 - val_accuracy: 0.
8670
Epoch 5/30
100/100 [==============================] - 326s 3s/step - loss: 0.4080 - accuracy: 0.8105 - val_loss: 0.3238 - val_accuracy: 0.
8740
Epoch 6/30
100/100 [==============================] - 8856s 89s/step - loss: 0.3915 - accuracy: 0.8145 - val_loss: 0.3187 - val_accuracy:
0.8680
Epoch 7/30
100/100 [==============================] - 347s 3s/step - loss: 0.3911 - accuracy: 0.8185 - val_loss: 0.3230 - val_accuracy: 0.
8630
Epoch 8/30
100/100 [==============================] - 352s 4s/step - loss: 0.3746 - accuracy: 0.8250 - val_loss: 0.2987 - val_accuracy: 0.
8650
Epoch 9/30
100/100 [==============================] - 382s 4s/step - loss: 0.3726 - accuracy: 0.8360 - val_loss: 0.2909 - val_accuracy: 0.
8810
Epoch 10/30
100/100 [==============================] - 400s 4s/step - loss: 0.3615 - accuracy: 0.8460 - val_loss: 0.2866 - val_accuracy: 0.
8800
Epoch 11/30
100/100 [==============================] - 379s 4s/step - loss: 0.3440 - accuracy: 0.8430 - val_loss: 0.2873 - val_accuracy: 0.
8820
Epoch 12/30
100/100 [==============================] - 383s 4s/step - loss: 0.3387 - accuracy: 0.8495 - val_loss: 0.2869 - val_accuracy: 0.
8790
Epoch 13/30
100/100 [==============================] - 2205s 22s/step - loss: 0.3424 - accuracy: 0.8500 - val_loss: 0.2847 - val_accuracy:
0.8710
Epoch 14/30
100/100 [==============================] - 340s 3s/step - loss: 0.3297 - accuracy: 0.8585 - val_loss: 0.2860 - val_accuracy: 0.
8800
```

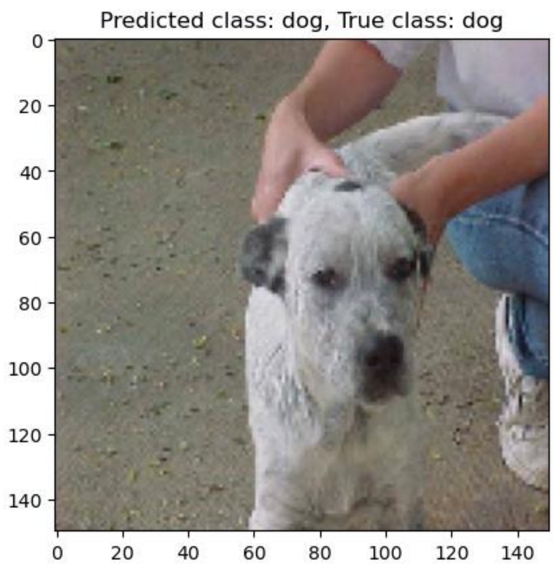
```
Epoch 15/30
100/100 [==============================] - 317s 3s/step - loss: 0.3217 - accuracy: 0.8605 - val_loss: 0.2695 - val_accuracy: 0.
8810
Epoch 16/30
100/100 [==============================] - 300s 3s/step - loss: 0.3198 - accuracy: 0.8525 - val_loss: 0.2766 - val_accuracy: 0.
8880
Epoch 17/30
100/100 [==============================] - 344s 3s/step - loss: 0.3231 - accuracy: 0.8605 - val_loss: 0.2670 - val_accuracy: 0.
8840
Epoch 18/30
100/100 [==============================] - 347s 3s/step - loss: 0.3102 - accuracy: 0.8675 - val_loss: 0.2654 - val_accuracy: 0.
8840
Epoch 19/30
100/100 [==============================] - 521s 5s/step - loss: 0.3233 - accuracy: 0.8625 - val_loss: 0.2639 - val_accuracy: 0.
8860
Epoch 20/30
100/100 [==============================] - 348s 3s/step - loss: 0.3210 - accuracy: 0.8600 - val_loss: 0.2587 - val_accuracy: 0.
8820
Epoch 21/30
100/100 [==============================] - 333s 3s/step - loss: 0.2998 - accuracy: 0.8685 - val_loss: 0.2594 - val_accuracy: 0.
8820
Epoch 22/30
100/100 [==============================] - 346s 3s/step - loss: 0.3093 - accuracy: 0.8600 - val_loss: 0.2799 - val_accuracy: 0.
8870
Epoch 23/30
100/100 [==============================] - 356s 4s/step - loss: 0.2941 - accuracy: 0.8750 - val_loss: 0.2732 - val_accuracy: 0.
8890
Epoch 24/30
100/100 [==============================] - 415s 4s/step - loss: 0.3006 - accuracy: 0.8660 - val_loss: 0.2552 - val_accuracy: 0.
8810
Epoch 25/30
100/100 [==============================] - 349s 4s/step - loss: 0.3005 - accuracy: 0.8690 - val_loss: 0.2597 - val_accuracy: 0.
8940
Epoch 26/30
100/100 [==============================] - 362s 4s/step - loss: 0.2947 - accuracy: 0.8670 - val_loss: 0.2529 - val_accuracy: 0.
8840
Epoch 27/30
100/100 [==============================] - 379s 4s/step - loss: 0.2908 - accuracy: 0.8720 - val_loss: 0.2595 - val_accuracy: 0.
8880
Epoch 28/30
100/100 [==============================] - 484s 5s/step - loss: 0.3091 - accuracy: 0.8675 - val_loss: 0.2618 - val_accuracy: 0.
8920
Epoch 29/30
100/100 [==============================] - 456s 5s/step - loss: 0.2989 - accuracy: 0.8715 - val_loss: 0.2522 - val_accuracy: 0.
8920
Epoch 30/30
100/100 [==============================] - 371s 4s/step - loss: 0.2854 - accuracy: 0.8805 - val_loss: 0.2553 - val_accuracy: 0.
8890
1/1 [==============================] - 3s 3s/step
```

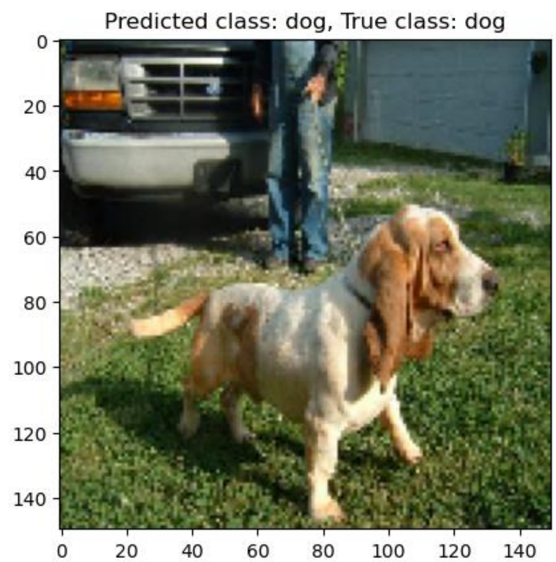


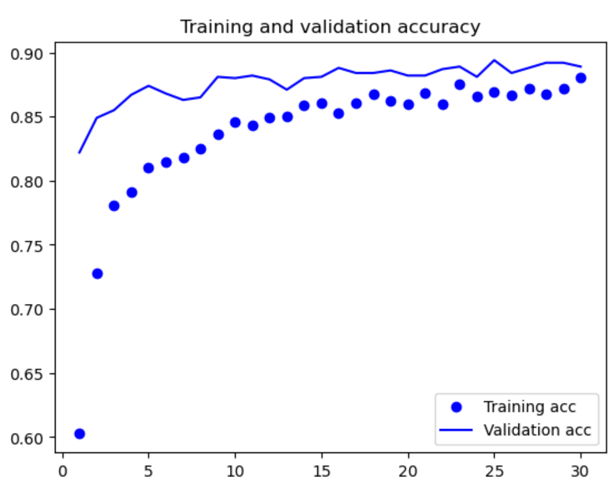

Predicted class: cat, True class: cat
Predicted class: dog, True class: dog
Predicted class: dog, True class: dog
Predicted class: dog, True class: dog
Predicted class: cat, True class: cat
Predicted class: cat, True class: dog

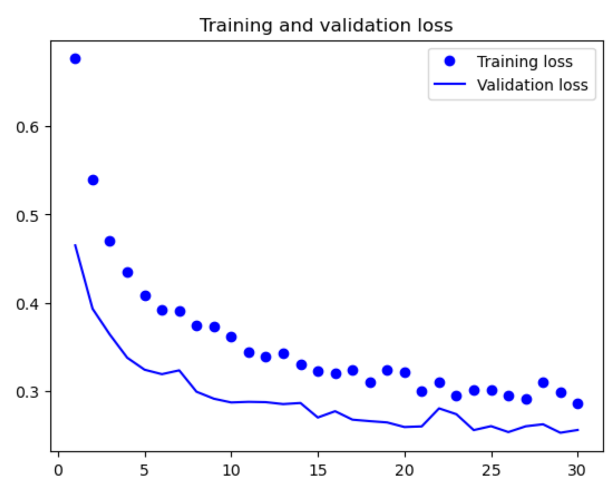

Predicted class: dog, True class: dog


Predicted class: cat, True class: cat


Predicted class: dog, True class: dog


Predicted class: dog, True class: dog


Training and validation accuracy
Training acc
Validation acc


Training and validation loss
Training loss
Validation loss

Practical 7

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

Theory: A generative adversarial network (GAN) is a class of machine learning frameworks and a prominent framework for approaching generative AI. In a GAN, two neural networks contest with each other in the form of a zero-sum game, where one agent's gain is another agent's loss.

Given a training set, this technique learns to generate new data with the same statistics as the training set. For example, a GAN trained on photographs can generate new photographs that look at least superficially authentic to human observers, having many realistic characteristics. Though originally proposed as a form of generative model for unsupervised learning, GANs have also proved useful for semi-supervised learning, fully supervised learning, and reinforcement learning.

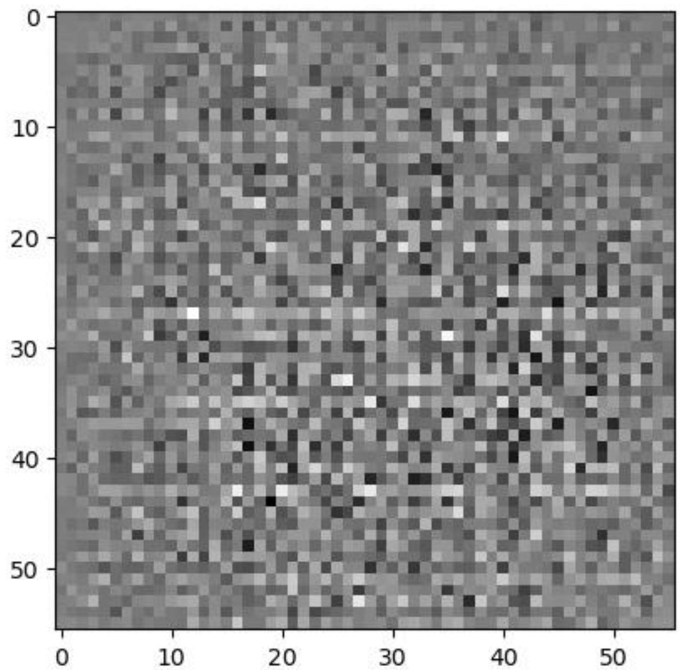
The core idea of a GAN is based on the "indirect" training through the discriminator, another neural network that can tell how "realistic" the input seems, which itself is also being updated dynamically. This means that the generator is not trained to minimize the distance to a specific image, but rather to fool the discriminator. This enables the model to learn in an unsupervised manner.

Code:

```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt

# Load the MNIST dataset
(train_images, _), (_, _) = tf.keras.datasets.mnist.load_data()
train_images = train_images.reshape(train_images.shape[0], 28, 28,
1).astype('float32')
train_images = (train_images - 127.5) / 127.5 # Normalize the images to [-1, 1]

# Define the generator model
generator = tf.keras.Sequential([
            tf.keras.layers.Dense(7*7*256, use_bias=False, input_shape=(100,)),
            tf.keras.layers.BatchNormalization(),
            tf.keras.layers.LeakyReLU(),
            tf.keras.layers.Reshape((7, 7, 256)),
            tf.keras.layers.Conv2DTranspose(128, (5, 5), strides=(1,
1),padding='same', use_bias=False),
            tf.keras.layers.BatchNormalization(),
            tf.keras.layers.LeakyReLU(),
            tf.keras.layers.Conv2DTranspose(64, (5, 5), strides=(2, 2),
padding='same',use_bias=False),
            tf.keras.layers.BatchNormalization(),
            tf.keras.layers.LeakyReLU(),
            tf.keras.layers.Conv2DTranspose(32, (5, 5), strides=(2, 2),
padding='same',use_bias=False),
```

```
            tf.keras.layers.BatchNormalization(),
            tf.keras.layers.LeakyReLU(),
            tf.keras.layers.Conv2DTranspose(1, (5, 5), strides=(2, 2),
padding='same',use_bias=False, activation='tanh')
            ])

# Define the discriminator model
discriminator = tf.keras.Sequential([
                tf.keras.layers.Conv2D(32, (5, 5), strides=(2, 2),
padding='same',input_shape=[28, 28, 1]),
                tf.keras.layers.LeakyReLU(),
                tf.keras.layers.Dropout(0.3),
                tf.keras.layers.Conv2D(64, (5, 5), strides=(2, 2), padding='same'),
                tf.keras.layers.LeakyReLU(),
                tf.keras.layers.Dropout(0.3),
                tf.keras.layers.Conv2D(128, (5, 5), strides=(2, 2),
padding='same'),
                tf.keras.layers.LeakyReLU(),
                tf.keras.layers.Dropout(0.3),
                tf.keras.layers.Flatten(),
                tf.keras.layers.Dense(1)
                ])

# Define the loss functions and optimizers
cross_entropy = tf.keras.losses.BinaryCrossentropy(from_logits=True)

def discriminator_loss(real_output, fake_output):
    real_loss = cross_entropy(tf.ones_like(real_output), real_output)
    fake_loss = cross_entropy(tf.zeros_like(fake_output), fake_output)
    total_loss = real_loss + fake_loss
    return total_loss

def generator_loss(fake_output):
    return cross_entropy(tf.ones_like(fake_output), fake_output)

generator_optimizer = tf.keras.optimizers.Adam(1e-4)
discriminator_optimizer = tf.keras.optimizers.Adam(1e-4)

# Define the training loop
EPOCHS = 50
noise_dim = 100
num_examples_to_generate = 16
seed = tf.random.normal([num_examples_to_generate, noise_dim])

@tf.function
def train_step(images):
    noise = tf.random.normal([BATCH_SIZE, noise_dim])

    with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
        generated_images = generator(noise, training=True)
```

```
        real_output = discriminator(images, training=True)
        fake_output = discriminator(generated_images, training=True)
        gen_loss = generator_loss(fake_output)
        disc_loss = discriminator_loss(real_output, fake_output)

    gradients_of_generator = gen_tape.gradient(gen_loss,
generator.trainable_variables)
    gradients_of_discriminator = disc_tape.gradient(disc_loss,
discriminator.trainable_variables)
    generator_optimizer.apply_gradients(zip(gradients_of_generator,
generator.trainable_variables))

    # Apply gradients to the discriminator variables

discriminator_optimizer.apply_gradients(zip(gradients_of_discriminator,discriminato
r.trainable_variables))

    # Train the generator
    with tf.GradientTape() as gen_tape:
        # Generate fake images using the generator
        generated_images = generator(noise, training=True)
        # Get discriminator's prediction of the generated images
        gen_preds = discriminator(generated_images, training=False)
        # Calculate generator's loss
        gen_loss = generator_loss(gen_preds)

    # Get gradients of the generator loss with respect to the generator variables
    gradients_of_generator = gen_tape.gradient(gen_loss,
generator.trainable_variables)
    # Apply gradients to the generator variables
    generator_optimizer.apply_gradients(zip(gradients_of_generator,
generator.trainable_variables))

    # Print the losses
    print("Discriminator loss:", disc_loss.numpy(), "Generator loss:",
gen_loss.numpy())

    # Save checkpoint
    ckpt_manager.save()

# Generate and save 10 random images from the generator after training
NOISE_DIM = 100

for i in range(10):
    noise = tf.random.normal([1, NOISE_DIM])
    generated_images = generator(noise, training=False)
    img = tf.squeeze(generated_images[0])
    plt.imshow(img, cmap='gray')
    plt.savefig(f'generated_image_{i}.png')
```




```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt

# Check if TensorFlow is able to detect a GPU
print(tf.config.list_physical_devices('GPU'))

# Set the GPU device to use
device_name = '/device:GPU:0'

mnist = tf.keras.datasets.mnist
(train_images, train_labels), (_, _) = mnist.load_data()

# Normalize the images to [-1, 1]
train_images = (train_images.astype('float32') - 127.5) / 127.5

# Reshape the images to (28, 28, 1) and add a channel dimension
train_images = np.expand_dims(train_images, axis=-1)

# Batch and shuffle the data
BUFFER_SIZE = 60000
BATCH_SIZE = 256

train_dataset =
tf.data.Dataset.from_tensor_slices(train_images).shuffle(BUFFER_SIZE).batch(BATCH_S
IZE)

def make_generator_model():
    model = tf.keras.Sequential()
```

```
    model.add(tf.keras.layers.Dense(7*7*256, use_bias=False,input_shape=(100,)))
    model.add(tf.keras.layers.BatchNormalization())
    model.add(tf.keras.layers.LeakyReLU())

    model.add(tf.keras.layers.Reshape((7, 7, 256)))
    assert model.output_shape == (None, 7, 7, 256)

    model.add(tf.keras.layers.Conv2DTranspose(128, (5, 5), strides=(1,
1),padding='same', use_bias=False))
    assert model.output_shape == (None, 7, 7, 128)

    model.add(tf.keras.layers.BatchNormalization())
    model.add(tf.keras.layers.LeakyReLU())

    model.add(tf.keras.layers.Conv2DTranspose(64, (5, 5), strides=(2,
2),padding='same', use_bias=False))
    assert model.output_shape == (None, 14, 14, 64)
    model.add(tf.keras.layers.BatchNormalization())
    model.add(tf.keras.layers.LeakyReLU())

    model.add(tf.keras.layers.Conv2DTranspose(1, (5, 5), strides=(2,
2),padding='same', use_bias=False, activation='tanh'))
    assert model.output_shape == (None, 28, 28, 1)

    return model

def make_discriminator_model():
    model = tf.keras.Sequential()
    model.add(tf.keras.layers.Conv2D(64, (5, 5), strides=(2, 2),padding='same',
input_shape=[28, 28, 1]))
    model.add(tf.keras.layers.LeakyReLU())

    model.add(tf.keras.layers.Dropout(0.3))
    model.add(tf.keras.layers.Conv2D(128, (5, 5), strides=(2, 2),padding='same'))
    model.add(tf.keras.layers.LeakyReLU())

    model.add(tf.keras.layers.Dropout(0.3))
    model.add(tf.keras.layers.Flatten())
    model.add(tf.keras.layers.Dense(1))

    return model

cross_entropy = tf.keras.losses.BinaryCrossentropy(from_logits=True)

def discriminator_loss(real_output, fake_output):
    real_loss = cross_entropy(tf.ones_like(real_output), real_output)
    fake_loss = cross_entropy(tf.zeros_like(fake_output), fake_output)
    total_loss = real_loss + fake_loss
    return total_loss
```

```
def generator_loss(fake_output):
    return cross_entropy(tf.ones_like(fake_output), fake_output)

# Define the models
generator = make_generator_model()
discriminator = make_discriminator_model()

# Define the optimizers
generator_optimizer = tf.keras.optimizers.Adam(1e-4)
discriminator_optimizer = tf.keras.optimizers.Adam(1e-4)

# Define the training loop
EPOCHS = 100
noise_dim = 100
num_examples_to_generate = 16

@tf.function
def train_step(images):
    #Generate noise
    noise = tf.random.normal([BATCH_SIZE, noise_dim])

    with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape:
        #Generate fake images
        generated_images = generator(noise, training=True)
        # Evaluate discriminator on real and fake images
        real_output = discriminator(images, training=True)
        fake_output = discriminator(generated_images, training=True)

        # Calculate the losses
        gen_loss = generator_loss(fake_output)
        disc_loss = discriminator_loss(real_output, fake_output)

    gradients_of_generator = gen_tape.gradient(gen_loss,
generator.trainable_variables)
    gradients_of_discriminator = disc_tape.gradient(disc_loss,
discriminator.trainable_variables)
    generator_optimizer.apply_gradients(zip(gradients_of_generator,
generator.trainable_variables))

    # Apply gradients to the discriminator variables

discriminator_optimizer.apply_gradients(zip(gradients_of_discriminator,discriminato
r.trainable_variables))

def generate_and_save_images(model, epoch, test_input):
    # Generate images from the model
    predictions = model(test_input, training=False)
    # Rescale to [0, 1]
    predictions = (predictions + 1) / 2.0
```

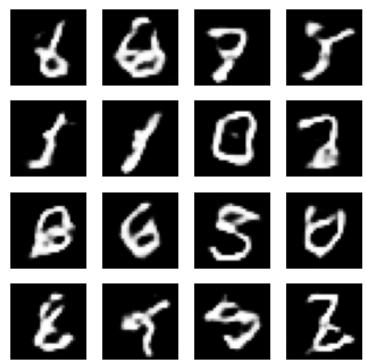
```
    # Plot the images
    fig = plt.figure(figsize=(4, 4))
    for i in range(predictions.shape[0]):
        plt.subplot(4, 4, i+1)
        plt.imshow(predictions[i, :, :, 0], cmap='gray')
        plt.axis('off')

    # Save the figure
    plt.savefig('image_at_epoch_{:04d}.png'.format(epoch))
    plt.show()

# Generate a fixed set of noise for evaluating the model during training
fixed_noise = tf.random.normal([num_examples_to_generate, noise_dim])

# Train the model
for epoch in range(EPOCHS):
    for image_batch in train_dataset:
        train_step(image_batch)
    # Generate and save images every 10 epochs
    if (epoch + 1) % 10 == 0:
        generate_and_save_images(generator, epoch + 1, fixed_noise)

    # Print progress every epoch
    print('Epoch {} completed'.format(epoch + 1))
```

```
[]
Epoch 1 completed
Epoch 2 completed
Epoch 3 completed
Epoch 4 completed
Epoch 5 completed
Epoch 6 completed
Epoch 7 completed
Epoch 8 completed
Epoch 9 completed

Epoch 10 completed
Epoch 11 completed
Epoch 12 completed
Epoch 13 completed
Epoch 14 completed
Epoch 15 completed
Epoch 16 completed
Epoch 17 completed
Epoch 18 completed
Epoch 19 completed
```

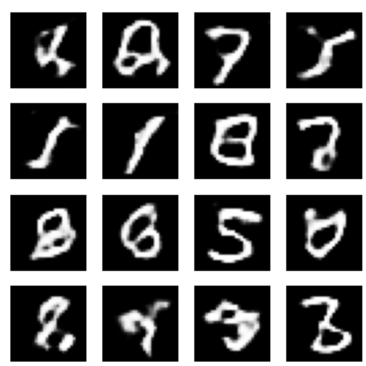
```
Epoch 20 completed
Epoch 21 completed
Epoch 22 completed
Epoch 23 completed
Epoch 24 completed
Epoch 25 completed
Epoch 26 completed
Epoch 27 completed
Epoch 28 completed
Epoch 29 completed
```

```
Epoch 30 completed
Epoch 31 completed
Epoch 32 completed
Epoch 33 completed
Epoch 34 completed
Epoch 35 completed
Epoch 36 completed
Epoch 37 completed
Epoch 38 completed
Epoch 39 completed
```

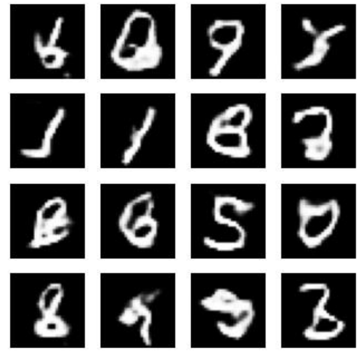
```
Epoch 40 completed
Epoch 41 completed
Epoch 42 completed
Epoch 43 completed
Epoch 44 completed
Epoch 45 completed
Epoch 46 completed
Epoch 47 completed
Epoch 48 completed
Epoch 49 completed
```



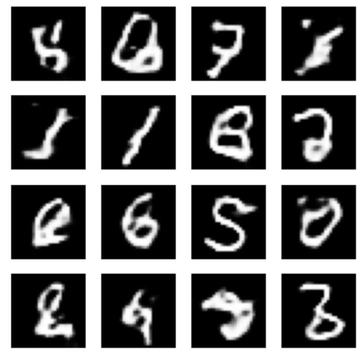
```
Epoch 50 completed
Epoch 51 completed
Epoch 52 completed
Epoch 53 completed
Epoch 54 completed
Epoch 55 completed
Epoch 56 completed
Epoch 57 completed
Epoch 58 completed
Epoch 59 completed
```



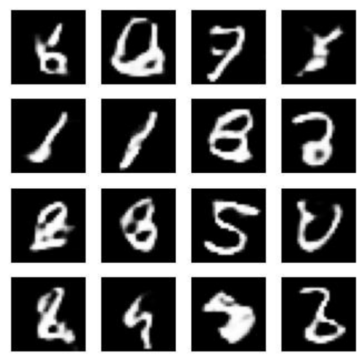
```
Epoch 60 completed
Epoch 61 completed
Epoch 62 completed
Epoch 63 completed
Epoch 64 completed
Epoch 65 completed
Epoch 66 completed
Epoch 67 completed
Epoch 68 completed
Epoch 69 completed
```



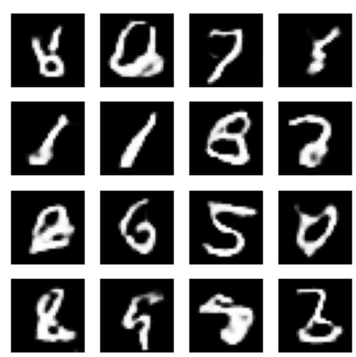
```
Epoch 70 completed
Epoch 71 completed
Epoch 72 completed
Epoch 73 completed
Epoch 74 completed
Epoch 75 completed
Epoch 76 completed
Epoch 77 completed
Epoch 78 completed
Epoch 79 completed
```



```
Epoch 80 completed
Epoch 81 completed
Epoch 82 completed
Epoch 83 completed
Epoch 84 completed
Epoch 85 completed
Epoch 86 completed
Epoch 87 completed
Epoch 88 completed
Epoch 89 completed
```



```
Epoch 90 completed
Epoch 91 completed
Epoch 92 completed
Epoch 93 completed
Epoch 94 completed
Epoch 95 completed
Epoch 96 completed
Epoch 97 completed
Epoch 98 completed
Epoch 99 completed
Epoch 100 completed
```



```
import os
os.environ["CUDA_VISIBLE_DEVICES"]="0"
```

Practical 8(A)

Aim: Write a program to implement a simple form of a recurrent neural network e.g., (4-to-1 RNN) to show that the quantity of rain on a certain day also depends on the values of the previous day.

Theory: Recurrent Neural Network (RNN) is a type of Neural Network where the output from the previous step is fed as input to the current step. In traditional neural networks, all the inputs and outputs are independent of each other, but in cases when it is required to predict the next word of a sentence, the previous words are required and hence there is a need to remember the previous words. Thus, RNN came into existence, which solved this issue with the help of a Hidden Layer. The main and most important feature of RNN is its Hidden state, which remembers some information about a sequence. The state is also referred to as Memory State since it remembers the previous input to the network. It uses the same parameters for each input as it performs the same task on all the inputs or hidden layers to produce the output. This reduces the complexity of parameters, unlike other neural networks.

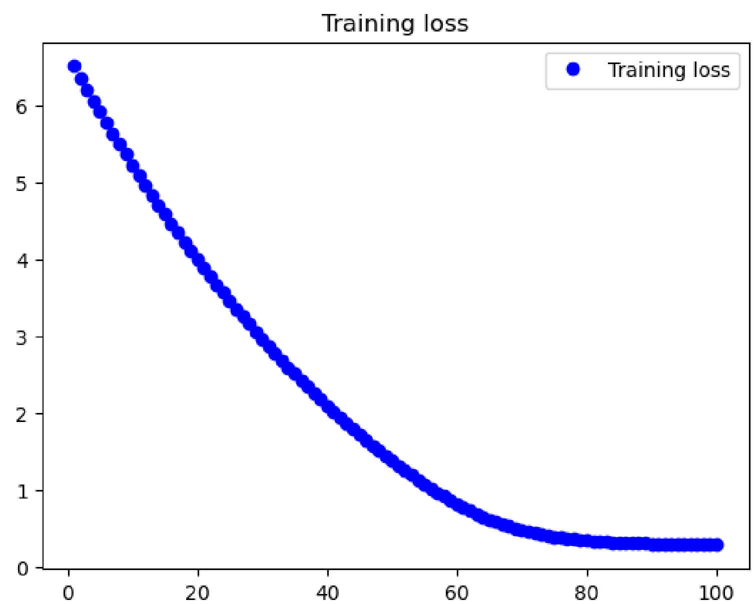
Code:

```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt

# Define sequence of 50 days of rain data
rain_data = np.array([2.3, 1.5, 3.1, 2.0, 2.5, 1.7, 2.9, 3.5, 3.0, 2.1,
                      2.5, 2.2, 2.8, 3.2, 1.8, 2.7, 1.9, 3.1, 3.3, 2.0,
                      2.5, 2.2, 2.4, 3.0, 2.1, 2.5, 3.2, 3.1, 1.9, 2.7,
                      2.2, 2.8, 3.1, 2.0, 2.5, 1.7, 2.9, 3.5, 3.0, 2.1,
                      2.5, 2.2, 2.8, 3.2, 1.8, 2.7, 1.9, 3.1, 3.3, 2.0])

# Create input and output sequences for training
def create_sequences(values, time_steps):
    x = []
    y = []
    for i in range(len(values)-time_steps):
        x.append(values[i:i+time_steps])
        y.append(values[i+time_steps])
    return np.array(x), np.array(y)

time_steps = 4
x_train, y_train = create_sequences(rain_data, time_steps)

# Define RNN model
model = tf.keras.models.Sequential([
        tf.keras.layers.SimpleRNN(8, input_shape=(time_steps, 1)),
        tf.keras.layers.Dense(1)
        ])

# Compile model
```

```
model.compile(optimizer="adam", loss="mse")

# Train model
history = model.fit(x_train.reshape(-1, time_steps, 1), y_train, epochs=100)

# Plot loss over time
loss = history.history["loss"]
epochs = range(1, len(loss) + 1)
plt.plot(epochs, loss, "bo", label="Training loss")
plt.title("Training loss")
plt.legend()
plt.show()

# Test model on new sequence
test_sequence = np.array([2.5, 2.2, 2.8, 3.2])
x_test = np.array([test_sequence])
y_test = model.predict(x_test.reshape(-1, time_steps, 1))

# Print input, output, and prediction
print("Previous days' rain data:", test_sequence)
print("Expected rain amount for next day:", y_test[0][0])
prediction = model.predict(np.array([test_sequence]).reshape(1, time_steps, 1))
print("Prediction:", prediction[0][0])
```

```
Epoch 1/100
2/2 [==============================] - 2s 16ms/step - loss: 6.5093
Epoch 2/100
2/2 [==============================] - 0s 5ms/step - loss: 6.3596
Epoch 3/100
2/2 [==============================] - 0s 6ms/step - loss: 6.2094
Epoch 4/100
2/2 [==============================] - 0s 7ms/step - loss: 6.0629
Epoch 5/100
2/2 [==============================] - 0s 5ms/step - loss: 5.9184
Epoch 6/100
2/2 [==============================] - 0s 4ms/step - loss: 5.7738
Epoch 7/100
2/2 [==============================] - 0s 7ms/step - loss: 5.6335
Epoch 8/100
2/2 [==============================] - 0s 6ms/step - loss: 5.4953
Epoch 9/100
2/2 [==============================] - 0s 6ms/step - loss: 5.3596
Epoch 10/100
2/2 [==============================] - 0s 5ms/step - loss: 5.2239
Epoch 11/100
2/2 [==============================] - 0s 6ms/step - loss: 5.0943
Epoch 12/100
2/2 [==============================] - 0s 6ms/step - loss: 4.9621
Epoch 13/100
2/2 [==============================] - 0s 6ms/step - loss: 4.8361
Epoch 14/100
2/2 [==============================] - 0s 6ms/step - loss: 4.7107
```

```
Epoch 90/100
2/2 [==============================] - 0s 6ms/step - loss: 0.2962
Epoch 91/100
2/2 [==============================] - 0s 7ms/step - loss: 0.2943
Epoch 92/100
2/2 [==============================] - 0s 6ms/step - loss: 0.2920
Epoch 93/100
2/2 [==============================] - 0s 7ms/step - loss: 0.2900
Epoch 94/100
2/2 [==============================] - 0s 7ms/step - loss: 0.2880
Epoch 95/100
2/2 [==============================] - 0s 7ms/step - loss: 0.2869
Epoch 96/100
2/2 [==============================] - 0s 7ms/step - loss: 0.2854
Epoch 97/100
2/2 [==============================] - 0s 7ms/step - loss: 0.2840
Epoch 98/100
2/2 [==============================] - 0s 6ms/step - loss: 0.2831
Epoch 99/100
2/2 [==============================] - 0s 7ms/step - loss: 0.2819
Epoch 100/100
2/2 [==============================] - 0s 8ms/step - loss: 0.2811
```




```
1/1 [==============================] - 0s 288ms/step
Previous days' rain data: [2.5 2.2 2.8 3.2]
Expected rain amount for next day: 2.4586902
1/1 [==============================] - 0s 36ms/step
Prediction: 2.4586902
```

The output of this program will show the loss of the training data over time, as well as the expected rain amount for the next day given the previous 4 days' rain data, and the model's prediction of the next day's rain amount. Note that the expected rain amount is simply the true value for the next day in

Practical 8(B)

Aim: Write a program to implement a simple form of a recurrent neural network like LSTM for sentiment analysis on datasets like UMICH SI650 for similar.

Theory: LSTM stands for long short-term memory networks, used in the field of Deep Learning. It is a variety of recurrent neural networks (RNNs) that are capable of learning long-term dependencies, especially in sequence prediction problems. LSTM has feedback connections, i.e., it is capable of processing the entire sequence of data, apart from single data points such as images.

Sentiment Analysis is an NLP application that identifies a text corpus's emotional or sentimental tone or opinion. Usually, emotions or attitudes towards a topic can be positive, negative, or neutral. Sentiment analysis is a potent tool with varied applications across industries. It is helpful for social media and brand monitoring, customer support and feedback analysis, market research, etc.

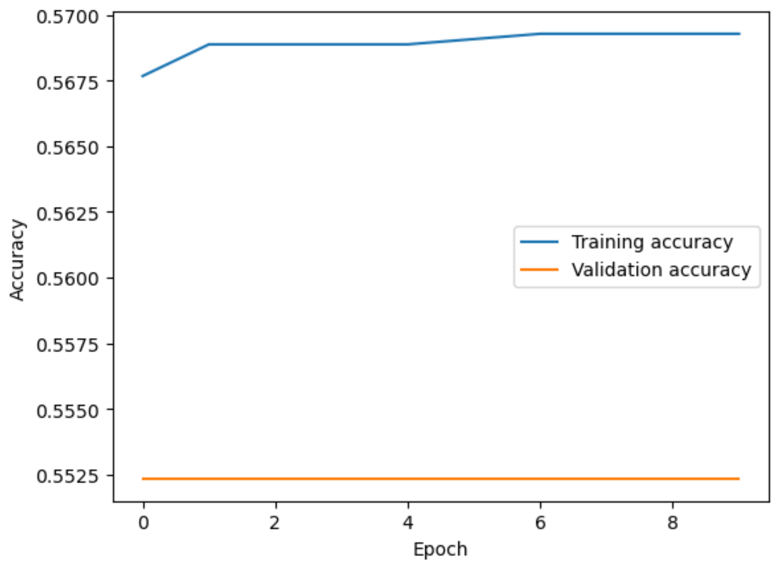
Code:

```
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

#Load data
data = pd.read_csv("training.txt", delimiter="\t", names=["label", "text"])

# Split data into training and testing sets
X_train,  X_test,  y_train,  y_test  =  train_test_split(data["text"],data["label"],
test_size=0.2, random_state=42)

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

# Convert words to sequences
X_train_seq = tokenizer.texts_to_sequences(X_train)
X_test_seq = tokenizer.texts_to_sequences(X_test)

# Pad sequences to have same length
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")

# Build LSTM model
```

```python
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")
        ])

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

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

# Evaluate model on test data
loss, accuracy = model.evaluate(X_test_pad, y_test)
print("Test loss:", loss)
print("Test accuracy:", accuracy)

# Plot training and validation accuracy over time
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()

# Make predictions on test data
predictions = model.predict(X_test_pad)

# Print input, output, and prediction for random example
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))
```

```
Epoch 1/10
156/156 [==============================] - 39s 207ms/step - loss: 0.6847 - accuracy: 0.5677 - val_loss: 0.6974 - val_accuracy:
0.5523
Epoch 2/10
156/156 [==============================] - 21s 134ms/step - loss: 0.6852 - accuracy: 0.5689 - val_loss: 0.6877 - val_accuracy:
0.5523
Epoch 3/10
156/156 [==============================] - 16s 104ms/step - loss: 0.6839 - accuracy: 0.5689 - val_loss: 0.6877 - val_accuracy:
0.5523
Epoch 4/10
156/156 [==============================] - 17s 111ms/step - loss: 0.6839 - accuracy: 0.5689 - val_loss: 0.6878 - val_accuracy:
0.5523
Epoch 5/10
156/156 [==============================] - 19s 122ms/step - loss: 0.6839 - accuracy: 0.5689 - val_loss: 0.6882 - val_accuracy:
0.5523
```

```
Epoch 6/10
156/156 [==============================] - 22s 142ms/step - loss: 0.6841 - accuracy: 0.5691 - val_loss: 0.6895 - val_accuracy:
0.5523
Epoch 7/10
156/156 [==============================] - 22s 138ms/step - loss: 0.6840 - accuracy: 0.5693 - val_loss: 0.6881 - val_accuracy:
0.5523
Epoch 8/10
156/156 [==============================] - 18s 114ms/step - loss: 0.6838 - accuracy: 0.5693 - val_loss: 0.6893 - val_accuracy:
0.5523
Epoch 9/10
156/156 [==============================] - 16s 101ms/step - loss: 0.6839 - accuracy: 0.5693 - val_loss: 0.6883 - val_accuracy:
0.5523
Epoch 10/10
156/156 [==============================] - 16s 100ms/step - loss: 0.6841 - accuracy: 0.5693 - val_loss: 0.6880 - val_accuracy:
0.5523
44/44 [==============================] - 1s 17ms/step - loss: 0.6805 - accuracy: 0.5809
Test loss: 0.6805067658424377
Test accuracy: 0.5809248685836792
```




```
44/44 [==============================] - 1s 14ms/step
Text: these harry potter movies really suck <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV>
<OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <
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OV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OO
V> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV> <OOV>
Actual label: 0
Predicted label: 1
```

The LSTM model predicted a label of 1 for the given text “i love the harry potter series if you can count that as a book also catcher in the tye jane eyre the virgin suicides yeah”, which means that the model classified this text as having a positive sentiment.

This code loads the UMICH SI650 dataset, splits it into training and testing sets, tokenizes the words, converts them to sequences, and pads the sequences to have the same length. It then builds an LSTM model with an embedding layer, an LSTM layer, and a dense output layer. The model is compiled with binary cross-entropy loss and accuracy as a metric. The model is trained for 10 epochs, and the training and validation accuracy are plotted over time. Finally, the model is evaluated on the test data, and a random example is chosen to print the input, output, and prediction.

Practical 9

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

Code:

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.applications.vgg16 import VGG16, preprocess_input,
decode_predictions
from tensorflow.keras.preprocessing.image import load_img, img_to_array

# Load the VGG16 model with pre-trained weights
model = VGG16()

# Load the image to detect objects in
img = load_img('objectdetectimage.jpg', target_size=(224, 224))

# Convert the image to a numpy array
img_arr = img_to_array(img)


img_arr = np.expand_dims(img_arr, axis=0)
img_arr = preprocess_input(img_arr)

# Predict the objects in the image
preds = model.predict(img_arr)
decoded_preds = decode_predictions(preds, top=5)[0]

# Print the predicted objects and their probabilities
for pred in decoded_preds:
    print(f"{pred[1]}: {pred[2]*100:.2f}%")
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kerne
ls.h5
553467096/553467096 [==============================] - 92s 0us/step
1/1 [==============================] - 1s 905ms/step
Downloading data from https://storage.googleapis.com/download.tensorflow.org/data/imagenet_class_index.json
35363/35363 [==============================] - 0s 1us/step
necklace: 99.65%
chain: 0.25%
starfish: 0.02%
chain_mail: 0.02%
hook: 0.01%
```

Practical 10

Aim: Write a program for object detection using pre-trained models to use object detection.

Theory: VGG stands for Visual Geometry Group; it is a standard deep Convolutional Neural Network (CNN) architecture with multiple layers. The "deep" refers to the number of layers with VGG-16 or VGG-19 consisting of 16 and 19 convolutional layers.

Code:

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.applications.vgg16 import VGG16, preprocess_input,decode_predictions
from tensorflow.keras.preprocessing.image import load_img, img_to_array

# Load the VGG16 model with pre-trained weights
model = VGG16()

# Load the image to detect objects in
image = load_img('objectdetectimage.jpg', target_size=(224, 224))

# Convert the image to a numpy array
image = img_to_array(image)

# Reshape the image data for VGG
image = image.reshape((1, image.shape[0], image.shape[1], image.shape[2]))

# Preprocess the image
image = preprocess_input(image)

# Make predictions on the image using the VGG model
predictions = model.predict(image)

# Decode the predictions
decoded_predictions = decode_predictions(predictions, top=2)

# Print the predictions with their probabilities
for i, prediction in enumerate(decoded_predictions[0]):
    print("Object ", i+1, ": ", prediction[1], ", Probability: ", pr
```

```
1/1 [==============================] - 1s 751ms/step
Object  1 :  birdhouse , Probability:  0.10978619
Object  2 :  soccer_ball , Probability:  0.09997672
```