EXPERIMENT NO - 1

1. Implement multilayer perceptron algorithm for MNIST Hand written Digit Classification.

Software and Hardware requirements:

Procedure:

MNIST Handwritten Digit Classification DataSet :

The MNIST dataset is a popular benchmark dataset for image classification tasks. It consists of 60,000 grayscale images of handwritten digits (0 to 9) for training and 10,000 images for testing. Each image is 28 x 28 pixels in size, and each pixel value ranges from 0 to 255. The goal of the task is to correctly classify each image into one of the 10 possible digit classes.

Multilayer Perceptron (MLP) Algorithm :

The MLP algorithm is a type of artificial neural network that consists of multiple layers of interconnected nodes or neurons. It is a feedforward neural network, meaning that the data flows from the input layer to the output layer through one or more hidden layers, with each layer performing a nonlinear transformation on the input.

The basic building block of an MLP is the perceptron, which is a mathematical model of a neuron that takes a set of inputs, computes a weighted sum of the inputs, and applies a nonlinear activation function to produce an output. The MLP is called a multilayer perceptron because it contains multiple layers of perceptrons.

To train an MLP for a classification task like the MNIST digit classification task, we need to define the architecture of the network, the loss function to optimize, and the optimization algorithm to use. Typically, the architecture of an MLP for image classification consists of an input layer, one or more hidden layers, and an output layer. The number of neurons in the input layer is equal to the number of features in the input data, and the number of neurons in the output layer is equal to the number of classes in the classification task.

```
# Import necessary libraries
import numpy as np
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Dropout
from tensorflow.keras.utils import to_categorical
```

In this implementation, we first load the MNIST dataset using the mnist.load_data() function from Keras

```
# Load MNIST dataset
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

In this step, we use the mnist.load_data() function from Keras to load the MNIST dataset. The training data consists of the x_train images and their corresponding y_train labels, while the test data consists of the x_test images and their corresponding y_test labels.

```
# Reshape input data
X_train = X_train.reshape(X_train.shape[0], 28*28)
X_test = X_test.reshape(X_test.shape[0], 28*28)
```

In this step, we preprocess the data by reshaping the images to 1D arrays, normalizing the pixel values to be between 0 and 1, and

```
# Normalize input data
X_train = X_train / 255
X_test = X_test / 255
```

. We then preprocess the data by flattening the input images into 1D arrays of size 784 (28x28), scaling the pixel values to the range of 0 to 1, and dividing by 255.0 to normalize the data.

```
# One-hot encode target variables
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
```

converting the labels to one-hot encoding using the to_categorical() function from Keras.

```
# Define MLP model
model = Sequential()
model.add(Dense(512, input_shape=(784,), activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(10, activation='softmax'))
```

Next, we define the neural network model with three fully connected (dense) layers. The first two hidden layers have 256 and 128 units, respectively, and use ReLU activation functions. The dropout layers randomly drop out 20% of the input units during training to prevent overfitting. The output layer has 10 units with softmax activation for multi-class classification

```
# Compile model
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

# Train model
model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=10, batch_size=128)
```

We compile the model with the Adam optimizer, sparse categorical cross-entropy loss, and accuracy metric. We train the model on the training data for 10 epochs with a batch size of 128. Finally, we evaluate the model on the test data and print the accuracy score.

```
# Evaluate model on test data
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
```

Output *:*

```
Epoch 1/10
469/469 [==============================] - 6s 9ms/step - loss: 0.2501 - accuracy: 0.9255 - val_loss: 0.1090 - val_accuracy: 0.9660
Epoch 2/10
469/469 [==============================] - 4s 9ms/step - loss: 0.1027 - accuracy: 0.9678 - val_loss: 0.0902 - val_accuracy: 0.9714
Epoch 3/10
469/469 [==============================] - 4s 8ms/step - loss: 0.0700 - accuracy: 0.9784 - val_loss: 0.0668 - val_accuracy: 0.9795
Epoch 4/10
469/469 [==============================] - 4s 8ms/step - loss: 0.0542 - accuracy: 0.9829 - val_loss: 0.0699 - val_accuracy: 0.9785
Epoch 5/10
469/469 [==============================] - 5s 10ms/step - loss: 0.0450 - accuracy: 0.9853 - val_loss: 0.0640 - val_accuracy: 0.9802
Epoch 6/10
469/469 [==============================] - 5s 11ms/step - loss: 0.0407 - accuracy: 0.9865 - val_loss: 0.0742 - val_accuracy: 0.9776
Epoch 7/10
469/469 [==============================] - 4s 9ms/step - loss: 0.0340 - accuracy: 0.9889 - val_loss: 0.0726 - val_accuracy: 0.9786
Epoch 8/10
469/469 [==============================] - 4s 9ms/step - loss: 0.0309 - accuracy: 0.9897 - val_loss: 0.0655 - val_accuracy: 0.9823
Epoch 9/10
469/469 [==============================] - 5s 11ms/step - loss: 0.0288 - accuracy: 0.9903 - val_loss: 0.0695 - val_accuracy: 0.9817
Epoch 10/10
469/469 [==============================] - 5s 10ms/step - loss: 0.0248 - accuracy: 0.9916 - val_loss: 0.0815 - val_accuracy: 0.9802
Accuracy: 9.80%
```

EXPERIMENT NO -2

Design a neural network for classifying movie reviews (Binary Classification) using IMDB dataset.

Procedure :

IMDB DataSet :

The IMDB (Internet Movie Database) dataset is a popular benchmark dataset for sentiment analysis, which is the task of classifying text into positive or negative categories. The dataset consists of 50,000 movie reviews, where 25,000 are used for training and 25,000 are used for testing. Each review is already preprocessed and encoded as a sequence of integers, where each integer represents a word in the review.

The goal of designing a neural network for binary classification of movie reviews using the IMDB dataset is to build a model that can classify a given movie review as either positive or negative based on the sentiment expressed in the review.

```
# Import necessary libraries
from tensorflow.keras.datasets import imdb
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

```
# Load the dataset
(X_train, y_train), (X_test, y_test) = imdb.load_data(num_words=10000)
```

In this step, we load the IMDB dataset using the imdb.load_data() function from Keras. We set the num_words parameter to 10000 to limit the number of words in each review to 10,000, which helps to reduce the dimensionality of the input data and improve model performance.

```
# Preprocess the data
maxlen = 200
X_train = pad_sequences(X_train, maxlen=maxlen)
X_test = pad_sequences(X_test, maxlen=maxlen)
```

In this step, we preprocess the data by padding the sequences with zeros to a maximum length of 200 using the pad_sequences() function from Keras. This ensures that all input sequences have the same length and can be fed into the neural network.

```
# Define the model
model = Sequential()
model.add(Dense(128, activation='relu', input_shape=(maxlen,)))
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1, activation='sigmoid'))
```

In this step, we define the neural network architecture using the Sequential() class from Keras. Next, we define the neural network model with three fully connected layers. The first layer has 128 units with ReLU activation, the second layer has 64 units with ReLU activation, and the final layer has a single unit with sigmoid activation for binary classification.

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

In this step, we compile the model using the compile() method from Keras. We set the loss function to binary cross-entropy, which is appropriate for binary classification problems. We use the adam optimizer and track the accuracy metric during training.

```
# Train the model
model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=10, batch_size=128)
```

In this step, we train the model on the training data using the fit() method from Keras. We set the number of epochs to 10 and the batch size to 128. We also pass in the test data as the validation data to monitor the performance of the model on unseen data during training.

```
# Evaluate the model on test data
scores = model.evaluate(X_test, y_test, verbose=0)
print("Accuracy: %.2f%%" % (scores[1]*100))
```

Finally, we can evaluate the performance of the model on the test data using the evaluate() function from Keras.

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz
17464789/17464789 [==============================] - 1s 0us/step
Epoch 1/10
196/196 [==============================] - 2s 7ms/step - loss: 257.8831 - accuracy: 0.4990 - val_loss: 3.1933 - val_accuracy: 0.5036
Epoch 2/10
196/196 [==============================] - 1s 6ms/step - loss: 18.6795 - accuracy: 0.5094 - val_loss: 0.7013 - val_accuracy: 0.5010
Epoch 3/10
196/196 [==============================] - 1s 6ms/step - loss: 4.7280 - accuracy: 0.4982 - val_loss: 0.6967 - val_accuracy: 0.4960
Epoch 4/10
196/196 [==============================] - 1s 6ms/step - loss: 2.4193 - accuracy: 0.5012 - val_loss: 0.6952 - val_accuracy: 0.4974
Epoch 5/10
196/196 [==============================] - 1s 5ms/step - loss: 1.5178 - accuracy: 0.5043 - val_loss: 0.6936 - val_accuracy: 0.4989
Epoch 6/10
196/196 [==============================] - 1s 6ms/step - loss: 1.2867 - accuracy: 0.5026 - val_loss: 0.6937 - val_accuracy: 0.5003
Epoch 7/10
196/196 [==============================] - 1s 6ms/step - loss: 1.1111 - accuracy: 0.5014 - val_loss: 0.6932 - val_accuracy: 0.5002
Epoch 8/10
196/196 [==============================] - 2s 8ms/step - loss: 1.0110 - accuracy: 0.4982 - val_loss: 0.6932 - val_accuracy: 0.5002
```

```
Epoch 9/10

196/196 [==============================] - 1s 7ms/step - loss: 0.8932 - accuracy:
0.4972 - val_loss: 0.6932 - val_accuracy: 0.5004

Epoch 10/10

196/196 [==============================] - 1s 6ms/step - loss: 0.8888 - accuracy:
0.4971 - val_loss: 0.6931 - val_accuracy: 0.5002

    Accuracy: 50.02%
```

EXPERIMENT NO -3

Design a neural Network for classifying news wires (Multi class classification) using Reuters dataset

Procedure :

Reuters DataSet :

The Reuters dataset is a collection of newswire articles and their categories. It consists of 11,228 newswire articles that are classified into 46 different topics or categories. The goal of this task is to train a neural network to accurately classify newswire articles into their respective categories.

Input layer: This layer will take in the vectorized representation of the news articles in the Reuters dataset.

Hidden layers: You can use one or more hidden layers with varying number of neurons in each layer. You can experiment with the number of layers and neurons to find the optimal configuration for your specific problem.

Output layer: This layer will output a probability distribution over the possible categories for each input news article. Since this is a multi-class classification problem, you can use a softmax activation function in the output layer to ensure that the predicted probabilities sum to 1.

```
import numpy as np
from tensorflow.keras.datasets import reuters
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.utils import to_categorical
```

We will import all the necessary libraries for the model and We will use the Keras library to load the dataset and preprocess it.

```
# Load the Reuters dataset
(x_train, y_train), (x_test, y_test) = reuters.load_data(num_words=10000)
```

The first step is to load the Reuters dataset and preprocess it for training. We will also split the dataset into train and test sets.

In this step, we load the IMDB dataset using the reuters.load_data() function from Keras. We set the num_words parameter to 10000 to limit the number of words in each review to 10,000, which helps to reduce the dimensionality of the input data and improve model performance.

```
# Vectorize the data using one-hot encoding
def vectorize_sequences(sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
      results[i, sequence] = 1
    return results


x_train = vectorize_sequences(x_train)
x_test = vectorize_sequences(x_test)

# Convert the labels to one-hot vectors
num_classes = max(y_train) + 1
y_train = to_categorical(y_train, num_classes)
y_test = to_categorical(y_test, num_classes)

# Define the neural network architecture
model = Sequential()
model.add(Dense(64, activation='relu', input_shape=(10000,)))
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))
```

The next step is to design the neural network architecture. For this task, we will use a fully connected neural network with an input layer, multiple hidden layers, and an output layer. We will use the Dense class in Keras to add the layers to our model. Since we have 46 categories, the output layer will have 46 neurons, and we will use the softmax activation function to ensure that the output of the model represents a probability distribution over the 46 categories.

Compile the model

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

Once we have defined the model architecture, the next step is to compile the model. We need to specify the loss function, optimizer, and evaluation metrics for the model. Since this is a multi-class classification problem, we will use the categorical_crossentropy loss function. We will use the adam optimizer and accuracy as the evaluation metric.

Train the model on the training set

history = model.fit(x_train, y_train,

epochs=20,

batch_size=512,

validation_data=(x_test, y_test))

After compiling the model, the next step is to train it on the training data. We will use the fit method in Keras to train the model. We will also specify the validation data and the batch size.

Evaluate the model on the test set

test_loss, test_acc = model.evaluate(x_test, y_test)

print('Test accuracy:', test_acc)

Evaluate the performance of the neural network on the validation set and tune the hyperparameters such as learning rate, number of layers, number of neurons, etc., based on the validation performance.

```
Epoch 1/20
18/18 [==============================] - 2s 53ms/step - loss: 3.5441 - accuracy:
0.1880 - val_loss: 2.9635 - val_accuracy: 0.4809
Epoch 2/20
18/18 [==============================] - 1s 38ms/step - loss: 2.6812 - accuracy:
0.4036 - val_loss: 1.9865 - val_accuracy: 0.5610
Epoch 3/20
18/18 [==============================] - 1s 44ms/step - loss: 2.0019 - accuracy:
0.5345 - val_loss: 1.6289 - val_accuracy: 0.6394
Epoch 4/20
```

```
18/18 [==============================] - 1s 38ms/step - loss: 1.6804 - accuracy:
0.6021 - val_loss: 1.4734 - val_accuracy: 0.6772
Epoch 5/20
18/18 [==============================] - 1s 39ms/step - loss: 1.4998 - accuracy:
0.6431 - val_loss: 1.3653 - val_accuracy: 0.6874
Epoch 6/20
18/18 [==============================] - 1s 39ms/step - loss: 1.3755 - accuracy:
0.6711 - val_loss: 1.2938 - val_accuracy: 0.6968
Epoch 7/20
18/18 [==============================] - 1s 44ms/step - loss: 1.2737 - accuracy:
0.6915 - val_loss: 1.2457 - val_accuracy: 0.7070
Epoch 8/20
18/18 [==============================] - 1s 38ms/step - loss: 1.1878 - accuracy:
0.7150 - val_loss: 1.2033 - val_accuracy: 0.7168
Epoch 9/20
18/18 [==============================] - 1s 66ms/step - loss: 1.0933 - accuracy:
0.7280 - val_loss: 1.1682 - val_accuracy: 0.7320
Epoch 10/20
18/18 [==============================] - 1s 61ms/step - loss: 1.0417 - accuracy:
0.7455 - val_loss: 1.1414 - val_accuracy: 0.7480
Epoch 11/20
18/18 [==============================] - 1s 38ms/step - loss: 0.9840 - accuracy:
0.7562 - val_loss: 1.1134 - val_accuracy: 0.7547
Epoch 12/20
18/18 [==============================] - 1s 38ms/step - loss: 0.9252 - accuracy:
0.7701 - val_loss: 1.0935 - val_accuracy: 0.7631
Epoch 13/20
18/18 [==============================] - 1s 38ms/step - loss: 0.8799 - accuracy:
0.7859 - val_loss: 1.0739 - val_accuracy: 0.7694
Epoch 14/20
18/18 [==============================] - 1s 38ms/step - loss: 0.8282 - accuracy:
0.7931 - val_loss: 1.0629 - val_accuracy: 0.7703
Epoch 15/20
18/18 [==============================] - 1s 42ms/step - loss: 0.7916 - accuracy:
0.7973 - val_loss: 1.0557 - val_accuracy: 0.7720
Epoch 16/20
18/18 [==============================] - 1s 38ms/step - loss: 0.7636 - accuracy:
0.8055 - val_loss: 1.0515 - val_accuracy: 0.7787
Epoch 17/20
18/18 [==============================] - 1s 38ms/step - loss: 0.7293 - accuracy:
0.8127 - val_loss: 1.0626 - val_accuracy: 0.7743
Epoch 18/20
18/18 [==============================] - 1s 38ms/step - loss: 0.7039 - accuracy:
0.8233 - val_loss: 1.0591 - val_accuracy: 0.7765
Epoch 19/20
18/18 [==============================] - 1s 39ms/step - loss: 0.6743 - accuracy:
0.8253 - val_loss: 1.0495 - val_accuracy: 0.7809
Epoch 20/20
18/18 [==============================] - 1s 38ms/step - loss: 0.6579 - accuracy:
0.8272 - val_loss: 1.0723 - val_accuracy: 0.7769
71/71 [==============================] - 0s 4ms/step - loss: 1.0723 - accuracy:
0.7769
Test accuracy: 0.7769367694854736
```

EXPERIMENT NO -4

Design a neural network for predicting house prices using Boston Housing Price dataset.

Procedure:

The Boston Housing Price dataset is a collection of 506 samples of housing prices in the Boston area, where each sample has 13 features such as crime rate, average number of rooms per dwelling, and others. The goal of this task is to train a neural network to accurately predict the median value of owner-occupied homes in $1000's.

Input layer: This layer will take in the 13 features of each house.

Hidden layers: You can use one or more hidden layers with varying number of neurons in each layer. You can experiment with the number of layers and neurons to find the optimal configuration for your specific problem.

Output layer: This layer will output a single numerical value, which is the predicted price of the house.

```
from tensorflow.keras.datasets import boston_housing

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Dense

from tensorflow.keras.utils import normalize
```

We will import all the necessary libraries for the model and We will use the Keras library to load the dataset and preprocess it.

```
# Load the Boston Housing Price dataset

(x_train, y_train), (x_test, y_test) = boston_housing.load_data()
```

We will also split the dataset into training and validation sets.

```
# Normalize the data

x_train = normalize(x_train, axis=0)

x_test = normalize(x_test, axis=0)
```

Define the neural network architecture

model = Sequential()

model.add(Dense(64, activation='relu', input_shape=(13,)))

model.add(Dense(64, activation='relu'))

model.add(Dense(1))

The next step is to design the neural network architecture. For this task, we will use a fully connected neural network with an input layer, multiple hidden layers, and an output layer. We will use the Dense class in Keras to add the layers to our model. Since this is a regression problem, the output layer will have only one neuron, and we will not use any activation function

Compile the model

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

Once we have defined the model architecture, the next step is to compile the model. We need to specify the loss function, optimizer, and evaluation metrics for the model. Since this is a regression problem, we will use the mean_squared_error loss function. We will use the adam optimizer and mean_absolute_error as the evaluation metric. Train the model on the training set

history = model.fit(x_train, y_train,

epochs=100,

batch_size=32,

validation_data=(x_test, y_test))

After compiling the model, the next step is to train it on the training data. We will use the fit method in Keras to train the model. We will also specify the validation data and the batch size.

Evaluate the model on the test set

test_loss = model.evaluate(x_test, y_test)

print('Test loss:', test_loss)

Once the model is trained, the next step is to evaluate its performance on the test data. We will use the evaluate method in Keras to evaluate the model.

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/boston_housing.npz
57026/57026 [==============================] - 0s 0us/step
Epoch 1/100
13/13 [==============================] - 3s 71ms/step - loss: 581.6057 - val_loss:
600.8628
Epoch 2/100
13/13 [==============================] - 0s 10ms/step - loss: 568.9142 - val_loss:
578.0995
Epoch 3/100
13/13 [==============================] - 0s 11ms/step - loss: 547.0474 - val_loss:
539.9392
Epoch 4/100
```

```
13/13 [==============================] - 0s 9ms/step - loss: 510.9485 - val_loss:
479.1323
Epoch 5/100
13/13 [==============================] - 0s 6ms/step - loss: 455.0125 - val_loss:
393.1474
Epoch 6/100
13/13 [==============================] - 0s 7ms/step - loss: 379.5060 - val_loss:
288.2769
Epoch 7/100
13/13 [==============================] - 0s 6ms/step - loss: 289.0050 - val_loss:
187.7191
Epoch 8/100
13/13 [==============================] - 0s 6ms/step - loss: 198.9047 - val_loss:
123.9099
Epoch 9/100
13/13 [==============================] - 0s 5ms/step - loss: 133.4827 - val_loss:
118.9333
Epoch 10/100
13/13 [==============================] - 0s 5ms/step - loss: 103.5629 - val_loss:
148.6580
Epoch 11/100
13/13 [==============================] - 0s 5ms/step - loss: 96.0384 - val_loss:
157.2076
Epoch 12/100
13/13 [==============================] - 0s 6ms/step - loss: 94.3371 - val_loss:
151.7262
Epoch 13/100
13/13 [==============================] - 0s 6ms/step - loss: 91.8126 - val_loss:
139.2459
Epoch 14/100
13/13 [==============================] - 0s 5ms/step - loss: 89.3874 - val_loss:
128.9134
Epoch 15/100
13/13 [==============================] - 0s 7ms/step - loss: 87.6433 - val_loss:
122.3881
Epoch 16/100
13/13 [==============================] - 0s 7ms/step - loss: 85.5203 - val_loss:
118.5746
Epoch 17/100
13/13 [==============================] - 0s 6ms/step - loss: 83.6930 - val_loss:
117.3677
Epoch 18/100
13/13 [==============================] - 0s 6ms/step - loss: 81.8004 - val_loss:
107.7317
Epoch 19/100
13/13 [==============================] - 0s 6ms/step - loss: 80.0276 - val_loss:
108.8664
Epoch 20/100
13/13 [==============================] - 0s 6ms/step - loss: 78.1314 - val_loss:
101.8108
Epoch 21/100
13/13 [==============================] - 0s 5ms/step - loss: 76.4282 - val_loss:
97.4463
Epoch 22/100
13/13 [==============================] - 0s 7ms/step - loss: 74.9360 - val_loss:
96.3559
Epoch 23/100
13/13 [==============================] - 0s 6ms/step - loss: 73.3877 - val_loss:
87.7806
Epoch 24/100
13/13 [==============================] - 0s 7ms/step - loss: 71.7510 - val_loss:
89.5797
Epoch 25/100
```

```
13/13 [==============================] - 0s 8ms/step - loss: 70.0859 - val_loss:
84.9000
Epoch 26/100
13/13 [==============================] - 0s 9ms/step - loss: 68.7180 - val_loss:
81.1061
Epoch 27/100
13/13 [==============================] - 0s 8ms/step - loss: 67.2199 - val_loss:
80.6916
Epoch 28/100
13/13 [==============================] - 0s 6ms/step - loss: 65.8538 - val_loss:
78.3895
Epoch 29/100
13/13 [==============================] - 0s 6ms/step - loss: 64.5018 - val_loss:
75.4445
Epoch 30/100
13/13 [==============================] - 0s 9ms/step - loss: 63.2297 - val_loss:
75.0658
Epoch 31/100
13/13 [==============================] - 0s 6ms/step - loss: 62.0135 - val_loss:
72.5331
Epoch 32/100
13/13 [==============================] - 0s 6ms/step - loss: 61.0150 - val_loss:
72.5535
Epoch 33/100
13/13 [==============================] - 0s 6ms/step - loss: 59.7378 - val_loss:
70.0550
Epoch 34/100
13/13 [==============================] - 0s 6ms/step - loss: 58.8055 - val_loss:
71.9888
Epoch 35/100
13/13 [==============================] - 0s 6ms/step - loss: 57.8878 - val_loss:
70.7422
Epoch 36/100
13/13 [==============================] - 0s 6ms/step - loss: 57.4425 - val_loss:
68.0706
Epoch 37/100
13/13 [==============================] - 0s 6ms/step - loss: 56.2824 - val_loss:
73.5046
Epoch 38/100
13/13 [==============================] - 0s 6ms/step - loss: 55.7446 - val_loss:
72.7915
Epoch 39/100
13/13 [==============================] - 0s 6ms/step - loss: 55.0651 - val_loss:
71.6527
Epoch 40/100
13/13 [==============================] - 0s 7ms/step - loss: 54.5890 - val_loss:
71.9477
Epoch 41/100
13/13 [==============================] - 0s 5ms/step - loss: 54.0848 - val_loss:
74.4059
Epoch 42/100
13/13 [==============================] - 0s 6ms/step - loss: 53.6057 - val_loss:
72.6524
Epoch 43/100
13/13 [==============================] - 0s 5ms/step - loss: 53.2400 - val_loss:
72.7631
Epoch 44/100
13/13 [==============================] - 0s 7ms/step - loss: 52.7545 - val_loss:
74.9595
Epoch 45/100
13/13 [==============================] - 0s 7ms/step - loss: 52.3954 - val_loss:
74.4425
Epoch 46/100
```

```
13/13 [==============================] - 0s 8ms/step - loss: 51.8754 - val_loss:
75.4689
Epoch 47/100
13/13 [==============================] - 0s 6ms/step - loss: 51.5840 - val_loss:
75.5107
Epoch 48/100
13/13 [==============================] - 0s 7ms/step - loss: 51.3794 - val_loss:
74.1811
Epoch 49/100
13/13 [==============================] - 0s 7ms/step - loss: 50.7736 - val_loss:
77.1227
Epoch 50/100
13/13 [==============================] - 0s 6ms/step - loss: 50.6973 - val_loss:
75.3571
Epoch 51/100
13/13 [==============================] - 0s 7ms/step - loss: 50.3545 - val_loss:
75.5459
Epoch 52/100
13/13 [==============================] - 0s 9ms/step - loss: 50.0110 - val_loss:
74.9539
Epoch 53/100
13/13 [==============================] - 0s 7ms/step - loss: 49.5859 - val_loss:
75.7610
Epoch 54/100
13/13 [==============================] - 0s 7ms/step - loss: 49.2332 - val_loss:
75.3416
Epoch 55/100
13/13 [==============================] - 0s 7ms/step - loss: 48.9296 - val_loss:
74.7842
Epoch 56/100
13/13 [==============================] - 0s 7ms/step - loss: 48.5693 - val_loss:
73.6319
Epoch 57/100
13/13 [==============================] - 0s 7ms/step - loss: 48.2237 - val_loss:
74.5521
Epoch 58/100
13/13 [==============================] - 0s 5ms/step - loss: 47.9942 - val_loss:
74.2557
Epoch 59/100
13/13 [==============================] - 0s 5ms/step - loss: 47.6148 - val_loss:
72.9914
Epoch 60/100
13/13 [==============================] - 0s 7ms/step - loss: 47.3916 - val_loss:
73.7292
Epoch 61/100
13/13 [==============================] - 0s 5ms/step - loss: 47.1164 - val_loss:
71.3105
Epoch 62/100
13/13 [==============================] - 0s 7ms/step - loss: 46.8377 - val_loss:
73.0056
Epoch 63/100
13/13 [==============================] - 0s 7ms/step - loss: 46.1684 - val_loss:
71.6649
Epoch 64/100
13/13 [==============================] - 0s 7ms/step - loss: 45.9518 - val_loss:
71.3532
Epoch 65/100
13/13 [==============================] - 0s 6ms/step - loss: 45.8064 - val_loss:
71.3245
Epoch 66/100
13/13 [==============================] - 0s 6ms/step - loss: 45.3031 - val_loss:
70.0585
Epoch 67/100
```

```
13/13 [==============================] - 0s 7ms/step - loss: 44.8652 - val_loss:
70.1172
Epoch 68/100
13/13 [==============================] - 0s 6ms/step - loss: 44.7074 - val_loss:
69.8758
Epoch 69/100
13/13 [==============================] - 0s 5ms/step - loss: 44.4409 - val_loss:
69.5317
Epoch 70/100
13/13 [==============================] - 0s 7ms/step - loss: 43.9173 - val_loss:
68.3756
Epoch 71/100
13/13 [==============================] - 0s 7ms/step - loss: 43.6754 - val_loss:
68.1564
Epoch 72/100
13/13 [==============================] - 0s 7ms/step - loss: 43.0529 - val_loss:
67.8396
Epoch 73/100
13/13 [==============================] - 0s 6ms/step - loss: 42.8460 - val_loss:
67.5689
Epoch 74/100
13/13 [==============================] - 0s 8ms/step - loss: 42.5708 - val_loss:
67.1981
Epoch 75/100
13/13 [==============================] - 0s 7ms/step - loss: 42.2138 - val_loss:
66.7805
Epoch 76/100
13/13 [==============================] - 0s 7ms/step - loss: 41.8676 - val_loss:
66.0953
Epoch 77/100
13/13 [==============================] - 0s 7ms/step - loss: 41.4192 - val_loss:
65.9270
Epoch 78/100
13/13 [==============================] - 0s 8ms/step - loss: 40.9319 - val_loss:
65.6209
Epoch 79/100
13/13 [==============================] - 0s 6ms/step - loss: 40.6032 - val_loss:
64.8652
Epoch 80/100
13/13 [==============================] - 0s 8ms/step - loss: 40.3409 - val_loss:
65.0239
Epoch 81/100
13/13 [==============================] - 0s 6ms/step - loss: 40.0193 - val_loss:
64.4650
Epoch 82/100
13/13 [==============================] - 0s 6ms/step - loss: 39.5756 - val_loss:
64.0286
Epoch 83/100
13/13 [==============================] - 0s 6ms/step - loss: 39.0019 - val_loss:
63.1940
Epoch 84/100
13/13 [==============================] - 0s 6ms/step - loss: 39.1355 - val_loss:
63.2680
Epoch 85/100
13/13 [==============================] - 0s 6ms/step - loss: 38.4614 - val_loss:
63.4833
Epoch 86/100
13/13 [==============================] - 0s 6ms/step - loss: 38.2256 - val_loss:
62.5658
Epoch 87/100
13/13 [==============================] - 0s 7ms/step - loss: 37.5265 - val_loss:
63.4185
Epoch 88/100
```

```
13/13 [==============================] - 0s 7ms/step - loss: 37.2877 - val_loss:
62.3244
Epoch 89/100
13/13 [==============================] - 0s 5ms/step - loss: 37.2992 - val_loss:
61.4046
Epoch 90/100
13/13 [==============================] - 0s 4ms/step - loss: 36.6447 - val_loss:
62.3672
Epoch 91/100
13/13 [==============================] - 0s 4ms/step - loss: 36.2271 - val_loss:
60.2370
Epoch 92/100
13/13 [==============================] - 0s 6ms/step - loss: 36.5574 - val_loss:
61.8120
Epoch 93/100
13/13 [==============================] - 0s 5ms/step - loss: 35.8656 - val_loss:
60.5489
Epoch 94/100
13/13 [==============================] - 0s 4ms/step - loss: 35.2197 - val_loss:
62.9568
Epoch 95/100
13/13 [==============================] - 0s 5ms/step - loss: 34.7053 - val_loss:
61.1308
Epoch 96/100
13/13 [==============================] - 0s 4ms/step - loss: 34.6180 - val_loss:
62.5150
Epoch 97/100
13/13 [==============================] - 0s 5ms/step - loss: 34.1021 - val_loss:
62.0751
Epoch 98/100
13/13 [==============================] - 0s 5ms/step - loss: 33.7709 - val_loss:
61.6955
Epoch 99/100
13/13 [==============================] - 0s 5ms/step - loss: 33.4811 - val_loss:
61.1410
Epoch 100/100
13/13 [==============================] - 0s 6ms/step - loss: 33.0442 - val_loss:
61.5967
4/4 [==============================] - 0s 3ms/step - loss: 61.5967
Test loss: 61.5966682434082
```

EXPERIMENT NO – 5

Build a Convolution Neural Network for MNIST Hand written Digit Classification.

MNIST Handwritten Digit Classification DataSet :

The MNIST dataset is a popular benchmark dataset for image classification tasks. It consists of 60,000 grayscale images of handwritten digits (0 to 9) for training and 10,000 images for testing. Each image is 28 x 28 pixels in size, and each pixel value ranges from 0 to 255. The goal of the task is to correctly classify each image into one of the 10 possible digit classes.

```
from tensorflow.keras.datasets import mnist

# Load the MNIST dataset

(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

In this implementation, we first load the MNIST dataset using the mnist.load_data() function from Keras.

In this step, we use the mnist.load_data() function from Keras to load the MNIST dataset. The training data consists of the x_train images and their corresponding y_train labels, while the test data consists of the x_test images and their corresponding y_test labels.

```
# Normalize the pixel values to be between 0 and 1

x_train = x_train / 255.0

x_test = x_test / 255.0
```

In this step, we preprocess the data by reshaping the images to 1D arrays, normalizing the pixel values to be between 0 and 1, and. . We then preprocess the data by flattening the input images into 1D arrays of size 784 (28x28), scaling the pixel values to the range of 0 to 1, and dividing by 255.0 to normalize the data.

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz

11490434/11490434 [==============================] - 0s 0us/step

import numpy as np


# Reshape the data to add a channel dimension

x_train = np.expand_dims(x_train, axis=-1)

x_test = np.expand_dims(x_test, axis=-1)
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout


# Define the CNN architecture
model = Sequential()
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(10, activation='softmax'))
```

The next step is to define the CNN architecture. For this task, we will use a simple CNN architecture with three convolutional layers with 'relu' activation function and followed by two max pooling layers, then a flatten layer and two fully connected (dense) layers. The final output layer will have 10 neurons, one for each digit class, and we will use the softmax activation function to produce probabilities for each class.

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

We compile the model with the Adam optimizer, sparse_categorical_crossentropy loss, and accuracy metric.

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

We train the model on the training data for 10 epochs with a batch size of 128. Finally, we evaluate the model on the test data and print the accuracy score.

```
Epoch 1/10
1875/1875 [==============================] - 72s 38ms/step - loss: 0.2613 - accuracy: 0.9220 - val_loss: 0.0447 - val_accuracy: 0.9859
Epoch 2/10
1875/1875 [==============================] - 66s 35ms/step - loss: 0.0927 - accuracy: 0.9752 - val_loss: 0.0491 - val_accuracy: 0.9852
```

Epoch 3/10

1875/1875 [==============================] - 69s 37ms/step - loss: 0.0650 - accuracy: 0.9821 - val_loss: 0.0339 - val_accuracy: 0.9892

Epoch 4/10

1875/1875 [==============================] - 68s 36ms/step - loss: 0.0516 - accuracy: 0.9855 - val_loss: 0.0328 - val_accuracy: 0.9895

Epoch 5/10

1875/1875 [==============================] - 68s 36ms/step - loss: 0.0413 - accuracy: 0.9887 - val_loss: 0.0315 - val_accuracy: 0.9907

Epoch 6/10

1875/1875 [==============================] - 65s 35ms/step - loss: 0.0359 - accuracy: 0.9898 - val_loss: 0.0270 - val_accuracy: 0.9925

Epoch 7/10

1875/1875 [==============================] - 65s 35ms/step - loss: 0.0312 - accuracy: 0.9910 - val_loss: 0.0278 - val_accuracy: 0.9920

Epoch 8/10

1875/1875 [==============================] - 68s 36ms/step - loss: 0.0283 - accuracy: 0.9920 - val_loss: 0.0365 - val_accuracy: 0.9908

Epoch 9/10

1875/1875 [==============================] - 65s 35ms/step - loss: 0.0233 - accuracy: 0.9931 - val_loss: 0.0324 - val_accuracy: 0.9927

Epoch 10/10

1875/1875 [==============================] - 67s 36ms/step - loss: 0.0197 - accuracy: 0.9938 - val_loss: 0.0346 - val_accuracy: 0.9941

```
# Evaluate the model on the test set

test_loss, test_acc = model.evaluate(x_test, y_test)

print('Test accuracy:', test_acc)
```

Once the model is trained, the next step is to evaluate its performance on the test data. We will use the evaluate method in Keras to evaluate the model.

313/313 [==============================] - 4s 11ms/step - loss: 0.0346 - accuracy: 0.9941

Test accuracy: 0.9940999746322632

EXPERIMENT NO – 6

Build a Convolution Neural Network for simple image (dogs and Cats) Classification

Image classification is the task of categorizing images into different classes based on their content. In this case, we want to build a model that can distinguish between images of dogs and cats.

```
# import the libraries as shown below

from tensorflow.keras.layers import Input, Lambda, Dense, Flatten
from tensorflow.keras.models import Model
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.preprocessing import image
from tensorflow.keras.preprocessing.image import ImageDataGenerator,load_img
from tensorflow.keras.models import Sequential
import numpy as np
from glob import glob
```

in this step we are importing the required modules from keras and tensorflow . Here we are using the pre-defined neural network called VGG16 .

```
from google.colab import drive
drive.mount('/content/drive')
```

```
In this step we are  mounting our Google colab with our drive
```

```
Mounted at /content/drive
```

```
ROOT_PATH = '/content/drive/MyDrive/cat-dog-project-20230412T173959Z-001/cat-dog-project'
```

```
!pwd
```

```
/content
```

```
import os
os.chdir(ROOT_PATH)
os.getcwd()
```

/content/drive/MyDrive/cat-dog-project-20230412T173959Z-001/cat-dog-project

```
# re-size all the images to this
IMAGE_SIZE = [224, 224]

train_path = 'PetImages/train'
valid_path = 'PetImages/validation'
```

```
# Import the VGG16 library as shown below and add preprocessing layer to the front of VGG
# Here we will be using imagenet weights

vgg16 = VGG16(input_shape=IMAGE_SIZE + [3], weights='imagenet', include_top=False)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5

58889256/58889256 [==============================] - 0s 0us/step
```

```
# don't train existing weights
for layer in vgg16.layers:
  print(layer)
```

```
<keras.engine.input_layer.InputLayer object at 0x7fa764e92190>
<keras.layers.convolutional.conv2d.Conv2D object at 0x7fa764e92b20>
<keras.layers.convolutional.conv2d.Conv2D object at 0x7fa7645e4310>
<keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7fa7645ae6d0>
<keras.layers.convolutional.conv2d.Conv2D object at 0x7fa7645e4910>
<keras.layers.convolutional.conv2d.Conv2D object at 0x7fa7645c6880>
<keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7fa7640cf4f0>
<keras.layers.convolutional.conv2d.Conv2D object at 0x7fa7645c61f0>
<keras.layers.convolutional.conv2d.Conv2D object at 0x7fa7640d2970>
<keras.layers.convolutional.conv2d.Conv2D object at 0x7fa7640d9610>
<keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7fa7640df700>
<keras.layers.convolutional.conv2d.Conv2D object at 0x7fa7640e5190>
<keras.layers.convolutional.conv2d.Conv2D object at 0x7fa7640e5d30>
<keras.layers.convolutional.conv2d.Conv2D object at 0x7fa7640df8b0>
<keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7fa7640efca0>
<keras.layers.convolutional.conv2d.Conv2D object at 0x7fa7640ef760>
<keras.layers.convolutional.conv2d.Conv2D object at 0x7fa7640d9970>
<keras.layers.convolutional.conv2d.Conv2D object at 0x7fa76407c520>
<keras.layers.pooling.max_pooling2d.MaxPooling2D object at 0x7fa7640f57f0>
```

```
# don't train existing weights
for layer in vgg16.layers:
    layer.trainable = False
```

```
for layer in vgg16.layers:
  print(layer.name,layer.trainable)
```

```
input_1 False
block1_conv1 False
block1_conv2 False
block1_pool False
block2_conv1 False
block2_conv2 False
block2_pool False
block3_conv1 False
block3_conv2 False
block3_conv3 False
block3_pool False
block4_conv1 False
block4_conv2 False
block4_conv3 False
block4_pool False
block5_conv1 False
block5_conv2 False
block5_conv3 False
block5_pool False
```

```
vgg16.summary()
```

```
Model: "vgg16"
```

```
 Layer (type)                 Output Shape              Param #
=================================================================
 input_1 (InputLayer)         [(None, 224, 224, 3)]     0

 block1_conv1 (Conv2D)        (None, 224, 224, 64)      1792

 block1_conv2 (Conv2D)        (None, 224, 224, 64)      36928

 block1_pool (MaxPooling2D)   (None, 112, 112, 64)      0

 block2_conv1 (Conv2D)        (None, 112, 112, 128)     73856

 block2_conv2 (Conv2D)        (None, 112, 112, 128)     147584

 block2_pool (MaxPooling2D)   (None, 56, 56, 128)       0

 block3_conv1 (Conv2D)        (None, 56, 56, 256)       295168

 block3_conv2 (Conv2D)        (None, 56, 56, 256)       590080

 block3_conv3 (Conv2D)        (None, 56, 56, 256)       590080

 block3_pool (MaxPooling2D)   (None, 28, 28, 256)       0

 block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160

 block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808

 block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808

 block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0

 block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808

 block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808

 block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808

 block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0

=================================================================
Total params: 14,714,688
Trainable params: 0
Non-trainable params: 14,714,688
```

```
  # useful for getting number of output classes
folders = glob('PetImages/train/*')
```

```
len(folders)
```

```
model = Sequential()

model.add(vgg16)
model.add(Flatten())
model.add(Dense(256,activation='relu'))
model.add(Dense(2,activation='softmax'))
```

```
# view the structure of the model
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 7, 7, 512)         14714688

 flatten (Flatten)           (None, 25088)             0

 dense (Dense)               (None, 256)               6422784

 dense_1 (Dense)             (None, 2)                 514

=================================================================
Total params: 21,137,986
Trainable params: 6,423,298
Non-trainable params: 14,714,688
```

```
# tell the model what cost and optimization method to use
model.compile(
  loss='categorical_crossentropy',
  optimizer='adam',
  metrics=['accuracy']
)
```

```
# Use the Image Data Generator to import the images from the dataset
from tensorflow.keras.preprocessing.image import ImageDataGenerator

train_datagen = ImageDataGenerator(rescale = 1./255,
                                   shear_range = 0.2,
                                   zoom_range = 0.2,
                                   horizontal_flip = True)

test_datagen = ImageDataGenerator(rescale = 1./255)
```

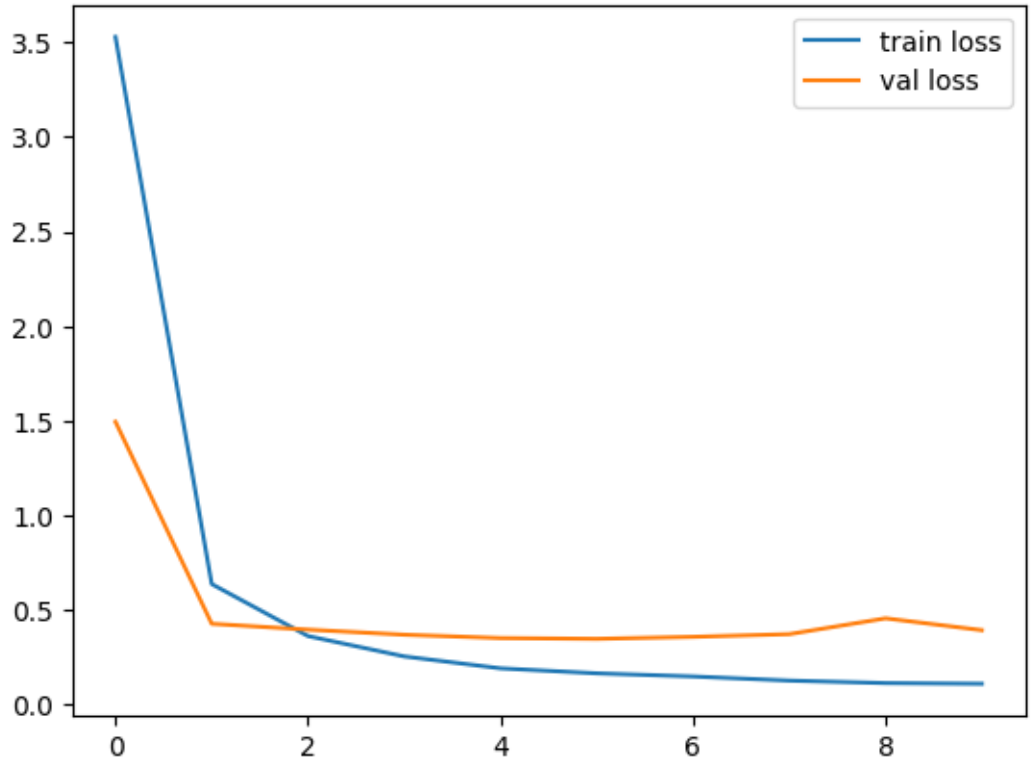
```
# Make sure you provide the same target size as initialied for the image size
training_set = train_datagen.flow_from_directory('PetImages/train',
                                                 target_size = (224, 224),
                                                 batch_size = 32,
                                                 class_mode = 'categorical')
```

```
test_set = test_datagen.flow_from_directory('PetImages/validation',
                                            target_size = (224, 224),
                                            batch_size = 32,
                                            class_mode = 'categorical')
```

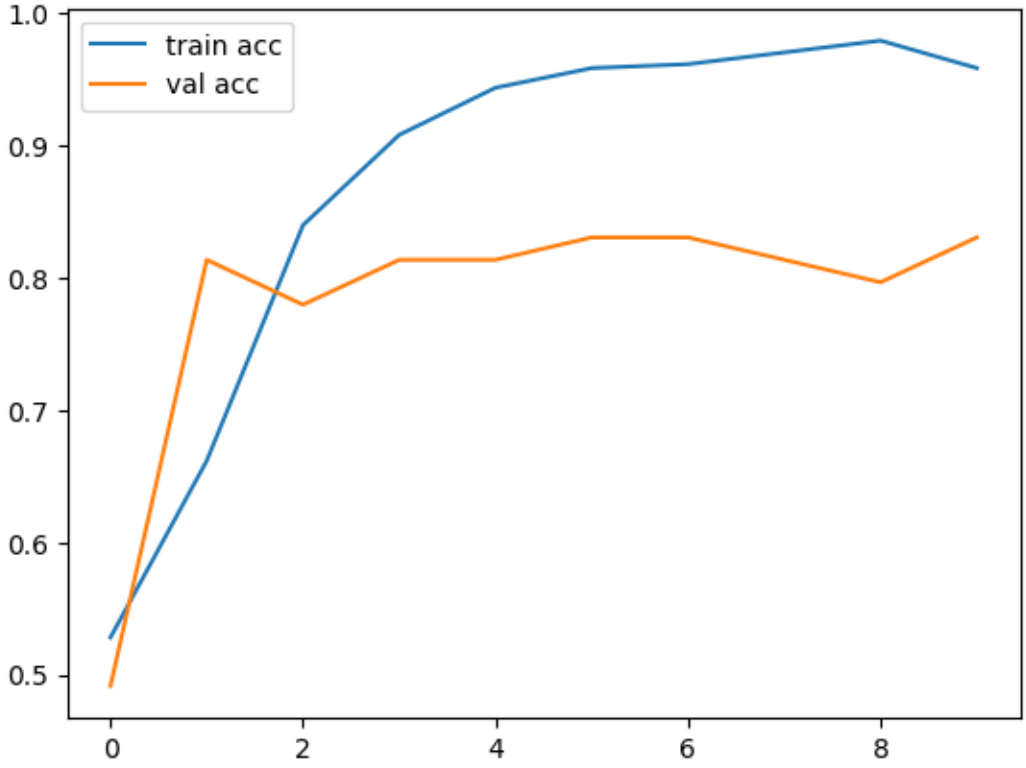
```
# fit the model
# Run the cell. It will take some time to execute
r = model.fit(
  training_set,
```

```
  validation_data=test_set,
  epochs=10,
  steps_per_epoch=len(training_set),
  validation_steps=len(test_set)
)
import matplotlib.pyplot as plt
```

```
# plot the loss
plt.plot(r.history['loss'], label='train loss')
plt.plot(r.history['val_loss'], label='val loss')
plt.legend()
plt.show()
plt.savefig('LossVal_loss')
```




```
# plot the accuracy
plt.plot(r.history['accuracy'], label='train acc')
plt.plot(r.history['val_accuracy'], label='val acc')
plt.legend()
plt.show()
plt.savefig('AccVal_acc')
```




```
# save it as a h5 file
from tensorflow.keras.models import load_model

model.save('model_vgg16.h5')
```

```
y_pred = model.predict(test_set)
```

```
y_pred
```

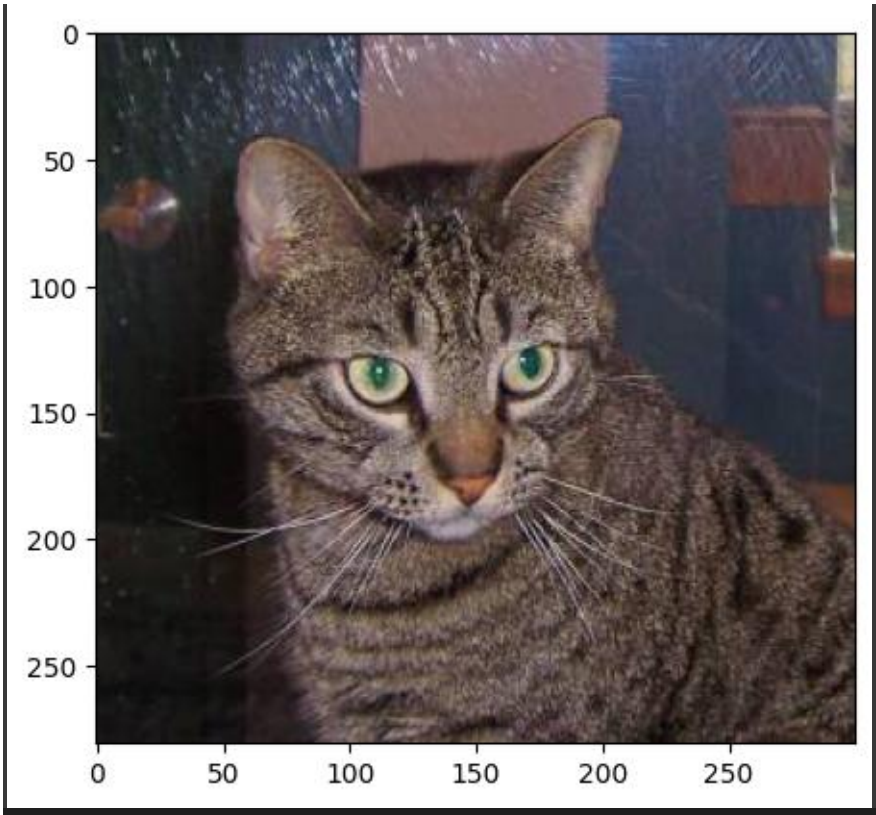
```
import numpy as np
y_pred = np.argmax(y_pred, axis=1)
```

```
y_pred
```

```
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
model=load_model('model_vgg16.h5')
img=image.load_img('cat.jpg',target_size=(224,224))
x=image.img_to_array(img)
x
```

```
Z = plt.imread('cat.jpg')
plt.imshow(Z)
```

```
<matplotlib.image.AxesImage at 0x7fa6ca436130>
```




```
x.shape
x=x/255
from keras.applications.vgg16 import preprocess_input
import numpy as np
x=np.expand_dims(x,axis=0)
img_data=preprocess_input(x)
img_data.shape
model.predict(img_data)
result = np.argmax(model.predict(img_data), axis=1)
result[0]
if result[0] == 1:
    prediction = 'dog'
    print(prediction)
else:
    prediction = 'cat'
    print(prediction)
```

```
cat
```

EXPERIMENT N0 – 7

Use a pre-trained convolution neural network (VGG16) for image classification.

Procedure:

VGG16 is a convolutional neural network (CNN) architecture that was developed by researchers at the Visual Geometry Group (VGG) at the University of Oxford. It was introduced in the paper titled "Very Deep Convolutional Networks for Large-Scale Image Recognition" by Karen Simonyan and Andrew Zisserman in 2014.

The VGG16 architecture consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. The input to the network is an RGB image of size 224x224. The network uses small 3x3 convolutional filters throughout the network, which allows the network to learn more complex features with fewer parameters.

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

Import the necessary libraries: You'll need to import Keras and other required libraries for this task.

```
model = VGG16(weights='imagenet', include_top=True)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels.h5

553467096/553467096 [==============================] - 20s 0us/step
```

Load the pre-trained VGG16 model: You can load the pre-trained VGG16 model by calling the VGG16() function from the Keras library.

```
img_path = '/cat.jpg'
img = image.load_img(img_path, target_size=(224, 224))
```

Load an image for classification: You can use any image that you want to classify.

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
x = image.img_to_array(img)
x = np.expand_dims(x, axis=0)
x = preprocess_input(x)
```

You'll need to preprocess the image before feeding it to the VGG16 model. You can do this using the preprocess_input() function from the Keras library.

```
preds = model.predict(x)
```

Predict the class of the image: You can predict the class of the image using the predict() function of the VGG16 model.

```
pred_classes = decode_predictions(preds, top=3)[0]
for i, pred_class in enumerate(pred_classes):
    print("{}. {}: {:.2f}%".format(i+1, pred_class[1], pred_class[2]*100))
```

Decode the predictions: You can decode the predictions using the decode_predictions() function from the Keras library.

Result:

```
Downloading data from https://storage.googleapis.com/download.tensorflow.org/data/imagenet_class_index.json
35363/35363 [==============================] - 0s 0us/step
1. tabby: 44.72%
2. tiger_cat: 42.62%
3. Egyptian_cat: 6.74%
```

EXPERIMENT N0 – 8

Implement one hot encoding of words or characters.

Procedure :

One-hot encoding is a technique used to represent categorical data as numerical data. In the context of natural language processing (NLP), one-hot encoding can be used to represent words or characters as vectors of numbers.

In one-hot encoding, each word or character is assigned a unique index, and a vector of zeros is created with the length equal to the total number of words or characters in the vocabulary. The index of the word or character is set to 1 in the corresponding position in the vector, and all other positions are set to 0.

For example, suppose we have a vocabulary of four words: "apple", "banana", "cherry", and "date". Each word is assigned a unique index: 0, 1, 2, and 3, respectively. The one-hot encoding of the word "banana" would be [0, 1, 0, 0], because it is in the second position in the vocabulary.

In Python, we can implement one-hot encoding using the keras.preprocessing.text.one_hot() function from the Keras library. This function takes as input a list of text strings, the size of the vocabulary, and a hash function to convert words to integers. It returns a list of one-hot encoded vectors.

```
from tensorflow.keras.preprocessing.text import one_hot

# Define the list of words
words = ['apple', 'banana', 'cherry', 'apple', 'cherry', 'banana', 'apple']

# Create a vocabulary of unique words
vocab = set(words)

# Assign a unique integer to each word in the vocabulary
word_to_int = {word: i for i, word in enumerate(vocab)}

# Convert the list of words to a list of integers using the vocabulary
int_words = [word_to_int[word] for word in words]

# Perform one-hot encoding of the integer sequence
one_hot_words = []
for int_word in int_words:
    one_hot_word = [0] * len(vocab)
    one_hot_word[int_word] = 1
    one_hot_words.append(one_hot_word)

print(one_hot_words)
```

[[0, 0, 1], [1, 0, 0], [0, 1, 0], [0, 0, 1], [0, 1, 0], [1, 0, 0], [0, 0, 1]]

```
import string

# Define the input string
input_string = 'hello world'

# Create a vocabulary of unique characters
vocab = set(input_string)

# Assign a unique integer to each character in the vocabulary
char_to_int = {char: i for i, char in enumerate(vocab)}

# Convert the input string to a list of integers using the vocabulary
int_chars = [char_to_int[char] for char in input_string]

# Perform one-hot encoding of the integer sequence
one_hot_chars = []
for int_char in int_chars:
    one_hot_char = [0] * len(vocab)
    one_hot_char[int_char] = 1
    one_hot_chars.append(one_hot_char)

print(one_hot_chars)
```

```
[[0, 0, 0, 1, 0, 0, 0, 0], [0, 0, 0, 0, 1, 0, 0, 0], [1, 0, 0, 0, 0, 0, 0, 0], [1, 0, 0, 0, 0, 0, 0, 0], [0, 1, 0, 0, 0, 0, 0, 0], [0, 0, 0, 0, 0, 0, 1, 0], [0, 0, 1, 0, 0, 0, 0, 0], [0, 1, 0, 0, 0, 0, 0, 0], [0, 0, 0, 0, 0, 0, 0, 1], [1, 0, 0, 0, 0, 0, 0, 0], [0, 0, 0, 0, 0, 1, 0, 0]]
```

EXPERIMENT NO – 9

Implement word embeddings for IMDB dataset

Procedure :

Word embeddings are a type of representation learning that can be used to convert words into numerical vectors. In natural language processing (NLP), word embeddings are commonly used to represent words as dense vectors in a high-dimensional space. This allows us to perform various NLP tasks such as text classification, sentiment analysis, and language translation.

In this example, we will implement word embeddings for the IMDB dataset, which consists of movie reviews labeled as positive or negative. We will use the Keras library to implement the word embeddings.

First, we will load the IMDB dataset using Keras. The dataset consists of 50,000 movie reviews, with 25,000 reviews for training and 25,000 reviews for testing. Each review is a sequence of words, and the label is either 0 (negative) or 1 (positive).

```
from keras.datasets import imdb

from tensorflow.keras.preprocessing.sequence import pad_sequences

from keras.models import Sequential

from keras.layers import Dense, Flatten, Embedding


# Set the vocabulary size and the maximum length of a sequence

vocab_size = 5000

maxlen = 100


# Load the IMDB dataset and split it into training and testing sets

(X_train, y_train), (X_test, y_test) = imdb.load_data(num_words=vocab_size)
```

We set num_words to 5000, which means we will only use the top 5000 most frequent words in the dataset.

Next, we will preprocess the data by padding the sequences to a fixed length and truncating sequences that are longer than the fixed length.

Pad the sequences to ensure that they all have the same length

X_train = pad_sequences(X_train, maxlen=maxlen)

X_test = pad_sequences(X_test, maxlen=maxlen)

The pad_sequences function pads the sequences with zeros to ensure they are all the same length. Here, we set maxlen to 100, which means that all sequences will be truncated or padded to 100 words.

Define the embedding dimension

embedding_dim = 50

Define the model architecture

model = Sequential()

model.add(Embedding(input_dim=vocab_size, output_dim=embedding_dim, input_length=maxlen))

model.add(Flatten())

model.add(Dense(units=1, activation='sigmoid'))

We set the input_dim to 5000, which is the size of the vocabulary, and output_dim to 50, which is the dimensionality of the word embeddings. The GlobalMaxPooling1D layer takes the maximum value of each dimension in the embedding vectors, which allows us to obtain a fixed-length representation of each review. The final Dense layer uses a sigmoid activation function, which outputs a probability score between 0 and 1.

Compile the model

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

We compile the model with the Adam optimizer, binary_crossentropy loss, and accuracy metric.

Train the model

model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=10, batch_size=32)

We train the model on the training data for 10 epochs with a batch size of 32. Finally, we evaluate the model on the test data and print the accuracy score.

Evaluate the model on the test set

test_loss, test_accuracy = model.evaluate(X_test, y_test)

print('Test accuracy:', test_accuracy)

Once the model is trained, the next step is to evaluate its performance on the test data. We will use the evaluate method in Keras to evaluate the model.

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz

17464789/17464789 [==============================] - 0s 0us/step

Epoch 1/10

782/782 [==============================] - 7s 8ms/step - loss: 0.4746 - accuracy: 0.7688 - val_loss: 0.3402 - val_accuracy: 0.8478

Epoch 2/10

782/782 [==============================] - 7s 9ms/step - loss: 0.2593 - accuracy: 0.8955 - val_loss: 0.3311 - val_accuracy: 0.8531

Epoch 3/10

782/782 [==============================] - 6s 8ms/step - loss: 0.1545 - accuracy: 0.9526 - val_loss: 0.3563 - val_accuracy: 0.8437

Epoch 4/10

782/782 [==============================] - 7s 9ms/step - loss: 0.0689 - accuracy: 0.9909 - val_loss: 0.3924 - val_accuracy: 0.8410

Epoch 5/10

782/782 [==============================] - 6s 8ms/step - loss: 0.0281 - accuracy: 0.9990 - val_loss: 0.4303 - val_accuracy: 0.8392

Epoch 6/10

782/782 [==============================] - 7s 9ms/step - loss: 0.0128 - accuracy: 0.9997 - val_loss: 0.4633 - val_accuracy: 0.8410

Epoch 7/10

782/782 [==============================] - 6s 8ms/step - loss: 0.0066 - accuracy: 0.9999 - val_loss: 0.4977 - val_accuracy: 0.8404

Epoch 8/10

782/782 [==============================] - 7s 9ms/step - loss: 0.0036 - accuracy: 1.0000 - val_loss: 0.5372 - val_accuracy: 0.8384

Epoch 9/10

782/782 [==============================] - 6s 8ms/step - loss: 0.0021 - accuracy: 1.0000 - val_loss: 0.5627 - val_accuracy: 0.8386

Epoch 10/10

782/782 [==============================] - 8s 11ms/step - loss: 0.0013 - accuracy: 1.0000 - val_loss: 0.5935 - val_accuracy: 0.8391

782/782 [==============================] - 2s 2ms/step - loss: 0.5935 - accuracy: 0.8391

Test accuracy: 0.83911997079849
```

EXPERIMENT NO – 10

. Implement a Recurrent Neural Network for IMDB movie review classification problem.

Procedure :

To implement a Recurrent Neural Network (RNN) for the IMDB movie review classification problem, we will use the Keras deep learning library, which provides a simple and intuitive interface for building and training neural networks.

The IMDB movie review classification problem is a binary classification task, where the goal is to classify movie reviews as either positive or negative. The dataset contains 50,000 movie reviews, split into 25,000 for training and 25,000 for testing. Each review is a sequence of words, and the task is to predict whether the overall sentiment of the review is positive or negative.

To build our RNN, we will use an architecture called Long Short-Term Memory (LSTM), which is a type of RNN that is particularly good at processing sequential data. The basic idea behind LSTMs is to allow the network to selectively remember or forget information from previous time steps, which makes them well-suited for tasks like natural language processing.

```
from tensorflow.keras.datasets import imdb
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
```

We start by importing the necessary modules from Keras

```
# Set the vocabulary size and maximum sequence length
vocab_size = 10000
maxlen = 200
```

We set the maximum number of words to use from the IMDB dataset to 10,000.

```
# Load the IMDB dataset
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=vocab_size)
```

We load the IMDB dataset using the imdb.load_data() function, which returns the training and testing data as a tuple of (x_train, y_train) and (x_test, y_test), where x_train and x_test are arrays of sequences, and y_train and y_test are the corresponding labels.

```
# Pad the sequences to have the same length
x_train = pad_sequences(x_train, maxlen=maxlen)
x_test = pad_sequences(x_test, maxlen=maxlen)
```

We pad the sequences to a fixed length of 200 using the pad_sequences() function from Keras. This is necessary because the input sequences to an RNN must be of the same length.

```
# Define the model architecture
model = Sequential()
model.add(Embedding(input_dim=vocab_size, output_dim=32))
model.add(LSTM(units=64))
model.add(Dense(units=1, activation='sigmoid'))
```

We build the model using a Sequential() model from Keras. The model consists of an Embedding() layer, an LSTM() layer, and a Dense() layer. The Embedding() layer maps the input sequences of integers to vectors of fixed size, which allows the model to learn meaningful representations of the words in the sequences. The LSTM() layer processes the sequences, using the information from previous time steps to make predictions. The Dense() layer

outputs a single value between 0 and 1, which represents the probability that the sentiment of the input sequence is positive.

Compile the model

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

We compile the model using the compile() function, specifying the loss function, optimizer, and metrics to use during training.

Train the model

model.fit(x_train, y_train, validation_data=(x_test, y_test), epochs=5, batch_size=64)

We train the model using the fit() function

Evaluate the model

test_loss, test_accuracy = model.evaluate(x_test, y_test)

print('Test accuracy:', test_accuracy)

Once the model is trained, the next step is to evaluate its performance on the test data. We will use the evaluate method in Keras to evaluate the model.

```
Epoch 1/5
391/391 [==============================] - 90s 224ms/step - loss: 0.4158 -
accuracy: 0.8017 - val_loss: 0.2988 - val_accuracy: 0.8741
Epoch 2/5
391/391 [==============================] - 85s 216ms/step - loss: 0.2428 -
accuracy: 0.9062 - val_loss: 0.3196 - val_accuracy: 0.8702
Epoch 3/5
391/391 [==============================] - 85s 217ms/step - loss: 0.1863 -
accuracy: 0.9306 - val_loss: 0.3453 - val_accuracy: 0.8642
Epoch 4/5
```

```
391/391 [==============================] - 86s 220ms/step - loss: 0.1401 -
accuracy: 0.9495 - val_loss: 0.3542 - val_accuracy: 0.8557
Epoch 5/5
391/391 [==============================] - 86s 220ms/step - loss: 0.1171 -
accuracy: 0.9586 - val_loss: 0.3992 - val_accuracy: 0.8589
782/782 [==============================] - 27s 34ms/step - loss: 0.3992 - accuracy:
0.8589
    Test accuracy: 0.8588799834251404
```