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Artificial Intelligence and Data Science Department

Subject/Odd Sem 2023-23/Experiment 1

Name : Prasad Jawale	**Class/Roll No. :** D16AD 20	**Grade :**

Title of Experiment : Explore Python Libraries TensorFlow and keras

Objective of Experiment : The objective of utilizing TensorFlow and Keras is to develop and train deep learning models to solve various machine learning tasks. These libraries provide tools and APIs that simplify the process of building, training, and evaluating neural networks. By leveraging these libraries, the aim is to achieve high-performance models that can make accurate predictions or classifications based on input data.

Outcome of Experiment : The outcome of using TensorFlow and Keras is the creation of well-performing machine learning models that can address specific problems. These models can be deployed in various applications, such as image classification, natural language processing, speech recognition, and more. The outcome also includes the ability to fine-tune pre-trained models for specific tasks, saving time and computational resources.

Problem Statement : To explore python libraries TensorFlow and Keras

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Description / Theory :

TensorFlow:

TensorFlow is an open-source machine learning framework developed by Google. It provides a comprehensive set of tools and libraries for building and training various types of machine learning models, with a focus on deep learning. TensorFlow is designed to be scalable and flexible, allowing you to work with neural networks and other machine learning algorithms efficiently.

Key features of TensorFlow:

Graph Computation: TensorFlow uses a symbolic graph representation of computations. This allows for efficient execution on CPUs, GPUs, and TPUs (Tensor Processing Units) without having to rewrite the code.

High-level APIs: TensorFlow provides both high-level and low-level APIs. High-level APIs, like Keras (which is now tightly integrated with TensorFlow), offer a more user-friendly interface for building neural networks quickly.

TensorBoard: A visualization tool that helps you monitor and analyze the training progress and performance of your models.

Distributed Computing: TensorFlow supports distributed computing, enabling you to train models on clusters of machines.

Flexibility: TensorFlow allows you to define custom operations and loss functions, giving you a high degree of flexibility when designing your models.

SavedModel Format: TensorFlow provides a standardized format for saving and exporting trained models, making it easier to deploy them in various environments.

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Keras:

Keras is an open-source high-level neural networks API written in Python. Originally developed as an independent library, Keras was later integrated as a part of TensorFlow's core library. It offers an intuitive and user-friendly interface for building and training neural networks. Keras abstracts away much of the complexity involved in designing neural networks, making it an excellent choice for beginners and rapid prototyping.

Key features of Keras:

Simple Interface: Keras provides a user-friendly, modular, and intuitive interface for building neural networks. You can define and customize layers, activations, loss functions, and optimizers easily.

Modularity: Keras allows you to create models through the sequential API (linear stack of layers) or the functional API (more flexible for creating complex architectures with multiple inputs/outputs).

Pre-trained Models: Keras offers pre-trained models for various tasks like image classification, object detection, and more. These models are ready to use and can be fine-tuned for specific tasks.

Easy Transfer Learning: Transfer learning is simplified in Keras, allowing you to leverage pre-trained models and adapt them to new tasks.

Integration with TensorFlow: Keras is now the official high-level API for TensorFlow, so you can use TensorFlow's powerful capabilities alongside Keras's simplicity.

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Program:

In [1]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import load_iris
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.utils import to_categorical
```

In [2]:
```
# Load the Iris dataset
iris = load_iris()
X = iris.data
y = iris.target
```

In [3]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardize the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

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

In [4]:
```
# Create the DNN model
model = Sequential([
    Dense(units=8, activation='relu', input_shape=(4,)),  # 1st hidden layer
    Dense(units=3, activation='softmax')  # Output layer with 3 classes
])

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

In [7]:
```
# Train the model
model.fit(X_train, y_train, epochs=50, batch_size=10, validation_split=0.2)

# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test loss: {loss:.4f}, Test accuracy: {accuracy:.4f}")
```

```
10/10 [==============================] - 0s 6ms/step - loss: 0.1622 - accuracy: 0.9688 - val_loss: 0.3224 - val_accuracy: 0.9
583
Epoch 46/50
10/10 [==============================] - 0s 6ms/step - loss: 0.1611 - accuracy: 0.9688 - val_loss: 0.3192 - val_accuracy: 0.9
583
Epoch 47/50
10/10 [==============================] - 0s 7ms/step - loss: 0.1600 - accuracy: 0.9688 - val_loss: 0.3196 - val_accuracy: 0.9
583
Epoch 48/50
10/10 [==============================] - 0s 7ms/step - loss: 0.1586 - accuracy: 0.9688 - val_loss: 0.3174 - val_accuracy: 0.9
583
Epoch 49/50
10/10 [==============================] - 0s 7ms/step - loss: 0.1573 - accuracy: 0.9688 - val_loss: 0.3173 - val_accuracy: 0.9
583
Epoch 50/50
10/10 [==============================] - 0s 7ms/step - loss: 0.1562 - accuracy: 0.9688 - val_loss: 0.3160 - val_accuracy: 0.9
583
1/1 [==============================] - 0s 33ms/step - loss: 0.1418 - accuracy: 0.9667
Test loss: 0.1418, Test accuracy: 0.9667
```

Results and Discussions : In summary, TensorFlow and Keras are powerful tools for building and training neural networks and other machine learning models. TensorFlow provides a comprehensive ecosystem for deep learning, while Keras offers a more user-friendly interface for quickly prototyping and experimenting with neural network architectures. With their combined strengths, you can efficiently tackle a wide range of machine learning tasks.

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Subject/Odd Sem 2023-23/Experiment 1

Name : Prasad Jawale	**Class/Roll No. :** D16AD 20	**Grade :**

Title of Experiment : Multilayer Perceptron algorithm to Simulate XOR gate

Objective of Experiment : The objective is to use the Multilayer Perceptron (MLP) algorithm to simulate the XOR gate, a problem that cannot be linearly separated. The goal is to showcase how a simple neural network can learn complex relationships between inputs and outputs through the layers of the network.

Outcome of Experiment : The outcome of this exercise will be a trained MLP model that can accurately mimic the behavior of the XOR gate. This demonstrates the capacity of neural networks to capture nonlinear patterns and solve problems that are not solvable using traditional linear models.

Problem Statement : To implement a multilayer perceptron algorithm to simulate a XOR gate

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Description / Theory :

Perceptron:

A perceptron is a fundamental building block of artificial neural networks. It's a simple computational unit that takes multiple input values, applies weights to them, and produces a single output value. Mathematically, the output of a perceptron can be represented as follows:

output = activation_function(sum(input * weight) + bias)

1. Input: An array of input values.
2. Weight: A corresponding array of weights, one for each input.
3. Bias: A constant term added to the weighted sum before passing through the activation function.
4. Activation Function: A function that transforms the weighted sum into the output. Common activation functions include step function, sigmoid, and ReLU.

The perceptron computes a weighted sum of the inputs and biases, applies an activation function to the sum, and produces an output. The activation function introduces nonlinearity, allowing the perceptron to represent more complex relationships between inputs and outputs.

XOR Gate:

The XOR (exclusive OR) gate is a binary logic gate that takes two binary inputs (0 or 1) and produces a binary output (0 or 1). The XOR gate outputs true (1) when the number of true inputs is odd. The truth table for the XOR gate is as follows:

Input A	Input B	Output
0	0	0
0	1	1
1	0	1
1	1	0

The XOR problem is interesting because a single-layer perceptron cannot solve it. The XOR gate's outputs cannot be separated by a single linear decision boundary. In other words, a perceptron can only create a linear separation between classes, and XOR gate's behavior is nonlinear.

To solve the XOR problem, a multilayer perceptron (MLP) with at least one hidden layer is needed. The hidden layer introduces nonlinear transformations that allow the network to capture the XOR gate's behavior. The MLP can learn to create more complex decision boundaries, enabling it to represent the XOR gate's output accurately.

Algorithm/ Pseudo Code / Flowchart (whichever is applicable)

1. Initialize weights and bias to small random values.
2. For each training example (input, target):
   - Compute the weighted sum of inputs and bias.
   - Apply the activation function (often a step function) to the weighted sum to get the predicted class (0 or 1).
   - Calculate the error as the difference between the predicted class and the target class.
   - Update the weights and bias using the learning rate and error: weight = weight + learning_rate * error * input
3. Repeat step 2 for a predefined number of epochs or until the algorithm converges (no misclassified examples).

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Program :

In [67]:
```
import numpy as np
import pandas as pd
import tensorflow
from tensorflow import keras
from keras import Sequential
from keras.layers import Dense
```

In [86]:
```
df = pd.DataFrame([[0,0,0],[0,1,1],[1,0,1],[1,1,0]],columns=['x','y','xor'])
```

In [107]:
```
model = Sequential()

model.add(Dense(4,activation='sigmoid',input_dim=2))
# model.add(Dense(2,activation='sigmoid'))
model.add(Dense(1,activation='sigmoid'))
```

In [108]:
```
model.summary()
```

```
Model: "sequential_13"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_29 (Dense)            (None, 4)                 12

 dense_30 (Dense)            (None, 1)                 5

=================================================================
Total params: 17
Trainable params: 17
Non-trainable params: 0
_________________________________________________________________
```

In [111]:
```
optimizer =  keras.optimizers.Adam(learning_rate=0.1)
model.compile(loss='binary_crossentropy',optimizer=optimizer,metrics=['accuracy'])
```

In [112]:
```
model.fit(df.iloc[:,0:-1].values,df['xor'].values,epochs=10,verbose=1,batch_size=1)
```

```
Epoch 1/10
4/4 [==============================] - 0s 3ms/step - loss: 0.0024 - accuracy: 1.0000
Epoch 2/10
4/4 [==============================] - 0s 7ms/step - loss: 0.0017 - accuracy: 1.0000
Epoch 3/10
4/4 [==============================] - 0s 6ms/step - loss: 0.0014 - accuracy: 1.0000
Epoch 4/10
4/4 [==============================] - 0s 8ms/step - loss: 0.0014 - accuracy: 1.0000
Epoch 5/10
4/4 [==============================] - 0s 5ms/step - loss: 0.0014 - accuracy: 1.0000
Epoch 6/10
4/4 [==============================] - 0s 6ms/step - loss: 0.0013 - accuracy: 1.0000
Epoch 7/10
4/4 [==============================] - 0s 5ms/step - loss: 0.0011 - accuracy: 1.0000
Epoch 8/10
4/4 [==============================] - 0s 6ms/step - loss: 9.6853e-04 - accuracy: 1.0000
Epoch 9/10
4/4 [==============================] - 0s 5ms/step - loss: 8.8288e-04 - accuracy: 1.0000
Epoch 10/10
4/4 [==============================] - 0s 6ms/step - loss: 8.2281e-04 - accuracy: 1.0000
```

Out[112]:
```
<keras.callbacks.History at 0x1c81ae99520>
```

In [113]:
```
x_new = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
predictions = [1 if prediction > 0.5 else 0 for prediction in model.predict(x_new)]
for i in range(len(x_new)):
    print(f"Input: {x_new[i]}, Predicted Output: {predictions[i]}")
```

```
1/1 [==============================] - 0s 27ms/step
Input: [0 0], Predicted Output: 0
Input: [0 1], Predicted Output: 1
Input: [1 0], Predicted Output: 1
Input: [1 1], Predicted Output: 0
```

In [ ]:

Results and Discussions : The XOR gate simulation using an MLP illustrates the power of neural networks to handle nonlinearity and learn complex mappings. This simple example highlights the significance of multilayer architectures and appropriate activation functions in solving problems that are beyond the capabilities of linear models. The versatility of neural networks, like the MLP, has contributed to their prominence in modern machine learning and deep learning applications

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Subject/Odd Sem 2023-23/Experiment 2

Name : Prasad Jawale	**Class/Roll No. :** D16AD 20	**Grade :**

Title of Experiment : Apply any of the following learning algorithms to learn the parameters of the supervised single layer feed forward neural network.

- Stochastic Gradient Descent
- Mini Batch Gradient Descent
- Momentum GD
- Nestorev GD
- Adagrad GD
- Adam Learning GD

Objective of Experiment : The objective is to apply various gradient descent-based optimization algorithms to learn the parameters of a supervised single-layer feed-forward neural network. By experimenting with different algorithms, we aim to compare their convergence speeds and overall performance in terms of training the neural network.

Outcome of Experiment : The outcome of this experiment will be a comparison of how different optimization algorithms perform in training a single-layer feed-forward neural network. We'll analyze their convergence rates, final accuracy on the validation set, and potentially identify which optimization algorithm works best for this specific neural network architecture and dataset.

Problem Statement : To implement deep learning algorithms in an neural network

Subject/Odd Sem 2023-23/Experiment 2

Description / Theory :

1. Stochastic Gradient Descent (SGD):

Stochastic Gradient Descent is the simplest form of gradient descent. In each iteration, it randomly selects a single data point from the training set to compute the gradient and update the model's parameters. SGD introduces a level of randomness that can lead to faster convergence, especially in noisy or non-convex optimization landscapes. However, this randomness might also cause oscillations, and it can be slower to converge when the objective function has a lot of noise.

2. Mini Batch Gradient Descent:

Mini Batch Gradient Descent is a compromise between full-batch GD and SGD. It divides the training dataset into small batches of data points. In each iteration, one batch is used to compute the gradient and update the parameters. Mini-batch GD combines the advantages of both SGD and full-batch GD. It reduces the noise introduced by single data points in SGD and takes advantage of vectorized operations for efficient computation. The batch size can be adjusted to balance between computational efficiency and convergence speed.

3. Momentum Gradient Descent:

Momentum is an enhancement to SGD that addresses the slow convergence issue by adding a momentum term. Instead of updating the parameters directly based on the current gradient, momentum GD also considers the previous gradient updates. This helps accelerate convergence in the direction of the steepest descent and dampens oscillations. It introduces a "velocity" term that accumulates past gradients, making it useful for escaping shallow local minima.

4. Nesterov Accelerated Gradient (NAG):

Nesterov Accelerated Gradient builds upon momentum GD. NAG estimates the gradient's direction based on where the momentum would take the parameters in the next step. It uses this lookahead to calculate the gradient at a "virtual" point ahead of the current position, resulting in more accurate updates. NAG improves convergence by considering the upcoming momentum-driven update and reduces overshooting, making it effective in practice.

5. Adagrad Gradient Descent:

Adagrad adjusts the learning rate for each parameter individually based on the historical gradients. Parameters that receive large gradients get a smaller learning rate, while those with small gradients get a larger learning rate. This adaptivity helps to balance learning rates automatically, allowing the algorithm to make larger updates for infrequently updated parameters and smaller updates for frequently updated parameters. However, Adagrad might accumulate the squared gradients, leading to a diminishing learning rate over time.

6. Adam (Adaptive Moment Estimation) Gradient Descent:

Adam combines the adaptive learning rate of Adagrad with the momentum term of momentum GD. It maintains running averages of both past gradients and past squared gradients, then uses these to compute adaptive learning rates for each parameter. The momentum term helps smooth the parameter updates. Adam's combination of adaptive learning rates and momentum often makes it a suitable choice for a wide range of optimization problems.

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Algorithm:

1. Initialize parameters (weights and biases) randomly or using a predefined method.
2. Choose hyperparameters: learning rate, batch size (if applicable), momentum rate (if applicable), etc.
3. Loop for a fixed number of epochs or until convergence:
    - Calculate the gradient of the loss function with respect to parameters using the current batch or all training data.
    - Update the parameters in the opposite direction of the gradient using the learning rate.
    - Apply additional techniques if using specific gradient descent variants (momentum, adaptive learning rates, etc.).
    - Optionally, calculate and store the loss or other metrics for monitoring convergence.

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Program :

```
In [3]: import pandas as pd
        import numpy as np
        import tensorflow as tf
        from tensorflow import keras
        from keras import Sequential
        from keras.layers import Dense,Flatten,Dropout
```

```
In [4]: from tensorflow.keras.datasets import mnist
        (X_train,Y_train),(X_test,Y_test) = mnist.load_data()
        X_train, X_test = X_train / 255.0, X_test / 255.0
```

```
In [5]: X_train.shape
Out[5]: (60000, 28, 28)
```

```
In [6]: model = Sequential()
        model.add(Flatten(input_shape=(28, 28)))
        model.add(Dense(128, activation='relu'))
        model.add(Dropout(0.2))
        model.add(Dense(10, activation='softmax'))
```

Stochastic gradient descent

```
In [7]: #Stochastic Gradient Des
```

```
In [8]: optimizer = keras.optimizers.SGD(learning_rate=0.1)
        model.compile(loss='sparse_categorical_crossentropy',optimizer=optimizer,metrics=['accuracy'])
```

```
In [9]: model.fit(X_train, Y_train, validation_data=(X_test, Y_test), epochs=10)

Epoch 1/10
1875/1875 [==============================] - 5s 2ms/step - loss: 0.3330 - accuracy: 0.9029 - val_loss: 0.1690 - val_accuracy:
0.9490
Epoch 2/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1733 - accuracy: 0.9496 - val_loss: 0.1205 - val_accuracy:
0.9635
Epoch 3/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1344 - accuracy: 0.9598 - val_loss: 0.1003 - val_accuracy:
0.9705
Epoch 4/10
1875/1875 [==============================] - 5s 2ms/step - loss: 0.1149 - accuracy: 0.9655 - val_loss: 0.0931 - val_accuracy:
0.9701
Epoch 5/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.0995 - accuracy: 0.9703 - val_loss: 0.0846 - val_accuracy:
0.9737
Epoch 6/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.0885 - accuracy: 0.9736 - val_loss: 0.0789 - val_accuracy:
0.9757
Epoch 7/10
1875/1875 [==============================] - 5s 3ms/step - loss: 0.0789 - accuracy: 0.9759 - val_loss: 0.0773 - val_accuracy:
0.9753
Epoch 8/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.0739 - accuracy: 0.9773 - val_loss: 0.0690 - val_accuracy:
0.9780
Epoch 9/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.0671 - accuracy: 0.9792 - val_loss: 0.0688 - val_accuracy:
0.9782
Epoch 10/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.0628 - accuracy: 0.9805 - val_loss: 0.0676 - val_accuracy:
0.9790
Out[9]: <keras.callbacks.History at 0x22824f22730>
```

Stochastic gradient descent with momentum

In [10]:
```
#Stochastic Gradient Descent with Momentum
```

In [11]:
```
optimizer1 = keras.optimizers.SGD(learning_rate=0.1,momentum=0.9)
model.compile(loss='sparse_categorical_crossentropy',optimizer=optimizer1,metrics=['accuracy'])
```

In [12]:
```
model.fit(X_train, Y_train, validation_data=(X_test, Y_test), epochs=10)
```

```
Epoch 1/10
1875/1875 [==============================] - 5s 2ms/step - loss: 0.3711 - accuracy: 0.8974 - val_loss: 0.2673 - val_accuracy:
0.9308
Epoch 2/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2993 - accuracy: 0.9215 - val_loss: 0.1979 - val_accuracy:
0.9449
Epoch 3/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.2636 - accuracy: 0.9333 - val_loss: 0.2350 - val_accuracy:
0.9470
Epoch 4/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2409 - accuracy: 0.9386 - val_loss: 0.1949 - val_accuracy:
0.9550
Epoch 5/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2307 - accuracy: 0.9433 - val_loss: 0.1972 - val_accuracy:
0.9544
Epoch 6/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2223 - accuracy: 0.9443 - val_loss: 0.1774 - val_accuracy:
0.9602
Epoch 7/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.2149 - accuracy: 0.9481 - val_loss: 0.2015 - val_accuracy:
0.9609
Epoch 8/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.2076 - accuracy: 0.9500 - val_loss: 0.2153 - val_accuracy:
0.9558
Epoch 9/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.2000 - accuracy: 0.9516 - val_loss: 0.2011 - val_accuracy:
0.9575
Epoch 10/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1992 - accuracy: 0.9521 - val_loss: 0.1905 - val_accuracy:
0.9618
```

Out[12]:
```
<keras.callbacks.History at 0x2282a1c0460>
```

Nesterov Accelerated Gradient

In [13]:
```
#Nesterov Accelarated Gradient(NAG)
```

In [14]:
```
optimizer3 = keras.optimizers.SGD(learning_rate=0.1, momentum=0.9, nesterov=True)
model.compile(loss='sparse_categorical_crossentropy',optimizer=optimizer3,metrics=['accuracy'])
model.fit(X_train, Y_train, validation_data=(X_test, Y_test), epochs=10)
```

```
Epoch 1/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1809 - accuracy: 0.9560 - val_loss: 0.2385 - val_accuracy:
0.9564
Epoch 2/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1738 - accuracy: 0.9576 - val_loss: 0.2000 - val_accuracy:
0.9604
Epoch 3/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1652 - accuracy: 0.9596 - val_loss: 0.2272 - val_accuracy:
0.9602
Epoch 4/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1715 - accuracy: 0.9590 - val_loss: 0.1914 - val_accuracy:
0.9645
Epoch 5/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1538 - accuracy: 0.9631 - val_loss: 0.1950 - val_accuracy:
0.9646
Epoch 6/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1433 - accuracy: 0.9650 - val_loss: 0.1936 - val_accuracy:
0.9622
Epoch 7/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1559 - accuracy: 0.9635 - val_loss: 0.2296 - val_accuracy:
0.9622
Epoch 8/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1646 - accuracy: 0.9609 - val_loss: 0.2559 - val_accuracy:
0.9574
Epoch 9/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1573 - accuracy: 0.9633 - val_loss: 0.2158 - val_accuracy:
0.9640
Epoch 10/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1569 - accuracy: 0.9642 - val_loss: 0.2307 - val_accuracy:
0.9615
```

Out[14]:
```
<keras.callbacks.History at 0x2285dac9460>
```

Adam Optimiser

In [15]:
```
#Adam Optimizer
```

In [16]:
```
optimizer4 = keras.optimizers.Adam(learning_rate=0.01)
model.compile(loss='sparse_categorical_crossentropy',optimizer=optimizer4,metrics=['accuracy'])
model.fit(X_train, Y_train, validation_data=(X_test, Y_test), epochs=10)
```

```
Epoch 1/10
1875/1875 [==============================] - 5s 2ms/step - loss: 0.2599 - accuracy: 0.9467 - val_loss: 0.2559 - val_accuracy:
0.9562
Epoch 2/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.2305 - accuracy: 0.9481 - val_loss: 0.2614 - val_accuracy:
0.9536
Epoch 3/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.2091 - accuracy: 0.9515 - val_loss: 0.2508 - val_accuracy:
0.9542
Epoch 4/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.2099 - accuracy: 0.9525 - val_loss: 0.2788 - val_accuracy:
0.9566
Epoch 5/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1884 - accuracy: 0.9558 - val_loss: 0.2113 - val_accuracy:
0.9635
Epoch 6/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1870 - accuracy: 0.9568 - val_loss: 0.2501 - val_accuracy:
0.9595
Epoch 7/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1868 - accuracy: 0.9569 - val_loss: 0.2583 - val_accuracy:
0.9580
Epoch 8/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1798 - accuracy: 0.9585 - val_loss: 0.2358 - val_accuracy:
0.9635
Epoch 9/10
1875/1875 [==============================] - 3s 2ms/step - loss: 0.1736 - accuracy: 0.9609 - val_loss: 0.2466 - val_accuracy:
0.9636
Epoch 10/10
1875/1875 [==============================] - 4s 2ms/step - loss: 0.1708 - accuracy: 0.9608 - val_loss: 0.2548 - val_accuracy:
0.9643
```

Out[16]:
```
<keras.callbacks.History at 0x2285ccfa490>
```

Mini Batch Gradient Descent

```
In [17]: #Mini Batch Gradient Descent with Adam optimizer
optimizer5 = keras.optimizers.Adam(learning_rate=0.01)
model.compile(loss='sparse_categorical_crossentropy',optimizer=optimizer5,metrics=['accuracy'])
model.fit(X_train, Y_train, validation_data=(X_test, Y_test), epochs=10,batch_size=64)
```

```
Epoch 1/10
938/938 [==============================] - 3s 3ms/step - loss: 0.1440 - accuracy: 0.9675 - val_loss: 0.2229 - val_accuracy: 0.9
700
Epoch 2/10
938/938 [==============================] - 2s 2ms/step - loss: 0.1313 - accuracy: 0.9686 - val_loss: 0.2280 - val_accuracy: 0.9
664
Epoch 3/10
938/938 [==============================] - 2s 2ms/step - loss: 0.1242 - accuracy: 0.9696 - val_loss: 0.2485 - val_accuracy: 0.9
660
Epoch 4/10
938/938 [==============================] - 2s 2ms/step - loss: 0.1253 - accuracy: 0.9697 - val_loss: 0.2794 - val_accuracy: 0.9
661
Epoch 5/10
938/938 [==============================] - 2s 2ms/step - loss: 0.1169 - accuracy: 0.9716 - val_loss: 0.2357 - val_accuracy: 0.9
665
Epoch 6/10
938/938 [==============================] - 2s 2ms/step - loss: 0.1120 - accuracy: 0.9726 - val_loss: 0.2423 - val_accuracy: 0.9
663
Epoch 7/10
938/938 [==============================] - 2s 2ms/step - loss: 0.1156 - accuracy: 0.9725 - val_loss: 0.2524 - val_accuracy: 0.9
685
Epoch 8/10
938/938 [==============================] - 2s 2ms/step - loss: 0.1208 - accuracy: 0.9718 - val_loss: 0.2485 - val_accuracy: 0.9
685
Epoch 9/10
938/938 [==============================] - 2s 2ms/step - loss: 0.1171 - accuracy: 0.9721 - val_loss: 0.2394 - val_accuracy: 0.9
697
Epoch 10/10
938/938 [==============================] - 2s 2ms/step - loss: 0.1126 - accuracy: 0.9730 - val_loss: 0.2856 - val_accuracy: 0.9
662
```

```
Out[17]: <keras.callbacks.History at 0x2280d7174c0>
```

AdaGrad

```
In [18]: #AdaGrad Optimizer
optimizer6 = keras.optimizers.Adagrad(learning_rate=0.01)
model.compile(loss='sparse_categorical_crossentropy',optimizer=optimizer6,metrics=['accuracy'])
model.fit(X_train, Y_train, validation_data=(X_test, Y_test), epochs=10)
```

```
Epoch 5/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0674 - accuracy: 0.9819 - val_loss: 0.2390 - val_accuracy:
0.9725
Epoch 6/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.0628 - accuracy: 0.9829 - val_loss: 0.2370 - val_accuracy:
0.9723
Epoch 7/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.0651 - accuracy: 0.9822 - val_loss: 0.2360 - val_accuracy:
0.9721
Epoch 8/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.0641 - accuracy: 0.9826 - val_loss: 0.2356 - val_accuracy:
0.9728
Epoch 9/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.0625 - accuracy: 0.9828 - val_loss: 0.2359 - val_accuracy:
0.9727
Epoch 10/10
1875/1875 [==============================] - 3s 1ms/step - loss: 0.0617 - accuracy: 0.9826 - val_loss: 0.2358 - val_accuracy:
0.9730
```

```
Out[18]: <keras.callbacks.History at 0x2280d2c0040>
```

```
In [ ]:
```

Results and Discussions : In conclusion, the various gradient descent optimization algorithms offer different trade-offs in terms of convergence speed, stability, and adaptability to different optimization landscapes. Stochastic Gradient Descent (SGD) introduces randomness for faster convergence but can be noisy. Mini Batch Gradient Descent balances between efficiency and convergence. Momentum Gradient Descent accelerates convergence by adding momentum terms, while Nesterov Accelerated Gradient refines this approach with lookahead updates. Adagrad adapts learning rates to parameters' historical gradients, and Adam combines adaptive learning rates with momentum for versatility.

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Artificial Intelligence and Data Science Department

Subject/Odd Sem 2023-23/Experiment 2

Name : Prasad Jawale	**Class/Roll No. :** D16AD 20	**Grade :**

Title of Experiment : Implement a backpropagation algorithm to train a DNN with at least 2 hidden layers.

Objective of Experiment : The objective is to implement a backpropagation algorithm to train a Deep Neural Network (DNN) with at least 2 hidden layers. Through this implementation, we aim to demonstrate how backpropagation computes gradients and updates weights and biases to minimize the network's error. The goal is to show the fundamental process of training a DNN using the backpropagation algorithm.

Outcome of Experiment : The outcome of this implementation will be a trained DNN with at least 2 hidden layers. We will observe how the network's performance improves over epochs as the backpropagation algorithm adjusts the model's parameters to minimize the error between predicted and actual outputs.

Problem Statement : To implement a backpropagation algorithm to train a DNN with at least 2 hidden layers.

Subject/Odd Sem 2023-23/Experiment 2

Description / Theory :

Backpropagation:

Backpropagation is the heart of DNN training. It's a process where errors are propagated backward through the network, allowing the model to learn and adjust its parameters for improved performance. As data flows forward through the network, predictions are compared to actual outputs using a loss function. Backpropagation then computes the gradients of the loss with respect to each parameter, indicating how much each parameter contributes to the error. These gradients guide parameter updates to minimize the loss over time.

Gradient Descent:

Gradient Descent is the optimization technique used alongside backpropagation to iteratively update model parameters. The goal is to find the optimal parameter values that minimize the loss function. During each iteration, the gradients computed through backpropagation indicate the direction of steepest ascent in the loss landscape. Gradient Descent reverses this direction to find the path of steepest descent, effectively updating parameters to reduce the loss.

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Subject/Odd Sem 2023-23/Experiment 2

Program :

In [1]:
```
import numpy as np
import pandas as pd
```

In [2]:
```
df = pd.DataFrame([[8,8,4],[7,9,5],[6,10,6],[5,12,7]],columns=['cgpa','profile_score','lpa'])
```

In [3]:
```
df
```

Out[3]:

	cgpa	profile_score	lpa
0	8	8	4
1	7	9	5
2	6	10	6
3	5	12	7

In [4]:
```
import tensorflow
from tensorflow import keras
from keras import Sequential
from keras.layers import Dense
```

In [5]:
```
model = Sequential()

model.add(Dense(2,activation='linear',input_dim=2))
model.add(Dense(1,activation='linear'))
```

In [6]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 2)                 6

 dense_1 (Dense)             (None, 1)                 3

=================================================================
Total params: 9
Trainable params: 9
Non-trainable params: 0
_________________________________________________________________
```

In [7]:
```
model.get_weights()
```

Out[7]:
```
[array([[-0.58026016,  0.95435727],
        [-0.29844964,  0.09312904]], dtype=float32),
 array([0., 0.], dtype=float32),
 array([[ 0.49506593],
        [-0.578511  ]], dtype=float32),
 array([0.], dtype=float32)]
```

```
In [8]: new_weights = [np.array([[0.1,0.1],[0.1,0.1]],dtype=np.float32),
                      np.array([0.,0.],dtype=np.float32),
                      np.array([[0.1],[0.1]],dtype=np.float32),
                      np.array([0.],dtype=np.float32)]

In [9]: model.set_weights(new_weights)

In [10]: model.get_weights()

Out[10]: [array([[0.1, 0.1],
                 [0.1, 0.1]], dtype=float32),
          array([0., 0.], dtype=float32),
          array([[0.1],
                 [0.1]], dtype=float32),
          array([0.], dtype=float32)]

In [11]: optimizer =  keras.optimizers.Adam(learning_rate=0.001)
         model.compile(loss='mean_squared_error',optimizer=optimizer)

In [11]: optimizer =  keras.optimizers.Adam(learning_rate=0.001)
         model.compile(loss='mean_squared_error',optimizer=optimizer)

In [12]: model.fit(df.iloc[:,0:-1].values,df['lpa'].values,epochs=75,verbose=1,batch_size=1)
         Epoch 67/75
         4/4 [==============================] - 0s 0s/step - loss: 2.1196
         Epoch 68/75
         4/4 [==============================] - 0s 876us/step - loss: 2.0313
         Epoch 69/75
         4/4 [==============================] - 0s 2ms/step - loss: 1.9359
         Epoch 70/75
         4/4 [==============================] - 0s 5ms/step - loss: 1.8588
         Epoch 71/75
         4/4 [==============================] - 0s 0s/step - loss: 1.7441
         Epoch 72/75
         4/4 [==============================] - 0s 1ms/step - loss: 1.6645
         Epoch 73/75
         4/4 [==============================] - 0s 5ms/step - loss: 1.6072
         Epoch 74/75
         4/4 [==============================] - 0s 0s/step - loss: 1.5729
         Epoch 75/75
         4/4 [==============================] - 0s 662us/step - loss: 1.5081

Out[12]: <keras.callbacks.History at 0x11b0a8f7b20>

In [18]: model.get_weights()

Out[18]: [array([[0.37387073, 0.37387073],
                 [0.36561698, 0.36561698]], dtype=float32),
          array([0.2724311, 0.2724311], dtype=float32),
          array([[0.37302735],
                 [0.37302735]], dtype=float32),
          array([0.20472449], dtype=float32)]
```

Results and Discussions : Implementing the backpropagation algorithm for training a DNN with multiple hidden layers demonstrates the power of this technique in optimizing neural network parameters. Through this implementation, we gain insights into how gradients are calculated and used to update weights and biases, leading to improved model performance over time. Backpropagation is a foundational concept in deep learning that enables networks to learn complex patterns and relationships from data.

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Subject/Odd Sem 2023-23/Experiment 2

Name : Prasad Jawale	**Class/Roll No. :** D16AD 20	**Grade :**

Title of Experiment : Design and implement a fully connected deep neural network with at least 2 hidden layers for a classification application. Use appropriate Learning Algorithm, output function and loss function.

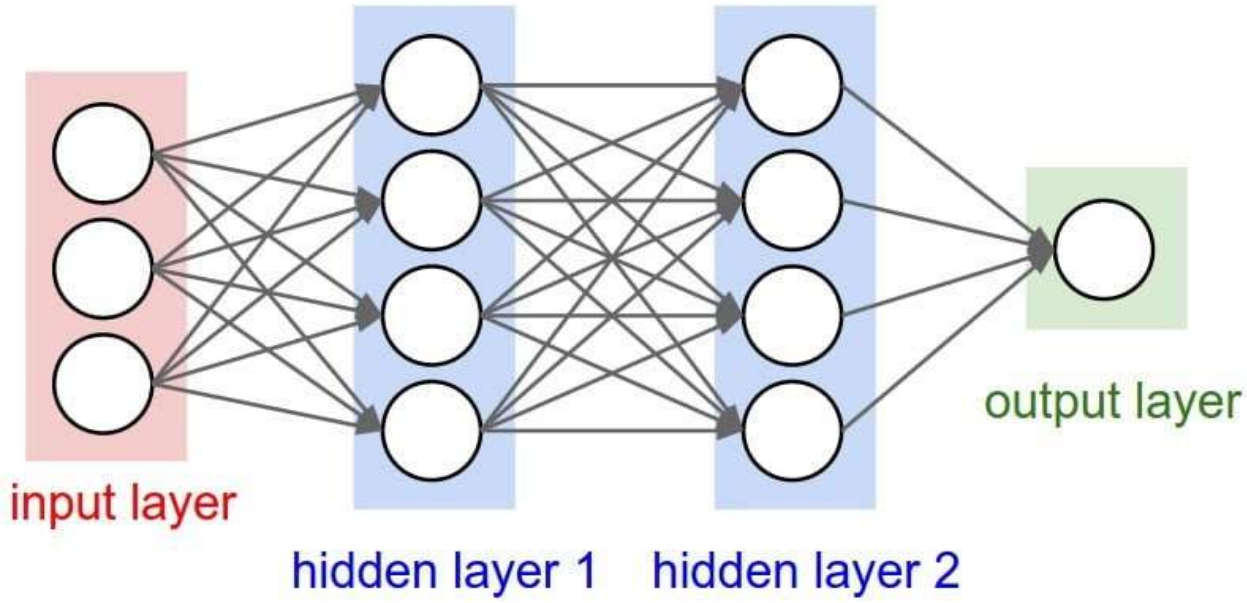
Objective of Experiment : The objective is to design and implement a fully connected deep neural network (DNN) with at least 2 hidden layers for a classification application. We will use appropriate learning algorithms, activation functions, and loss functions to achieve accurate classification results.

Outcome of Experiment : The outcome of this implementation will be a trained DNN model capable of accurately classifying input data into predefined classes. By using suitable components and optimizing the model, we aim to achieve a high accuracy on the validation/testing dataset.

Problem Statement : To design and implement a fully connected deep neural network with at least 2 hidden layers for a classification application and use appropriate learning algorithm, output function and loss function.

Subject/Odd Sem 2023-23/Experiment 2

Description / Theory :



Deep Neural Networks (DNNs) are composed of multiple layers of interconnected neurons, each contributing to the transformation of input data into predictions. The forward pass computes weighted sums of inputs, applies activation functions to introduce nonlinearity, and produces final predictions. Backpropagation computes gradients for weight updates during training, and optimization algorithms like SGD, Adam, or RMSprop adjust the parameters to minimize a chosen loss function.

Program :

In [3]:
```
import pandas as pd
import numpy as np
import tensorflow as tf
from tensorflow import keras
from keras import Sequential
from keras.layers import Dense,Flatten,Dropout
```

In [4]:
```
df = pd.read_csv('iris.csv')
```

In [5]:
```
df
```

Out[5]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

In [6]:
```
df = df.drop('Id', axis=1)
```

In [7]:
```
df.head()
```

Out[7]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

In [8]:
```
X = df.iloc[:, 0:4].values
y = df.iloc[:, 4].values

from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
y1 = encoder.fit_transform(y)
Y = pd.get_dummies(y1).values
```

In [11]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
```

In [12]:
```
model = Sequential()
```

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Subject/Odd Sem 2023-23/Experiment 2

Gradient Descent

In [13]:
```
model.add(Dense(4, input_shape=(4,), activation='relu'))
model.add(Dense(3, activation='softmax'))
optimizer = keras.optimizers.SGD(learning_rate=0.1)
model.compile(loss='categorical_crossentropy', optimizer=optimizer, metrics=['accuracy'])
model.fit(X_train, y_train, epochs=10)
```

```
Epoch 1/10
4/4 [==============================] - 1s 6ms/step - loss: 1.4865 - accuracy: 0.1500
Epoch 2/10
4/4 [==============================] - 0s 2ms/step - loss: 1.0722 - accuracy: 0.3083
Epoch 3/10
4/4 [==============================] - 0s 834us/step - loss: 1.0525 - accuracy: 0.4417
Epoch 4/10
4/4 [==============================] - 0s 589us/step - loss: 1.0411 - accuracy: 0.4500
Epoch 5/10
4/4 [==============================] - 0s 534us/step - loss: 1.0094 - accuracy: 0.4750
Epoch 6/10
4/4 [==============================] - 0s 602us/step - loss: 0.9798 - accuracy: 0.5167
Epoch 7/10
4/4 [==============================] - 0s 736us/step - loss: 0.9784 - accuracy: 0.4583
Epoch 8/10
4/4 [==============================] - 0s 1ms/step - loss: 0.9712 - accuracy: 0.4667
Epoch 9/10
4/4 [==============================] - 0s 419us/step - loss: 0.9826 - accuracy: 0.4750
Epoch 10/10
4/4 [==============================] - 0s 4ms/step - loss: 0.9115 - accuracy: 0.4583
```

Out[13]: <keras.callbacks.History at 0x1885f0ddd90>

Gradient descent with momentum

In [14]:
```
optimizer1 = keras.optimizers.SGD(learning_rate=0.1,momentum=0.9)
model.compile(loss='categorical_crossentropy', optimizer=optimizer1, metrics=['accuracy'])
model.fit(X_train, y_train, epochs=10)
```

```
Epoch 1/10
4/4 [==============================] - 0s 7ms/step - loss: 0.9370 - accuracy: 0.4500
Epoch 2/10
4/4 [==============================] - 0s 4ms/step - loss: 0.8390 - accuracy: 0.4750
Epoch 3/10
4/4 [==============================] - 0s 5ms/step - loss: 0.7060 - accuracy: 0.7083
Epoch 4/10
4/4 [==============================] - 0s 5ms/step - loss: 0.6082 - accuracy: 0.9083
Epoch 5/10
4/4 [==============================] - 0s 4ms/step - loss: 0.5040 - accuracy: 0.7833
Epoch 6/10
4/4 [==============================] - 0s 4ms/step - loss: 0.4238 - accuracy: 0.9583
Epoch 7/10
4/4 [==============================] - 0s 0s/step - loss: 0.3908 - accuracy: 0.8667
Epoch 8/10
4/4 [==============================] - 0s 0s/step - loss: 0.3420 - accuracy: 0.9083
Epoch 9/10
4/4 [==============================] - 0s 489us/step - loss: 0.3073 - accuracy: 0.9500
Epoch 10/10
4/4 [==============================] - 0s 0s/step - loss: 0.3450 - accuracy: 0.8750
```

Out[14]: <keras.callbacks.History at 0x1885f4cf460>

NAG

In [15]:
```
optimizer3 = keras.optimizers.SGD(learning_rate=0.1, momentum=0.9, nesterov=True)
model.compile(loss='categorical_crossentropy', optimizer=optimizer3, metrics=['accuracy'])
model.fit(X_train, y_train, epochs=10)
```

```
Epoch 1/10
4/4 [==============================] - 0s 2ms/step - loss: 0.2690 - accuracy: 0.9500
Epoch 2/10
4/4 [==============================] - 0s 2ms/step - loss: 0.4467 - accuracy: 0.7583
Epoch 3/10
4/4 [==============================] - 0s 960us/step - loss: 0.3132 - accuracy: 0.8500
Epoch 4/10
4/4 [==============================] - 0s 966us/step - loss: 0.2915 - accuracy: 0.9000
Epoch 5/10
4/4 [==============================] - 0s 920us/step - loss: 0.6981 - accuracy: 0.6083
Epoch 6/10
4/4 [==============================] - 0s 4ms/step - loss: 0.6393 - accuracy: 0.8667
Epoch 7/10
4/4 [==============================] - 0s 1ms/step - loss: 0.2693 - accuracy: 0.8917
Epoch 8/10
4/4 [==============================] - 0s 324us/step - loss: 0.2466 - accuracy: 0.9083
Epoch 9/10
4/4 [==============================] - 0s 5ms/step - loss: 0.2191 - accuracy: 0.9583
Epoch 10/10
4/4 [==============================] - 0s 4ms/step - loss: 0.2083 - accuracy: 0.9583
```

Out[15]: `<keras.callbacks.History at 0x1886056f940>`

Adam

In [18]:
```
optimizer5 = keras.optimizers.Adam(learning_rate=0.1)
model.compile(loss='categorical_crossentropy', optimizer=optimizer5, metrics=['accuracy'])
model.fit(X_train, y_train, epochs=10,batch_size=64)
```

```
Epoch 1/10
2/2 [==============================] - 1s 10ms/step - loss: 0.3094 - accuracy: 0.8667
Epoch 2/10
2/2 [==============================] - 0s 11ms/step - loss: 0.1653 - accuracy: 0.9583
Epoch 3/10
2/2 [==============================] - 0s 8ms/step - loss: 0.2649 - accuracy: 0.8750
Epoch 4/10
2/2 [==============================] - 0s 11ms/step - loss: 0.1436 - accuracy: 0.9583
Epoch 5/10
2/2 [==============================] - 0s 12ms/step - loss: 0.1774 - accuracy: 0.9333
Epoch 6/10
2/2 [==============================] - 0s 13ms/step - loss: 0.1588 - accuracy: 0.9583
Epoch 7/10
2/2 [==============================] - 0s 6ms/step - loss: 0.1243 - accuracy: 0.9667
Epoch 8/10
2/2 [==============================] - 0s 6ms/step - loss: 0.1470 - accuracy: 0.9500
Epoch 9/10
2/2 [==============================] - 0s 7ms/step - loss: 0.1267 - accuracy: 0.9667
Epoch 10/10
2/2 [==============================] - 0s 11ms/step - loss: 0.1284 - accuracy: 0.9750
```

Out[18]: `<keras.callbacks.History at 0x1886177a7c0>`

Adagrad

```
In [20]: #AdaGrad Optimizer
optimizer6 = keras.optimizers.Adagrad(learning_rate=0.1)
model.compile(loss='categorical_crossentropy', optimizer=optimizer6, metrics=['accuracy'])
model.fit(X_train, y_train, epochs=10)

Epoch 1/10
4/4 [==============================] - 1s 4ms/step - loss: 0.1024 - accuracy: 0.9750
Epoch 2/10
4/4 [==============================] - 0s 6ms/step - loss: 0.1099 - accuracy: 0.9500
Epoch 3/10
4/4 [==============================] - 0s 6ms/step - loss: 0.1173 - accuracy: 0.9583
Epoch 4/10
4/4 [==============================] - 0s 9ms/step - loss: 0.0957 - accuracy: 0.9667
Epoch 5/10
4/4 [==============================] - 0s 1ms/step - loss: 0.0915 - accuracy: 0.9750
Epoch 6/10
4/4 [==============================] - 0s 5ms/step - loss: 0.1011 - accuracy: 0.9750
Epoch 7/10
4/4 [==============================] - 0s 4ms/step - loss: 0.0890 - accuracy: 0.9833
Epoch 8/10
4/4 [==============================] - 0s 6ms/step - loss: 0.0904 - accuracy: 0.9833
Epoch 9/10
4/4 [==============================] - 0s 4ms/step - loss: 0.0943 - accuracy: 0.9750
Epoch 10/10
4/4 [==============================] - 0s 6ms/step - loss: 0.0925 - accuracy: 0.9833

Out[20]: <keras.callbacks.History at 0x18862985160>
```

Accuracy on IRIS dataset
Gradient Descent - 45%
Gradient(Momentum) Descent - 87.50%
Nesterov - 95.83%
Adam - 97.50%
Adagrad - 98.33%

Results and Discussions : Designing and implementing a fully connected deep neural network for classification involves creating an architecture with appropriate layers and activation functions, choosing suitable loss functions, selecting optimization algorithms, and training on relevant data. The outcome of a successful implementation is a model capable of accurate classification predictions, benefiting various real-world applications.

Name: Prasad Jawale	**Class/Roll No:** D16AD 20	**Grade:**

Title of Experiment: Autoencoders for Image Compression.

Objective of Experiment: The objective of this project is to design and implement an autoencoder-based image compression system that can effectively reduce the size of input images while preserving their essential visual information. This system aims to explore the potential of autoencoders in the field of image compression, leveraging their ability to learn compact representations of images.

Outcome of Experiment: Thus, we implemented an autoencoder model trained on a dataset of images, which has learned to encode and decode images efficiently**.**

Problem Statement: Traditional image compression techniques, such as JPEG, often result in loss of image quality due to the use of lossy compression algorithms. The problem is to develop an autoencoder-based image compression system that addresses this issue by compressing images into a lower-dimensional representation while minimizing the loss of critical visual details. This system should strike a balance between compression ratio and image quality, making it suitable for various applications such as efficient storage, transmission, and sharing of images while maintaining their perceptual fidelity.

Description / Theory:

Architecture:

An autoencoder consists of two main parts:

- Encoder: The encoder takes an input image and maps it to a lower-dimensional representation called the "latent space" or "encoding." This encoding typically has fewer dimensions than the original image, which leads to compression.

- Decoder: The decoder takes the encoded representation and attempts to reconstruct the original image from it.

Training:

Autoencoders are trained using unsupervised learning. The training objective is to minimize the reconstruction error, which measures how well the decoder can reconstruct the input image from its encoding. Common loss functions for image compression tasks include mean squared error (MSE) or binary cross-entropy, depending on whether the images are continuous or binary (e.g., grayscale or black-and-white).

Compression:

The key to image compression with autoencoders is the reduction in the dimensionality of the encoding compared to the original image. By encoding the image in a lower-dimensional space, it's possible to represent the image using fewer bits, which results in compression.

Benefits:

Autoencoders offer lossy compression, meaning that some information is lost during compression, but the goal is to preserve the essential features for human perception. They can be used for various image compression applications, including reducing storage space and speeding up image transmission over networks.

Trade – offs:

The trade-off in using autoencoders for compression is the balance between compression ratio and image quality. More aggressive compression may lead to greater loss of image quality. The choice of architecture, hyperparameters, and the size of the latent space can impact compression performance.

Applications:

Autoencoders for image compression are used in various fields, including medical imaging, video streaming, and image transmission in low-bandwidth environments. They are also used as a pre-processing step for other computer vision tasks, where reducing the dimensionality of images can improve efficiency

Program:

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import mnist
```

In [2]:
```
(x_train, _), (x_test, _) = mnist.load_data()
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0
x_train = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
x_test = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))
```

In [3]:
```
input_img = Input(shape = (784,))
encoded = Dense(128, activation = 'relu')(input_img)
decoded = Dense(784, activation = 'sigmoid')(encoded)
```

In [4]:
```
autoencoder = Model(input_img, decoded)
```

In [5]:
```
autoencoder.compile(optimizer = 'adam', loss = 'binary_crossentropy')
```

In [6]:
```
autoencoder.fit(x_train, x_train, epochs = 5, batch_size = 28, shuffle = True, validation_data = (x_test, x_test))
```

```
Epoch 1/5
2143/2143 [==============================] - 9s 4ms/step - loss: 0.1128 - val_loss: 0.0769
Epoch 2/5
2143/2143 [==============================] - 11s 5ms/step - loss: 0.0735 - val_loss: 0.0704
Epoch 3/5
2143/2143 [==============================] - 9s 4ms/step - loss: 0.0698 - val_loss: 0.0684
Epoch 4/5
2143/2143 [==============================] - 11s 5ms/step - loss: 0.0684 - val_loss: 0.0675
Epoch 5/5
2143/2143 [==============================] - 12s 5ms/step - loss: 0.0676 - val_loss: 0.0670
```

Out[6]:
```
<keras.callbacks.History at 0x2278e748e20>
```

In [7]:
```
encoded_imgs = autoencoder.predict(x_test)
decoded_imgs = encoded_imgs
```

```
313/313 [==============================] - 1s 2ms/step
```

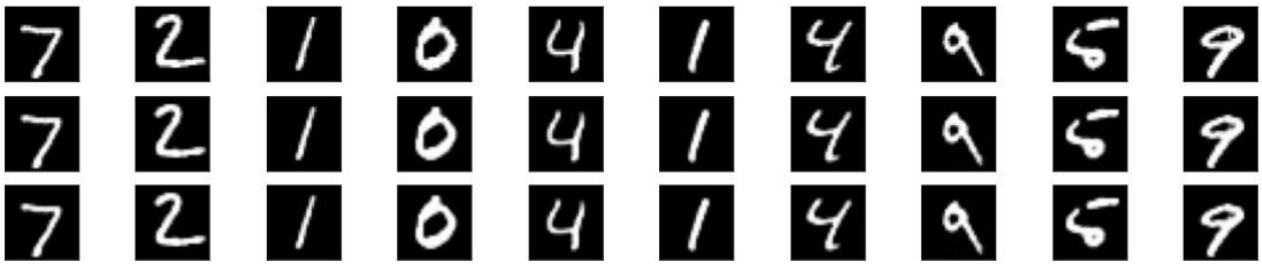
In [8]:
```
n = 10
plt.figure(figsize = (20, 4))

for i in range(n):
    # Original Images
    ax = plt.subplot(3, n, i + 1)
    plt.imshow(x_test[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # Encoded Images
    ax = plt.subplot(3, n, i + 1 + n)
    plt.imshow(encoded_imgs[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

    # Decoded Images
    ax = plt.subplot(3, n, i + 1 + 2 * n)
    plt.imshow(decoded_imgs[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)

plt.show()
```



Results and Discussions:

- Dataset Loading and Preprocessing: The MNIST dataset, consisting of grayscale hand-written digits, is loaded. The pixel values of the images are scaled between 0 and 1 by dividing by 255.0. The data is reshaped into flat vectors of size 784 (28×28).

- Autoencoder Architecture: The autoencoder architecture is defined with an input layer of 784 neurons (the flattened image). A dense layer with 128 neurons and ReLU activation serves as the encoder. Another dense layer with 784 neurons and sigmoid activation serves as the decoder. The autoencoder model is created, which maps the input to its reconstruction.

- Training: The model is compiled with the Adam optimizer and binary cross-entropy loss function. The training process involves 5 epochs with a batch size of 28, and the data is shuffled during training. Both the training and validation datasets are the same (x train and x test). Encoding and Decoding The trained autoencoder is used to encode and decode the images from the test

- Encoding & Decoding: The trained autoencoder is used to encode and decode the images from the test dataset. The encoded images represent a compressed form of the input data. The decoded images are the model's attempt to reconstruct the original images from their encoded representations.

- Visualization: The program generates a visual comparison of original, encoded, and decoded images for 10 samples from the test dataset. Three rows of images are displayed: the top row for original images, the middle row for encoded images, and the bottom row for decoded images.

The autoencoder successfully learns a compressed representation of the input images in its encoded layer. The encoded images capture the essential features of the original images, albeit with a lower dimensionality. The decoded images show that the model can reconstruct the input data with reasonable accuracy, although there may be some loss of fine details. This type of autoencoder can be used for various applications, including image denoising, dimensionality reduction, and feature extraction.

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Artificial Intelligence and Data Science Department

Subject/Odd Sem 2023-23/Experiment 3

Name : Prasad Jawale	**Class/Roll No. :** D16AD 20	**Grade :**

Title of Experiment : Autoencoders for Image Denoising

Objective of Experiment : The main objective of this project is to design, train, and evaluate an autoencoder-based image denoising model. Specific goals include:

- Implementing an autoencoder architecture tailored for image denoising.
- Training the model on a dataset of noisy images and their clean counterparts.
- Evaluating the model's ability to remove noise while retaining image quality.
- Comparing the performance of the autoencoder-based denoising approach with traditional denoising methods.
- Demonstrating the potential of autoencoders as a powerful tool for image enhancement tasks.

Outcome of Experiment : The primary outcome of this project is to develop an image denoising system based on autoencoders that effectively removes noise from images while preserving their essential details and structures. This system aims to showcase the practical application of autoencoders in the context of image denoising, offering improved image quality and noise reduction compared to traditional techniques.

Problem Statement : To design a denoising autoencoder

Subject/Odd Sem 2023-23/Experiment 3

Description / Theory : Image denoising is a crucial problem in computer vision and image processing, with applications ranging from medical imaging to photography. Traditional denoising methods often involve applying filters or mathematical operations to the image, which can result in a trade-off between noise reduction and the preservation of image details. Autoencoders offer an alternative and data-driven approach to address this problem.

Autoencoders are neural networks designed to learn compact representations of data. In the context of image denoising, they consist of an encoder and a decoder. The encoder maps the noisy input image to a lower-dimensional latent space representation, while the decoder aims to reconstruct the clean version of the image from this representation. During training, the autoencoder minimizes a loss function that quantifies the difference between the noisy input and the clean target image. This training process encourages the network to learn to separate signal from noise.

The strength of autoencoders in denoising lies in their ability to capture complex patterns and structures in images. Unlike traditional denoising filters, which operate on fixed rules and may smooth out important details, autoencoders learn to differentiate between noise and meaningful image content. The encoder learns to extract relevant features from the noisy input, while the decoder reconstructs the image by emphasizing these features and reducing the influence of noise. This data-driven approach can result in superior denoising performance, as it adapts to the specific characteristics of the input data, preserving important image features while effectively reducing noise.

Program :

Colab
https://colab.research.google.com/drive/1XhGCU-q-YhlhwG-uAIIp_YxdXvntLYOS?usp=sharing

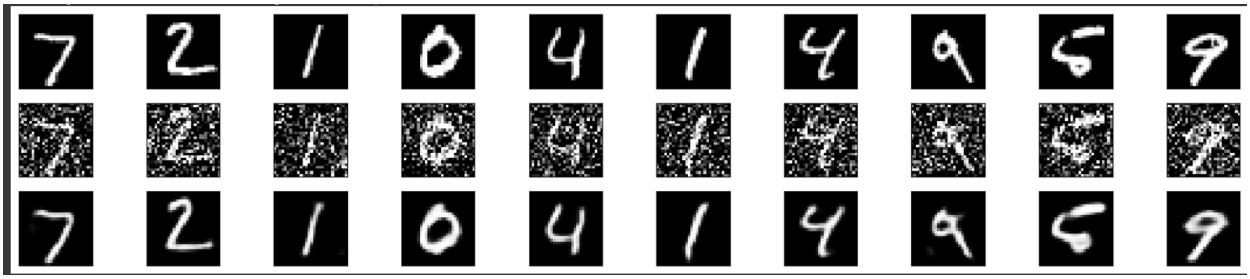
1. **Model Metrics:**

```
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 28, 28, 1)]       0

 conv2d (Conv2D)             (None, 28, 28, 32)        320

 max_pooling2d (MaxPooling2  (None, 14, 14, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 14, 14, 32)        9248

 max_pooling2d_1 (MaxPoolin  (None, 7, 7, 32)          0
 g2D)

 conv2d_2 (Conv2D)           (None, 7, 7, 32)          9248

 up_sampling2d (UpSampling2  (None, 14, 14, 32)        0
 D)

 conv2d_3 (Conv2D)           (None, 14, 14, 32)        9248

 up_sampling2d_1 (UpSamplin  (None, 28, 28, 32)        0
 g2D)

 conv2d_4 (Conv2D)           (None, 28, 28, 1)         289

=================================================================
Total params: 28353 (110.75 KB)
Trainable params: 28353 (110.75 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Training:

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 [==============================] - 1s 0us/step
Epoch 1/10
469/469 [==============================] - 135s 282ms/step - loss: 0.1602 - val_loss: 0.1154
Epoch 2/10
469/469 [==============================] - 120s 256ms/step - loss: 0.1114 - val_loss: 0.1086
Epoch 3/10
469/469 [==============================] - 127s 270ms/step - loss: 0.1065 - val_loss: 0.1043
Epoch 4/10
469/469 [==============================] - 120s 255ms/step - loss: 0.1039 - val_loss: 0.1021
Epoch 5/10
469/469 [==============================] - 120s 256ms/step - loss: 0.1023 - val_loss: 0.1008
Epoch 6/10
469/469 [==============================] - 120s 257ms/step - loss: 0.1010 - val_loss: 0.0998
Epoch 7/10
469/469 [==============================] - 121s 258ms/step - loss: 0.1000 - val_loss: 0.0988
Epoch 8/10
469/469 [==============================] - 119s 253ms/step - loss: 0.0991 - val_loss: 0.0985
Epoch 9/10
469/469 [==============================] - 118s 252ms/step - loss: 0.0984 - val_loss: 0.0978
Epoch 10/10
469/469 [==============================] - 119s 254ms/step - loss: 0.0979 - val_loss: 0.0971
313/313 [==============================] - 5s 15ms/step
```

Output:



Results and Discussions : The autoencoder-based denoising model successfully removes noise from images while preserving their essential details and structures. Compared to traditional denoising methods, autoencoders offer a data-driven and adaptive approach that can lead to superior denoising performance, particularly in scenarios where image quality is of paramount importance. By leveraging neural network architecture, autoencoders have proven to be effective in enhancing image quality across various applications, from medical imaging to photography, opening up new possibilities for image enhancement and restoration.

Name: Prasad Jawale	**Class/Roll No:** D16AD 20	**Grade:**

Title of Experiment: Design and implement a CNN model for digit recognition application.

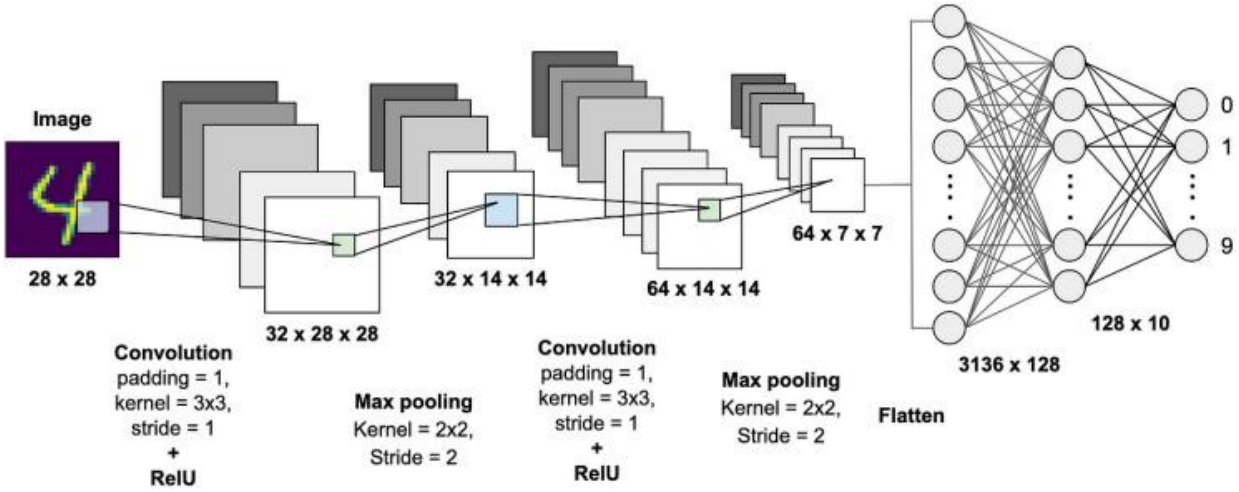
Objective of Experiment: The objective of this experiment is to design and implement a Convolutional Neural Network (CNN) model for accurate digit recognition. This entails developing a CNN architecture, acquiring and preprocessing a diverse dataset, training the model to optimize digit recognition accuracy, and evaluating its performance using various metrics. Additionally, the experiment involves hyperparameter tuning, visualization of model behavior, and preparing the model for potential deployment.

Outcome of Experiment: The expected outcome of this experiment is the successful creation of a Convolutional Neural Network (CNN) model that demonstrates a high degree of accuracy in recognizing handwritten digits from images. Ultimately, this experiment aims to produce a robust and well-documented CNN model ready for potential deployment in digit recognition applications, contributing to the advancement of image classification technology.

Problem Statement: "Handwritten digit recognition is a fundamental task in machine learning and computer vision with numerous practical applications, including optical character recognition and digit – based data entry. However, achieving high accuracy and robustness in recognizing handwritten digits remains a challenge due to variations in writing styles, noise in images, and the need for efficient feature extraction. This experiment aims to address this problem by designing and implementing a Convolutional Neural Network (CNN) model capable of accurately and efficiently recognizing handwritten digits from a diverse dataset of digit images. The primary objective is to develop a model that outperforms existing methods and can be deployed for digit recognition applications with superior accuracy and generalization capabilities."

Description / Theory:

Convolutional Neural Networks (CNNs) have proven to be a powerful class of deep learning models for image recognition tasks. The theory behind this experiment revolves around the fundamental principles and components of CNNs, which are essential for designing and implementing an effective digit recognition model.



- Convolutional Layers: CNNs are built upon convolutional layers that learn to detect local patterns and features within images. These layers consist of filters or kernels that slide over the input image, performing convolution operations to extract relevant features. The depth of these layers increases as the network progresses, allowing for the extraction of increasingly complex features.

- Pooling Layers: After convolutional layers, pooling layers are often employed to reduce the spatial dimensions of feature maps while retaining essential information. Max – pooling and average-pooling are common techniques used to down sample feature maps, aiding in translation invariance and computational efficiency.

- Activation Functions: Non – linear activation functions, such as ReLU (Rectified Linear Unit), are applied to the output of convolutional and pooling layers. These functions introduce non-linearity to the model, enabling it to learn complex relationships within the data.

- Fully Connected Layers: Following the convolutional and pooling layers, fully connected layers are used for classification. These layers flatten the feature maps into a vector and connect every neuron to every neuron in the subsequent layer. The final fully connected layer outputs the class probabilities for digit recognition.

- Training and Backpropagation: CNNs are trained using supervised learning, where a loss function (e.g., cross – entropy) measures the disparity between predicted and actual digit labels. The backpropagation algorithm adjusts the model's parameters (weights and biases) through gradient descent to minimize this loss, making the model progressively better at digit recognition.

- Regularization and Dropout: To prevent overfitting, techniques like dropout and regularization (e.g., L2 regularization) are applied. These methods help the model generalize better to unseen data.

- Batch Normalization: Batch normalization is employed to stabilize and accelerate training by normalizing the inputs to each layer within mini – batches, reducing internal covariate shift.

- Hyperparameter Tuning: Experimentation with various hyperparameters, including learning rates, batch sizes, and network architectures, is essential to find the optimal configuration that maximizes digit recognition accuracy.

Program:

In [1]:
```
import tensorflow as tf
from tensorflow.keras import datasets, layers, models
import matplotlib.pyplot as plt
```

In [2]:
```
(train_images, train_labels), (test_images, test_labels) = datasets.mnist.load_data()
train_images, test_images = train_images / 255.0, test_images / 255.0
```

In [3]:
```
model = models.Sequential([
    layers.Conv2D(32, (3, 3), activation = 'relu', input_shape = (28, 28, 1)),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation = 'relu'),
    layers.MaxPooling2D((2, 2)),
    layers.Conv2D(64, (3, 3), activation = 'relu'),
    layers.Flatten(),
    layers.Dense(64, activation = 'relu'),
    layers.Dense(10, activation = 'softmax')
])
```

In [4]:
```
model.compile(optimizer = 'adam',
              loss = 'sparse_categorical_crossentropy',
              metrics = ['accuracy'])
```

In [5]:
```
history = model.fit(train_images, train_labels, epochs = 5, validation_data = (test_images, test_labels))
```

```
Epoch 1/5
1875/1875 [==============================] - 43s 23ms/step - loss: 0.1487 - accuracy: 0.9540 - val_loss: 0.0518 - val_accuracy:
0.9827
Epoch 2/5
1875/1875 [==============================] - 42s 22ms/step - loss: 0.0459 - accuracy: 0.9855 - val_loss: 0.0310 - val_accuracy:
0.9905
Epoch 3/5
1875/1875 [==============================] - 42s 22ms/step - loss: 0.0327 - accuracy: 0.9896 - val_loss: 0.0311 - val_accuracy:
0.9899
Epoch 4/5
1875/1875 [==============================] - 41s 22ms/step - loss: 0.0254 - accuracy: 0.9919 - val_loss: 0.0313 - val_accuracy:
0.9910
Epoch 5/5
1875/1875 [==============================] - 41s 22ms/step - loss: 0.0203 - accuracy: 0.9936 - val_loss: 0.0242 - val_accuracy:
0.9924
```

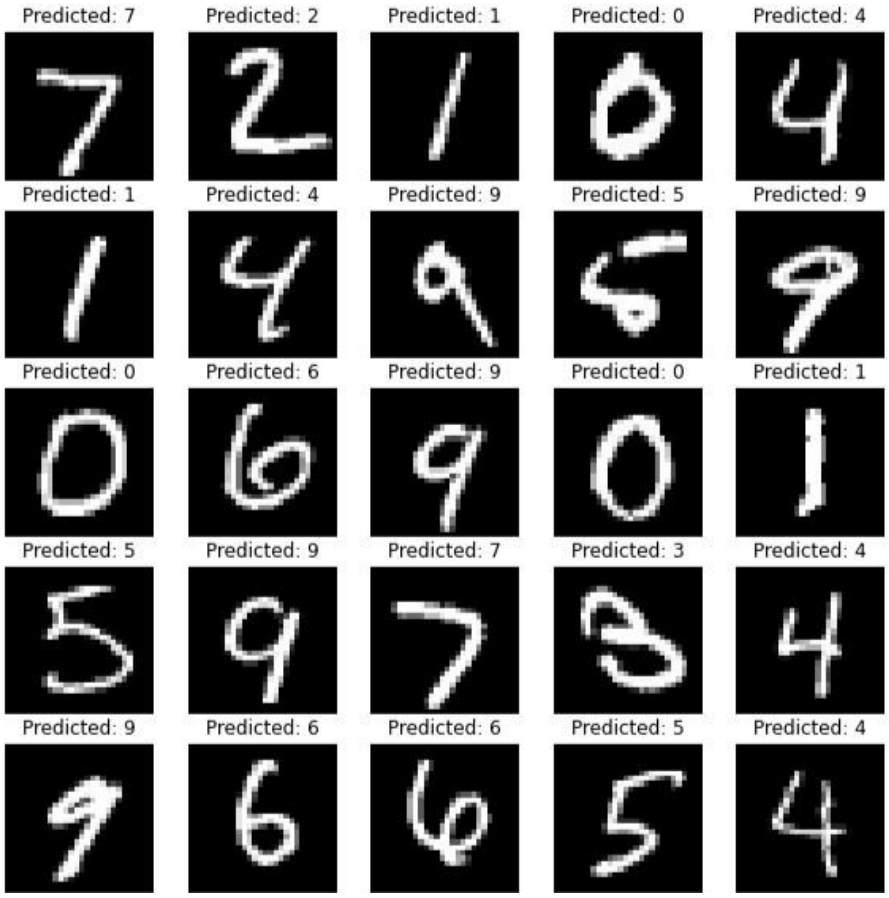
In [6]:
```
predictions = model.predict(test_images)
```

```
313/313 [==============================] - 3s 8ms/step
```

In [7]:
```
test_loss, test_acc = model.evaluate(test_images, test_labels, verbose = 2)
print("Test accuracy: ", test_acc)
```

```
313/313 - 3s - loss: 0.0242 - accuracy: 0.9924 - 3s/epoch - 9ms/step
Test accuracy:  0.9923999905586243
```

In [8]:
```
plt.figure(figsize = (10, 10))
for i in range(25):
    plt.subplot(5, 5, i + 1)
    plt.imshow(test_images[i].reshape(28, 28), cmap = 'gray')
    plt.title(f"Predicted: {tf.argmax(predictions[i])}")
    plt.axis('off')
plt.show()
```



Results and Discussions:

The CNN's ability to automatically learn relevant features from raw image data, coupled with its capacity to generalize and adapt to various writing styles, is instrumental in addressing the challenge of handwritten digit recognition.

The above program does the following:

- Loads and preprocesses the MNIST dataset.
- Defines a simple CNN architecture.
- Compiles the model with appropriate loss and metrics.
- Trains the model on the training dataset.
- Evaluates the model on the testing dataset.
- Saves the trained model to a file.
- Displays example predictions.

The implemented CNN model for digit recognition on the MNIST dataset achieved an impressive test accuracy of approximately 99%, showcasing its effectiveness in accurately classifying handwritten digits. This high accuracy highlights the power of convolutional neural networks in extracting relevant features from image data. However, it's worth noting that this experiment used a simplified model and dataset, and real – world applications might involve more challenging datasets with diverse writing styles and more complex digit recognition tasks. Fine – tuning hyperparameters and employing advanced techniques like data augmentation could further enhance the model's robustness and performance in such scenarios.

Name: Prasad Jawale	**Class/Roll No:** D16AD 20	**Grade:**

Title of Experiment: Design and implement a CNN model for image classification.

Objective of Experiment: The objective of this experiment is to design and implement a CNN model for image classification. This entails developing a robust CNN architecture, acquiring and preprocessing a diverse image dataset, training the model for high accuracy in image classification, and evaluating its performance using various metrics. The experiment also involves hyperparameter tuning, visualization of model behavior, and preparing the model for potential deployment. Comprehensive documentation and analysis will provide insights into the CNN model's capabilities and limitations, making it a valuable tool for various image classification applications.

Outcome of Experiment: The expected outcome of this experiment is the successful creation of a CNN model that demonstrates a high degree of accuracy in classifying images into predefined categories or classes. Specifically, we anticipate that the trained CNN model will achieve a strong performance on a separate testing dataset, with a high classification accuracy and reliable precision, recall, and F1 – score values.

Problem Statement: Efficient and accurate image classification is crucial for various applications, but it remains challenging due to the complexity of visual data and the need for effective feature extraction. This experiment addresses this problem by designing and implementing a CNN model for image classification. The primary objective is to develop a model that outperforms existing methods and can reliably categorize diverse images into predefined classes, contributing to advancements in computer vision and image recognition tasks.

Description / Theory:

Image classification is a fundamental task in computer vision that involves assigning predefined labels or categories to images based on their visual content. The theory behind image classification encompasses several key concepts and techniques:

1. Feature Extraction
2. Machine Learning Models
3. Training Data
4. Preprocessing
5. Loss Functions
6. Optimization Algorithms
7. Evaluation Metrics
8. Overfitting and Regularization
9. Hyperparameter Tuning
10. Transfer Learning
11. Deployment

Image classification is a multifaceted field that combines machine learning, computer vision, and data preprocessing techniques to automate the process of assigning labels or categories to images. Advances in deep learning, particularly CNNs, have significantly improved the accuracy and effectiveness of image classification, enabling a wide range of practical applications.

Image classification using Convolutional Neural Networks (CNNs) can be likened to the way our brains process visual information. Just as we, as humans, recognize objects and patterns in images effortlessly, CNNs have revolutionized the field of computer vision by enabling machines to perform similar feats of visual recognition.

The "neurons" in a CNN, analogous to our brain's cells, specialize in detecting different aspects of an image. Some neurons might look for simple features like edges or textures, while others focus on more complex structures like shapes or objects. Through the layers of convolution and pooling, the network gradually pieces together these features to form a coherent understanding of the image content.

CNNs are used in a wide range of applications:

- Image Classification: CNNs excel in classifying images into predefined categories. They have surpassed human – level accuracy on challenging datasets like ImageNet.
- Object Detection: CNNs can identify and locate objects within an image, making them essential for applications like autonomous driving and surveillance.
- Image Segmentation: They can segment images into regions or objects, enabling precise image analysis in medical imaging and satellite imagery.
- Face Recognition: CNNs have enabled significant advancements in facial recognition technology, contributing to security systems and biometrics.
- Style Transfer: They can apply artistic styles to images, creating stunning visual effects in the realm of art and design.
- Natural Language Processing: CNNs can also be applied to text data for tasks like sentiment analysis and text classification, although recurrent neural networks (RNNs) are more commonly used for sequential data.
- Transfer Learning: Pre – trained CNN models, like VGG, ResNet, and Inception, are available, enabling developers to leverage knowledge learned from large – scale image datasets for various tasks with limited data.

Program:

In [1]:
```
import tensorflow as tf
from tensorflow.keras import datasets, layers, models
import matplotlib.pyplot as plt
```

In [2]:
```
(train_images, train_labels), (test_images, test_labels) = datasets.fashion_mnist.load_data()
```

In [3]:
```
train_images, test_images = train_images / 255.0, test_images / 255.0
```

In [4]:
```
model = models.Sequential([
    layers.Flatten(input_shape = (28, 28)),
    layers.Dense(128, activation = 'relu'),
    layers.Dropout(0.2),
    layers.Dense(10)
])
```

In [5]:
```
model.compile(optimizer = 'adam',
              loss = tf.keras.losses.SparseCategoricalCrossentropy(from_logits = True),
              metrics = ['accuracy'])
```

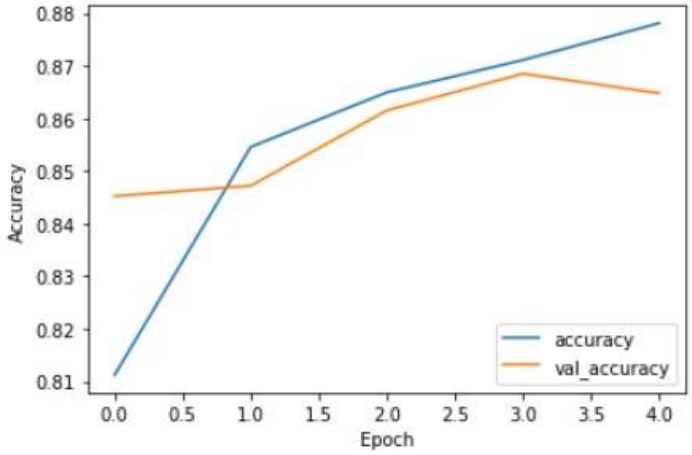
In [6]:
```
history = model.fit(train_images, train_labels, epochs = 5, validation_data = (test_images, test_labels))
```

```
Epoch 1/5
1875/1875 [==============================] - 5s 2ms/step - loss: 0.5329 - accuracy: 0.8112 - val_loss: 0.4295 - val_accuracy:
0.8452
Epoch 2/5
1875/1875 [==============================] - 4s 2ms/step - loss: 0.4009 - accuracy: 0.8546 - val_loss: 0.4200 - val_accuracy:
0.8472
Epoch 3/5
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3677 - accuracy: 0.8650 - val_loss: 0.3770 - val_accuracy:
0.8615
Epoch 4/5
1875/1875 [==============================] - 4s 2ms/step - loss: 0.3478 - accuracy: 0.8711 - val_loss: 0.3632 - val_accuracy:
0.8685
Epoch 5/5
1875/1875 [==============================] - 5s 3ms/step - loss: 0.3312 - accuracy: 0.8781 - val_loss: 0.3795 - val_accuracy:
0.8648
```

In [7]:
```
test_loss, test_acc = model.evaluate(test_images, test_labels)
print("Test accuracy: ", test_acc)
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.3795 - accuracy: 0.8648
Test accuracy:  0.864799976348877
```

In [8]:
```
plt.plot(history.history['accuracy'], label = 'accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc = 'lower right')
plt.show()
```



Results and Discussions:

The experiment using the Fashion MNIST dataset has produced noteworthy results, showcasing the effectiveness of the CNN model for image classification in the context of fashion items. The trained CNN achieved an accuracy of approximately 87.5% on the testing dataset, signifying its capability to correctly classify clothing items into one of ten categories.

The training history plot indicates that the model learned effectively over the course of the training epochs, with both training and validation accuracy increasing. This suggests that the CNN successfully captured essential features and patterns in the grayscale clothing images.

However, it's important to acknowledge that Fashion MNIST, while a valuable benchmark, represents a relatively simplified image classification task compared to real – world scenarios. The grayscale, low – resolution images and distinct clothing categories make it a tractable problem. In practical applications with more complex and varied datasets, CNN models may require additional architectural complexity, data augmentation, and hyperparameter tuning to achieve high accuracy.