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☑ UNDERSTANDING NEURAL NETWORKS: PERCEPTRON, ACTIVATION FUNCTIONS

📌 CHAPTER 1: INTRODUCTION TO NEURAL NETWORKS

1.1 WHAT ARE NEURAL NETWORKS?

NEURAL NETWORKS ARE **COMPUTATIONAL MODELS** INSPIRED BY THE HUMAN BRAIN. THEY ARE USED IN **MACHINE LEARNING AND DEEP LEARNING** TO RECOGNIZE PATTERNS, CLASSIFY DATA, AND MAKE PREDICTIONS.

A NEURAL NETWORK CONSISTS OF:

- **NEURONS (NODES)** – PROCESS INFORMATION.
- **WEIGHTS** – INFLUENCE NEURON CONNECTIONS.
- **ACTIVATION FUNCTIONS** – DECIDE WHETHER NEURONS SHOULD BE ACTIVATED.
- **LAYERS** – ORGANIZE NEURONS INTO AN INPUT LAYER, HIDDEN LAYERS, AND AN OUTPUT LAYER.

📌 Chapter 2: Perceptron – The Foundation of Neural Networks

2.1 What is a Perceptron?

The **Perceptron** is the simplest type of neural network, used for **binary classification** problems. It mimics a **biological neuron**, deciding whether to "fire" based on input.

A perceptron takes **multiple inputs**, applies **weights**, sums them up, and passes the result through an **activation function** to produce an output.

2.2 Structure of a Perceptron

A perceptron consists of:

1. **Inputs ($x_1, x_2, \ldots, x_n$)** – Feature values.
2. **Weights ($w_1, w_2, \ldots, w_n$)** – Assigned to inputs.
3. **Bias (b)** – Helps shift the decision boundary.
4. **Summation Function** – Computes the weighted sum:

$$z = (w_1x_1 + w_2x_2 + \ldots + w_nx_n) + b$$

5. **Activation Function** – Determines the output.

2.3 Perceptron Algorithm

1. Initialize weights and bias randomly.
2. Compute weighted sum:

$$z = \sum w_i x_i + b$$

3. Apply an activation function (e.g., step function).
4. Adjust weights using learning rules (training).
5. Repeat until the model reaches convergence.

2.4 Example: Perceptron for AND Logic Gate

x_1	x_2	Output (y)
0	0	0
0	1	0
1	0	0
1	1	1

Perceptron Model Implementation

```
IMPORT NUMPY AS NP



# DEFINE INPUT DATA AND LABELS

X = NP.ARRAY([[0,0], [0,1], [1,0], [1,1]])  # INPUTS

Y = NP.ARRAY([0, 0, 0, 1])  # EXPECTED OUTPUTS (AND GATE)



# INITIALIZE WEIGHTS AND BIAS

WEIGHTS = NP.RANDOM.RAND(2)

BIAS = NP.RANDOM.RAND(1)
```

```
# Define step activation function
def step_function(z):
    return 1 if z >= 0 else 0


# Train Perceptron
learning_rate = 0.1
epochs = 10


for epoch in range(epochs):
    for i in range(len(X)):
        z = np.dot(X[i], weights) + bias  # Compute weighted sum
        y_pred = step_function(z)  # Apply activation function
        error = y[i] - y_pred  # Compute error
        weights += learning_rate * error * X[i]  # Update weights
        bias += learning_rate * error  # Update bias


# Print final weights
print("Trained Weights:", weights)
```

```
PRINT("TRAINED BIAS:", BIAS)
```

📌 CHAPTER 3: ACTIVATION FUNCTIONS

3.1 WHAT IS AN ACTIVATION FUNCTION?

AN **ACTIVATION FUNCTION** DETERMINES WHETHER A NEURON SHOULD BE ACTIVATED BASED ON ITS INPUT. IT INTRODUCES **NON-LINEARITY** IN NEURAL NETWORKS, ENABLING THEM TO LEARN COMPLEX PATTERNS.

3.2 TYPES OF ACTIVATION FUNCTIONS

1. STEP FUNCTION

- USED IN **PERCEPTRONS** (BINARY OUTPUT: 0 OR 1).
- FORMULA:

$$f(z) = \begin{cases} 1, & \text{if } z \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

- **LIMITATION**: CANNOT HANDLE NON-LINEAR PROBLEMS.

2. SIGMOID FUNCTION (LOGISTIC ACTIVATION)

- USED IN **BINARY CLASSIFICATION** TASKS.
- FORMULA:

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

- **PROS**: OUTPUTS VALUES BETWEEN 0 AND 1.
- **CONS**: CAUSES **VANISHING GRADIENT PROBLEM**.

```
IMPORT NUMPY AS NP

IMPORT MATPLOTLIB.PYPLOT AS PLT



DEF SIGMOID(Z):

   RETURN 1 / (1 + NP.EXP(-Z))



X = NP.LINSPACE(-10, 10, 100)

Y = SIGMOID(X)



PLT.PLOT(X, Y)

PLT.TITLE("SIGMOID ACTIVATION FUNCTION")

PLT.SHOW()
```

3. TANH (HYPERBOLIC TANGENT)

- SIMILAR TO SIGMOID BUT OUTPUTS VALUES BETWEEN **-1 AND 1**.
- FORMULA:

$$\tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

- **PROS**: CENTERS DATA AROUND 0.
- **CONS**: STILL SUFFERS FROM **VANISHING GRADIENT**.

4. RELU (RECTIFIED LINEAR UNIT)

- Most widely used in **Deep Learning**.
- Formula:

$$f(z) = \max(0, z)$$

- **Pros**: Helps **reduce vanishing gradient**.
- **Cons**: Can cause **dead neurons** (output = 0 for negative values).

```
def relu(z):
    return np.maximum(0, z)

x = np.linspace(-10, 10, 100)
y = relu(x)

plt.plot(x, y)
plt.title("ReLU Activation Function")
plt.show()
```

5. Leaky ReLU

- Variant of ReLU that allows small negative values.
- Formula: f(z)=

$$f(z) = \begin{cases} z, & \text{if } z > 0 \\ 0.01z, & \text{otherwise} \end{cases}$$

6. Softmax Function

- Used in **multi-class classification** (e.g., Image Recognition).
- Converts values into probabilities:

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

📌 Chapter 4: Perceptron vs Modern Neural Networks

Feature	Perceptron	Modern Neural Networks
Type	Single-layer	Multi-layer (Deep Learning)
Activation Function	Step Function	Sigmoid, ReLU, Softmax
Learning Ability	Only linear problems	Handles non-linear relationships
Used In	Simple binary classification	Complex tasks (Image Recognition, NLP)

📌 Chapter 5: Case Study – Predicting Handwritten Digits

5.1 Problem Statement

We use **the MNIST dataset** (handwritten digits 0-9) and apply a **basic neural network** with activation functions.

5.2 Implementing a Simple Neural Network

```
import tensorflow as tf

from tensorflow import keras

import matplotlib.pyplot as plt



# Load dataset

mnist = keras.datasets.mnist

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



# Normalize data

x_train, x_test = x_train / 255.0, x_test / 255.0



# Define neural network model

model = keras.Sequential([

  keras.layers.Flatten(input_shape=(28, 28)),  # Input layer

  keras.layers.Dense(128, activation='relu'),  # Hidden layer

  keras.layers.Dense(10, activation='softmax')  # Output layer (10 classes)
```

```
])



# Compile model

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



# Train model

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



# Evaluate model

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

print(f"Test Accuracy: {test_acc:.2f}")
```

📌 Chapter 6: Summary

✅ **Perceptrons** are the building blocks of neural networks.
✅ **Activation functions** help neural networks learn **non-linear patterns**.
✅ **ReLU and Softmax** are commonly used in deep learning.
✅ **Modern neural networks** extend beyond perceptrons for complex problems.

☑ Deep Learning Frameworks: TensorFlow & Keras

📌 Chapter 1: Introduction to Deep Learning Frameworks

1.1 What are Deep Learning Frameworks?

Deep Learning frameworks are **libraries** that provide pre-built functions and tools to simplify the implementation of **Neural Networks** and **Deep Learning models**. Instead of coding everything from scratch, these frameworks offer:

- **Automatic differentiation** for training models.
- **Predefined layers** to build architectures easily.
- **GPU acceleration** for faster computation.

1.2 Why Use Deep Learning Frameworks?

✅ Reduce the complexity of writing mathematical computations.
✅ Allow easy implementation of deep learning architectures.
✅ Speed up training with GPU and TPU acceleration.
✅ Provide built-in models and datasets.

1.3 Popular Deep Learning Frameworks

Some widely used deep learning frameworks include:

- **TensorFlow** (Google)
- **Keras** (Runs on TensorFlow)
- **PyTorch** (Facebook)

- **MXNet** (Amazon)
- **CNTK** (Microsoft)
- **Theano** (Now deprecated)

In this study material, we will focus on **TensorFlow** and **Keras**.

📌 Chapter 2: Introduction to TensorFlow

2.1 What is TensorFlow?

TensorFlow is an open-source **deep learning library** developed by Google. It allows building and training **machine learning models** efficiently with CPU and GPU support.

2.2 Features of TensorFlow

- **Scalability**: Works on small projects to enterprise-level applications.
- **Graph Computation**: Uses computational graphs to optimize execution.
- **Flexible Deployment**: Can run on mobile devices, cloud, and edge computing.
- **Integration with Keras**: Keras is now a high-level API within TensorFlow.

2.3 Installing TensorFlow

Use the following command to install TensorFlow:

```
!pip install tensorflow
```

2.4 Importing TensorFlow

```
import tensorflow as tf

print(tf.__version__)  # Check TensorFlow version
```

2.5 Tensors in TensorFlow

TensorFlow's core data structure is the **tensor**, which is a multi-dimensional array.

```
# Creating a tensor

tensor = tf.constant([[1, 2], [3, 4]])

print(tensor)
```

📌 CHAPTER 3: INTRODUCTION TO KERAS

3.1 What is Keras?

Keras is a high-level deep learning framework **built on top of TensorFlow**. It simplifies building neural networks by providing:

- **User-friendly API**
- **Predefined layers**
- **Easy debugging and prototyping**
- **Automatic GPU acceleration**

3.2 Installing Keras

Keras is now integrated into TensorFlow, so installing TensorFlow automatically includes Keras.

To check Keras version:

```
import tensorflow.keras as keras
```

```
print(keras.__version__)
```

3.3 Creating a Simple Neural Network Using Keras

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Define a simple neural network
model = Sequential([
    Dense(16, activation='relu', input_shape=(10,)),  # Input layer
    Dense(8, activation='relu'),                      # Hidden layer
    Dense(1, activation='sigmoid')                    # Output layer
])

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

# Display model architecture
model.summary()
```

📌 CHAPTER 4: BUILDING A NEURAL NETWORK WITH TENSORFLOW & KERAS

4.1 Dataset Preparation

We use the **MNIST dataset** (handwritten digits) to demonstrate a simple classification model.

```
from tensorflow.keras.datasets import mnist

import matplotlib.pyplot as plt


# Load dataset

(X_train, y_train), (X_test, y_test) = mnist.load_data()


# Display an example image

plt.imshow(X_train[0], cmap='gray')

plt.title(f"Label: {y_train[0]}")

plt.show()
```

4.2 Preprocessing the Data

Neural networks perform better when inputs are **normalized**.

```
# Normalize pixel values (0 to 1)

X_train = X_train / 255.0

X_test = X_test / 255.0


# Reshape data for the model

X_train = X_train.reshape(-1, 28*28)

X_test = X_test.reshape(-1, 28*28)
```

4.3 Building the Model

```
from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Dense


# Create a neural network

model = Sequential([

  Dense(128, activation='relu', input_shape=(784,)),  # Input layer

  Dense(64, activation='relu'),  # Hidden layer

  Dense(10, activation='softmax')  # Output layer (10 classes)

])


# Compile the model

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


# Display model summary

model.summary()
```

4.4 Training the Model

```
# Train the model

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

4.5 Evaluating the Model

```
# Evaluate the model on the test dataset
test_loss, test_acc = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {test_acc:.4f}")
```

📌 Chapter 5: Advanced Features in TensorFlow & Keras

5.1 Using CNNs for Image Classification

```
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten

# CNN model
cnn_model = Sequential([
    Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1)),
    MaxPooling2D((2,2)),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(10, activation='softmax')
])

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

cnn_model.summary()
```

5.2 Transfer Learning (Using Pretrained Models)

```
from tensorflow.keras.applications import VGG16


# Load pre-trained model
vgg16 = VGG16(weights="imagenet", include_top=False, input_shape=(224, 224, 3))
vgg16.summary()
```

📌 Chapter 6: TensorFlow & Keras in Real-World Applications

Application	Framework Used
Image Classification	CNNs in TensorFlow/Keras
Text Classification	NLP models using Keras
Speech Recognition	DeepSpeech with TensorFlow
Autonomous Vehicles	TensorFlow for object detection
Healthcare (Medical Imaging)	Transfer learning with Keras

📌 Chapter 7: Summary & Conclusion

7.1 Key Takeaways

✅ **TensorFlow** provides a powerful deep learning platform for training models efficiently.
✅ **Keras** simplifies building neural networks with its easy-to-use

API.

✅ **Both frameworks support GPU acceleration** for fast computation.

✅ **You can use deep learning for a variety of tasks,** including image recognition, text analysis, and more.

7.2 Next Steps

- Learn **PyTorch,** another deep learning framework.
- Try building **LSTM models** for text classification.
- Deploy TensorFlow/Keras models using **Flask or FastAPI**.

📌 Chapter 8: Exercises & Assignments

8.1 Multiple Choice Questions

1. Which company developed TensorFlow?

☐ a) Microsoft
☐ b) Facebook
☐ c) Google ✅
☐ d) Apple

2. What is the default activation function in a dense layer?

☐ a) Sigmoid
☐ b) ReLU ✅
☐ c) Softmax
☐ d) Tanh

8.2 Practical Assignment

🎯 **Build a CNN model using Keras to classify CIFAR-10 images.**

🎯 **Use TensorFlow's Transfer Learning to train an image classification model.**

☑ FEEDFORWARD & BACKPROPAGATION ALGORITHM

📌 CHAPTER 1: INTRODUCTION TO NEURAL NETWORKS

1.1 What are Neural Networks?

A **Neural Network** is a computational model inspired by the human brain. It consists of **neurons (nodes)** arranged in layers that process inputs and learn patterns to make predictions.

1.2 Structure of a Neural Network

A typical neural network consists of:

- **Input Layer**: Receives the raw input features.
- **Hidden Layers**: Perform computations and extract features.
- **Output Layer**: Produces the final result (classification or regression).

1.3 How Neural Networks Learn?

Neural networks learn by:

1. **Feedforward Propagation** (Forward Pass) – Computing the output.
2. **Loss Calculation** – Measuring error (difference between predicted and actual values).
3. **Backpropagation** (Backward Pass) – Adjusting weights using **Gradient Descent**.
4. **Updating Weights** – Optimizing to reduce error.

📌 Chapter 2: Feedforward Propagation

2.1 What is Feedforward Propagation?

Feedforward propagation is the **process of passing inputs through the neural network** to compute the output. It involves:

1. **Multiplying inputs by weights**
2. **Applying activation functions**
3. **Passing results to the next layer**

2.2 Mathematical Formulation

For a **single-layer neural network**:

For a **single-layer neural network**:

$$Z = W \cdot X + B$$

$$A = f(Z)$$

where:

- X = Input
- W = Weights
- B = Bias
- Z = Weighted sum of inputs
- $f(Z)$ = Activation function

2.3 Activation Functions

Activation functions introduce **non-linearity** into the network.

- **Sigmoid**: $f(x) = \frac{1}{1+e^{-x}}$ → Output in range (0,1).
- **ReLU (Rectified Linear Unit)**: $f(x) = \max(0, x)$ → Faster convergence.
- **Softmax**: Used for multi-class classification.

2.4 Example: Feedforward Calculation

Consider a neuron with:

- Inputs $X_1 = 0.5, X_2 = 0.8$
- Weights $W_1 = 0.3, W_2 = 0.7$
- Bias $B = 0.2$

$$Z = (0.5 \times 0.3) + (0.8 \times 0.7) + 0.2 = 0.64$$

Applying **Sigmoid Activation**:

$$A = \frac{1}{1 + e^{-0.64}} \approx 0.65$$

📌 CHAPTER 3: BACKPROPAGATION ALGORITHM

3.1 What is Backpropagation?

Backpropagation is a **learning algorithm** that adjusts weights in a neural network by minimizing the **loss function**. It computes the gradient of the loss function and updates weights using **Gradient Descent**.

3.2 Steps in Backpropagation

1. **Compute Loss**: Compare the predicted output with the actual output.
2. **Calculate Gradients**: Measure how changes in weights affect the loss.

3. **Update Weights**: Adjust weights using **Gradient Descent**.
4. **Repeat** for multiple iterations (epochs).

3.3 Loss Function

The **Loss Function** measures the error in predictions. Common loss functions:

- **Mean Squared Error (MSE):** $L = \frac{1}{n}\sum(Y_{true} - Y_{pred})^2$ (for regression)
- **Cross-Entropy Loss:** $L = -\sum Y_{true}\log(Y_{pred})$ (for classification)

3.4 Gradient Descent

Gradient Descent updates weights in the direction that reduces the loss.

Gradient Descent updates weights in the direction that reduces the loss.

$$W_{new} = W_{old} - \eta\frac{\partial L}{\partial W}$$

where:

- W = Weight
- η = Learning rate (small step size)
- $\frac{\partial L}{\partial W}$ = Gradient of loss w.r.t. weight

3.5 Example: Backpropagation Step

Given:

- $Y_{true} = 1$ (actual output)
- $Y_{pred} = 0.65$ (predicted output)
- Learning rate $\eta = 0.01$

Compute **Gradient**:

$$\frac{\partial L}{\partial W} = 2(Y_{pred} - Y_{true})$$
$$= 2(0.65 - 1) = -0.7$$

Update **Weight**:

$$W_{new} = W_{old} - 0.01 \times (-0.7)$$
$$W_{new} = W_{old} + 0.007$$

The weight **increases slightly** to reduce error.

📌 CHAPTER 4: IMPLEMENTING FEEDFORWARD & BACKPROPAGATION IN PYTHON

We implement a **simple neural network** with **one hidden layer**.

4.1 Import Libraries

```
import numpy as np
```

4.2 Define Activation Functions

```
def sigmoid(x):
    return 1 / (1 + np.exp(-x))


def sigmoid_derivative(x):
    return x * (1 - x)
```

4.3 Initialize Weights & Biases

```
np.random.seed(42)

weights_input_hidden = np.random.rand(2, 2)  # 2 input nodes → 2 hidden nodes

weights_hidden_output = np.random.rand(2, 1)  # 2 hidden nodes → 1 output node

bias_hidden = np.zeros((1, 2))

bias_output = np.zeros((1, 1))
```

4.4 Forward Pass

```
def forward_pass(X):
    global hidden_output, final_output
    hidden_input = np.dot(X, weights_input_hidden) + bias_hidden
    hidden_output = sigmoid(hidden_input)
    final_input = np.dot(hidden_output, weights_hidden_output) + bias_output
    final_output = sigmoid(final_input)
    return final_output
```

4.5 Backpropagation

```
def backward_pass(X, y, learning_rate=0.1):
    global weights_input_hidden, weights_hidden_output, bias_hidden, bias_output


    # Compute error
```

```
    error = y - final_output


    # Compute gradients
    d_output = error * sigmoid_derivative(final_output)
    d_hidden = d_output.dot(weights_hidden_output.T) *
sigmoid_derivative(hidden_output)


    # Update weights & biases
    weights_hidden_output += hidden_output.T.dot(d_output) *
learning_rate
    weights_input_hidden += X.T.dot(d_hidden) * learning_rate
    bias_output += np.sum(d_output, axis=0, keepdims=True) *
learning_rate
    bias_hidden += np.sum(d_hidden, axis=0, keepdims=True) *
learning_rate
```

4.6 Train the Neural Network

```
# Sample dataset
X = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])  # XOR dataset
y = np.array([[0], [1], [1], [0]])  # XOR outputs


# Training loop
epochs = 10000
for epoch in range(epochs):
```

```
    forward_pass(X)

    backward_pass(X, y)


# Print final predictions

print("Final Predictions:")

print(forward_pass(X))
```

📌 Chapter 5: Summary

Concept	Description
Feedforward	Computes the output by passing data through the network
Activation Function	Introduces non-linearity (e.g., Sigmoid, ReLU)
Loss Function	Measures error in prediction (e.g., MSE, Cross-Entropy)
Backpropagation	Adjusts weights using Gradient Descent
Gradient Descent	Optimizes weights to reduce loss

📌 Chapter 6: Conclusion

✅ **Feedforward Propagation** computes outputs layer by layer.
✅ **Backpropagation** updates weights to minimize errors.

✅ **Gradient Descent** optimizes learning over time.
✅ These techniques form the **foundation of deep learning**.

📌 Next Steps

- Implement a **multi-layer neural network**.
- Use a **real-world dataset** (e.g., image classification).
- Try **Advanced optimizers** (e.g., Adam, RMSprop).

☑ Convolutional Neural Networks (CNNs) for Image Recognition

📌 Chapter 1: Introduction to Convolutional Neural Networks (CNNs)

1.1 What is a Convolutional Neural Network (CNN)?

A **Convolutional Neural Network (CNN)** is a type of **deep learning model** designed specifically for **image processing and computer vision tasks**. Unlike traditional artificial neural networks (ANNs), CNNs preserve the spatial structure of an image, making them highly effective for recognizing patterns, shapes, and objects.

1.2 Why Use CNNs for Image Recognition?

- **Captures spatial hierarchies** (local patterns → edges → shapes → objects).
- **Reduces computational complexity** (shared weights and sparse connections).
- **Automatically learns features** from images (no need for manual feature engineering).
- **Performs better than traditional machine learning models** on image data.

1.3 Applications of CNNs

✅ **Image Classification** – Face recognition, object detection (e.g., self-driving cars).
✅ **Medical Imaging** – Cancer detection, X-ray analysis.
✅ **Autonomous Vehicles** – Lane detection, pedestrian recognition.

✅ **Facial Recognition** – Security systems, biometric authentication.
✅ **Augmented Reality** – Snapchat filters, real-time image processing.

📌 Chapter 2: Architecture of a CNN

2.1 Components of a CNN

A CNN consists of multiple layers that process images hierarchically:

1. **Input Layer** – Takes the raw image as input.
2. **Convolutional Layer (Conv Layer)** – Extracts features using filters/kernels.
3. **Activation Function (ReLU)** – Introduces non-linearity.
4. **Pooling Layer** – Reduces dimensionality while preserving important features.
5. **Fully Connected Layer (FC Layer)** – Performs classification.
6. **Output Layer** – Predicts class labels (e.g., cat/dog).

2.2 How CNNs Work

1. **An image is passed through multiple convolutional layers.**
2. **Pooling layers reduce the dimensionality,** keeping essential features.
3. **Fully connected layers process the extracted features** and classify the image.
4. **Softmax function** is used in the output layer to produce class probabilities.

📌 Chapter 3: Understanding CNN Layers

3.1 Convolutional Layer

The **Convolutional Layer** is the most important part of CNNs. It applies **filters (kernels)** to an image, detecting **features like edges, textures, and patterns**.

Mathematical Operation (Convolution)

Each filter moves across the image and applies a dot product operation:

$$\text{Feature Map} = \sum(\text{Filter} \times \text{Image Region})$$

Example

If we have a **3×3 filter**:

```
less

Image Patch:
[ 1, 2, 3 ]
[ 4, 5, 6 ]
[ 7, 8, 9 ]

Filter:
[ 0, 1, 0 ]
[ 1, -4, 1 ]
[ 0, 1, 0 ]
```

Applying the filter extracts edges or patterns from the image.

3.2 Activation Function (ReLU)

The **ReLU (Rectified Linear Unit)** function applies **non-linearity** to the feature maps:

$$f(x) = \max(0, x)$$

This helps CNNs **learn complex patterns and avoid vanishing gradients**.

3.3 Pooling Layer

Pooling layers reduce **spatial size,** improving computational efficiency.

Types of Pooling

- **Max Pooling**: Takes the maximum value from each region.
- **Average Pooling**: Takes the average value.

Example of **2×2 Max Pooling**:

```
less

Feature Map:
[ 1, 3, 2, 0 ]
[ 4, 6, 5, 1 ]
[ 8, 9, 7, 2 ]
[ 3, 5, 4, 0 ]

After Max Pooling:
[ 6, 5 ]
[ 9, 7 ]
```

This reduces computation while retaining essential information.

3.4 Fully Connected Layer

After feature extraction, the **flattened output** is passed to a fully connected **neural network** for classification.

📌 Chapter 4: Building a CNN for Image Recognition

Now, let's build a **CNN model** using Python and **TensorFlow/Keras**.

4.1 Install Dependencies

```
!pip install tensorflow keras matplotlib numpy
```

4.2 Import Required Libraries

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

4.3 Load and Preprocess Data

We will use the **MNIST dataset** (handwritten digits 0-9).

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

```
# Normalize pixel values (0-255 → 0-1)
X_train, X_test = X_train / 255.0, X_test / 255.0

# Reshape for CNN input (28x28 grayscale → 28x28x1)
X_train = X_train.reshape(-1, 28, 28, 1)
X_test = X_test.reshape(-1, 28, 28, 1)

# Display some sample images
plt.figure(figsize=(10,5))
for i in range(10):
    plt.subplot(2,5,i+1)
    plt.imshow(X_train[i].reshape(28,28), cmap='gray')
    plt.axis('off')
plt.show()
```

4.4 Define CNN Architecture

```
# Define CNN model
model = keras.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.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dense(10, activation='softmax')  # 10 classes (digits 0-9)
])

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

# Model summary
model.summary()
```

4.5 Train the CNN Model

```
# Train model
history = model.fit(X_train, y_train, epochs=5,
validation_data=(X_test, y_test))
```

4.6 Evaluate the Model

```
# Evaluate on test data
```

```
test_loss, test_acc = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {test_acc:.2f}")
```

4.7 Make Predictions

```
# Predict on test images
y_pred = np.argmax(model.predict(X_test), axis=1)

# Display predictions
plt.figure(figsize=(10,5))
for i in range(10):
    plt.subplot(2,5,i+1)
    plt.imshow(X_test[i].reshape(28,28), cmap='gray')
    plt.title(f"Predicted: {y_pred[i]}")
    plt.axis('off')
plt.show()
```

📌 CHAPTER 5: SUMMARY

Layer	Function
Convolutional Layer	Extracts features using filters/kernels
ReLU Activation	Introduces non-linearity

Pooling Layer	Reduces dimensionality (Max Pooling, Avg Pooling)
Fully Connected Layer	Classifies extracted features
Softmax Output	Produces class probabilities

📌 Chapter 6: Conclusion & Next Steps

6.1 Key Takeaways

✅ CNNs are **powerful deep learning models** for image recognition.
✅ **Convolutional layers extract features, pooling layers reduce size**, and **fully connected layers classify images**.
✅ CNNs **achieve high accuracy** and are widely used in AI applications.

6.2 Next Steps

🚀 **Try CNN on different datasets** (e.g., CIFAR-10, ImageNet).
🚀 **Experiment with deeper architectures** (ResNet, VGG, MobileNet).
🚀 **Apply CNNs to real-world tasks** (face recognition, object detection).

☑ Recurrent Neural Networks (RNN) & Long Short-Term Memory (LSTM)

📌 Chapter 1: Introduction to Recurrent Neural Networks (RNN)

1.1 What is an RNN?

A **Recurrent Neural Network (RNN)** is a type of artificial neural network designed for **sequential data processing**. Unlike traditional feedforward networks, RNNs have an internal **memory** that enables them to process sequences by retaining information about previous inputs.

1.2 Why Use RNNs?

RNNs are useful for tasks where **previous inputs influence future predictions**, such as:

- **Natural Language Processing (NLP)** (e.g., text generation, sentiment analysis)
- **Speech Recognition** (e.g., voice assistants)
- **Time-Series Forecasting** (e.g., stock market prediction)
- **Machine Translation** (e.g., Google Translate)

1.3 How RNNs Work

- In an RNN, **each neuron receives input from both the current data point and the previous step**.

- The **hidden state** maintains memory of past computations.
- The same weights are **shared across all time steps**, making RNNs efficient for sequential tasks.

1.4 Key Components of an RNN

Component	Description
Input Layer	Takes sequential data as input (e.g., a sentence, time-series values).
Hidden Layer	Maintains a memory state that updates at each time step.
Output Layer	Produces the final prediction based on the learned sequence.

📌 CHAPTER 2: UNDERSTANDING THE RNN ARCHITECTURE

2.1 Mathematical Representation

For a given time step t, an RNN computes:

$$h_t = \sigma(W_h h_{t-1} + W_x x_t + b_h)$$

$$y_t = W_y h_t + b_y$$

where:

- x_t is the input at time step t.
- h_t is the hidden state at time step t.
- y_t is the output.
- W_h, W_x, W_y are weight matrices.
- b_h, b_y are biases.
- σ is an activation function (e.g., tanh, ReLU).

2.2 Challenges with RNNs

Despite their advantages, RNNs face major challenges:

- **Vanishing Gradient Problem**: Gradients become too small during backpropagation, making training difficult.
- **Exploding Gradient Problem**: Gradients become excessively large, leading to instability.
- **Short-Term Memory Limitation**: RNNs struggle to retain information from earlier time steps in long sequences.

Solution? ✅ Long Short-Term Memory (LSTM) Networks!

📌 Chapter 3: Introduction to Long Short-Term Memory (LSTM)

3.1 What is an LSTM?

Long Short-Term Memory (LSTM) is a special type of RNN that **solves the vanishing gradient problem** by introducing **gates** that regulate the flow of information. This allows LSTMs to **remember information for long sequences**.

3.2 How LSTMs Work

LSTMs introduce a **cell state** and **gates** to control information flow:

1. **Forget Gate** (ftf_t) – Decides what information to discard.
2. **Input Gate** (iti_t) – Determines what new information to store.
3. **Cell State Update** (CtC_t) – Updates the long-term memory.
4. **Output Gate** (oto_t) – Determines the final output.

3.3 LSTM Mathematical Equations

Each time step in an LSTM is computed as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot \tanh(C_t)$$

where:

- W_f, W_i, W_C, W_o are weight matrices.
- b_f, b_i, b_C, b_o are biases.
- σ is the sigmoid activation function.
- $\tanh$ is the hyperbolic tangent function.

3.4 Why Use LSTMs?

✅ **Handles long-term dependencies** effectively.
✅ **Prevents vanishing gradient problem** using memory gates.
✅ **Works well for complex sequential tasks** like language modeling and speech recognition.

📌 Chapter 4: Implementing RNN & LSTM in Python

We will use **TensorFlow/Keras** to build an **RNN and LSTM** for text classification.

4.1 Install Dependencies

!pip install numpy pandas tensorflow keras

4.2 Load Sample Dataset

```
import numpy as np

import pandas as pd

import tensorflow as tf

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import SimpleRNN, LSTM, Dense,
Embedding


# Load a dataset (IMDB sentiment analysis)

from tensorflow.keras.datasets import imdb

from tensorflow.keras.preprocessing import sequence


# Load dataset with only 10,000 most frequent words

max_features = 10000

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


# Pad sequences to ensure equal length

max_len = 200

X_train = sequence.pad_sequences(X_train, maxlen=max_len)

X_test = sequence.pad_sequences(X_test, maxlen=max_len)
```

4.3 Build and Train an RNN Model

```
# Define an RNN model
rnn_model = Sequential([
  Embedding(max_features, 128, input_length=max_len),
  SimpleRNN(64, activation='tanh'),
  Dense(1, activation='sigmoid')
])

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

# Train model
rnn_model.fit(X_train, y_train, epochs=5, batch_size=32, validation_data=(X_test, y_test))
```

4.4 Build and Train an LSTM Model

```
# Define an LSTM model
lstm_model = Sequential([
  Embedding(max_features, 128, input_length=max_len),
  LSTM(64, return_sequences=False),
  Dense(1, activation='sigmoid')
])
```

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

# Train model
lstm_model.fit(X_train, y_train, epochs=5, batch_size=32, validation_data=(X_test, y_test))
```

📌 Chapter 5: RNN vs. LSTM

Feature	RNN	LSTM
Memory Handling	Short-term	Long-term
Gradient Issues	Vanishing Gradient	No Vanishing Gradient
Performance	Works for small datasets	Works for large sequences
Use Case	Basic time-series tasks	Complex NLP tasks

📌 Chapter 6: Real-World Applications

✅ **Text Generation** (e.g., Chatbots, Email Auto-Reply)
✅ **Speech Recognition** (e.g., Siri, Google Assistant)
✅ **Stock Price Prediction**

✅ **Machine Translation** (e.g., Google Translate)
✅ **Healthcare** (e.g., Patient condition prediction)

📌 Chapter 7: Summary

✅ **RNNs** are great for sequential data but struggle with long-term dependencies.
✅ **LSTMs** solve the **vanishing gradient problem** using gates.
✅ **LSTMs outperform RNNs** for complex NLP and time-series tasks.
✅ **Practical Implementation** shows LSTMs are better suited for text classification.

📌 Next Steps

🚀 Try **Bidirectional LSTMs** for even better performance.
🚀 Experiment with **GRUs (Gated Recurrent Units),** a simpler alternative to LSTMs.
🚀 Implement **LSTM for stock price prediction** using historical data.

📌 ✨ ASSIGNMENT 1: 🎯 TRAIN A NEURAL NETWORK FOR SENTIMENT ANALYSIS USING LSTM.

📌 ✨ Assignment Solution 1: Train a Neural Network for Sentiment Analysis using LSTM

🎯 Objective

The goal of this assignment is to train a **Long Short-Term Memory (LSTM)** neural network for **Sentiment Analysis** on a dataset of text reviews. LSTMs are a type of **Recurrent Neural Network (RNN)** that excel in handling **sequential data** like text.

We will: ✅ Load and preprocess a dataset of movie reviews.
✅ Convert text into numerical data using **Tokenization & Embeddings**.
✅ Train an **LSTM model** to classify sentiment (positive/negative).
✅ Evaluate the model's accuracy.

🛠️ Step 1: Install and Import Required Libraries

We will use **TensorFlow, Keras, and NLTK** for text processing and LSTM modeling.

🔹 Install Dependencies (if not installed)

```
!pip install tensorflow numpy pandas matplotlib nltk
```

🔹 Import Required Libraries

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt
```

```
import nltk

import re

import tensorflow as tf


from tensorflow.keras.preprocessing.text import Tokenizer

from tensorflow.keras.preprocessing.sequence import
pad_sequences

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Embedding, LSTM, Dense,
Dropout

from sklearn.model_selection import train_test_split

from tensorflow.keras.utils import to_categorical


nltk.download('stopwords')

from nltk.corpus import stopwords

stop_words = set(stopwords.words('english'))
```

📥 Step 2: Load and Explore the Dataset

We will use the **IMDB Movie Reviews dataset,** which consists of **text reviews** and their corresponding **sentiment labels** (0 = Negative, 1 = Positive).

- **Load the Dataset**

```
# Load dataset (Example dataset with 'review' and 'sentiment' columns)

df = pd.read_csv("https://raw.githubusercontent.com/laxmimerit/IMDB-Movie-Reviews-LSTM/master/IMDB%20Dataset.csv")


# Display first few rows

print(df.head())
```

- **Check Dataset Information**

```
# Check for missing values and dataset info

print(df.info())


# Check class distribution

print(df['sentiment'].value_counts())
```

Expected Output:

- The dataset contains **50,000 reviews** labeled as "positive" or "negative".
- Balanced class distribution.

🧹 Step 3: Preprocess the Text Data

Text data needs **cleaning and tokenization** before training the LSTM.

- **Define a Function to Clean Text**

```
def clean_text(text):
    text = text.lower()  # Convert to lowercase
    text = re.sub(r'<.*?>', '', text)  # Remove HTML tags
    text = re.sub(r'[^a-zA-Z\s]', '', text)  # Remove special characters
    text = ' '.join(word for word in text.split() if word not in stop_words)
# Remove stopwords
    return text
```

- **Apply Cleaning to Dataset**

```
df['cleaned_review'] = df['review'].apply(clean_text)
print(df.head())
```

- **Convert Sentiment Labels to Binary (0 and 1)**

```
df['sentiment'] = df['sentiment'].map({'positive': 1, 'negative': 0})
```

🔢 Step 4: Tokenization and Padding

Neural networks need numerical input, so we convert text into **tokenized sequences**.

- **Tokenize the Text**

```
max_words = 5000  # Maximum number of unique words
max_length = 100  # Maximum review length

tokenizer = Tokenizer(num_words=max_words,
oov_token="<OOV>")
```

```
tokenizer.fit_on_texts(df['cleaned_review'])


# Convert text to sequences

X = tokenizer.texts_to_sequences(df['cleaned_review'])


# Pad sequences to ensure uniform length

X_padded = pad_sequences(X, maxlen=max_length, padding='post', truncating='post')


# Convert labels to numpy array

y = np.array(df['sentiment'])
```

📊 Step 5: Split Data into Training and Testing Sets

```
X_train, X_test, y_train, y_test = train_test_split(X_padded, y, test_size=0.2, random_state=42)


print("Training Data Shape:", X_train.shape)

print("Testing Data Shape:", X_test.shape)
```

🤖 Step 6: Build the LSTM Model

LSTMs are specialized for **sequence-based data**, making them ideal for sentiment analysis.

```
embedding_dim = 32  # Size of word embeddings


# Define LSTM model
model = Sequential([
  Embedding(input_dim=max_words, output_dim=embedding_dim, input_length=max_length),
  LSTM(64, return_sequences=True),  # LSTM layer
  Dropout(0.3),  # Prevent overfitting
  LSTM(32),
  Dense(1, activation='sigmoid')  # Output layer (binary classification)
])


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


# Display model architecture
model.summary()
```

📌 Step 7: Train the Model

We train the model for **5-10 epochs**.

```
epochs = 5

batch_size = 64


# Train the LSTM model

history = model.fit(X_train, y_train, epochs=epochs,
batch_size=batch_size, validation_data=(X_test, y_test))
```

📈 Step 8: Evaluate the Model

We check the **accuracy** and **loss** of the trained model.

```
# Evaluate on test data

loss, accuracy = model.evaluate(X_test, y_test)

print(f"Test Accuracy: {accuracy:.2f}")
```

- **Plot Training Accuracy & Loss**

```
plt.figure(figsize=(10,4))


# Accuracy Plot

plt.subplot(1,2,1)

plt.plot(history.history['accuracy'], label='Train Accuracy')

plt.plot(history.history['val_accuracy'], label='Validation Accuracy')

plt.xlabel("Epochs")

plt.ylabel("Accuracy")
```

```
plt.title("Training & Validation Accuracy")
plt.legend()

# Loss Plot
plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("Training & Validation Loss")
plt.legend()

plt.show()
```

📝 Step 9: Test on New Reviews

We test the model on custom **movie reviews**.

```
def predict_sentiment(text):
    text = clean_text(text)  # Clean text
    text_seq = tokenizer.texts_to_sequences([text])  # Convert to sequence
    text_pad = pad_sequences(text_seq, maxlen=max_length)  # Pad sequence
```

```
    prediction = model.predict(text_pad)[0, 0]  # Predict sentiment
    return "Positive" if prediction > 0.5 else "Negative"

# Example reviews
review1 = "This movie was fantastic! The acting was great, and I loved the story."
review2 = "I didn't like the movie. The plot was boring and the acting was terrible."

print("Review 1 Sentiment:", predict_sentiment(review1))
print("Review 2 Sentiment:", predict_sentiment(review2))
```

✅ Final Summary

Step	Description
Step 1	Install and import necessary libraries
Step 2	Load and explore the dataset
Step 3	Preprocess text (cleaning, tokenization)
Step 4	Convert text into numerical sequences
Step 5	Split data into training and testing sets
Step 6	Build the LSTM model
Step 7	Train the model

Step 8	Evaluate model performance
Step 9	Test on new reviews

🌟 CONCLUSION

- **LSTM-based models** are highly effective for **sentiment analysis**.
- The model learns from **sequential text** and predicts positive/negative sentiment.
- **Preprocessing (cleaning & tokenization) is crucial** for accuracy.
- LSTMs work better than traditional ML models for **text-based problems**.

📌 ✨ ASSIGNMENT 2: 🎯 IMPLEMENT A CNN FOR IMAGE CLASSIFICATION USING KERAS.

📌 ✨ Assignment Solution 2: Implement a CNN for Image Classification using Keras

---

🎯 Objective

The goal of this assignment is to **implement a Convolutional Neural Network (CNN) using Keras** for **image classification**. We will train the model on the **CIFAR-10 dataset,** which consists of **10 classes of images**.

🛠️ Step 1: Install and Import Necessary Libraries

We will use the following libraries:

- **TensorFlow/Keras** for building the CNN.
- **Matplotlib** for visualizing images and results.
- **NumPy** and **Pandas** for data handling.

🔹 Install Dependencies (if not installed)

```
!pip install tensorflow numpy matplotlib
```

🔹 Import Required Libraries

```
import tensorflow as tf

from tensorflow.keras import layers, models

import matplotlib.pyplot as plt

import numpy as np
```

📥 Step 2: Load and Explore the Dataset

We will use the **CIFAR-10 dataset**, which consists of **60,000 images (32x32 pixels) across 10 categories**.

🔹 Load the CIFAR-10 Dataset

```
from tensorflow.keras.datasets import cifar10


# Load dataset (divided into training and test sets)
(X_train, y_train), (X_test, y_test) = cifar10.load_data()


# Display dataset shape
print(f"Training Data Shape: {X_train.shape}")  # (50000, 32, 32, 3)
print(f"Testing Data Shape: {X_test.shape}")    # (10000, 32, 32, 3)
```

🔹 Display Sample Images

```
# CIFAR-10 class names
class_names = ['Airplane', 'Automobile', 'Bird', 'Cat', 'Deer',
               'Dog', 'Frog', 'Horse', 'Ship', 'Truck']


# Display 10 images from dataset
plt.figure(figsize=(10,5))
for i in range(10):
    plt.subplot(2, 5, i+1)
    plt.imshow(X_train[i])
```

```
    plt.title(class_names[y_train[i][0]])
    plt.axis("off")
plt.show()
```

🖌️ Step 3: Preprocess the Data

Neural networks perform better when inputs are **normalized**.

🔹 Normalize Pixel Values

```
# Convert pixel values from range 0-255 to range 0-1
X_train = X_train / 255.0
X_test = X_test / 255.0
```

🔹 Convert Labels to One-Hot Encoding

```
from tensorflow.keras.utils import to_categorical

# Convert class labels to one-hot encoding
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)

# Display new shape of labels
print("Shape of y_train:", y_train.shape)  # (50000, 10)
print("Shape of y_test:", y_test.shape)    # (10000, 10)
```

🖥️ Step 4: Build the CNN Model

A CNN consists of **convolutional layers**, **pooling layers**, and **fully connected layers**.

- **Define the CNN Architecture**

```
model = models.Sequential([
    # Convolutional Layer 1
    layers.Conv2D(32, (3,3), activation='relu', input_shape=(32,32,3)),
    layers.MaxPooling2D((2,2)),

    # Convolutional Layer 2
    layers.Conv2D(64, (3,3), activation='relu'),
    layers.MaxPooling2D((2,2)),

    # Convolutional Layer 3
    layers.Conv2D(128, (3,3), activation='relu'),

    # Flattening Layer
    layers.Flatten(),

    # Fully Connected Layer
    layers.Dense(128, activation='relu'),
    layers.Dense(10, activation='softmax')  # Output layer (10 classes)
])
```

```
# Display model summary
model.summary()
```

📊 Step 5: Compile and Train the Model

🔹 Compile the Model

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

🔹 Train the CNN

```
history = model.fit(X_train, y_train, epochs=10, batch_size=64, validation_data=(X_test, y_test))
```

📈 Step 6: Evaluate the Model

🔹 Evaluate on Test Set

```
test_loss, test_acc = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {test_acc:.2f}")
```

🔹 Plot Training Performance

```
plt.figure(figsize=(12,5))

# Plot training accuracy
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title("Model Accuracy")
```

```
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()

# Plot training loss
plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title("Model Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()

plt.show()
```

📌 Step 7: Make Predictions

We will test the model on some images and verify the results.

```
# Predict the first 10 images in the test set
predictions = model.predict(X_test[:10])

# Convert probabilities to class labels
predicted_labels = np.argmax(predictions, axis=1)
```

```
actual_labels = np.argmax(y_test[:10], axis=1)


# Display predictions
plt.figure(figsize=(10,5))
for i in range(10):
    plt.subplot(2, 5, i+1)
    plt.imshow(X_test[i])
    plt.title(f"Pred: {class_names[predicted_labels[i]]}\nActual: {class_names[actual_labels[i]]}")
    plt.axis("off")
plt.show()
```

✅ Final Summary

Step	Description
Step 1	Install and import necessary libraries
Step 2	Load and explore the CIFAR-10 dataset
Step 3	Preprocess the data (normalize & encode labels)
Step 4	Build the CNN model using Keras
Step 5	Compile and train the model
Step 6	Evaluate performance on test set
Step 7	Make predictions and visualize results

🌟 Conclusion

- CNNs are powerful for **image classification**.
- The **trained model achieved good accuracy** on CIFAR-10.
- We used **convolutional layers** to extract features and **fully connected layers** for classification.
- The model can be further **improved with data augmentation and fine-tuning**.

📌 Next Steps

- **Improve the CNN by adding dropout layers** to reduce overfitting.
- **Use Data Augmentation** to improve generalization.
- **Apply Transfer Learning** using a pre-trained model (e.g., VGG16, ResNet).
- **Deploy the model** as a web application using **Flask or FastAPI**.