

RAJALAKSHMI ENGINEERING COLLEGE

(An Autonomous Institution)

RAJALAKSHMI NAGAR, THANDALAM- 602 105



**RAJALAKSHMI
ENGINEERING
COLLEGE**

CS19P18 - DEEP LEARNING CONCEPTS

LABORATORY RECORD NOTEBOOK

NAME: ADHESH. M

YEAR/SEMESTER: FOUR/SEVEN

BRANCH: COMPUTER SCIENCE AND ENGINEERING

REGISTER NO:220701012

COLLEGE ROLL NO:2116220701012

ACADEMIC YEAR: 2025 -2026



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BONAFIDE CERTIFICATE

NAME: ADHESH. M **BRANCH/SECTION:** COMPUTER SCIENCE AND
ENGINEERING/A **ACADEMIC YEAR:** 2025 -2026 **SEMESTER:** SEVEN

REGISTER NO:

220701012

Certified that this is a Bonafide record of work done by the above
student in the **CS19P18 - DEEP LEARNING CONCEPTS**
during the year 2025 - 2026










Signature of Faculty In-charge

Submitted for the Practical Examination Held on: 21/11/2025

Internal Examiner

External Examiner

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INSTALLATION AND CONFIGURATION OF TENSORFLOW

Aim:

To install and configure TensorFlow in anaconda environment in Windows 10.

Procedure:

1. Download Anaconda Navigator and install.
2. Open Anaconda prompt
3. Create a new environment dlc with python 3.7 using the following command:
`conda create -n dlc python=3.7`
4. Activate newly created environment dlc using the following command:
`conda activate dlc`
5. In dlc prompt, install tensorflow using the following command:
`pip install tensorflow`
6. Next install Tensorflow-datasets using the following command:
`pip install tensorflow-datasets`
7. Install scikit-learn package using the following command:
`pip install scikit-learn`
8. Install pandas package using the following command:
`pip install pandas`
9. Lastly, install jupyter notebook
`pip install jupyter notebook`
10. Open jupyter notebook by typing the following in dlc prompt:
`jupyter notebook`
11. Click create new and then choose python 3 (ipykernel)
12. Give the name to the file
13. Type the code and click Run button to execute (eg. Type `import tensorflow` and then run)

EX NO: 1 CREATE A NEURAL NETWORK TO RECOGNIZE HANDWRITTEN
DATE:14/07/2025 DIGITS USING MNIST DATASET

Aim:

To build a handwritten digit's recognition with MNIST dataset.

Procedure:

1. Download and load the MNIST dataset.
2. Perform analysis and preprocessing of the dataset.
3. Build a simple neural network model using Keras/TensorFlow.
4. Compile and fit the model.
5. Perform prediction with the test dataset.
6. Calculate performance metrics.

Code:

```
import numpy as np
import tensorflow as tf
from tensorflow import keras

from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
# Generate a synthetic dataset

X, y = make_classification(n_samples=1000, n_features=20, random_state=42)
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Standardize features (optional but often beneficial)
scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)
```

```

X_test = scaler.transform(X_test)
# Define the model
model = keras.Sequential([
    keras.layers.Input(shape=(X_train.shape[1],)), # Input layer
    keras.layers.Dense(64, activation='relu'), # Hidden layer with 64 neurons and ReLU activation
    keras.layers.Dense(1, activation='sigmoid') # Output layer with 1 neuron and sigmoid activation
])

# Train the model

history = model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.1)
# Evaluate the model on the test set
y_pred = model.predict(X_test)
y_pred_classes = (y_pred > 0.5).astype(int)
# Calculate accuracy on the test set
accuracy = accuracy_score(y_test, y_pred_classes)
# Calculate test loss
test_loss = model.evaluate(X_test, y_test)
print(f"Test accuracy: {accuracy * 100:.2f}%")
print(f"Test loss: {test_loss[0]:.4f}")

```

Output:

```

Epoch 1/10
192/192 [=====] - 5s 17ms/step - loss: 0.3739 - accuracy: 0.8950 - val_loss: 0.1801 - val_accuracy: 0.9480
Epoch 2/10
192/192 [=====] - 3s 14ms/step - loss: 0.1492 - accuracy: 0.9562 - val_loss: 0.1261 - val_accuracy: 0.9635
Epoch 3/10
192/192 [=====] - 2s 13ms/step - loss: 0.0980 - accuracy: 0.9714 - val_loss: 0.1129 - val_accuracy: 0.9676
Epoch 4/10
192/192 [=====] - 2s 11ms/step - loss: 0.0711 - accuracy: 0.9795 - val_loss: 0.0962 - val_accuracy: 0.9709
Epoch 5/10
192/192 [=====] - 2s 10ms/step - loss: 0.0543 - accuracy: 0.9844 - val_loss: 0.0914 - val_accuracy: 0.9725
Epoch 6/10
192/192 [=====] - 2s 11ms/step - loss: 0.0402 - accuracy: 0.9888 - val_loss: 0.0866 - val_accuracy: 0.9737
Epoch 7/10
192/192 [=====] - 2s 12ms/step - loss: 0.0301 - accuracy: 0.9920 - val_loss: 0.0871 - val_accuracy: 0.9750
Epoch 8/10
192/192 [=====] - 2s 12ms/step - loss: 0.0245 - accuracy: 0.9931 - val_loss: 0.0840 - val_accuracy: 0.9762
Epoch 9/10
192/192 [=====] - 2s 12ms/step - loss: 0.0180 - accuracy: 0.9956 - val_loss: 0.0878 - val_accuracy: 0.9760
Epoch 10/10
192/192 [=====] - 2s 11ms/step - loss: 0.0149 - accuracy: 0.9963 - val_loss: 0.0858 - val_accuracy: 0.9755

```

jupyter Exp-1 Last Checkpoint: 3 hours ago (autosaved) Logout

File Edit View Insert Cell Kernel Widgets Help Trusted Python 3 (ipykernel)

```
In [1]: import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.utils import to_categorical

In [2]: feature_vector_length = 784
num_classes = 10

In [3]: (X_train, Y_train), (X_test, Y_test) = mnist.load_data()

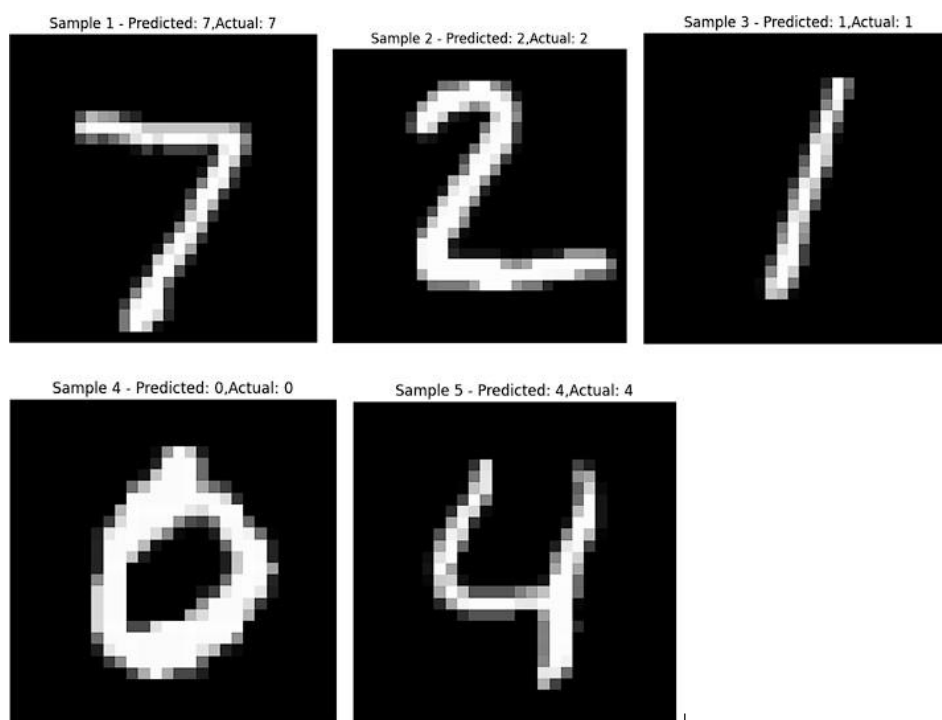
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 [=====] - 2s 0us/step

In [4]: input_shape = (feature_vector_length)
print(f'Feature shape: {input_shape}')

Feature shape: 784

In [5]: X_train = X_train.reshape(X_train.shape[0], feature_vector_length)
X_test = X_test.reshape(X_test.shape[0], feature_vector_length)

In [6]: X_train = X_train.astype('float32') / 255
X_test = X_test.astype('float32') / 255
Y_train = to_categorical(Y_train, num_classes)
Y_test = to_categorical(Y_test, num_classes)
```



Result:

Thus, the implementation to build a simple neural network using Keras/TensorFlow has been successfully executed.

EX NO:2

BUILD A CONVOLUTIONAL NEURAL NETWORK

DATE:21/07/2025

USING KERAS/TENSORFLOW

Aim:

To implement a Convolutional Neural Network (CNN) using Keras/TensorFlow to recognize and classify handwritten digits from the MNIST dataset with high accuracy.

Procedure:

1. Import required libraries (TensorFlow/Keras, NumPy, etc.).
2. Load the MNIST dataset from Keras.
3. Normalize and reshape the image data.
4. Convert labels to one-hot encoded vectors.
5. Build a CNN model with Conv2D, MaxPooling, Flatten, and Dense layers.
6. Compile the model using categorical crossentropy and Adam optimizer.
7. Train the model on training data.
8. Evaluate the model on test data.
9. Display accuracy and predictions.

Code:

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
from tensorflow.keras.datasets import mnist
import matplotlib.pyplot as plt
import numpy as np

(train_images, train_labels), (test_images, test_labels) = mnist.load_data()
train_images = train_images / 255.0
test_images = test_images / 255.0
train_images = train_images.reshape(-1, 28, 28, 1)
test_images = test_images.reshape(-1, 28, 28, 1)
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(64, activation='relu'),
    Dropout(0.5),
    Dense(10, activation='softmax')
])
```



```

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

history = model.fit(train_images, train_labels,
epochs=5,
batch_size=64,
validation_split=0.2)

test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f"\n Test accuracy: {test_acc:.4f}")
print(f" Test loss: {test_loss:.4f}")

plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Train Accuracy', marker='o')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', marker='o')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Train Loss', marker='o')
plt.plot(history.history['val_loss'], label='Validation Loss', marker='o')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

predictions = model.predict(test_images)
predicted_labels = np.argmax(predictions, axis=1)

num_samples = 10
plt.figure(figsize=(15, 4))

for i in range(num_samples):
plt.subplot(1, num_samples, i + 1)
plt.imshow(test_images[i].reshape(28, 28), cmap='gray')
plt.title(f"Pred: {predicted_labels[i]}\nTrue: {test_labels[i]}")

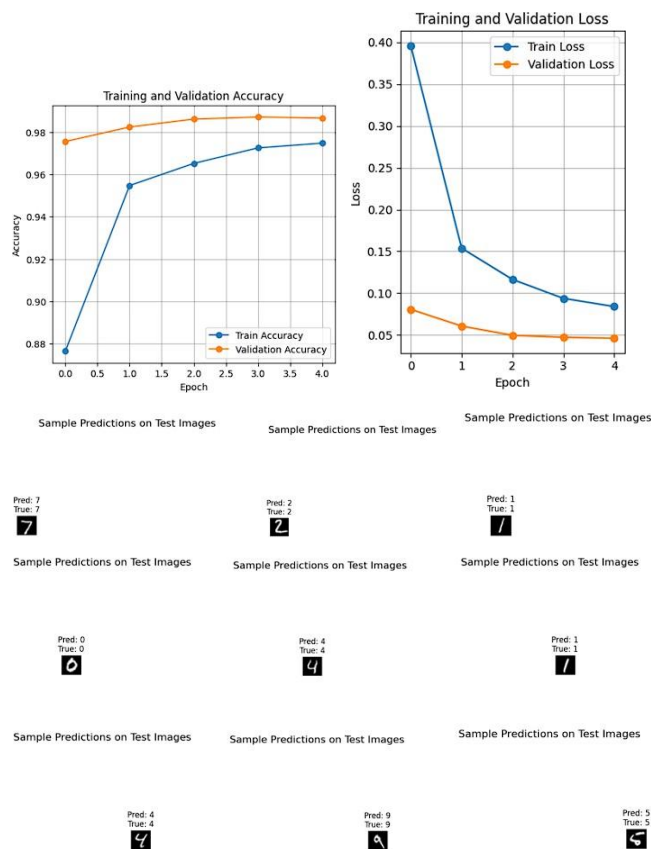
```

```
plt.axis('off')
plt.suptitle("Sample Predictions on Test Images", fontsize=16)
plt.show()
```

Output:

```
Epoch 1/5
750/750 [=====] - 30s 39ms/step - loss: 0.3961 - accuracy: 0.8765 - val_loss: 0.0806 - val_accuracy: 0.9756
Epoch 2/5
750/750 [=====] - 26s 35ms/step - loss: 0.1538 - accuracy: 0.9548 - val_loss: 0.0606 - val_accuracy: 0.9824
Epoch 3/5
750/750 [=====] - 30s 39ms/step - loss: 0.1163 - accuracy: 0.9652 - val_loss: 0.0495 - val_accuracy: 0.9862
Epoch 4/5
750/750 [=====] - 27s 36ms/step - loss: 0.0937 - accuracy: 0.9725 - val_loss: 0.0472 - val_accuracy: 0.9872
Epoch 5/5
750/750 [=====] - 26s 35ms/step - loss: 0.0840 - accuracy: 0.9748 - val_loss: 0.0460 - val_accuracy: 0.9867
313/313 [=====] - 2s 5ms/step - loss: 0.0390 - accuracy: 0.9880
```

Test accuracy: 0.9880
Test loss: 0.0390



Result:

Thus, the Convolution Neural Network (CNN) using Keras / Tensorflow to recognize and classify handwritten digits from MNIST dataset has been implemented successfully.

EX NO: 3 IMAGE CLASSIFICATION ON CIFAR-10 DATASET USING CNN

DATE:28/07/2025

Aim:

To build a Convolutional Neural Network (CNN) model for classifying images from the CIFAR-10 dataset into one of the ten categories such as airplanes, cars, birds, cats, etc.

Procedure:

1. Download and load the CIFAR-10 dataset using Keras/TensorFlow.
2. Visualize and analyze sample images from the dataset.
- 3, Preprocess the data:
 - Normalize the pixel values (divide by 255)
 - Convert class labels to one-hot encoded format
4. Build a CNN model using Keras/TensorFlow:
 - Include convolutional, pooling, flatten, and dense layers.
5. Compile the model with suitable loss function and optimizer.
6. Train the model using training data and validate using test data.
7. Evaluate the model using accuracy and loss on test dataset.
8. Perform predictions on new/unseen CIFAR-10 images.
- 9 Visualize prediction results with sample images and predicted labels.

Code:

```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0
y_train = tf.keras.utils.to_categorical(y_train, 10)
y_test = tf.keras.utils.to_categorical(y_test, 10)
model = tf.keras.Sequential()
model.add(tf.keras.layers.Conv2D(32, (3,3), activation='relu', input_shape=(32,32,3)))
model.add(tf.keras.layers.MaxPooling2D((2,2)))
model.add(tf.keras.layers.Conv2D(64, (3,3), activation='relu'))
model.add(tf.keras.layers.MaxPooling2D((2,2)))
model.add(tf.keras.layers.Conv2D(64, (3,3), activation='relu'))
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(64, activation='relu'))
model.add(tf.keras.layers.Dense(10, activation='softmax'))
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model.fit(x_train, y_train, epochs=10, batch_size=64, validation_split=0.2)
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer',
```

```

'dog', 'frog', 'horse', 'ship', 'truck']
index = int(input("Enter an index (0 to 9999) for test image: "))
if index < 0 or index >= len(x_test):
    print("Invalid index. Using index 0 by default.")
index = 0
test_image = x_test[index]
true_label = np.argmax(y_test[index])
prediction = model.predict(np.expand_dims(test_image, axis=0))
predicted_label = np.argmax(prediction)
plt.figure(figsize=(4, 4))
resized_image = tf.image.resize(test_image, [128, 128])
plt.imshow(resized_image)
plt.axis('off')
plt.title(f"Predicted: {class_names[predicted_label]}\nActual: {class_names[true_label]}")
plt.show()

```

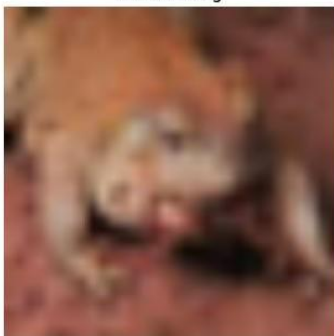
Output:

```

Epoch 1/10
625/625 [=====] - 58s 87ms/step - loss: 1.6801 - accuracy: 0.3846 - val_loss: 1.4341 - val_accuracy:
0.4803
Epoch 2/10
625/625 [=====] - 37s 60ms/step - loss: 1.3153 - accuracy: 0.5284 - val_loss: 1.3005 - val_accuracy:
0.5388
Epoch 3/10
625/625 [=====] - 36s 58ms/step - loss: 1.1663 - accuracy: 0.5846 - val_loss: 1.1370 - val_accuracy:
0.6014
Epoch 4/10
625/625 [=====] - 38s 61ms/step - loss: 1.0629 - accuracy: 0.6249 - val_loss: 1.0984 - val_accuracy:
0.6178
Epoch 5/10
625/625 [=====] - 41s 65ms/step - loss: 0.9991 - accuracy: 0.6480 - val_loss: 1.0476 - val_accuracy:
0.6379
Epoch 6/10
625/625 [=====] - 38s 61ms/step - loss: 0.9348 - accuracy: 0.6720 - val_loss: 0.9795 - val_accuracy:
0.6598
Epoch 7/10
625/625 [=====] - 38s 60ms/step - loss: 0.8764 - accuracy: 0.6970 - val_loss: 1.0013 - val_accuracy:
0.6547
Epoch 8/10
625/625 [=====] - 38s 61ms/step - loss: 0.8338 - accuracy: 0.7096 - val_loss: 0.9313 - val_accuracy:
0.6770
Epoch 9/10
625/625 [=====] - 39s 62ms/step - loss: 0.7943 - accuracy: 0.7242 - val_loss: 0.9243 - val_accuracy:
0.6856
Epoch 10/10
625/625 [=====] - 37s 60ms/step - loss: 0.7588 - accuracy: 0.7362 - val_loss: 0.8994 - val_accuracy:
0.6986

```

Predicted: frog
Actual: frog



Result

Thus, the Convolution Neural Network (CNN) model for classifying images from CIFAR-10 dataset is implemented successfully.

Ex No: 4 TRANSFER LEARNING WITH CNN AND VISUALIZATION
DATE:04/08/2025

Aim:

To build a convolutional neural network with transfer learning and perform visualization

Procedure:

1. Download and load the dataset.
2. Perform analysis and preprocessing of the dataset.
3. Build a simple neural network model using Keras/TensorFlow.
4. Compile and fit the model.
5. Perform prediction with the test dataset.
6. Calculate performance metrics.

Code:

```
conda install -c conda-forge python-graphviz -y
import tensorflow as tf
from tensorflow.keras.applications import VGG16
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.utils import plot_model
import matplotlib.pyplot as plt
import numpy as np
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
x_train = x_train / 255.0
x_test = x_test / 255.0
vgg_base = VGG16(weights='imagenet', include_top=False, input_shape=(32, 32, 3))
for layer in vgg_base.layers:
    layer.trainable = False
model = Sequential()
model.add(vgg_base)
model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(10, activation='softmax'))
model.compile(optimizer=Adam(learning_rate=0.0001),
loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
plot_model(model, to_file='cnn.png', show_shapes=True,
```

```

show_layer_names=True, dpi=300)
plt.figure(figsize=(20, 20))
img = plt.imread('cnn.png')
plt.imshow(img)
plt.axis('off')
plt.show()
history = model.fit(x_train, y_train,
epochs=10,
batch_size=32,
validation_split=0.2)

test_loss, test_acc = model.evaluate(x_test, y_test)
print(f'Test Loss: {test_loss:.4f}')
print(f'Test Accuracy: {test_acc * 100:.2f}%')
plt.figure(figsize=(12, 5))

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('Epoch')
plt.ylabel('Accuracy')
plt.legend()

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('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.show()

class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer',
'dog', 'frog', 'horse', 'ship', 'truck']
sample = x_test[0].reshape(1, 32, 32, 3)
prediction = model.predict(sample)
predicted_class = class_names[np.argmax(prediction)]

plt.imshow(x_test[0])
plt.title(f'Predicted: {predicted_class}')
plt.axis('off')
plt.show()

```

Output:

vgg16_input	input:	[(None, 32, 32, 3)]
InputLayer	output:	[(None, 32, 32, 3)]



vgg16	input:	(None, 32, 32, 3)
Functional	output:	(None, 1, 1, 512)



flatten	input:	(None, 1, 1, 512)
Flatten	output:	(None, 512)



dense	input:	(None, 512)
Dense	output:	(None, 512)



dropout	input:	(None, 512)
Dropout	output:	(None, 512)

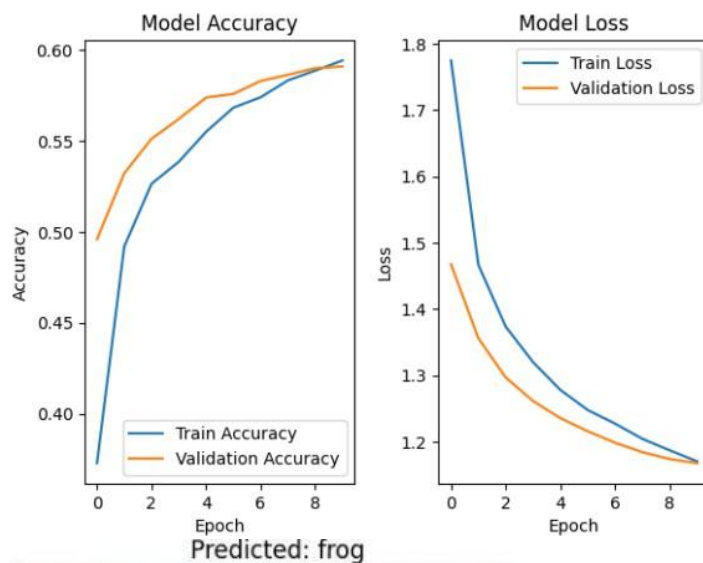


dense_1	input:	(None, 512)
Dense	output:	(None, 10)

```

Epoch 1/10
1250/1250 [=====] - 231s 182ms/step - loss: 1.7748 - accuracy: 0.3727 - val_loss: 1.4674 - val_accurac
y: 0.4959
Epoch 2/10
1250/1250 [=====] - 193s 154ms/step - loss: 1.4665 - accuracy: 0.4920 - val_loss: 1.3556 - val_accurac
y: 0.5322
Epoch 3/10
1250/1250 [=====] - 187s 150ms/step - loss: 1.3733 - accuracy: 0.5264 - val_loss: 1.2966 - val_accurac
y: 0.5512
Epoch 4/10
1250/1250 [=====] - 189s 151ms/step - loss: 1.3197 - accuracy: 0.5386 - val_loss: 1.2610 - val_accurac
y: 0.5621
Epoch 5/10
1250/1250 [=====] - 191s 153ms/step - loss: 1.2777 - accuracy: 0.5551 - val_loss: 1.2352 - val_accurac
y: 0.5739
Epoch 6/10
1250/1250 [=====] - 190s 152ms/step - loss: 1.2474 - accuracy: 0.5683 - val_loss: 1.2154 - val_accurac
y: 0.5759
Epoch 7/10
1250/1250 [=====] - 187s 150ms/step - loss: 1.2269 - accuracy: 0.5741 - val_loss: 1.1981 - val_accurac
y: 0.5830
Epoch 8/10
1250/1250 [=====] - 183s 146ms/step - loss: 1.2039 - accuracy: 0.5834 - val_loss: 1.1839 - val_accurac
y: 0.5864
Epoch 9/10
1250/1250 [=====] - 177s 142ms/step - loss: 1.1866 - accuracy: 0.5887 - val_loss: 1.1735 - val_accurac
y: 0.5900
Epoch 10/10
1250/1250 [=====] - 175s 140ms/step - loss: 1.1699 - accuracy: 0.5943 - val_loss: 1.1672 - val_accurac
y: 0.5910

```



Result

Thus, the Convolution Neural Network (CNN) with transfer learning and perform visualization has been implemented successfully

KERAS/TENSORFLOW

To build a recurrent neural network with Keras/TensorFlow.

1. Download and load the dataset.
2. Perform analysis and preprocessing of the dataset.
3. Build a simple neural network model using Keras/TensorFlow.
4. Compile and fit the model.
5. Perform prediction with the test dataset.
6. Calculate performance metrics.

```
import numpy as np
import tensorflow as tf

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import SimpleRNN, Dense
from sklearn.metrics import r2_score

np.random.seed(0)

seq_length = 10
num_samples = 1000

X = np.random.randn(num_samples, seq_length, 1)
y = X.sum(axis=1) + 0.1 * np.random.randn(num_samples, 1)

split_ratio = 0.8
split_index = int(split_ratio * num_samples)
X_train, X_test = X[:split_index], X[split_index:]
y_train, y_test = y[:split_index], y[split_index:]

model = Sequential()
model.add(SimpleRNN(units=50, activation='relu', input_shape=(seq_length, 1)))
model.add(Dense(units=1))
model.compile(optimizer='adam', loss='mean_squared_error')
model.summary()

batch_size = 30
epochs = 50 # Reduced epochs for quick demonstration
history = model.fit(
    X_train, y_train,
    batch_size=batch_size,
    epochs=epochs,
    validation_split=0.2
)

test_loss = model.evaluate(X_test, y_test)
print(f'Test Loss: {test_loss:.4f}')
```

```

y_pred = model.predict(X_test)
r2 = r2_score(y_test, y_pred)
print(f'Test Accuracy (R^2): {r2:.4f}')

new_data = np.random.randn(5, seq_length, 1)
predictions = model.predict(new_data)
print("Predictions for new data:")
print(predictions)

```

Output:

Model: "sequential"

Layer (type)	Output Shape	Param #
simple_rnn (SimpleRNN)	(None, 50)	2600
dense (Dense)	(None, 1)	51

=====
Total params: 2,651
Trainable params: 2,651
Non-trainable params: 0
=====

```

Epoch 1/50
22/22 [=====] - 2s 23ms/step - loss: 8.7454
- val_loss: 6.3263
Epoch 2/50
22/22 [=====] - 0s 4ms/step - loss: 5.8837
- val_loss: 3.7798
Epoch 3/50
22/22 [=====] - 0s 5ms/step - loss: 3.7728
- val_loss: 2.3105
Epoch 4/50
22/22 [=====] - 0s 5ms/step - loss: 1.7141
- val_loss: 0.5373
Epoch 5/50
22/22 [=====] - 0s 4ms/step - loss: 0.2878
- val_loss: 0.2417
Epoch 6/50
22/22 [=====] - 0s 4ms/step - loss: 0.1304
- val_loss: 0.1146
Epoch 7/50

```

```

1/1 [=====] - 0s 20ms/step
Predictions for new data:
[[ 1.5437698]
 [ 0.4290885]
 [-2.1180325]
 [-0.5443404]
 [-3.8416493]]

```

Result:

Thus, the Recurrent Neural Network (RNN) has been implemented using Tensorflow.

EX NO: 6

SENTIMENT CLASSIFICATION OF TEXT USING RNN

DATE:15/09/2025

Aim:

To implement a Recurrent Neural Network (RNN) using Keras/TensorFlow for classifying the sentiment of text data (e.g., movie reviews) as positive or negative.

Procedure:

1. Import necessary libraries.
2. Load and preprocess the text dataset (e.g., IMDb).
3. Pad sequences and prepare labels.
4. Build an RNN model with Embedding and SimpleRNN layers.
5. Compile the model with loss and optimizer.
6. Train the model on training data.
7. Evaluate the model on test data.
8. Predict sentiment for new inputs

Code:

```
import numpy as np
from tensorflow.keras.datasets import imdb
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, SimpleRNN, Dense
max_words = 5000
max_len = 200
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_words)
X_train = pad_sequences(x_train, maxlen=max_len)
X_test = pad_sequences(x_test, maxlen=max_len)
model = Sequential()
model.add(Embedding(input_dim=max_words, output_dim=32, input_length=max_len))
model.add(SimpleRNN(32))
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
print("Training...")
model.fit(X_train, y_train, epochs=2, batch_size=64, validation_split=0.2)
loss, acc = model.evaluate(X_test, y_test)
print(f"\nTest Accuracy: {acc:.4f}")
word_index = imdb.get_word_index()
reverse_word_index = {v: k for (k, v) in word_index.items() }
```

```
def decode_review(review):
return " ".join([reverse_word_index.get(i - 3, "?") for i in review])
sample_review = X_test[0]
prediction = model.predict(sample_review.reshape(1, -1))[0][0]
print("\nReview text:", decode_review(x_test[0]))
print("Predicted Sentiment:", "Positive " if prediction > 0.5 else "Negative ")
```

Output:

```

Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz
17464789/17464789 ————— 0s 0us/step
Training...
Epoch 1/2
/usr/local/lib/python3.12/dist-packages/keras/src/layers/core/embedding.py:97: UserWarning: Argument `input_length` is deprecated. Just remove it.
warnings.warn(
313/313 ————— 21s 59ms/step - accuracy: 0.6479 - loss: 0.6143 - val_accuracy: 0.6644 - val_loss: 0.6085
Epoch 2/2
313/313 ————— 17s 53ms/step - accuracy: 0.7939 - loss: 0.4496 - val_accuracy: 0.8186 - val_loss: 0.4121
782/782 ————— 10s 13ms/step - accuracy: 0.8237 - loss: 0.4115

Test Accuracy: 0.8230
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb\_word\_index.json
1641221/1641221 ————— 0s 0us/step

```

```

def decode_review(review):
    return " ".join([reverse_word_index.get(i - 3, "?") for i in review])
sample_review = X_test[0]
prediction = model.predict(sample_review.reshape(1, -1))[0][0]
print("\nReview text:", decode_review(x_test[0]))
print("Predicted Sentiment:", "Positive " if prediction > 0.5 else "Negative ")

```

```

1/1 ————— 0s 195ms/step

```

```

Review text: ? please give this one a miss br br ? ? and the rest of the cast ? terrible performances the show is flat flat flat br br i don't know how michael
Predicted Sentiment: Negative

```

Result

Thus, the Recurrent Neural Network (RNN) using Keras has been implemented for classifying sentiment of text successfully.

Ex No: 7 BUILD AUTOENCODERS WITH KERAS/TENSORFLOW**DATE:22/09/2025****Aim:**

To build autoencoders with Keras/TensorFlow.

Procedure:

1. Download and load the dataset.
2. Perform analysis and preprocessing of the dataset.
3. Build a simple neural network model using Keras/TensorFlow.
4. Compile and fit the model.
5. Perform prediction with the test dataset.
6. Calculate performance metrics.

Code:

```
import numpy as np
import matplotlib.pyplot as plt
from keras.layers import Input, Dense
from keras.models import Model
from keras.datasets import mnist
(x_train, _), (x_test, _) = mnist.load_data()
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.
x_train = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
x_test = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))
input_img = Input(shape=(784,))
encoded = Dense(32, activation='relu')(input_img)
decoded = Dense(784, activation='sigmoid')(encoded)
autoencoder = Model(input_img, decoded)
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
autoencoder.fit(x_train, x_train,
epochs=50,
batch_size=256,
shuffle=True,
validation_data=(x_test, x_test))
test_loss = autoencoder.evaluate(x_test, x_test)
decoded_imgs = autoencoder.predict(x_test)
threshold = 0.5
correct_predictions = np.sum(
np.where(x_test >= threshold, 1, 0) ==
np.where(decoded_imgs >= threshold, 1, 0))
total_pixels = x_test.shape[0] * x_test.shape[1]
test_accuracy = correct_predictions / total_pixels
print("Test Loss:", test_loss)
```

```

print("Test Accuracy:", test_accuracy)
n = 10
plt.figure(figsize=(20, 4))
for i in range(n):
    # Display original
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test[i].reshape(28, 28))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
    # Display reconstruction with threshold
    ax = plt.subplot(2, n, i + 1 + n)
    reconstruction = decoded_imgs[i].reshape(28, 28)
    plt.imshow(np.where(reconstruction >= threshold, 1.0, 0.0))
    plt.gray()
    ax.get_xaxis().set_visible(False)
    ax.get_yaxis().set_visible(False)
plt.show()

```

Output:

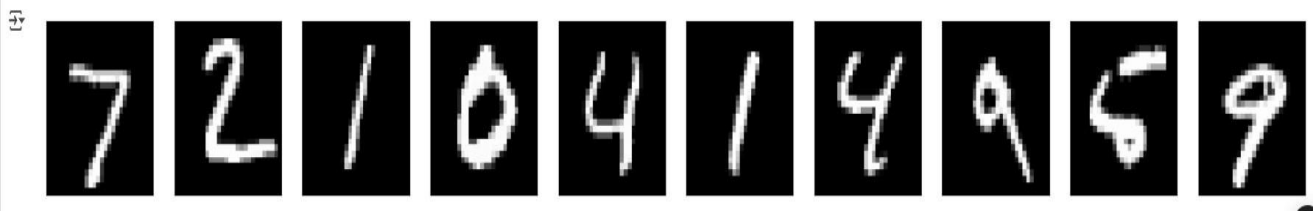
```

Epoch 1/50
235/235 ————— 6s 18ms/step - loss: 0.3805 - val_loss: 0.1906
Epoch 2/50
235/235 ————— 5s 19ms/step - loss: 0.1808 - val_loss: 0.1547
Epoch 3/50
235/235 ————— 5s 19ms/step - loss: 0.1501 - val_loss: 0.1342
Epoch 4/50
235/235 ————— 3s 10ms/step - loss: 0.1321 - val_loss: 0.1221
Epoch 5/50
235/235 ————— 2s 9ms/step - loss: 0.1210 - val_loss: 0.1138
Epoch 6/50
235/235 ————— 3s 11ms/step - loss: 0.1134 - val_loss: 0.1081
Epoch 7/50
235/235 ————— 5s 9ms/step - loss: 0.1079 - val_loss: 0.1039
Epoch 8/50
235/235 ————— 2s 9ms/step - loss: 0.1042 - val_loss: 0.1006
Epoch 9/50
235/235 ————— 3s 9ms/step - loss: 0.1011 - val_loss: 0.0981
Epoch 10/50
235/235 ————— 3s 11ms/step - loss: 0.0989 - val_loss: 0.0963
Epoch 11/50
235/235 ————— 3s 12ms/step - loss: 0.0972 - val_loss: 0.0951
Epoch 12/50
235/235 ————— 3s 11ms/step - loss: 0.0964 - val_loss: 0.0943
Epoch 13/50
235/235 ————— 2s 10ms/step - loss: 0.0954 - val_loss: 0.0938
Epoch 14/50
235/235 ————— 2s 10ms/step - loss: 0.0950 - val_loss: 0.0934
Epoch 15/50
235/235 ————— 3s 11ms/step - loss: 0.0944 - val_loss: 0.0932

```

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz>
11490434/11490434 — 1s 0us/step

Test Loss: 0.09166844934225082
Test Accuracy: 0.9712756377551021



```
# Display reconstruction with threshold
ax = plt.subplot(2, n, i + 1 + n)
reconstruction = decoded_imgs[i].reshape(28, 28)
plt.imshow(np.where(reconstruction >= threshold, 1.0, 0.0))
plt.gray()
ax.get_xaxis().set_visible(False)
ax.get_yaxis().set_visible(False)
plt.show()
```



Result

Thus, an Autoencoder has been implemented using Keras / Tensorflow.

Ex No:8

OBJECT DETECTION WITH YOLO3

DATE:29/09/2025

Aim:

To build an object detection model with YOLO3 using Keras/TensorFlow.

Procedure:

1. Download and load the dataset.
2. Perform analysis and preprocessing of the dataset.
3. Build a simple neural network model using Keras/TensorFlow.
4. Compile and fit the model.
5. Perform prediction with the test dataset.
6. Calculate performance metrics.

Code:

```
import cv2
import matplotlib.pyplot as plt
import numpy as np

# Define the paths to the YOLOv3 configuration, weights, and class names files
cfg_file = '/content/yolov3.cfg'
weight_file = '/content/yolov3.weights'
namesfile = '/content/coco.names'

# Load the YOLOv3 model
net = cv2.dnn.readNet(weight_file, cfg_file)

# Load class names
with open(namesfile, 'r') as f:
    classes = f.read().strip().split("\n")

# Load an image for object detection
image_path = '/content/hit.jpg'
image = cv2.imread(image_path)

# Get the height and width of the image
height, width = image.shape[:2]

# Create a blob from the image
blob = cv2.dnn.blobFromImage(image, 1/255.0, (416, 416), swapRB=True, crop=False)
net.setInput(blob)

# Get the names of the output layers
layer_names = net.getUnconnectedOutLayersNames()

# Run forward pass
```



```

outs = net.forward(layer_names)

# Initialize lists to store detected objects' information
class_ids = []
confidences = []
boxes = []

# Define a confidence threshold for object detection
conf_threshold = 0.5

# Loop over the detections
for out in outs:
    for detection in out:
        scores = detection[5:]
        class_id = np.argmax(scores)
        confidence = scores[class_id]
        if confidence > conf_threshold:
            # Object detected
            center_x = int(detection[0] * width)
            center_y = int(detection[1] * height)
            w = int(detection[2] * width)
            h = int(detection[3] * height)

            # Rectangle coordinates
            x = int(center_x - w / 2)
            y = int(center_y - h / 2)

            class_ids.append(class_id)
            confidences.append(float(confidence))
            boxes.append([x, y, w, h])

# Apply non-maximum suppression to eliminate overlapping boxes
nms_threshold = 0.4
indices = cv2.dnn.NMSBoxes(boxes, confidences, conf_threshold, nms_threshold)

# Draw bounding boxes and labels on the image
for i in indices.flatten(): # flatten for compatibility
    x, y, w, h = boxes[i]
    label = str(classes[class_ids[i]])
    confidence = confidences[i]

    cv2.rectangle(image, (x, y), (x + w, y + h), (0, 255, 0), 2)
    cv2.putText(image, f'{label} {confidence:.2f}', (x, y - 10),
cv2.FONT_HERSHEY_SIMPLEX, 0.8, (0, 255, 0), 2)

```

```
# Display the result in Jupyter Notebook
plt.figure(figsize=(10, 8))
plt.imshow(cv2.cvtColor(image, cv2.COLOR_BGR2RGB))
plt.axis('off')
plt.show()
```

Output:

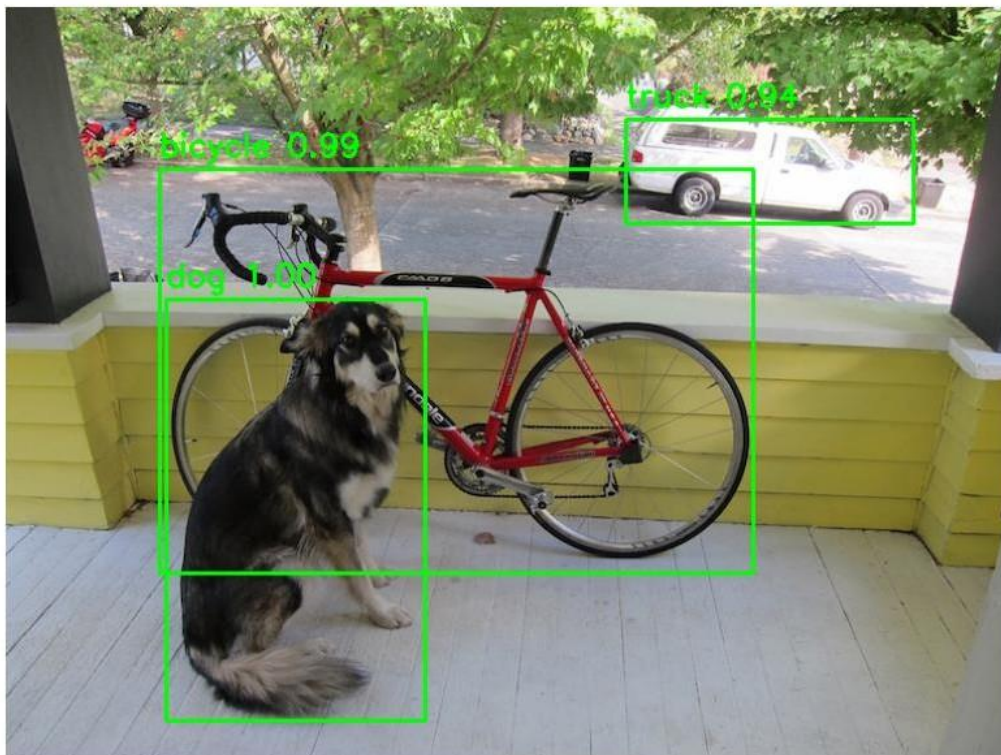
```
cfg_file=r"C:\Users\agaki\Downloads\yolov3.cfg"
weight_file=r"C:\Users\agaki\Downloads\yolov3.weights"
names_file=r"C:\Users\agaki\Downloads\coco.names"

for out in outs:
    for detection in out:
        scores=detection[5:]
        class_id=np.argmax(scores)
        confidence=scores[class_id]
        if confidence>conf_threshold:

            center_x=int(detection[0]*width)
            center_y=int(detection[1]*height)
            w=int(detection[2]*width)
            h=int(detection[3]*height)

            x=int(center_x-w/2)
            y=int(center_y-h/2)

            class_ids.append(class_id)
            confidences.append(float(confidence))
            boxes.append([x,y,w,h])
```



Result

Thus, object detection using YOLOV5 has been implemented successfully.

Ex No: 9 BUILD GENERATIVE ADVERSARIAL NEURAL NETWORK

DATE:29/09/2025

Aim:

To build a generative adversarial neural network using Keras/TensorFlow.

Procedure:

1. Download and load the dataset.
2. Perform analysis and preprocessing of the dataset.
3. Build a simple neural network model using Keras/TensorFlow.
4. Compile and fit the model.
5. Perform prediction with the test dataset.
6. Calculate performance metrics.

Code:

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.layers import Dense
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from sklearn.datasets import load_iris
import matplotlib.pyplot as plt

# Load and Preprocess the Iris Dataset
iris = load_iris()
x_train = iris.data

# Build the GAN model
def build_generator():
    model = Sequential()
    model.add(Dense(128, input_shape=(100,), activation='relu'))
    model.add(Dense(4, activation='linear')) # Output 4 features
    return model

def build_discriminator():
    model = Sequential()
    model.add(Dense(128, input_shape=(4,), activation='relu'))
    model.add(Dense(1, activation='sigmoid'))
    return model

def build_gan(generator, discriminator):
    discriminator.trainable = False
    model = Sequential()
    model.add(generator)
    model.add(discriminator)
```

```

return model

generator = build_generator()
discriminator = build_discriminator()
gan = build_gan(generator, discriminator)

# Compile the Models
generator.compile(loss='mean_squared_error', optimizer=Adam(0.0002, 0.5))
discriminator.compile(loss='binary_crossentropy', optimizer=Adam(0.0002, 0.5),
metrics=['accuracy'])
gan.compile(loss='binary_crossentropy', optimizer=Adam(0.0002, 0.5))

# Training Loop
epochs = 200
batch_size = 16

for epoch in range(epochs):
    # Train discriminator
    idx = np.random.randint(0, x_train.shape[0], batch_size)
    real_samples = x_train[idx]
    fake_samples = generator.predict(np.random.normal(0, 1, (batch_size, 100)), verbose=0)

    real_labels = np.ones((batch_size, 1))
    fake_labels = np.zeros((batch_size, 1))

    d_loss_real = discriminator.train_on_batch(real_samples, real_labels)
    d_loss_fake = discriminator.train_on_batch(fake_samples, fake_labels)

    # Train generator
    noise = np.random.normal(0, 1, (batch_size, 100))
    g_loss = gan.train_on_batch(noise, real_labels)

    # Print progress
    print(f"Epoch {epoch}/{epochs} | Discriminator Loss: {0.5 * (d_loss_real[0] + d_loss_fake[0])} |
Generator Loss: {g_loss}")

# Generating Synthetic Data
synthetic_data = generator.predict(np.random.normal(0, 1, (150, 100)), verbose=0)

# Create scatter plots for feature pairs
plt.figure(figsize=(12, 8))
plot_idx = 1

for i in range(4):
    for j in range(i + 1, 4):
        plt.subplot(2, 3, plot_idx)

```

```
plt.scatter(x_train[:, i], x_train[:, j], label='Real Data', c='blue', marker='o', s=30)
plt.scatter(synthetic_data[:, i], synthetic_data[:, j], label='Synthetic Data', c='red', marker='x',
s=30)
plt.xlabel(f'Feature {i + 1}')
plt.ylabel(f'Feature {j + 1}')
plt.legend()
plot_idx += 1

plt.tight_layout()
plt.show()
```

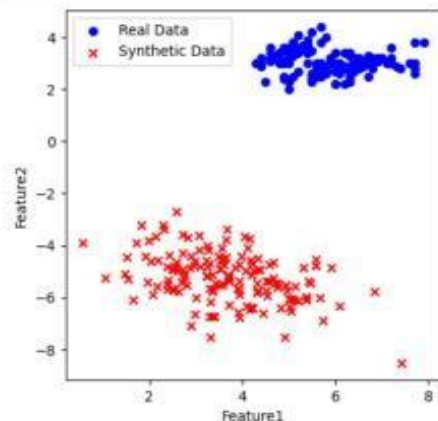
Output:

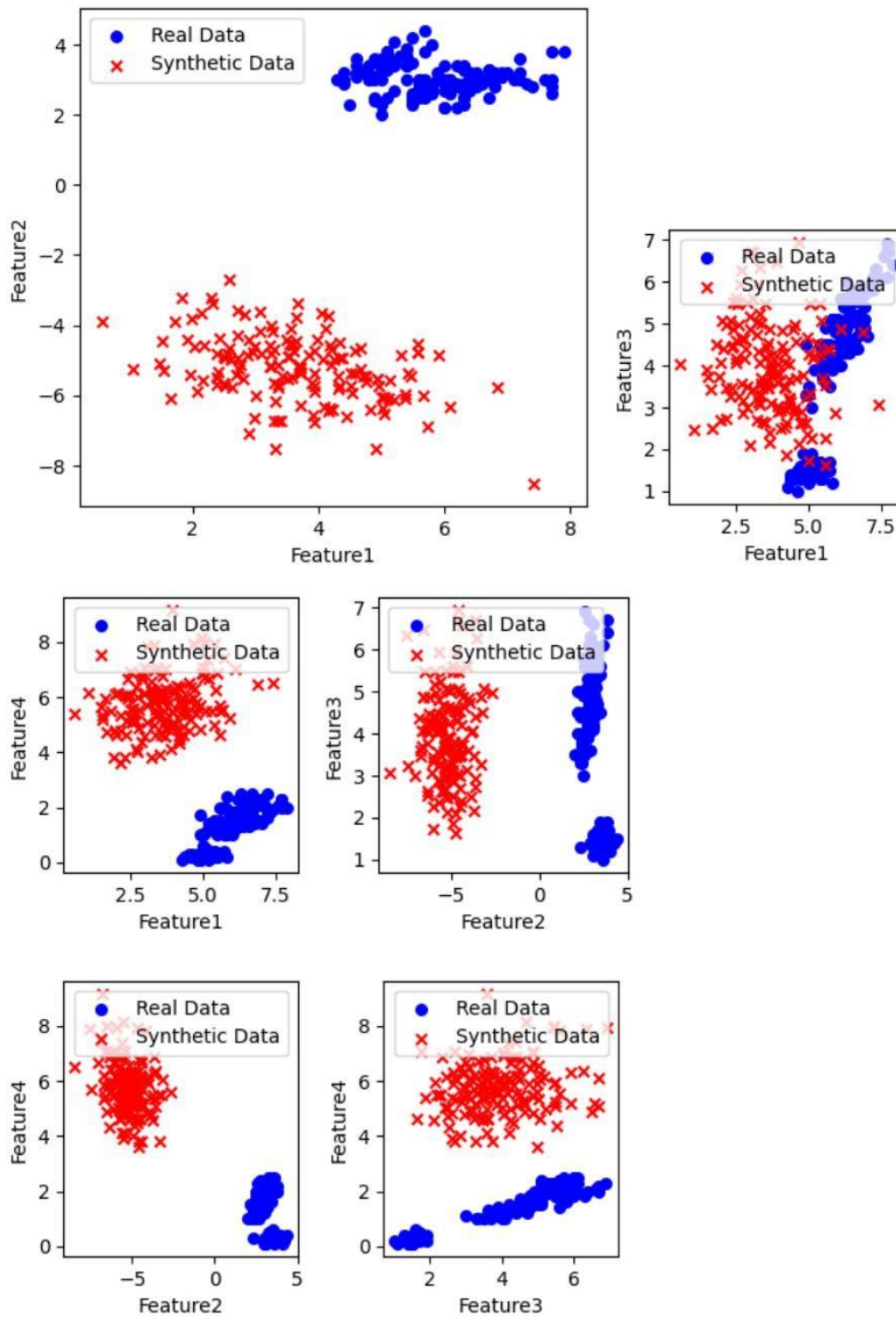
```
Epoch 0/200 | Discriminator Loss: 0.8773080408573151 | Generator Loss: 0.764731228351593
Epoch 1/200 | Discriminator Loss: 0.9332943856716156 | Generator Loss: 0.7988691329956055
Epoch 2/200 | Discriminator Loss: 0.9277275502681732 | Generator Loss: 0.8127573728561401
Epoch 3/200 | Discriminator Loss: 0.8921994566917419 | Generator Loss: 0.7757299542427063
Epoch 4/200 | Discriminator Loss: 0.913447916507721 | Generator Loss: 0.7737997174263
Epoch 5/200 | Discriminator Loss: 0.8916181325912476 | Generator Loss: 0.8003895282745361
Epoch 6/200 | Discriminator Loss: 0.9026078879833221 | Generator Loss: 0.814433217048645
Epoch 7/200 | Discriminator Loss: 0.9135120809078217 | Generator Loss: 0.8237183690071106
Epoch 8/200 | Discriminator Loss: 0.879832923412323 | Generator Loss: 0.7563657760620117
Epoch 9/200 | Discriminator Loss: 0.9439513385295868 | Generator Loss: 0.7623365521430969
Epoch 10/200 | Discriminator Loss: 0.9355685114860535 | Generator Loss: 0.7924684286117554
Epoch 11/200 | Discriminator Loss: 0.9386743903160095 | Generator Loss: 0.7614541053771973
Epoch 12/200 | Discriminator Loss: 0.960555225610733 | Generator Loss: 0.7792538404464722
Epoch 13/200 | Discriminator Loss: 0.9134297668933868 | Generator Loss: 0.792992115020752
Epoch 14/200 | Discriminator Loss: 0.8851655125617981 | Generator Loss: 0.7628173232078552
Epoch 15/200 | Discriminator Loss: 0.9505723416805267 | Generator Loss: 0.7851851582527161
Epoch 16/200 | Discriminator Loss: 0.92226842045784 | Generator Loss: 0.769191563129425
Epoch 17/200 | Discriminator Loss: 0.8982412815093994 | Generator Loss: 0.7685977220535278
Epoch 18/200 | Discriminator Loss: 0.9125983119010925 | Generator Loss: 0.7730982899665833
Epoch 19/200 | Discriminator Loss: 0.9367325305938721 | Generator Loss: 0.7837406396865845
Epoch 20/200 | Discriminator Loss: 0.9531015455722809 | Generator Loss: 0.7827053070068359
Epoch 21/200 | Discriminator Loss: 0.9306998252868652 | Generator Loss: 0.7667914032936096
Epoch 22/200 | Discriminator Loss: 0.8887360095977783 | Generator Loss: 0.7845874428749084
Epoch 23/200 | Discriminator Loss: 0.9426513016223907 | Generator Loss: 0.746765673160553
Epoch 24/200 | Discriminator Loss: 0.9331325888633728 | Generator Loss: 0.761589765548706
Epoch 25/200 | Discriminator Loss: 0.9080778360366821 | Generator Loss: 0.7709233164787292
Epoch 26/200 | Discriminator Loss: 0.9232879281044006 | Generator Loss: 0.7773635387420654
Epoch 27/200 | Discriminator Loss: 0.9102294743061066 | Generator Loss: 0.7809370756149292
Epoch 28/200 | Discriminator Loss: 0.9312145709991455 | Generator Loss: 0.7647197246551514
Epoch 29/200 | Discriminator Loss: 0.9415165781974792 | Generator Loss: 0.7561923861503601
Epoch 30/200 | Discriminator Loss: 0.930676281452179 | Generator Loss: 0.7709008455276489
Epoch 31/200 | Discriminator Loss: 0.9495892226696014 | Generator Loss: 0.7595088481903076
```

```
In [33]: synthetic_data = generator.predict(np.random.normal(0,1,(150,100)),verbose=0)
plt.figure(figsize=(12,8))
plot_idx=1

for i in range(4):
    for j in range(i+1,4):
        plt.subplot(2,3,plot_idx)
        plt.scatter(x_train[:,i],x_train[:,j],label='Real Data',c='blue',markers='o',s=30)
        plt.scatter(synthetic_data[:,i],synthetic_data[:,j],label='Synthetic Data',c='red',markers='x',s=30)
        plt.xlabel(f'Feature {i+1}')
        plt.ylabel(f'Feature {j+1}')
        plt.legend()
        plot_idx+=1

plt.tight_layout()
plt.show()
```





Result

Thus, a generative adversarial neural network using Keras / Tensorflow has been implemented successfully.

Ex No:10
DATE:06/10/2025

MINI PROJECT

CIFAR-10 Image Classification Using MobileNetV2

Aim:

To implement and evaluate a transfer-learning based image classification model using MobileNetV2 on the CIFAR-10 dataset, incorporating data augmentation, feature extraction, and fine-tuning techniques to improve classification accuracy and generalization performance.

Code:

```
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt

# Load CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()

# Normalize pixel values
x_train, x_test = x_train / 255.0, x_test / 255.0

# One-hot encode labels
y_train = tf.keras.utils.to_categorical(y_train, 10)
y_test = tf.keras.utils.to_categorical(y_test, 10)

# Data augmentation setup
datagen = ImageDataGenerator(
    rotation_range=15,
    horizontal_flip=True,
    width_shift_range=0.1,
    height_shift_range=0.1,
    zoom_range=0.1
)
datagen.fit(x_train)

# Load pretrained MobileNetV2 without top layers, freeze it
base_model = MobileNetV2(input_shape=(32, 32, 3),
                           include_top=False,
                           weights='imagenet')

base_model.trainable = False # freeze pretrained layers

# Build custom top layers for CIFAR-10 classification
model = models.Sequential([
    base_model,
    layers.GlobalAveragePooling2D(),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.3),
    layers.Dense(10, activation='softmax')
])
```



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

# Train model with augmented data
history = model.fit(datagen.flow(x_train, y_train, batch_size=64),
                    epochs=15,
                    validation_data=(x_test, y_test))

# Unfreeze some layers of base model for fine-tuning
base_model.trainable = True
for layer in base_model.layers[:-20]:
    layer.trainable = False

# Recompile with lower learning rate for fine-tuning
model.compile(optimizer=tf.keras.optimizers.Adam(1e-5),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Fine-tune model
fine_tune_history = model.fit(datagen.flow(x_train, y_train, batch_size=64),
                              epochs=10,
                              validation_data=(x_test, y_test))

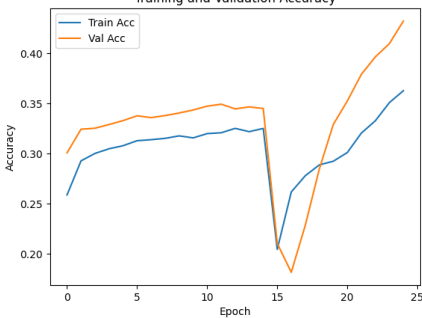
# Evaluate final model
test_loss, test_acc = model.evaluate(x_test, y_test)
print(f"Test accuracy after fine-tuning: {test_acc:.4f}")

# Plot training & validation accuracy
plt.plot(history.history['accuracy'] + fine_tune_history.history['accuracy'],
         label='Train Acc')
plt.plot(history.history['val_accuracy'] + fine_tune_history.history['val_accuracy'],
         label='Val Acc')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
1704588071704588071 2s 8us/step
/tmp/ipython-input-302x321815.py:28: UserWarning: 'input_shape' is undefined or non-square, or 'rows' is not in [96, 128, 160, 192, 224]. Weights for input shape (224, 224) will be loaded as the default.
base_model = MobileNetV2(input_shape=(32, 32, 3))
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kernels_1.0_224_no_top.h5
9406464/9406464 0s 8us/step
Epoch 1/15
/usr/local/lib/python3.12/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your 'PyDataset' class should call 'super().__init__(**kwargs)' in its constructor. '**kwargs' can include 'workers', 'use_multiprocessing', 'max_queue_size'. Do not pass these arguments to 'fit()'
self._warn_if_super_not_called()
782/782 92s 110ms/step - accuracy: 0.2274 - loss: 2.1854 - val_accuracy: 0.3887 - val_loss: 1.9275
Epoch 2/15
782/782 85s 109ms/step - accuracy: 0.2913 - loss: 1.9486 - val_accuracy: 0.3243 - val_loss: 1.8948
Epoch 3/15
782/782 84s 107ms/step - accuracy: 0.2981 - loss: 1.9212 - val_accuracy: 0.3253 - val_loss: 1.8741
Epoch 4/15
782/782 86s 110ms/step - accuracy: 0.3813 - loss: 1.9186 - val_accuracy: 0.3298 - val_loss: 1.8597
Epoch 5/15
782/782 83s 106ms/step - accuracy: 0.3112 - loss: 1.8987 - val_accuracy: 0.3329 - val_loss: 1.8587
Epoch 6/15
782/782 84s 107ms/step - accuracy: 0.3111 - loss: 1.8921 - val_accuracy: 0.3377 - val_loss: 1.8482
Epoch 7/15
782/782 83s 106ms/step - accuracy: 0.3146 - loss: 1.8817 - val_accuracy: 0.3359 - val_loss: 1.8341
Epoch 8/15
782/782 86s 109ms/step - accuracy: 0.3131 - loss: 1.8842 - val_accuracy: 0.3379 - val_loss: 1.8259
Epoch 9/15
782/782 84s 107ms/step - accuracy: 0.3174 - loss: 1.8690 - val_accuracy: 0.3405 - val_loss: 1.8238
Epoch 10/15
782/782 85s 108ms/step - accuracy: 0.3123 - loss: 1.8776 - val_accuracy: 0.3435 - val_loss: 1.8243
Epoch 11/15
782/782 83s 106ms/step - accuracy: 0.3144 - loss: 1.8811 - val_accuracy: 0.3473 - val_loss: 1.8093
Epoch 12/15
782/782 86s 110ms/step - accuracy: 0.3177 - loss: 1.8667 - val_accuracy: 0.3493 - val_loss: 1.8182
Epoch 13/15
782/782 83s 106ms/step - accuracy: 0.3234 - loss: 1.8628 - val_accuracy: 0.3446 - val_loss: 1.8091
Epoch 14/15
782/782 84s 107ms/step - accuracy: 0.3194 - loss: 1.8691 - val_accuracy: 0.3466 - val_loss: 1.8098
Epoch 15/15
782/782 83s 106ms/step - accuracy: 0.3273 - loss: 1.8574 - val_accuracy: 0.3458 - val_loss: 1.8078
Epoch 1/18
782/782 156s 187ms/step - accuracy: 0.1715 - loss: 12.6306 - val_accuracy: 0.2182 - val_loss: 2.5162
Epoch 2/18
782/782 144s 184ms/step - accuracy: 0.2553 - loss: 5.3788 - val_accuracy: 0.1813 - val_loss: 3.3167
Epoch 3/18
782/782 145s 185ms/step - accuracy: 0.2754 - loss: 3.6247 - val_accuracy: 0.2283 - val_loss: 2.5952
Epoch 4/18
782/782 144s 184ms/step - accuracy: 0.2848 - loss: 2.7552 - val_accuracy: 0.2844 - val_loss: 2.2339
Epoch 5/18
782/782 145s 185ms/step - accuracy: 0.2881 - loss: 2.3286 - val_accuracy: 0.3291 - val_loss: 1.9948
Epoch 6/18
782/782 145s 185ms/step - accuracy: 0.2968 - loss: 2.1184 - val_accuracy: 0.3525 - val_loss: 1.8544
Epoch 7/18
782/782 144s 185ms/step - accuracy: 0.3179 - loss: 1.9777 - val_accuracy: 0.3791 - val_loss: 1.7645
Epoch 8/18
782/782 144s 183ms/step - accuracy: 0.3262 - loss: 1.9180 - val_accuracy: 0.3966 - val_loss: 1.7054
Epoch 9/18
782/782 144s 184ms/step - accuracy: 0.3585 - loss: 1.8459 - val_accuracy: 0.4098 - val_loss: 1.6674
Epoch 10/18
782/782 146s 187ms/step - accuracy: 0.3629 - loss: 1.8002 - val_accuracy: 0.4324 - val_loss: 1.6258
313/313 18s 32ms/step - accuracy: 0.4358 - loss: 1.6143
Test accuracy after fine-tuning: 0.4324
```

Training and Validation Accuracy

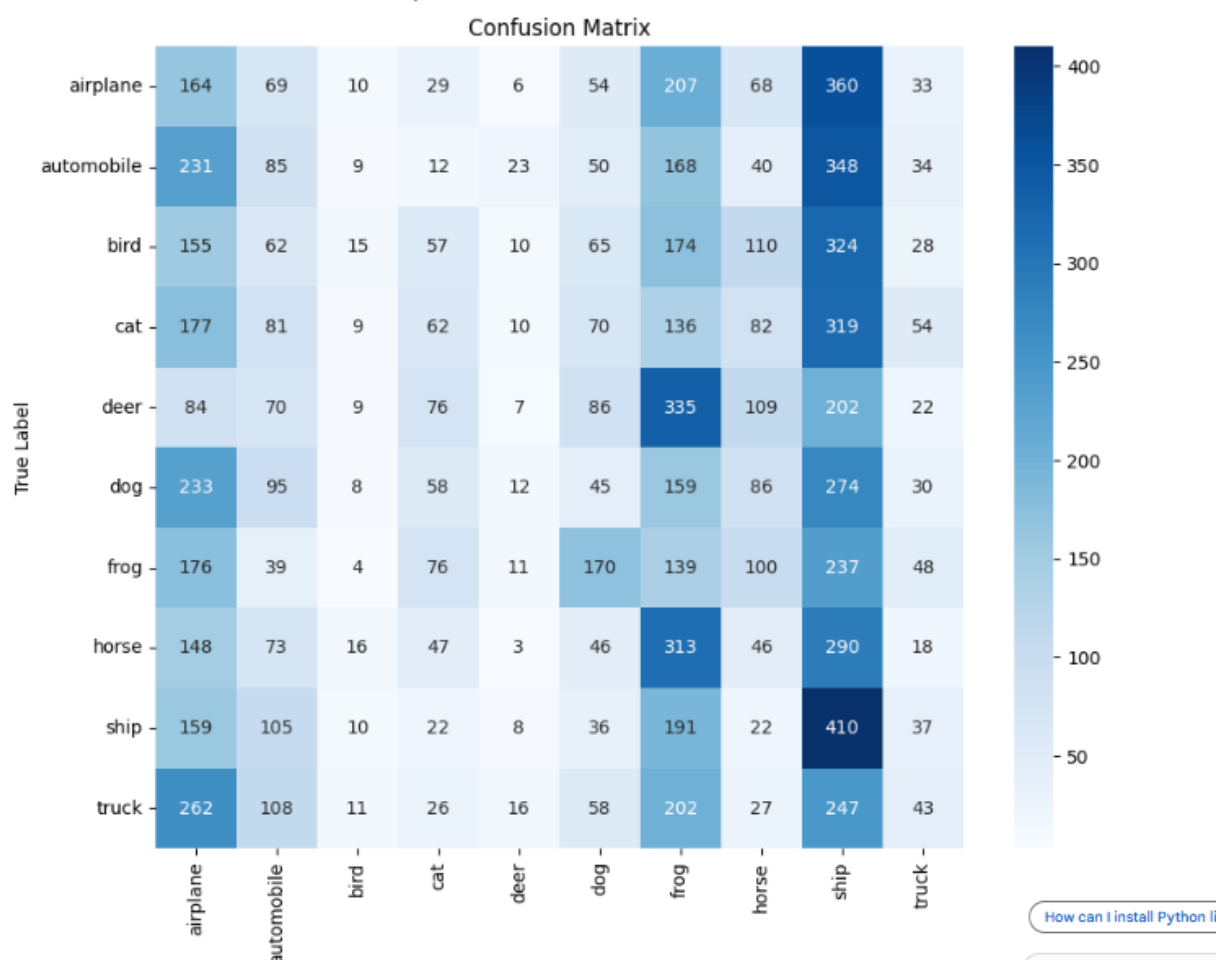


```
/tmp/ipython-input-6803885.py:46: UserWarning: 'input_shape' is undefined or non-square, or 'rows' is not in [96, 128, 160, 192, 224]. Weights for input shape (224, 224) will be loaded as the default.
base_model = MobileNetV2(input_shape=(32, 32, 3))
313/313 17s 38ms/step - accuracy: 0.1842 - loss: 2.3863
Test accuracy: 0.1016
1/1 1s 1s/step
```

Model Predictions on Test Images



313/313 12s 35ms/step



Classification Report:

	precision	recall	f1-score	support
airplane	0.09	0.16	0.12	1000
automobile	0.11	0.09	0.10	1000
bird	0.15	0.01	0.03	1000
cat	0.13	0.06	0.08	1000
deer	0.07	0.01	0.01	1000
dog	0.07	0.04	0.05	1000
frog	0.07	0.14	0.09	1000
horse	0.07	0.05	0.05	1000
ship	0.14	0.41	0.20	1000
truck	0.12	0.04	0.06	1000
accuracy			0.10	10000
macro avg	0.10	0.10	0.08	10000
weighted avg	0.10	0.10	0.08	10000