Unit-III: Neural Networks

Unit-III: Neural Networks: Anatomy of Neural Network, Introduction to Keras: Keras, TensorFlow, Theano and CNTK, setting up Deep Learning Workstation, Classifying Movie Reviews: Binary Classification, Classifying newswires: Multiclass Classification**.**

Anatomy of a Neural Network (Simplified Explanation with Examples)

A **neural network** is like a team of problem solvers working together to understand and predict things based on the data they receive. It mimics the human brain, where neurons (small processing units) work together to process information.

Let us break it down step by step.

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1. Layers of a Neural Network

A neural network has three main types of layers:

1.1 Input Layer

- This layer is like the **eyes and ears** of the network.
- It takes in the raw data (numbers, images, text, etc.) and passes it to the next layer.
- Each neuron in the input layer represents one feature of the data.

🔷 **Example:**
If we are building a neural network to predict house prices, the input layer might have neurons representing:

- Size of the house (sq. ft.)
- Number of bedrooms
- Location rating
- Age of the house

1.2 Hidden Layers

- These layers process the data by learning patterns and relationships.
- The more hidden layers a network has, the more complex patterns it can learn.
- Each neuron in a hidden layer takes input, applies a mathematical transformation, and passes it to the next layer.

🔷 **Example:**
For house price prediction, hidden layers might learn:

- How house size affects price.
- How location influences value.
- How different features interact.

🔷 **Real-Life Example:**
Think of hidden layers like the **chefs in a restaurant**.

- The **input layer** is the waiter taking orders.
- The **hidden layers (chefs)** prepare the meal based on the order details.
- The **output layer** delivers the final dish.

1.3 Output Layer

- This layer provides the final prediction or result.
- The number of neurons in this layer depends on the type of problem.

Types of Output Layers:

1. **Binary Classification (Yes/No, True/False):**
    - Example: Spam detection (Spam or Not Spam)
    - Uses **one neuron** with a **sigmoid activation function** (output is between 0 and 1).
2. **Multiclass Classification (Multiple Categories):**
    - Example: Recognizing different types of animals (Cat, Dog, Horse).
    - Uses **multiple neurons**, one for each category, with a **softmax activation function**.
3. **Regression (Numerical Prediction):**
    - Example: Predicting house prices.
    - Uses **one neuron** with a **linear activation function** (output is a real number).

🔷 **Real-Life Example:**
The output layer is like the **cashier at a restaurant** who gives the final bill based on the order and what the chefs prepared.

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2. Neurons (Processing Units)

- Each neuron receives input, processes it, and passes it forward.
- Neurons are connected by **weights**, which determine the importance of each input.

🔷 **Example:**
In a spam detection email classifier:

- A neuron might check if the subject line contains the word "FREE".
- Another neuron might check if the email contains too many links.
- If both neurons detect spam-like features, they pass a strong signal forward.

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3. Weights and Biases (How the Network Learns)

- **Weights:** Control the strength of connections between neurons.
- **Bias:** Helps adjust the output, making the network more flexible.

🔷 **Example:**

- If a house's **location** is very important in determining its price, the network will assign a **high weight** to that input.
- If a house's **paint color** is not important, the network will assign a **low weight** to that input.

🔷 **Real-Life Example:**
Think of weights like **teacher grading criteria**:

- Homework (20%)
- Tests (50%)
- Class participation (30%)
  Each factor is **weighted** differently in the final grade calculation.

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4. Activation Functions (Decision Makers in the Network)

- Activation functions decide whether a neuron should be "activated" (send information forward) or not.
- Without activation functions, the network would just be performing basic linear calculations.

🔷 **Types of Activation Functions:**

1. **Sigmoid:**
    - Used for binary classification (Yes/No).
    - Example: Detecting if an email is spam or not.
2. **ReLU (Rectified Linear Unit):**
    - Used in hidden layers because it helps train deep networks efficiently.
    - Example: Image recognition (detecting edges, colors, shapes).
3. **Softmax:**
    - Used for multi-class classification problems.
    - Example: Identifying different types of animals (dog, cat, bird).

🔷 **Real-Life Example:**
Think of activation functions like **light switches** in a house:

- Some switches turn on a little (dim light – sigmoid).
- Some turn on fully or not at all (on/off – ReLU).

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5. Loss Function (How Wrong is the Prediction?)

- The loss function tells the neural network how far off its prediction is from the actual value.
- The goal is to minimize this error during training.

🔷 **Types of Loss Functions:**

- **Binary Crossentropy:** Used for Yes/No classification.
- **Categorical Crossentropy:** Used for multi-class classification.
- **Mean Squared Error (MSE):** Used for predicting numbers (e.g., house prices).

🔷 **Real-Life Example:**

- A loss function is like **Google Maps estimating your travel time**.
- If it predicts you will take 30 minutes but you actually take 40, the loss function tells it to improve future estimates.

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6. Optimizers (How the Network Learns from Mistakes)

- Optimizers adjust the weights and biases based on the loss function to improve predictions.

🔷 **Common Optimizers:**

1. **Stochastic Gradient Descent (SGD):** Updates weights gradually.
2. **Adam Optimizer:** Adapts learning speed dynamically (most popular).

🔷 **Real-Life Example:**

- Think of an optimizer as a **coach helping an athlete improve**.
- If a runner is too slow, the coach suggests changes in training.
- The optimizer tweaks the neural network similarly.

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7. Backpropagation (Learning from Mistakes)

- The network calculates how wrong it was, then updates weights to improve.
- This is done using **gradient descent**.

🔷 **Real-Life Example:**

- Imagine a student taking a math test.
- If they get a question wrong, the teacher shows them their mistake.
- Next time, they try not to repeat the mistake.

Final Real-Life Example: Self-Driving Cars

A self-driving car uses a neural network to make decisions:

1. **Input Layer:** Sensors collect data (speed, road signs, objects).
2. **Hidden Layers:** Process patterns (detect red lights, pedestrians).
3. **Output Layer:** Decides whether to stop, slow down, or turn.
4. **Weights & Biases:** Adjust importance (pedestrians > lane markings).
5. **Loss Function:** If the car makes a bad decision, it learns from it.
6. **Optimizer:** Adjusts to improve future driving performance.

Introduction to Keras: Understanding Keras in AI & Deep Learning

1. What is Keras?

Keras is an **open-source deep learning framework** that provides a simple and intuitive interface for building neural networks. It is written in **Python** and is widely used in **Artificial Intelligence (AI) and Machine Learning (ML)** applications.

1.1 Why Use Keras?

✅ **User-Friendly** – Simple and easy to use for beginners.
✅ **Modular & Flexible** – Provides a high-level API for rapid development.
✅ **Runs on Multiple Backends** – Supports **TensorFlow, Theano, and Microsoft CNTK**.
✅ **Supports CPUs & GPUs** – Efficient computation for deep learning.
✅ **Pretrained Models** – Includes VGG, ResNet, MobileNet, etc., for transfer learning.

🔷 **Real-Life Analogy:**
Keras is like a **modern kitchen with pre-built tools** that help you cook faster, while TensorFlow is like **a professional kitchen** where you have to do everything manually.

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2. Why is Keras Important?

Keras **simplifies deep learning** by providing an easy-to-use interface while maintaining the power of advanced frameworks like **TensorFlow**.

🔷 **Key Benefits:**

1. **Rapid Prototyping** – Build and test models quickly.
2. **Scalability** – Works on small and large datasets.
3. **Community Support** – Large user base and active development.
4. **Integration with TensorFlow** – Keras is now part of TensorFlow as **tf.keras**.

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3. How Keras Works?

Keras acts as a **high-level wrapper** that runs on top of deep learning frameworks such as:

Backend	Description
TensorFlow	Google's powerful deep learning framework (Most popular backend)
Theano	Early framework for deep learning (Now deprecated)
Microsoft CNTK	Deep learning framework by Microsoft (Less popular)

--> **Keras now primarily uses TensorFlow as its backend.**

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4. Setting Up Keras

Before using Keras, we need to install it along with TensorFlow.

4.1 Installation

```
pip install tensorflow keras
```

4.2 Importing Keras

```
import keras
import tensorflow as tf

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

---

5. Building a Neural Network with Keras

Keras provides an easy way to build **deep learning models** using a **Sequential API**.

5.1 Step-by-Step Guide to Building a Simple Neural Network

We will create a **basic neural network** to classify **handwritten digits (MNIST dataset)**.

Step 1: Import Libraries

```
from keras.models import Sequential
from keras.layers import Dense, Flatten
from keras.datasets import mnist
from keras.utils import to_categorical
```

Step 2: Load & Preprocess Data

```
# Load the MNIST dataset
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
# Normalize images (scale pixel values between 0 and 1)
train_images = train_images / 255.0
test_images = test_images / 255.0
# Convert labels to categorical format (one-hot encoding)
train_labels = to_categorical(train_labels, 10)
```

```
test_labels = to_categorical(test_labels, 10)
```

Step 3: Create the Model

```
model = Sequential([
    Flatten(input_shape=(28, 28)),  # Convert 2D images to 1D
    Dense(128, activation='relu'),  # Hidden layer with 128 neurons
    Dense(10, activation='softmax') # Output layer with 10 neurons (for digits 0-9)
])
```

Step 4: Compile the Model

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

Step 5: Train the Model

```
model.fit(train_images, train_labels, epochs=5, batch_size=32, validation_split=0.2)
```

Step 6: Evaluate the Model

```
test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f'Test Accuracy: {test_acc}')
```

---

6. Keras Model APIs

Keras provides different ways to build models:

6.1 Sequential API (Easy & Quick)

- Builds models layer-by-layer in a **linear stack**.
- **Example:**

```
model = Sequential([
    Dense(64, activation='relu', input_shape=(784,)),
    Dense(10, activation='softmax')
])
```

6.2 Functional API (More Flexible)

- Allows creating complex architectures (multiple inputs/outputs).
- **Example:**

```
from keras.models import Model
from keras.layers import Input, Dense

input_layer = Input(shape=(784,))
hidden_layer = Dense(128, activation='relu')(input_layer)
output_layer = Dense(10, activation='softmax')(hidden_layer)

model = Model(inputs=input_layer, outputs=output_layer)
```

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7. Key Components of Keras

Component	Description	Example
Layers	Building blocks of neural networks	Dense(128, activation='relu')
Optimizers	Adjust weights to minimize loss	optimizer='adam'
Loss Functions	Measure prediction error	loss='categorical_crossentropy'
Metrics	Evaluate model performance	metrics=['accuracy']

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8. Pretrained Models in Keras (Transfer Learning)

Keras provides **pretrained models** that can be used for **image classification, object detection, and feature extraction**.

8.1 Using Pretrained Model (MobileNetV2)

```
from keras.applications import MobileNetV2
# Load MobileNetV2 model with pretrained weights
model = MobileNetV2(weights='imagenet')
```

✓ Used for Image Classification & Transfer Learning.

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9. Applications of Keras

🚀 Keras is widely used in various AI applications:

✅ **Image Recognition (Face Detection, Object Recognition)** – Used in **Self-driving Cars, Medical Imaging**.
✅ **Natural Language Processing (NLP)** – Used in **Chatbots, Speech Recognition**.
✅ **Recommendation Systems** – Used by **Netflix, Amazon, YouTube**.
✅ **Healthcare & Drug Discovery** – Used in **AI-based disease detection**.
✅ **Finance & Fraud Detection** – Used in **predicting stock prices & fraud detection**.

Here are some key topics:

1 **Keras Layers** – Understanding Dense, Convolutional, Recurrent layers, etc.
2 **Keras Optimizers** – Adam, SGD, RMSprop, and how they affect training.
3 **Keras Loss Functions** – How to choose the right loss function for classification & regression.
4 **Keras Callbacks** – How to use EarlyStopping, ModelCheckpoint, ReduceLROnPlateau, etc.
5 **Keras Functional API** – Building complex models with multiple inputs/outputs.
6 **Keras Transfer Learning** – Using pretrained models like VGG, ResNet, MobileNet.
7 **Keras for NLP** – Text processing, embedding layers, and LSTMs.
8 **Keras for Computer Vision** – Convolutional Neural Networks (CNNs).

Great! Let's go through all the important **Keras features** in detail, step by step.

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1. Keras Layers

Layers are the **building blocks** of a neural network in Keras.

1.1 Types of Layers in Keras

Layer Type	Purpose	Example Usage
Dense (Fully Connected)	Basic neural network layer	Dense(128, activation='relu')
Conv2D (Convolutional Layer)	Extracts features from images	Conv2D(32, kernel_size=3, activation='relu')
MaxPooling2D (Pooling Layer)	Reduces spatial dimensions in CNNs	MaxPooling2D(pool_size=2)
Flatten	Converts multi-dimensional input to 1D	Flatten()

Layer Type	Purpose	Example Usage
Dropout	Prevents overfitting	Dropout(0.5)
LSTM/GRU (Recurrent Layer)	Used in sequence models (NLP, Time Series)	LSTM(64)

1.2 Example: Using Different Layers in Keras

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

# Define model
model = Sequential([
    Conv2D(32, kernel_size=(3,3), activation='relu', input_shape=(28,28,1)),
    MaxPooling2D(pool_size=(2,2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(10, activation='softmax')
])
# Compile model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
# Model Summary
model.summary()
```

✓ Used in Image Classification, NLP, and other Deep Learning applications.

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2. Keras Optimizers

Optimizers **adjust the weights** of the neural network to minimize the loss function.

2.1 Common Optimizers in Keras

Optimizer	Description	Best Use Case
SGD (Stochastic Gradient Descent)	Simple, slow but stable	Small datasets, linear regression
Adam (Adaptive Moment Estimation)	Most widely used, fast convergence	Works well on most problems
RMSprop	Designed for RNNs, adapts learning rates	Time-series, speech recognition
Adagrad	Adjusts learning rates dynamically	Sparse data, NLP tasks

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2.2 Example: Using Different Optimizers

```
from keras.optimizers import Adam, SGD, RMSprop


# Compile model with different optimizers
model.compile(optimizer=Adam(learning_rate=0.001), loss='categorical_crossentropy', metrics=['accuracy'])
```

✓ **Adam is recommended for most deep learning applications.**

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3. Keras Loss Functions

Loss functions measure **how well the model is performing**.

3.1 Choosing the Right Loss Function

Problem Type	Loss Function
Binary Classification (Yes/No)	binary_crossentropy
Multiclass Classification	categorical_crossentropy
Regression (Predicting Numbers)	mean_squared_error

3.2 Example: Choosing a Loss Function

```
# Binary Classification
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
# Multiclass Classification
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
# Regression
model.compile(optimizer='adam', loss='mean_squared_error', metrics=['mae'])
```

✓ **Choosing the right loss function improves model accuracy.**

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4. Keras Callbacks

Callbacks are used to **monitor and control the training process**.

4.1 Common Callbacks

Callback	Purpose
EarlyStopping	Stops training if the model stops improving
ModelCheckpoint	Saves the best model during training
ReduceLROnPlateau	Reduces learning rate when the model stops improving

---

4.2 Example: Using Callbacks

```
from keras.callbacks import EarlyStopping, ModelCheckpoint, ReduceLROnPlateau

callbacks = [
    EarlyStopping(monitor='val_loss', patience=5),
    ModelCheckpoint('best_model.h5', save_best_only=True),
    ReduceLROnPlateau(monitor='val_loss', factor=0.1, patience=3)
]

model.fit(train_images, train_labels, epochs=50, batch_size=32, validation_split=0.2, callbacks=callbacks)
```

✓ **Callbacks help prevent overfitting and speed up training.**

---

5. Keras Functional API

The **Functional API** allows building complex models with **multiple inputs/outputs**.

5.1 Example: Functional API Model

```
from keras.models import Model
from keras.layers import Input, Dense

# Input Layer
input_layer = Input(shape=(784,))

# Hidden Layers
hidden_layer = Dense(128, activation='relu')(input_layer)

# Output Layer
output_layer = Dense(10, activation='softmax')(hidden_layer)

# Create Model
model = Model(inputs=input_layer, outputs=output_layer)

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

model.summary()
```

✓ **Used in advanced deep learning applications like multi-task learning.**

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6. Keras Transfer Learning

Transfer learning uses **pretrained models** to improve performance on new datasets.

6.1 Using a Pretrained Model (MobileNetV2)

```
from keras.applications import MobileNetV2
from keras.models import Model
from keras.layers import Dense, Flatten

# Load MobileNetV2 model
base_model = MobileNetV2(weights='imagenet', include_top=False, input_shape=(224,224,3))

# Freeze the base model layers
for layer in base_model.layers:
    layer.trainable = False

# Add new layers
x = Flatten()(base_model.output)
x = Dense(128, activation='relu')(x)
output_layer = Dense(10, activation='softmax')(x)

# Create model
model = Model(inputs=base_model.input, outputs=output_layer)

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

model.summary()
```

✓ **Used for Image Recognition & Object Detection.**

7. Keras for NLP (Text Processing)

Keras provides tools for **Natural Language Processing (NLP)**.

7.1 Example: Using Embedding Layer for NLP

```
from keras.layers import Embedding, LSTM
model = Sequential([
    Embedding(input_dim=10000, output_dim=128, input_length=100),
    LSTM(64),
    Dense(1, activation='sigmoid')
])

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

✓ **Used in Chatbots, Sentiment Analysis, and Speech Recognition.**

---

8. Keras for Computer Vision (CNNs)

CNNs are used for **image classification and object detection**.

8.1 Example: CNN Model

```
model = Sequential([
    Conv2D(32, kernel_size=(3,3), activation='relu', input_shape=(64,64,3)),
    MaxPooling2D(pool_size=(2,2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(10, activation='softmax')
])

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

✓ **Used in Face Recognition, Medical Imaging, and Self-Driving Cars.**

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1 **Keras Sequential API** – How to build deep learning models step by step.
2 **Keras Functional API** – Creating complex models with multiple inputs/outputs.
3 **Keras CNNs (Computer Vision)** – Building and training a Convolutional Neural Network (CNN).
4 **Keras NLP (Text Processing & LSTMs)** – Using Keras for text classification, sentiment analysis, and RNNs.
5 **Keras Transfer Learning** – Using pretrained models like VGG16, ResNet, and MobileNet.
6 **Keras Hyperparameter Tuning** – Optimizing model performance with Keras Tuner.
7 **Keras Callbacks & Model Saving** – Using EarlyStopping, ModelCheckpoint, and saving/loading models.

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1 Keras Sequential API

The **Sequential API** is the easiest way to build deep learning models in Keras. It allows stacking layers in a **linear fashion** (one after another).

1.1 Example: Build a Simple Neural Network (Sequential API)

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


# Create a Sequential model
model = Sequential([
    Dense(128, activation='relu', input_shape=(784,)),  # Hidden layer with 128 neurons
    Dense(10, activation='softmax')  # Output layer for 10 classes
])


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


# Summary of the model
model.summary()
```

✓ **Best for simple feedforward networks.**

---

2 Keras Functional API

The **Functional API** allows creating **complex architectures**, like multiple inputs/outputs and shared layers.

2.1 Example: Multi-Input Model (Functional API)

```
from keras.models import Model
from keras.layers import Input, Dense, concatenate

# Input layers
input_a = Input(shape=(64,))
input_b = Input(shape=(32,))

# Hidden layers
hidden_a = Dense(32, activation='relu')(input_a)
hidden_b = Dense(32, activation='relu')(input_b)

# Merge both branches
merged = concatenate([hidden_a, hidden_b])
output = Dense(1, activation='sigmoid')(merged)

# Create model
model = Model(inputs=[input_a, input_b], outputs=output)

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

# Summary of the model
model.summary()
```

✓ **Best for models with multiple inputs and outputs.**

---

3 Keras CNNs (Computer Vision)

Convolutional Neural Networks (**CNNs**) are used for **image classification, object detection, and facial recognition**.

3.1 Example: CNN for Image Classification

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

# Define CNN model
model = Sequential([
    Conv2D(32, kernel_size=(3,3), activation='relu', input_shape=(64,64,3)),
    MaxPooling2D(pool_size=(2,2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(10, activation='softmax')
])

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

# Model summary
model.summary()
```

✓ **Used in Face Recognition, Object Detection, and Medical Imaging.**

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4 Keras NLP (Text Processing & LSTMs)

Keras provides tools for **Natural Language Processing (NLP)** such as **word embeddings and LSTMs**.

4.1 Example: Using Embedding Layer for Text Classification

```
from keras.models import Sequential
from keras.layers import Embedding, LSTM, Dense
# Define NLP model
model = Sequential([
    Embedding(input_dim=10000, output_dim=128, input_length=100),
    LSTM(64),
    Dense(1, activation='sigmoid')
])
# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
# Model summary
model.summary()
```

✓ **Used in Chatbots, Sentiment Analysis, and Speech Recognition.**

---

5 Keras Transfer Learning

Transfer learning allows **using pretrained models** like **VGG16, ResNet, MobileNet** for image classification.

5.1 Example: Using MobileNetV2 for Transfer Learning

```
from keras.applications import MobileNetV2
from keras.models import Model
from keras.layers import Flatten, Dense
# Load pretrained MobileNetV2 model
base_model = MobileNetV2(weights='imagenet', include_top=False,
input_shape=(224,224,3))
# Freeze the base model layers
for layer in base_model.layers:
    layer.trainable = False
```

```
# Add new layers
x = Flatten()(base_model.output)
x = Dense(128, activation='relu')(x)
output_layer = Dense(10, activation='softmax')(x)
# Create model
model = Model(inputs=base_model.input, outputs=output_layer)
# Compile model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
# Model summary
model.summary()
```

✓ **Used in Image Recognition, Object Detection, and Medical Diagnosis AI.**

---

6 Keras Hyperparameter Tuning

Tuning hyperparameters like **learning rate, batch size, and number of layers** improves model performance.

6.1 Example: Hyperparameter Tuning with Keras Tuner

```
import keras_tuner as kt
from keras.models import Sequential
from keras.layers import Dense
# Function to build the model
def build_model(hp):
    model = Sequential()
    model.add(Dense(hp.Int('units', min_value=32, max_value=256, step=32), activation='relu', input_shape=(784,)))
    model.add(Dense(10, activation='softmax'))
    model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
    return model
# Define tuner
tuner = kt.RandomSearch(build_model, objective='val_accuracy', max_trials=5)
```

```
# Run the search
tuner.search(train_images, train_labels, epochs=10, validation_split=0.2)
```

✓ **Used to find the best hyperparameters automatically.**

---

7 Keras Callbacks & Model Saving

Callbacks help **control training** and **save the best model**.

7.1 Example: Using Callbacks

```
from keras.callbacks import EarlyStopping, ModelCheckpoint
callbacks = [
    EarlyStopping(monitor='val_loss', patience=5),
    ModelCheckpoint('best_model.h5', save_best_only=True)
]
# Train model with callbacks
model.fit(train_images, train_labels, epochs=50, batch_size=32, validation_split=0.2, callbacks=callbacks)
```

✓ **Used to prevent overfitting and save the best model.**

7.2 Saving and Loading a Model

```
# Save model
model.save('my_model.h5')

# Load model
from keras.models import load_model
loaded_model = load_model('my_model.h5')

# Check model summary
loaded_model.summary()
```

✓ **Ensures models can be reused without retraining.**

---

8 Full Example: Building & Training a Keras Model

Let's build and train a complete deep learning model using **Keras Sequential API**.

```
from keras.models import Sequential
from keras.layers import Dense, Flatten
from keras.datasets import mnist
from keras.utils import to_categorical
# Load the dataset
(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
# Normalize images
train_images, test_images = train_images / 255.0, test_images / 255.0
# Convert labels to categorical format
train_labels = to_categorical(train_labels, 10)
test_labels = to_categorical(test_labels, 10)
# Define model
model = Sequential([
    Flatten(input_shape=(28, 28)),
    Dense(128, activation='relu'),
    Dense(10, activation='softmax')
])
# Compile model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
# Train model
model.fit(train_images, train_labels, epochs=5, batch_size=32, validation_split=0.2)


# Evaluate model
test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f'Test Accuracy: {test_acc}')
```

✓ **Used for digit classification in the MNIST dataset.**

Keras provides a wide range of functions across different modules. Below is a categorized list of the most used functions in the Keras library.

---

1. Model Creation & Architecture

- tf.keras.Sequential()
- tf.keras.Model()
- tf.keras.models.load_model()
- tf.keras.models.clone_model()
- tf.keras.models.model_from_json()
- tf.keras.models.model_from_yaml()

---

2. Layers

- tf.keras.layers.Dense()
- tf.keras.layers.Conv2D()
- tf.keras.layers.MaxPooling2D()
- tf.keras.layers.Flatten()
- tf.keras.layers.Dropout()
- tf.keras.layers.BatchNormalization()
- tf.keras.layers.LSTM()
- tf.keras.layers.GRU()
- tf.keras.layers.Embedding()
- tf.keras.layers.Input()
- tf.keras.layers.Reshape()
- tf.keras.layers.ReLU()
- tf.keras.layers.Softmax()
- tf.keras.layers.Activation()

---

3. Model Compilation & Training

- tf.keras.Model.compile()
- tf.keras.Model.fit()
- tf.keras.Model.fit_generator()
- tf.keras.Model.evaluate()
- tf.keras.Model.predict()
- tf.keras.Model.train_on_batch()
- tf.keras.Model.test_on_batch()
- tf.keras.Model.predict_on_batch()

---

4. Optimizers

- tf.keras.optimizers.Adam()
- tf.keras.optimizers.SGD()
- tf.keras.optimizers.RMSprop()
- tf.keras.optimizers.Adagrad()
- tf.keras.optimizers.Adamax()
- tf.keras.optimizers.Nadam()

---

5. Loss Functions

- tf.keras.losses.MeanSquaredError()
- tf.keras.losses.BinaryCrossentropy()
- tf.keras.losses.CategoricalCrossentropy()
- tf.keras.losses.SparseCategoricalCrossentropy()
- tf.keras.losses.Hinge()
- tf.keras.losses.KLDivergence()

---

6. Metrics

- tf.keras.metrics.Accuracy()
- tf.keras.metrics.Precision()
- tf.keras.metrics.Recall()

- tf.keras.metrics.AUC()
- tf.keras.metrics.MeanSquaredError()
- tf.keras.metrics.CategoricalAccuracy()
- tf.keras.metrics.SparseCategoricalAccuracy()

---

7. Callbacks

- tf.keras.callbacks.EarlyStopping()
- tf.keras.callbacks.ModelCheckpoint()
- tf.keras.callbacks.ReduceLROnPlateau()
- tf.keras.callbacks.TensorBoard()
- tf.keras.callbacks.LearningRateScheduler()
- tf.keras.callbacks.CSVLogger()

---

8. Preprocessing & Data Augmentation

Image Processing

- tf.keras.preprocessing.image.load_img()
- tf.keras.preprocessing.image.img_to_array()
- tf.keras.preprocessing.image.array_to_img()
- tf.keras.preprocessing.image.ImageDataGenerator()

Text Processing

- tf.keras.preprocessing.text.Tokenizer()
- tf.keras.preprocessing.sequence.pad_sequences()

---

9. Regularization

- tf.keras.regularizers.l1()
- tf.keras.regularizers.l2()
- tf.keras.regularizers.l1_l2()

---

10. Saving & Loading

- tf.keras.models.save_model()
- tf.keras.models.load_model()
- tf.keras.models.model_from_json()
- tf.keras.models.model_from_yaml()

Detailed Explanation of Keras Functions

Keras provides a wide range of functions across different modules. Below is a detailed explanation of each function, its use case, and when to use it.

1. Model Creation & Architecture

tf.keras.Sequential()

- **Use:** Creates a linear stack of layers.
- **Used in:** Simple feedforward neural networks.

Example:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
model = Sequential([
    Dense(64, activation='relu', input_shape=(32,)),
    Dense(10, activation='softmax')
])
```

tf.keras.Model()

- **Use:** Defines a model using the Functional API.
- **Used in:** Complex models with multiple inputs/outputs.
- **Example:**

```
from tensorflow.keras.layers import Input, Dense
from tensorflow.keras.models import Model
inputs = Input(shape=(32,))
x = Dense(64, activation="relu")(inputs)
outputs = Dense(10, activation="softmax")(x)
model = Model(inputs, outputs)
```

tf.keras.models.load_model()

- **Use:** Loads a previously saved model.
- **Used in:** Deploying trained models.

Example:

```
from tensorflow.keras.models import load_model
model = load_model('my_model.h5')
```

tf.keras.models.clone_model()

- **Use:** Creates an exact copy of a model architecture.
- **Used in:** Transfer learning without copying weights.

Example:

```
from tensorflow.keras.models import clone_model
model_copy = clone_model(model)
```

tf.keras.models.model_from_json()

- **Use:** Loads a model from a JSON file.
- **Used in:** When sharing model architecture.

Example:

```
json_string = model.to_json()
new_model = tf.keras.models.model_from_json(json_string)
```

tf.keras.models.model_from_yaml()

- Deprecated in newer versions of Keras.

2. Layers

tf.keras.layers.Dense()

- **Use:** Fully connected layer.
- **Used in:** Feedforward neural networks.

tf.keras.layers.Conv2D()

- **Use:** Applies convolutional filters.
- **Used in:** Convolutional Neural Networks (CNNs).

tf.keras.layers.MaxPooling2D()

- **Use:** Reduces spatial size.
- **Used in:** CNNs for downsampling.

tf.keras.layers.Flatten()

- **Use:** Converts multi-dimensional input into 1D.
- **Used in:** Connecting CNNs to fully connected layers.

tf.keras.layers.Dropout()

- **Use:** Prevents overfitting.
- **Used in:** Any deep learning model.

tf.keras.layers.BatchNormalization()

- **Use:** Normalizes activations.
- **Used in:** Speeding up training.

tf.keras.layers.LSTM()

- **Use:** Long Short-Term Memory unit.
- **Used in:** Time series, NLP.

tf.keras.layers.GRU()

- **Use:** Gated Recurrent Unit.
- **Used in:** Faster alternative to LSTM.

tf.keras.layers.Embedding()

- **Use:** Converts words to vector representations.
- **Used in:** NLP models.

tf.keras.layers.Input()

- **Use:** Defines an input layer.

tf.keras.layers.Reshape()

- **Use:** Reshapes tensor without changing data.

tf.keras.layers.ReLU()

- **Use:** Applies Rectified Linear Activation function.

tf.keras.layers.Softmax()

- **Use:** Converts logits to probabilities.

tf.keras.layers.Activation()

- **Use:** Applies any activation function.

3. Model Compilation & Training

tf.keras.Model.compile()

- **Use:** Configures the model for training.
- **Used in:** Every model before training.

tf.keras.Model.fit()

- **Use:** Trains the model.
- **Used in:** Supervised learning models.

tf.keras.Model.evaluate()

- **Use:** Tests model performance.

tf.keras.Model.predict()

- **Use:** Makes predictions.

4. Optimizers

tf.keras.optimizers.Adam()

- **Use:** Adaptive learning rate optimizer.
- **Used in:** Most deep learning models.

tf.keras.optimizers.SGD()

- **Use:** Stochastic Gradient Descent.
- **Used in:** Classic ML models.

tf.keras.optimizers.RMSprop()

- **Use:** Adaptive learning for RNNs.

5. Loss Functions

tf.keras.losses.MeanSquaredError()

- **Use:** Measures squared loss.
- **Used in:** Regression problems.

tf.keras.losses.BinaryCrossentropy()

- **Use:** Binary classification loss.

tf.keras.losses.CategoricalCrossentropy()

- **Use:** Multi-class classification loss.

6. Metrics

tf.keras.metrics.Accuracy()

- **Use:** Measures accuracy.

tf.keras.metrics.Precision()

- **Use:** Measures precision.

7. Callbacks

tf.keras.callbacks.EarlyStopping()

- **Use:** Stops training when performance degrades.

tf.keras.callbacks.ModelCheckpoint()

- **Use:** Saves model checkpoints.

8. Preprocessing & Data Augmentation

tf.keras.preprocessing.image.load_img()

- **Use:** Loads an image from disk.

tf.keras.preprocessing.text.Tokenizer()

- **Use:** Tokenizes text.

9. Regularization

tf.keras.regularizers.l1()

- **Use:** L1 regularization.

tf.keras.regularizers.l2()

- **Use:** L2 regularization.

10. Saving & Loading

tf.keras.models.save_model()

- **Use:** Saves a trained model.

tf.keras.models.load_model()

- **Use:** Loads a trained model.

----------:-:----------

tf.keras.layers.Dense(): A Detailed Explanation

Overview

tf.keras.layers.Dense() is a fully connected (or dense) layer in a neural network, where each neuron in the layer receives input from all neurons in the previous layer. It is the fundamental building block of feedforward neural networks.

Syntax

```
tf.keras.layers.Dense(
    units,
    activation=None,
    use_bias=True,
    kernel_initializer='glorot_uniform',
    bias_initializer='zeros',
    kernel_regularizer=None,
    bias_regularizer=None,
    activity_regularizer=None,
    kernel_constraint=None,
    bias_constraint=None
)
```

Parameters

- units (int): The number of neurons (or output dimensions) in the layer.
- activation (str or function): Activation function to apply (e.g., 'relu', 'sigmoid', 'softmax'). Default is None (linear activation).
- use_bias (bool): Whether the layer uses a bias vector.
- kernel_initializer (str or function): Initialization method for weights (default: 'glorot_uniform').
- bias_initializer (str or function): Initialization method for bias (default: 'zeros').

- kernel_regularizer (function): Regularization method for weights (e.g., tf.keras.regularizers.l2(0.01)).
- bias_regularizer (function): Regularization method for bias.
- activity_regularizer (function): Regularization method for outputs.
- kernel_constraint (function): Constraint on weights (e.g., tf.keras.constraints.max_norm(2.0)).
- bias_constraint (function): Constraint on bias.

Use Cases of tf.keras.layers.Dense()

1. Basic Feedforward Neural Network

A Dense layer is widely used in fully connected neural networks.

Example: Simple Classification Model

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

# Define a simple feedforward network
model = Sequential([
    Dense(64, activation='relu', input_shape=(10,)),  # Hidden layer with 64 neurons
    Dense(32, activation='relu'),                     # Another hidden layer
    Dense(1, activation='sigmoid')                    # Output layer for binary classification
])

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

# Summary of the model
model.summary()

```

Use Case:

- Used in binary classification problems such as spam detection, fraud detection, and medical diagnosis.

---

2. Multi-Class Classification

For multi-class classification, the output layer uses softmax activation.

Example: Multi-Class Classification

```
model = Sequential([
    Dense(128, activation='relu', input_shape=(20,)),  # Hidden layer
    Dense(64, activation='relu'),                      # Another hidden layer
    Dense(10, activation='softmax')                    # Output layer (10 classes)
])

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

Use Case:

- Used in image classification, sentiment analysis, and handwritten digit recognition (MNIST).

---

3. Regression Model

For regression problems, Dense layers with **no activation** in the output layer are used.

Example: Regression Model

```
model = Sequential([
    Dense(64, activation='relu', input_shape=(15,)),   # Hidden layer
    Dense(32, activation='relu'),                      # Another hidden layer
    Dense(1)                                           # Output layer (No activation for regression)
])

model.compile(optimizer='adam', loss='mean_squared_error', metrics=['mae'])
```

Use Case:

- Used in predicting house prices, stock market predictions, and sales forecasting.

---

4. Autoencoder

Dense layers are used in **autoencoders** for dimensionality reduction.

Example: Autoencoder

```
input_dim = 100
encoding_dim = 32

# Encoder
encoder = Sequential([
    Dense(encoding_dim, activation='relu', input_shape=(input_dim,))
])

# Decoder
decoder = Sequential([
    Dense(input_dim, activation='sigmoid')
])

autoencoder = Sequential([encoder, decoder])

autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
```

Use Case:

- Used in anomaly detection, image denoising, and feature extraction.

---

5. Transfer Learning (Fully Connected Layers on Pretrained Models)

Dense layers are often added to **pretrained convolutional networks** (like VGG16) for custom classification.

Example: Transfer Learning

```
from tensorflow.keras.applications import VGG16
from tensorflow.keras.models import Model

# Load pre-trained VGG16 model (without the classification head)
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

# Flatten output and add Dense layers for custom classification
x = tf.keras.layers.Flatten()(base_model.output)
x = Dense(256, activation='relu')(x)
x = Dense(10, activation='softmax')(x)  # Output layer for 10 classes

# Define new model
model = Model(inputs=base_model.input, outputs=x)

# Freeze base model weights
for layer in base_model.layers:
    layer.trainable = False

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

Use Case:

- Used in medical image analysis, face recognition, and object detection.

Best Practices When Using tf.keras.layers.Dense()

1. **Use ReLU Activation in Hidden Layers:** Helps avoid vanishing gradient problems.
2. **Use Softmax for Multi-Class Output:** Converts logits into probabilities.
3. **Use No Activation for Regression Outputs:** Ensures continuous output.
4. **Apply Dropout and Batch Normalization:** Helps prevent overfitting.
5. **Use Regularization (l1, l2):** Helps improve generalization.
6. **Ensure Proper Input Shape:** The first Dense layer must define input_shape.

Summary

Scenario	Example Architecture	Activation
Binary Classification	[Dense(64, 'relu'), Dense(1, 'sigmoid')]	'sigmoid'
Multi-Class Classification	[Dense(128, 'relu'), Dense(10, 'softmax')]	'softmax'
Regression	[Dense(64, 'relu'), Dense(1)]	None
Autoencoder	[Dense(32, 'relu'), Dense(100, 'sigmoid')]	'relu', 'sigmoid'
Transfer Learning	VGG16 + Dense(256, 'relu') + Dense(10, 'softmax')	'relu', 'softmax'

Conclusion

- Dense() is a core layer in deep learning, commonly used in **classification, regression, autoencoders, and transfer learning**.
- Understanding activation functions, input shapes, and optimizers is **crucial** for its effective use.
- Regularization techniques help improve **generalization and prevent overfitting**.

Introduction to TensorFlow

TensorFlow is an **open-source machine learning framework** developed by Google Brain. It is widely used for **deep learning, artificial intelligence (AI), and numerical computation**. TensorFlow allows developers to create and train machine learning models efficiently, supporting both **CPU and GPU acceleration** for high-performance computing.

Key Features of TensorFlow

✅ **Scalability** – Can run on CPUs, GPUs, and TPUs (Tensor Processing Units).
✅ **Flexibility** – Supports both high-level APIs (like Keras) and low-level computational graph control.
✅ **Efficient Execution** – Uses dataflow graphs for optimized computation.
✅ **Support for Multiple Platforms** – Works on desktop, mobile, cloud, and edge devices.
✅ **Pre-trained Models** – Provides models via TensorFlow Hub.

Core Components of TensorFlow

1 Tensors: The Building Blocks

- A **tensor** is a multi-dimensional array (like a NumPy array).
- Used to store and process data in TensorFlow.

Example of a Tensor:

```
import tensorflow as tf

# Creating a tensor
tensor = tf.constant([[1, 2], [3, 4]])
print(tensor)
```

🔷 **Shape:** (2,2) → A matrix with 2 rows and 2 columns.
🔷 **Data Type:** Automatically inferred or can be specified (e.g., tf.float32).

---

2 TensorFlow Computational Graph

- TensorFlow **builds a graph of operations** where nodes represent computations and edges represent data (tensors).
- Graph execution improves performance by optimizing operations.

Example: Simple Graph Calculation

```
x = tf.constant(3.0)
y = tf.constant(4.0)
z = x * y # TensorFlow creates a computation graph
print(z)  # Output: tf.Tensor(12.0, shape=(), dtype=float32)
```

Even though we wrote simple multiplication, TensorFlow internally optimizes this using a computational graph.

---

3 Eager Execution (Dynamic Computation)

- By default, TensorFlow 2.x runs in **eager mode**, meaning operations execute immediately (like Python).
- No need to build and run a session separately, unlike TensorFlow 1.x.

Example: Eager Execution

```
a = tf.constant(5)
b = tf.constant(7)
c = a + b  # Executes immediately
print(c)  # Output: tf.Tensor(12, shape=(), dtype=int32)
```

This makes TensorFlow **more intuitive and easier to debug**.

---

4 TensorFlow Keras API: High-Level API

- TensorFlow includes **Keras**, which simplifies building deep learning models.
- Allows for fast prototyping and model training with just a few lines of code.

Example: Simple Neural Network in Keras

```
from tensorflow import keras
from tensorflow.keras import layers
# Define a simple sequential model
model = keras.Sequential([
    layers.Dense(64, activation='relu', input_shape=(10,)),
    layers.Dense(32, activation='relu'),
    layers.Dense(1, activation='sigmoid')
])
```

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

💡 **Explanation:**

- **Dense(64, activation='relu')** → Fully connected layer with 64 neurons using ReLU activation.
- **Binary classification output (sigmoid activation).**
- **adam optimizer and binary_crossentropy loss function.**

---

5 Training a Model in TensorFlow

- Use model.fit() to train on data.
- Supports batch training and validation.

Example: Training a Model

```
# Assume we have training data (X_train, y_train)
model.fit(X_train, y_train, epochs=10, batch_size=32)
```

---

6 TensorFlow for Deep Learning

TensorFlow is widely used for deep learning tasks such as:

- **Image Recognition** (e.g., CNNs for image classification).
- **Natural Language Processing (NLP)** (e.g., LSTMs, Transformers).
- **Reinforcement Learning** (e.g., Deep Q-Networks).

Example: CNN for Image Classification

```
model = keras.Sequential([
    layers.Conv2D(32, (3,3), activation='relu', input_shape=(28,28,1)),
    layers.MaxPooling2D((2,2)),
    layers.Flatten(),
    layers.Dense(128, activation='relu'),
    layers.Dense(10, activation='softmax')  # 10 classes output
])
```

Why Use TensorFlow?

✅ **Optimized Performance** – Uses **GPU/TPU acceleration** for speed.
✅ **Production-Ready** – Easily deploy models with TensorFlow Serving.
✅ **Mobile & Edge Support** – TensorFlow Lite for mobile and IoT devices.
✅ **Pre-trained Models** – Use **TensorFlow Hub** for transfer learning.

Let's build a **sentiment analysis model** using **TensorFlow** and **Keras** with the IMDB movie reviews dataset! 🎬📊

📌 Project: Sentiment Analysis using TensorFlow (IMDB Movie Reviews)

We will create a **text classification model** that predicts whether a movie review is **positive** or **negative**.

Step 1: Import Required Libraries

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

Step 2: Load the IMDB Dataset

- TensorFlow provides a preprocessed version of the IMDB dataset.
- Each review is **already tokenized and converted into integers**.

```
# Load dataset
(X_train, y_train), (X_test, y_test) = keras.datasets.imdb.load_data(num_words=10000)
# Show an example review (numerical format)
print(X_train[0])
print("Label:", y_train[0])  # 1 = Positive, 0 = Negative
```

Step 3: Preprocess the Data

- **Pad sequences** so that all reviews have the same length.

```
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Set maximum review length

max_length = 200

# Pad sequences to the same length

X_train = pad_sequences(X_train, maxlen=max_length, padding='post', truncating='post')

X_test = pad_sequences(X_test, maxlen=max_length, padding='post', truncating='post')

print("Shape of X_train:", X_train.shape)  # (25000, 200)
```

Step 4: Build the Neural Network Model

We will use an **Embedding layer** to represent words, followed by an **LSTM (Long Short-Term Memory) layer** for text understanding.

```
model = keras.Sequential([

    layers.Embedding(input_dim=10000, output_dim=128, input_length=max_length),  # Word embeddings

    layers.Bidirectional(layers.LSTM(64, return_sequences=True)),  # LSTM layer

    layers.Bidirectional(layers.LSTM(32)),  # Second LSTM layer

    layers.Dense(64, activation='relu'),

    layers.Dropout(0.5),  # Prevent overfitting

    layers.Dense(1, activation='sigmoid')  # Output layer (binary classification)

])

# Compile the model

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

# Show model summary

model.summary()
```

Step 5: Train the Model

```
history = model.fit(X_train, y_train, epochs=5, 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}")
```

Step 7: Make Predictions on New Reviews

We need to **convert text to tokenized format** before passing it to the model.

```
def predict_sentiment(review, model, word_index, max_length=200):
    from tensorflow.keras.preprocessing.text import text_to_word_sequence
    # Tokenize words
    words = text_to_word_sequence(review)

    # Convert words to their respective indices
    tokens = [word_index.get(word, 2) for word in words]  # 2 is the index for unknown words

    # Pad sequence
    tokens_padded = pad_sequences([tokens], maxlen=max_length, padding='post',
truncating='post')

    # Predict sentiment
    prediction = model.predict(tokens_padded)[0,0]
    sentiment = "Positive 😊" if prediction > 0.5 else "Negative 😠"
     print(f"Review Sentiment: {sentiment} (Score: {prediction:.2f})")

# Get word index mapping from IMDB dataset
word_index = keras.datasets.imdb.get_word_index()

# Test on a sample review
sample_review = "The movie was absolutely fantastic! I loved every moment of it."
predict_sentiment(sample_review, model, word_index)
```

📊 Step 8: Visualizing Training Performance

We can **plot accuracy and loss curves** to analyze our model's performance.

```
# Plot training history
plt.figure(figsize=(12, 5))
# Accuracy
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Accuracy over Epochs')
# Loss
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Loss over Epochs')
plt.show()
```

✅ Summary of What We Did

1. **Loaded the IMDB dataset** (preprocessed movie reviews).
2. **Preprocessed text** (padding sequences to the same length).
3. **Built an LSTM-based deep learning model** for text classification.
4. **Trained the model** on movie reviews.
5. **Evaluated model accuracy** on test data.
6. **Made predictions on new reviews**.
7. **Visualized training performance** using accuracy/loss plots.

---

you want to **deploy the sentiment analysis model as a web app**, we'll use **Flask** or **FastAPI**. Let's go step by step. 🚀

📌 **Steps to Deploy Sentiment Analysis Model as a Web App**

1 Train and Save the Model

2 Create a Flask/FastAPI Backend

3 Build a Simple Frontend (Optional)

4 Run and Test the Web App

Step 1: Train and Save the Model

We assume you've already trained the model. Now, let's save it.

```
# Save the trained model
model.save("sentiment_model.h5")


# Save the word index mapping
import json
word_index = keras.datasets.imdb.get_word_index()
with open("word_index.json", "w") as f:
    json.dump(word_index, f)
```

This saves:
✅ The **model** as sentiment_model.h5.
✅ The **word index dictionary** as word_index.json for text processing.

Step 2: Create a Flask API

Now, let's build a **Flask backend** to handle user input.

Install Flask First

```
pip install flask tensorflow
```

Flask API Code

Create a file **app.py** and add the following:

```
from flask import Flask, request, jsonify
import tensorflow as tf
from tensorflow.keras.preprocessing.sequence import pad_sequences
import json

# Load the trained model and word index
model = tf.keras.models.load_model("sentiment_model.h5")

with open("word_index.json", "r") as f:
    word_index = json.load(f)

# Flask app
app = Flask(__name__)

# Function to preprocess text
def preprocess_text(text, max_length=200):
    words = text.lower().split()
    tokens = [word_index.get(word, 2) for word in words]  # 2 = Unknown word
    return pad_sequences([tokens], maxlen=max_length, padding='post')

# API Route
@app.route("/predict", methods=["POST"])
def predict():
    data = request.get_json()
    review = data.get("review", "")

    if not review:
        return jsonify({"error": "No review provided"}), 400

    # Preprocess and predict
```

```
    processed_review = preprocess_text(review)
    prediction = model.predict(processed_review)[0, 0]

    sentiment = "Positive 😊" if prediction > 0.5 else "Negative 😠"
    return jsonify({"review": review, "sentiment": sentiment, "score": float(prediction)})

# Run the app
if __name__ == "__main__":
    app.run(debug=True)
```

Run Flask

python app.py

Your API will be live at **http://127.0.0.1:5000/predict**. 🎯

Step 3: Test the API

You can **test it using Postman or cURL**.

Using cURL

```
curl -X POST http://127.0.0.1:5000/predict -H "Content-Type: application/json" -d '{"review": "The movie was absolutely amazing!"}'
```

Expected Output

```
{
  "review": "The movie was absolutely amazing!",
  "sentiment": "Positive 😊",
  "score": 0.89
}
```

Step 4: Build a Simple Frontend (Optional)

You can create a basic **HTML + JavaScript frontend** to interact with the API.

Create a file index.html:

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Sentiment Analysis</title>
</head>
<body>
    <h1>Movie Review Sentiment Analysis</h1>
    <textarea id="review" rows="4" cols="50" placeholder="Enter your review..."></textarea><br>
    <button onclick="predictSentiment()">Analyze Sentiment</button>
    <h2 id="result"></h2>
    <script>
        async function predictSentiment() {
            let review = document.getElementById("review").value;
            let response = await fetch("http://127.0.0.1:5000/predict", {
                method: "POST",
                headers: {"Content-Type": "application/json"},
                body: JSON.stringify({review: review})
            });
            let result = await response.json();
            document.getElementById("result").innerText = `Sentiment: ${result.sentiment} (Score: ${result.score})`;
        }
    </script>
</body>
```

```
</html>
```

🚀 Running Everything Together

1 Start **Flask API**

```
python app.py
```

2 Open **index.html** in a browser.
3 Enter a review and click **Analyze Sentiment**! 🎉

🌍 Next Steps

1 **Deploy to the cloud** using **Render, AWS, or Heroku**.
2 **Improve the model** using **pre-trained embeddings (GloVe)**.
3 **Use FastAPI instead of Flask** for faster performance.

🔥 Use a pre-trained embedding model (like GloVe) instead of a trainable embedding layer?

Using **pre-trained embeddings like GloVe** can significantly improve the model's performance by leveraging knowledge from a vast corpus of text. Let's modify our model to use **GloVe embeddings** instead of a trainable embedding layer.

📌 Steps to Use GloVe in TensorFlow

1 Download Pre-trained GloVe embeddings
2 Load GloVe and create an embedding matrix
3 Modify the model to use GloVe embeddings
4 Train and evaluate the updated model

Step 1: Download Pre-trained GloVe Embeddings

We will use **GloVe (Global Vectors for Word Representation)**, which provides word vectors trained on massive datasets like Wikipedia.

```
# Download GloVe (6B tokens, 100D vectors)

wget https://nlp.stanford.edu/data/glove.6B.zip

unzip glove.6B.zip
```

This will extract files like:

- glove.6B.50d.txt

- glove.6B.100d.txt ✅ (We'll use this)
- glove.6B.200d.txt
- glove.6B.300d.txt

Step 2: Load GloVe and Create an Embedding Matrix

Now, let's load the GloVe embeddings and map them to our vocabulary.

```
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing.sequence import pad_sequences
# Load IMDB dataset
(X_train, y_train), (X_test, y_test) = keras.datasets.imdb.load_data(num_words=10000)

# Load the word index mapping
word_index = keras.datasets.imdb.get_word_index()

# Reverse the word index (map indices back to words)
reverse_word_index = {index + 3: word for word, index in word_index.items()}
reverse_word_index[0] = "<PAD>"
reverse_word_index[1] = "<START>"
reverse_word_index[2] = "<UNK>"
reverse_word_index[3] = "<UNUSED>"

# Load GloVe embeddings
embedding_dim = 100  # We use 100D vectors
embedding_index = {}

# Read GloVe file and create a dictionary
with open("glove.6B.100d.txt", encoding="utf-8") as f:
    for line in f:
```

```
    values = line.split()
    word = values[0]  # First column is the word
    vector = np.asarray(values[1:], dtype="float32")  # Remaining columns are the embedding values
    embedding_index[word] = vector

print(f"Loaded {len(embedding_index)} word vectors from GloVe.")

# Create an embedding matrix for our dataset
vocab_size = 10000
embedding_matrix = np.zeros((vocab_size, embedding_dim))

for word, i in word_index.items():
  if i < vocab_size:
    embedding_vector = embedding_index.get(word)  # Get GloVe vector for the word
    if embedding_vector is not None:
      embedding_matrix[i] = embedding_vector  # Assign it to the matrix

print("Embedding matrix shape:", embedding_matrix.shape)
```

Step 3: Modify the Model to Use GloVe

Now, let's replace the trainable embedding layer with our **pre-trained GloVe embeddings**.

```
from tensorflow.keras import layers

# Define the model with GloVe embeddings
model = keras.Sequential([
  layers.Embedding(input_dim=vocab_size,
            output_dim=embedding_dim,
            weights=[embedding_matrix],  # Load pre-trained embeddings
            input_length=200,
```

```
            trainable=False),  # Freeze embeddings
    layers.Bidirectional(layers.LSTM(64, return_sequences=True)),
    layers.Bidirectional(layers.LSTM(32)),
    layers.Dense(64, activation='relu'),
    layers.Dropout(0.5),
    layers.Dense(1, activation='sigmoid')
])

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

# Show model summary
model.summary()
```

Changes in the Model

✅ **weights=[embedding_matrix]** – Load GloVe embeddings.
✅ **trainable=False** – Keep embeddings frozen (we can fine-tune later).
✅ **No need to train embeddings from scratch!**

Step 4: Train and Evaluate the Model

```
# Pad sequences to the same length
max_length = 200
X_train = pad_sequences(X_train, maxlen=max_length, padding='post', truncating='post')
X_test = pad_sequences(X_test, maxlen=max_length, padding='post', truncating='post')
# Train the model
history = model.fit(X_train, y_train, epochs=5, batch_size=64, validation_data=(X_test,
y_test))
# Evaluate on test set
test_loss, test_acc = model.evaluate(X_test, y_test)
print(f"Test Accuracy: {test_acc:.2f}")
```

🚀 Expected Benefits of Using GloVe

✅ **Better Understanding of Word Semantics** – Pre-trained embeddings capture real-world word meanings.
✅ **Faster Training** – No need to learn embeddings from scratch.
✅ **Higher Accuracy** – Word vectors are already well-trained on massive text data.

----------:-:----------

Introduction to Theano

📌 What is Theano?

Theano is an **open-source numerical computation library** for Python, developed at the **University of Montreal** by the **MILA (Montreal Institute for Learning Algorithms)** research group. It was one of the first deep learning frameworks and is designed for:

✅ **Efficient mathematical computation** (especially for deep learning)
✅ **Automatic differentiation** for optimization
✅ **GPU acceleration** for faster computation

Theano is similar to **TensorFlow** and **PyTorch** but was widely used before they became popular. Although it is no longer actively developed (since 2017), it played a **key role** in the evolution of modern deep learning frameworks.

🔷 Features of Theano

1 Symbolic Computation

Theano uses **symbolic variables**, meaning that it first builds an **expression graph** (like defining a mathematical formula) and then compiles it into an optimized function.

2 Automatic Differentiation

It can automatically compute **gradients**, making it useful for deep learning models.

3 GPU Acceleration

It can run computations on both **CPU and GPU**, speeding up matrix operations.

4 Optimized Computation

Theano applies optimizations like **fusion of operations** and **loop unrolling** for efficiency.

5 Integration with NumPy

It integrates well with **NumPy**, allowing easy manipulation of large datasets.

📌 Installation of Theano

Even though **Theano is no longer actively developed**, you can still install it:

pip install Theano

🔷 Theano Basics

Let's start with some **basic operations** in Theano.

1 Import Theano and Define Variables

```
import theano
import theano.tensor as T

# Define symbolic variables
x = T.dscalar('x')
y = T.dscalar('y')

# Define an operation
z = x + y

# Compile into a function
f = theano.function([x, y], z)

# Evaluate the function
print(f(3, 5))  # Output: 8.0
```

📝 Explanation

- **T.dscalar** defines a scalar symbolic variable.
- **z = x + y** creates a symbolic expression.
- **theano.function([inputs], output)** compiles it into a callable function.

🔷 Theano Graph Representation

Theano **first constructs a computation graph** before execution.
Example:

```
import theano.tensor as T


a = T.dmatrix('a')

b = T.dmatrix('b')

c = a * b  # Element-wise multiplication


f = theano.function([a, b], c)


import numpy as np

A = np.array([[1, 2], [3, 4]])

B = np.array([[5, 6], [7, 8]])


print(f(A, B))
```

📝 Explanation

- **T.dmatrix** defines 2D matrices.
- **c = a * b** defines element-wise multiplication.
- **f(A, B)** computes the result.

🔷 Theano optimizes the computation **before execution**, making it faster.

🔷 Automatic Differentiation in Theano

A key feature of Theano is **automatic differentiation**, which is essential for deep learning.

```
import theano.tensor as T


x = T.dscalar('x')

y = x**2  # Define function y = x^2


grad_y = T.grad(y, x)  # Compute dy/dx
```

```
# Compile into a function
grad_function = theano.function([x], grad_y)

print(grad_function(5))  # Output: 10.0
```

📝 **Explanation**

- **T.grad(y, x)** computes the gradient ∂y/∂x.
- **Theano automatically differentiates functions**, making it useful for deep learning.

🔷 **Deep Learning with Theano**

Theano was widely used for **training deep learning models** before TensorFlow and PyTorch.

Simple Neural Network with Theano

```
import theano
import theano.tensor as T
import numpy as np

# Input variables
X = T.dmatrix('X')
W = theano.shared(np.random.randn(3, 2), name='W')
b = theano.shared(np.zeros(2), name='b')

# Neural network output
Y = T.nnet.sigmoid(T.dot(X, W) + b)

# Compile function
predict = theano.function([X], Y)
# Test with input data
x_data = np.array([[0.1, 0.2, 0.3]])
print(predict(x_data))
```

📝 Explanation

- **T.dot(X, W) + b** is a basic **linear transformation** (like in neural networks).
- **T.nnet.sigmoid** applies the activation function.
- **theano.function** compiles the model into an optimized function.

🔷 Why Did Theano Become Obsolete?

Even though Theano was **pioneering**, it had some **limitations**: ❌ **Difficult debugging** – The symbolic computation model made debugging harder.
❌ **Slower than TensorFlow/PyTorch** – Other libraries improved execution speed.
❌ **Lack of dynamic computation** – Theano was not designed for **dynamic graphs** like PyTorch.
❌ **Stopped Development** – Theano officially ended support in 2017.

✅ However, Theano **influenced modern deep learning frameworks** like TensorFlow, Keras, and PyTorch.

🔷 Alternatives to Theano

Today, better alternatives exist for deep learning: 🔲**TensorFlow** – Offers **high-performance computation**, GPU support, and an easy-to-use API.
2️⃣ **PyTorch** – More **flexible and dynamic**, great for research and production.
3️⃣ **JAX** – A modern alternative by Google, optimized for **automatic differentiation** and **fast execution**.

✅ Summary

- **Theano** was a powerful numerical computation library **widely used for deep learning**.
- It provided **symbolic computation, GPU acceleration, and automatic differentiation**.
- **Limitations** like debugging complexity and lack of dynamic computation led to its decline.
- **Modern frameworks (TensorFlow, PyTorch, JAX) have replaced Theano** but still use similar ideas.

🔍 Comparison: Theano vs. TensorFlow vs. PyTorch

Theano, TensorFlow, and PyTorch are all deep learning frameworks, but they differ in key ways. Let's break it down:

---

1 Overview

Feature	Theano 🏛️	TensorFlow 🔥	PyTorch ⚡
Developer	MILA (Montreal)	Google	Meta (Facebook)
Release Year	2007	2015	2016
Computation Model	**Symbolic Graph**	**Static Graph (TF 1.x), Dynamic (TF 2.x)**	**Dynamic Graph**
Ease of Use	Medium	Complex (TF 1.x), Easier (TF 2.x)	Very Easy
Speed	Slower	Faster	Fastest
GPU Support	Yes	Yes	Yes
Deployment	No	Yes	Yes
Active Development?	❌ No (stopped in 2017)	✅ Yes	✅ Yes

🔹 **Key Difference:** Theano was the **first** deep learning library but was later surpassed by TensorFlow and PyTorch, which offer better support for **dynamic computation** and **easier debugging**.

---

2 Theano vs. TensorFlow

Feature	Theano	TensorFlow
Computation Type	Symbolic	Static (TF 1.x) / Dynamic (TF 2.x)
Ease of Use	Medium	TF 1.x: Hard, TF 2.x: Easier
Performance	Decent	Optimized for speed
Deployment	No	Yes (via TensorFlow Serving)

✅ TensorFlow replaced Theano because it **offered more features**, including **better hardware acceleration** and **cloud deployment**.

---

3 Theano vs. PyTorch

Feature	Theano	PyTorch
Computation Type	Symbolic	Dynamic
Ease of Use	Medium	Very Easy
Debugging	Hard	Easy (Uses Python Debugging)
Speed	Decent	Faster
GPU Support	Yes	Yes

✅ **PyTorch is preferred for research** because it uses a **dynamic computation graph**, making it easier to experiment with models.

---

4 Which One Should You Use?

- If you need **legacy** support or study **deep learning history** → **Theano**
- If you want **scalability & production** (Google Cloud, TensorFlow Lite) → **TensorFlow**
- If you want **ease of use & research flexibility** → **PyTorch**

More details on real-world deep learning applications?

🚀 **Real-World Applications of Deep Learning**

Deep learning is transforming industries by enabling **automation, pattern recognition, and intelligent decision-making**. Here are **some of the most impactful applications**:

📌 **1 Natural Language Processing (NLP)**

Deep learning powers **text and speech-based applications** like:

✅ **Chatbots & Virtual Assistants** (Siri, Alexa, ChatGPT)
✅ **Sentiment Analysis** (IMDB movie review classification)
✅ **Machine Translation** (Google Translate)
✅ **Text Summarization** (News Summarization AI)

🛠 **Example Model**:

- **Transformers (BERT, GPT, T5, LLaMA)** for advanced text understanding
- **RNNs, LSTMs, GRUs** for sequential text data

📌 **2 Computer Vision (CV)**

Deep learning enables **image and video analysis** in multiple domains:

✅ **Object Detection & Recognition** (Face Unlock, Google Lens)
✅ **Medical Imaging** (Cancer detection in X-rays & MRIs)
✅ **Autonomous Vehicles** (Tesla, Waymo self-driving cars)
✅ **Security & Surveillance** (CCTV anomaly detection)

🛠 **Example Model**:

- **Convolutional Neural Networks (CNNs)** (ResNet, VGG, EfficientNet)
- **YOLO, Faster R-CNN** (for real-time object detection)

📌 **3 Healthcare & Medicine**

Deep learning is revolutionizing **diagnosis, drug discovery, and patient monitoring**:

✅ **Disease Diagnosis** (Detecting pneumonia, diabetic retinopathy)
✅ **Drug Discovery** (AI-generated pharmaceuticals)
✅ **Medical Chatbots** (AI doctors like Babylon Health)
✅ **Genome Sequencing** (Predicting genetic diseases)

🛠 **Example Model**:

- **Deep Neural Networks (DNNs)** for medical imaging
- **Recurrent Neural Networks (RNNs)** for patient data analysis

---

📌 **4 Autonomous Vehicles & Robotics**

Deep learning enables **self-driving cars and intelligent robots**:

✅ **Self-Driving Cars** (Tesla, Waymo, NVIDIA's AI-driven vehicles)
✅ **Industrial Robots** (Automating factories & warehouses)
✅ **Drones & UAVs** (AI-powered navigation)

🛠 **Example Model**:

- **Reinforcement Learning (RL)** (Deep Q-Networks, PPO, A3C)

- **CNNs for image recognition, LSTMs for decision-making**

📌 5 Finance & Fraud Detection

AI is transforming **banking and financial services** with deep learning:

✅ **Fraud Detection** (Detecting credit card fraud, money laundering)
✅ **Algorithmic Trading** (AI-powered stock market predictions)
✅ **Credit Scoring & Risk Analysis** (Loan approvals based on AI models)

🛠 **Example Model**:

- **Anomaly Detection Networks** (Autoencoders, Isolation Forests)
- **LSTMs & Transformer-based models** for time-series forecasting

---

📌 6 Generative AI & Creativity

Deep learning is powering **AI-generated content** in multiple industries:

✅ **Deepfake Technology** (AI-generated faces, videos)
✅ **AI Art & Music Generation** (DALL·E, Stable Diffusion, AIVA Music)
✅ **Text-to-Image Generation** (MidJourney, OpenAI's DALL·E)
✅ **Code Generation** (GitHub Copilot, OpenAI Codex)

🛠 **Example Model**:

- **GANs (Generative Adversarial Networks)**
- **VAEs (Variational Autoencoders)**
- **Transformer-based models (GPT, CLIP, Stable Diffusion)**

📌 7 Speech Processing & Voice Assistants

Deep learning enables **speech-to-text and text-to-speech applications**:

✅ **Speech Recognition** (Google Speech-to-Text, Siri, Alexa)
✅ **Voice Cloning & Synthesis** (AI-generated voices, text-to-speech tools)
✅ **Audio Enhancement** (Noise reduction, sound separation)

🛠 **Example Model**:

- **DeepSpeech (Mozilla's Speech Model)**
- **WaveNet (Google's TTS model)**
- **Transformer-based models like Whisper (OpenAI's speech recognition model)**

📌 8 Gaming & Reinforcement Learning

Deep learning is transforming gaming & AI decision-making:

✅ **AI-powered NPCs** (Smart enemies & teammates in video games)
✅ **Game AI Agents** (DeepMind's AlphaGo, AlphaZero)
✅ **Reinforcement Learning for Strategy Games** (AI playing StarCraft, Dota 2)

🛠 **Example Model**:

- **Deep Q-Learning (DQN)**
- **Proximal Policy Optimization (PPO)**
- **Monte Carlo Tree Search (MCTS) in AI strategy games**

📌 9 Recommendation Systems

AI enhances **personalized recommendations** across various platforms:

✅ **Movie & TV Recommendations** (Netflix, Disney+)
✅ **E-commerce Product Suggestions** (Amazon, eBay, Shopify)
✅ **Music & Podcast Recommendations** (Spotify, Apple Music)
✅ **YouTube Video Suggestions** (YouTube AI algorithms)

🛠 **Example Model**:

- **Collaborative Filtering & Neural Networks**
- **Autoencoders for content-based filtering**

📌 🔥 Future Trends in Deep Learning

1 **AGI (Artificial General Intelligence)** – Moving towards AI that thinks like humans.
2 **Multimodal AI** – AI that processes **text, images, video, and speech** together (e.g., Gemini, GPT-4 Turbo).
3 **Explainable AI (XAI)** – Making AI models more transparent and interpretable.
4 **Federated Learning** – AI training across multiple devices without data sharing (privacy-focused).
5 **Edge AI** – AI running on **low-power devices** like smartphones, IoT, and wearables.

A deep learning example using TensorFlow instead of Theano?

Let's build a **Sentiment Analysis model** using TensorFlow for **IMDB movie reviews classification**. This model will:

✅ Use **GloVe pre-trained word embeddings** (instead of training from scratch).
✅ Use a **Bidirectional LSTM** for improved accuracy.
✅ Be trained to classify movie reviews as **positive or negative**.

📌 Step 1: Install TensorFlow & Required Libraries

pip install tensorflow numpy pandas matplotlib

📌 Step 2: Import Libraries

```
import tensorflow as tf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
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, Bidirectional, Dense, Dropout
from tensorflow.keras.datasets import imdb
```

📌 Step 3: Load and Preprocess IMDB Dataset

```
# Load IMDB dataset
vocab_size = 10000  # Use top 10,000 words
max_length = 200  # Max words per review

(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=vocab_size)

# Pad sequences to ensure uniform length
```

```
x_train = pad_sequences(x_train, maxlen=max_length, padding='post', truncating='post')
x_test = pad_sequences(x_test, maxlen=max_length, padding='post', truncating='post')

print(f"Training data shape: {x_train.shape}, Labels shape: {y_train.shape}")
print(f"Testing data shape: {x_test.shape}, Labels shape: {y_test.shape}")
```

📌 Step 4: Load Pre-trained GloVe Embeddings

```
# Load GloVe word embeddings
embedding_dim = 100  # Use GloVe embeddings of 100 dimensions
embedding_index = {}

# Download and extract 'glove.6B.100d.txt' from https://nlp.stanford.edu/projects/glove/
glove_file = "glove.6B.100d.txt"

# Read GloVe embeddings
with open(glove_file, "r", encoding="utf-8") as file:
    for line in file:
        values = line.split()
        word = values[0]
        coefs = np.asarray(values[1:], dtype="float32")
        embedding_index[word] = coefs

print(f"Loaded {len(embedding_index)} word vectors from GloVe.")
```

📌 Step 5: Create the Embedding Matrix

```
# Initialize embedding matrix with zeros
embedding_matrix = np.zeros((vocab_size, embedding_dim))

# Load embeddings into the matrix
word_index = imdb.get_word_index()
```

```
for word, index in word_index.items():
    if index < vocab_size and word in embedding_index:
        embedding_matrix[index] = embedding_index[word]

print("Embedding matrix shape:", embedding_matrix.shape)
```

📌 Step 6: Build the Sentiment Analysis Model

```
# Build the model
model = Sequential([
    Embedding(vocab_size, embedding_dim, weights=[embedding_matrix],
input_length=max_length, trainable=False),
    Bidirectional(LSTM(64, return_sequences=True)),
    Bidirectional(LSTM(32)),
    Dense(64, activation='relu'),
    Dropout(0.5),
    Dense(1, activation='sigmoid')  # Output layer (binary classification)
])

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

# Model summary
model.summary()
```

📌 Step 7: Train the Model

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

)

📌 Step 8: Evaluate the Model

```
# Evaluate on test data
loss, accuracy = model.evaluate(x_test, y_test)
print(f"Test Accuracy: {accuracy * 100:.2f}%")
```

📌 Step 9: Plot Accuracy & Loss Curves

```
# Plot accuracy & loss curves
plt.figure(figsize=(12, 5))

# Accuracy plot
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Val Accuracy')
plt.legend()
plt.title("Model Accuracy")

# Loss plot
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.legend()
plt.title("Model Loss")
plt.show()
```

🚀 Results & Key Takeaways

✅ **Uses pre-trained GloVe embeddings** instead of training an embedding layer.
✅ **Bidirectional LSTM** improves performance by capturing **context from both directions**.
✅ **Dropout layer** prevents overfitting.
✅ **Achieves high accuracy** (usually ~85-90% on IMDB dataset).

🚀 Future Trends in Deep Learning

Deep learning is evolving rapidly, bringing revolutionary changes to AI. Here's a **detailed breakdown** of the top trends shaping the future:

---

1 Artificial General Intelligence (AGI) – Human-like AI

AGI aims to build **AI systems that can reason, learn, and adapt like humans**—not just in narrow domains but across multiple tasks.

🔷 **Current Progress:**

- Models like **GPT-4 Turbo, Gemini 1.5, and Claude** show signs of generalization but are still **narrow AI**.
- **DeepMind's Gato** can perform **multiple tasks** (e.g., playing games, image processing, NLP), but it's **not yet AGI**.
- **Recursive Self-Improvement** is a key research area—AI that can improve itself continuously.

🔷 **Challenges:**

- Lack of **common sense reasoning** and **causality understanding**.
- Energy efficiency and computing power required for true AGI.
- Ethical concerns: How do we control AGI safely?

✅ **Future Outlook:**

- **Hybrid AI models** combining **symbolic reasoning + deep learning** may lead to AGI.
- **Brain-inspired neural networks (Neuromorphic Computing)** could accelerate AGI development.

---

2 Multimodal AI – AI that Understands Everything

Traditional AI models specialize in **one type of input** (text, images, or speech). **Multimodal AI** can **process and integrate multiple formats** simultaneously.

🔷 **Examples of Multimodal AI:**

- **GPT-4 Turbo & Gemini 1.5** → Process text, images, code, and audio together.
- **Meta's ImageBind** → Connects **images, video, audio, depth, thermal, and IMU data**.
- **OpenAI's Sora** → Generates videos from text descriptions.

🔷 **Applications:**
✅ **AI-powered assistants** (e.g., ChatGPT seeing images, Siri understanding speech & context).
✅ **Self-driving cars** → Combining **LIDAR, cameras, and real-time data**.
✅ **Healthcare** → Merging **MRI scans + patient records + doctor's notes** for better diagnoses.

✅ **Future Outlook:**

- Advanced **Multimodal Transformers** (like GPT-V) will become standard.
- AI **agents that understand the world like humans**, fusing **vision, sound, and logic**.

---

3 Explainable AI (XAI) – Making AI Transparent

Many AI models (especially **deep learning** models) work as **"black boxes"**—we don't fully understand how they make decisions. **Explainable AI (XAI)** aims to make AI **interpretable and accountable**.

🔷 **Why XAI is Important?**

- **Medical AI:** Doctors must trust AI **diagnoses** before making life-critical decisions.
- **Finance AI:** Explainability is essential for **credit approvals and fraud detection**.
- **Legal AI:** AI in law enforcement must be **transparent & unbiased**.

🔷 **XAI Techniques:**
✅ **SHAP (SHapley Additive Explanations)** – Shows which features matter most in AI decisions.
✅ **LIME (Local Interpretable Model-agnostic Explanations)** – Highlights how changes affect AI outputs.
✅ **Attention Mechanisms in Transformers** – Shows what AI is "looking at" in NLP tasks.

✅ **Future Outlook:**

- AI models with **built-in transparency** will become a legal requirement.
- **Auditable AI systems** for **healthcare, finance, and government**.

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4 Federated Learning – Privacy-Focused AI Training

Federated Learning (FL) **trains AI models across multiple devices** without sharing raw data. Instead of sending data to a central server, each device trains the model locally and shares only **model updates**.

🔷 **Why Federated Learning is Important?**
✅ **Privacy-first AI** → No raw data leaves your device.

✅ **Faster AI training** → Edge devices process data instead of relying on cloud computing.
✅ **Personalized AI** → AI can adapt to your device **without exposing private data**.

🔷 **Real-World Examples:**

- **Google's Gboard** → Uses FL to improve text predictions while keeping data on your phone.
- **Apple's Face ID & Siri** → Learns from users **without sending raw data to Apple servers**.
- **Healthcare AI** → Hospitals train AI models **without sharing patient records**.

✅ **Future Outlook:**

- AI will become **more privacy-focused** and **secure**.
- **5G + FL = AI models that improve in real-time on millions of devices**.

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5 Edge AI – AI on Low-Power Devices

Edge AI allows **AI models to run directly on devices** like **smartphones, IoT sensors, drones, and AR/VR headsets** instead of relying on cloud computing.

🔷 **Why Edge AI is a Game-Changer?**
✅ **Faster Processing** → AI runs locally, reducing lag (great for real-time applications).
✅ **Lower Energy Consumption** → No need for constant cloud connectivity.
✅ **Better Privacy** → Data stays **on-device**, reducing risks.

🔷 **Examples of Edge AI:**

- **Tesla Autopilot** → Runs deep learning on an **AI chip inside the car**.
- **Apple Neural Engine (ANE)** → Enables **on-device AI for Face ID, Siri, and AR apps**.
- **Security Cameras (Ring, Nest)** → Detect intruders using **on-device AI**.
- **Wearables & Smartwatches** → AI models for **health tracking & ECG monitoring**.

✅ **Future Outlook:**

- **TinyML (Tiny Machine Learning)** → AI models optimized for **low-power microcontrollers**.
- **AI-powered IoT (Internet of Things)** → Smart cities, self-monitoring devices.

🚀 Final Thoughts – The Future of Deep Learning

The next **5-10 years** will bring **massive advancements** in AI:

✔ **AI models that can reason, adapt, and learn across multiple tasks (AGI)**
✔ **AI that processes text, images, and audio together (Multimodal AI)**
✔ **More transparent and accountable AI (Explainable AI, XAI)**
✔ **Privacy-first AI training (Federated Learning)**
✔ **AI running on phones, wearables, and smart home devices (Edge AI)**

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🚀 Hands-on Project: Implementing Edge AI with TensorFlow Lite (TFLite)

let's implement a **real-world Edge AI project** using **TensorFlow Lite (TFLite)** to deploy an AI model on a **low-power device (smartphone, Raspberry Pi, or IoT device).**

📌 Project: Real-Time Image Classification on Edge Devices

Goal:

We'll train an image classification model using **MobileNet**, convert it to **TensorFlow Lite (TFLite)**, and deploy it on an **Android/iOS device or Raspberry Pi** for real-time inference.

✅ **Uses a lightweight MobileNet model** (optimized for edge devices).
✅ **Converts the model to TensorFlow Lite** for efficient deployment.
✅ **Runs on low-power devices (smartphones, Raspberry Pi, etc.)**.

📌 Step 1: Install TensorFlow and TensorFlow Lite

Run this in your terminal:

pip install tensorflow tensorflow-datasets tflite-runtime

📌 Step 2: Train an Image Classification Model (MobileNetV2)

We'll use **MobileNetV2**, a lightweight deep learning model optimized for edge devices.

```
import tensorflow as tf
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D
from tensorflow.keras.models import Model

# Load pre-trained MobileNetV2 model (without top layer)
base_model = MobileNetV2(weights="imagenet", include_top=False, input_shape=(224, 224, 3))

# Add a custom classification head
x = GlobalAveragePooling2D()(base_model.output)
x = Dense(128, activation='relu')(x)
output_layer = Dense(10, activation='softmax')  # Assuming 10 classes

# Create the model
model = Model(inputs=base_model.input, outputs=output_layer)

# Freeze base model layers
for layer in base_model.layers:
    layer.trainable = False

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

# Print summary
model.summary()
```

📌 Step 3: Convert the Model to TensorFlow Lite (TFLite)

Now, let's convert the trained model to **TFLite format** for deployment.

```
# Convert the model to TensorFlow Lite format
converter = tf.lite.TFLiteConverter.from_keras_model(model)
converter.optimizations = [tf.lite.Optimize.DEFAULT]  # Optimize for smaller size
tflite_model = converter.convert()

# Save the converted model
with open("mobilenet_model.tflite", "wb") as f:
    f.write(tflite_model)

print("Model converted and saved as mobilenet_model.tflite")
```

📌 Step 4: Run Inference on Edge Devices (Raspberry Pi, Android, or iOS)

Once we have the .tflite model, we can run it on a **smartphone or Raspberry Pi** for real-time image classification.

Python Code for Running Inference on a Raspberry Pi

```
import numpy as np
import tensorflow.lite as tflite
from PIL import Image

# Load the TFLite model
interpreter = tflite.Interpreter(model_path="mobilenet_model.tflite")
interpreter.allocate_tensors()

# Get input/output details
input_details = interpreter.get_input_details()
output_details = interpreter.get_output_details()
```

```
# Load and preprocess an image
image = Image.open("test_image.jpg").resize((224, 224))
input_data = np.expand_dims(np.array(image, dtype=np.float32) / 255.0, axis=0)

# Run inference
interpreter.set_tensor(input_details[0]['index'], input_data)
interpreter.invoke()
output = interpreter.get_tensor(output_details[0]['index'])

# Get predicted class
predicted_class = np.argmax(output)
print(f"Predicted class: {predicted_class}")
```

📌 Step 5: Deploy on Android or iOS

For **Android/iOS deployment**, use **TensorFlow Lite Interpreter** in a mobile app.

- **Android:** Use **ML Kit or Android Studio with TFLite**.
- **iOS:** Use **Core ML + TFLite for iOS apps**.

🚀 Final Thoughts: Why Edge AI is the Future?

✅ **No internet required** – AI models run **locally on devices**.
✅ **Faster processing** – No cloud latency.
✅ **Better privacy** – Sensitive data stays **on-device**.
✅ **Energy-efficient AI** – Runs on **low-power devices**.
