RAJALAKSHMI ENGINEERING COLLEGE

(An Autonomous Institution)

RAJALAKSHMI NAGAR, THANDALAM- 602 105

CS19P18 - DEEP LEARNING CONCEPTS

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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

[illegible]

Signature of Faculty In-charge

Submitted for the Practical Examination Held on: ………………………………………..

[illegible]

Internal Examiner **External Examiner**

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INSTALLATION AND CONFIGURATION OF TENSORFLOW

Aim:

To install and configure TensorFlow in the 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
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
    keras.layers.Dense(1, activation='sigmoid')     # Output layer
])

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

# Train the model
history = model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.1)

# Evaluate the model
y_pred = model.predict(X_test)
y_pred_classes = (y_pred > 0.5).astype(int)

# Calculate accuracy and loss
accuracy = accuracy_score(y_test, y_pred_classes)
test_loss, test_acc = model.evaluate(X_test, y_test)

print(f"\nTest Accuracy: {accuracy * 100:.2f}%")
print(f"Test Loss: {test_loss:.4f}")

# Plot training performance
import matplotlib.pyplot as plt

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

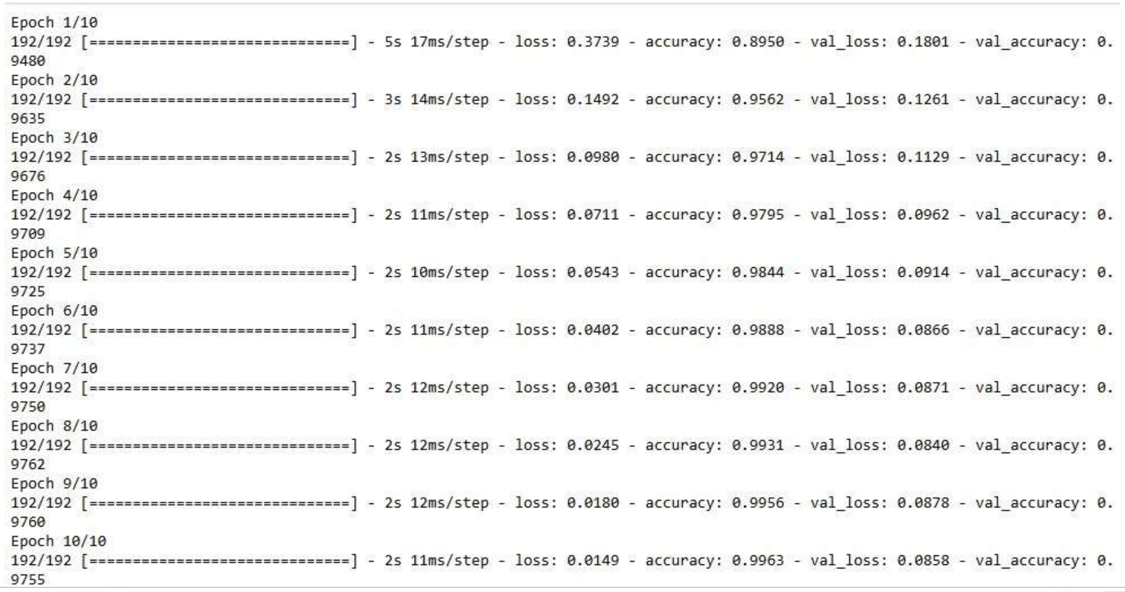
plt.ylabel('Loss')

plt.legend()

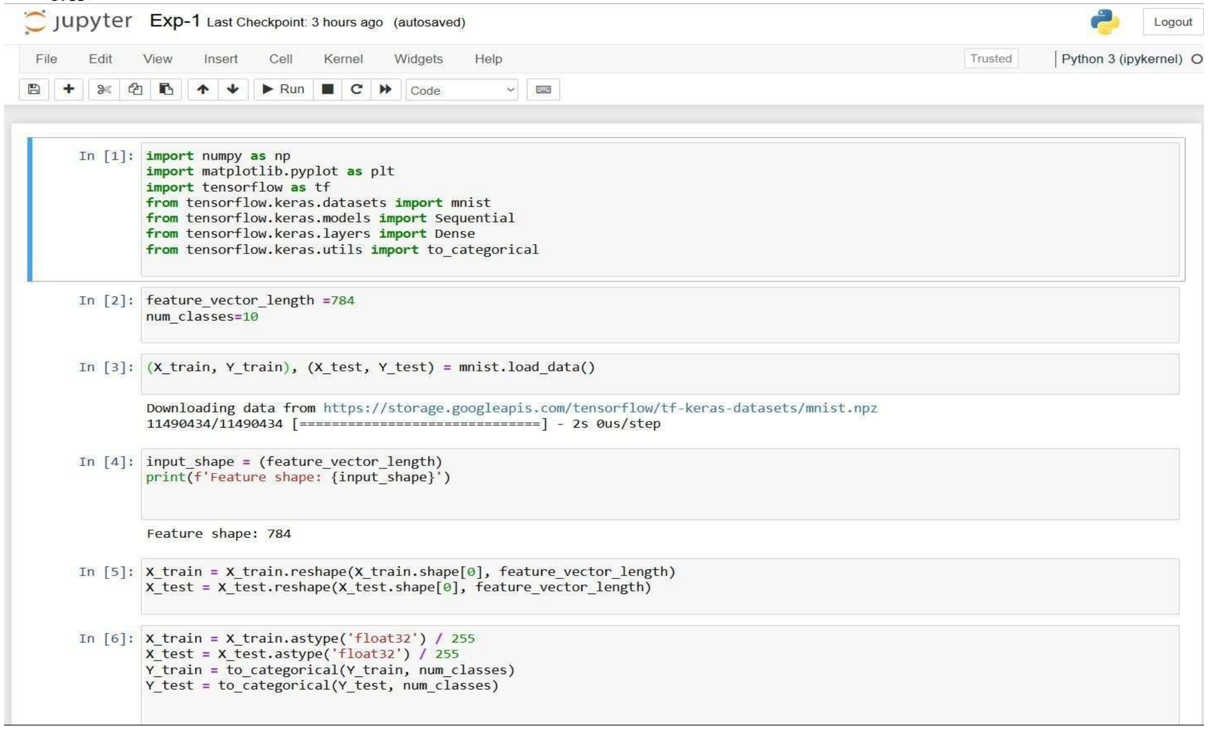
plt.tight_layout()

plt.show()

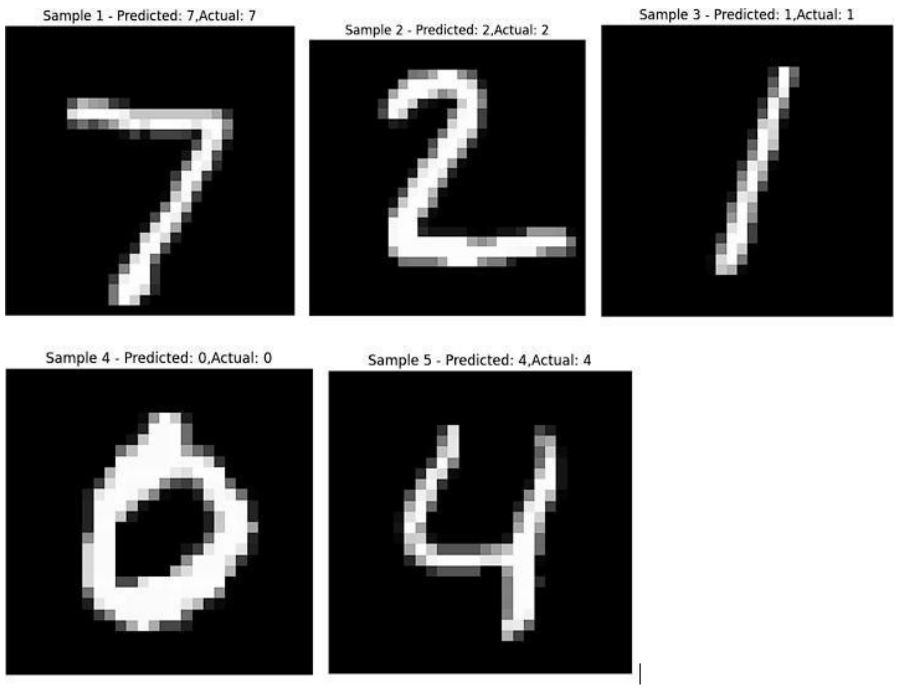
Output:



```
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
```



```
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)
```


Sample 1 - Predicted: 7,Actual: 7
Sample 2 - Predicted: 2,Actual: 2
Sample 3 - Predicted: 1,Actual: 1
Sample 4 - Predicted: 0,Actual: 0
Sample 5 - Predicted: 4,Actual: 4

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:

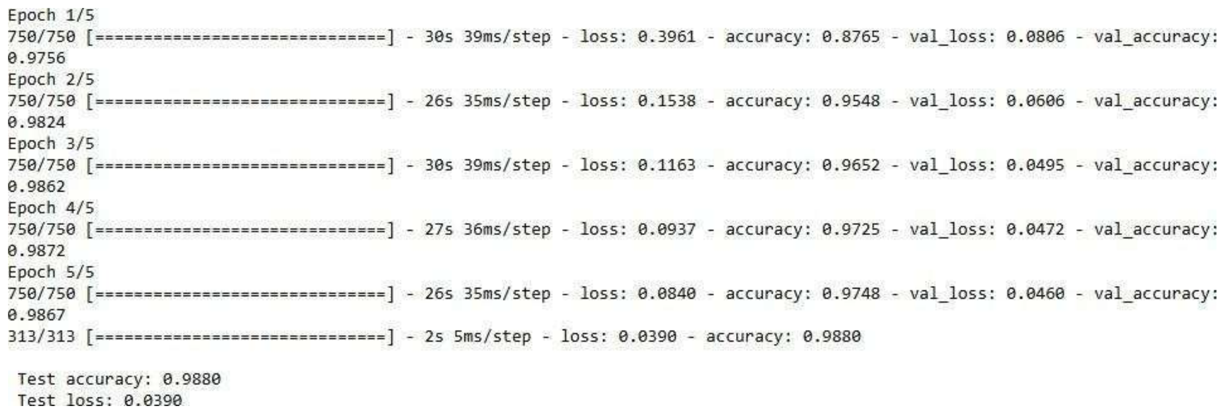
0. Import required libraries (TensorFlow/Keras, NumPy, etc.).
1. Load the MNIST dataset from Keras.
2. Normalize and reshape the image data.
3. Convert labels to one-hot encoded vectors.
4. Build a CNN model with Conv2D, MaxPooling, Flatten, and Dense layers.
5. Compile the model using categorical crossentropy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

Code:

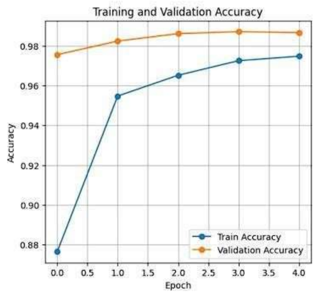
```
import tensorflow as tf from tensorflow.keras.models import Sequential from
tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout from
tensorflow.keras.datasets import mnist import matplotlib.pyplot as plt import numpy
as np

(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'])
```

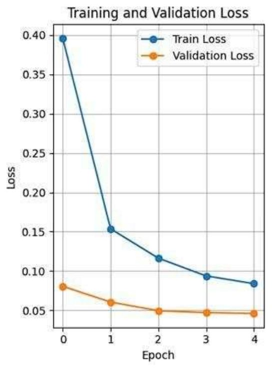
```
history = model.fit(train_images,
train_labels, epochs=5, batch_size=64,
validation_split=0.2)

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()
```

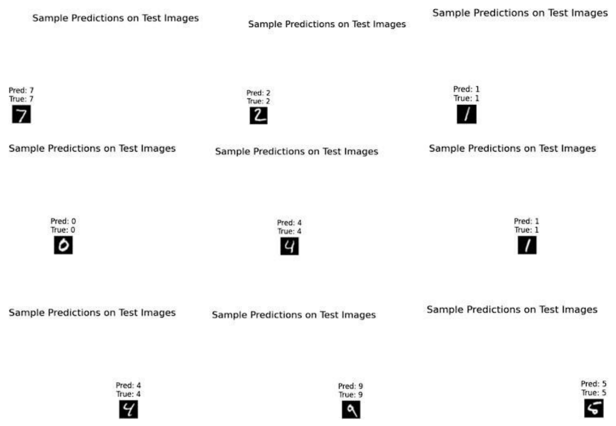
Output:



```
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
```






Sample Predictions on Test Images
Pred: 7
True: 7
Sample Predictions on Test Images
Pred: 2
True: 2
Sample Predictions on Test Images
Pred: 1
True: 1
Sample Predictions on Test Images
Pred: 0
True: 0
Sample Predictions on Test Images
Pred: 4
True: 4
Sample Predictions on Test Images
Pred: 1
True: 1
Sample Predictions on Test Images
Pred: 4
True: 4
Sample Predictions on Test Images
Pred: 9
True: 9
Sample Predictions on Test Images
Pred: 5
True: 5

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:

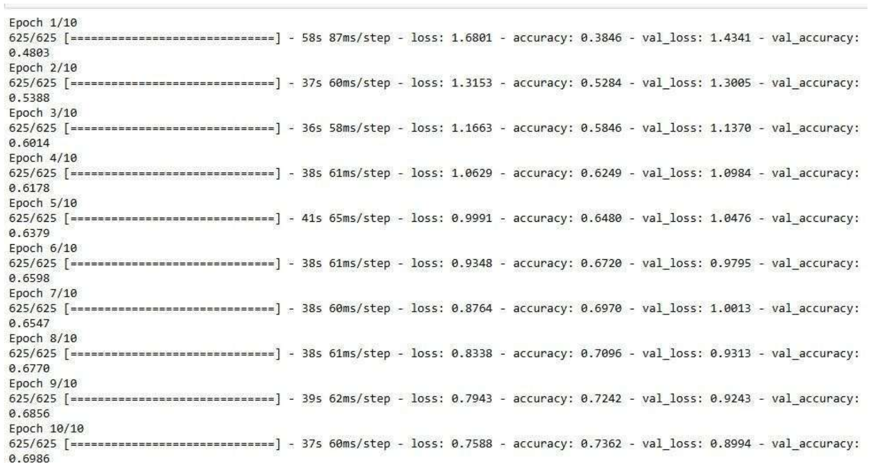
- Normalize the pixel values (divide by 255) •
  Convert class labels to one-hot encoded format

4. Build a CNN model using Keras/TensorFlow:
   - Include convolutional, pooling, flatten, and dense layers.
5. Compile the model with a 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 the 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

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

# Normalize pixel values between 0 and 1
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 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)

# Define the CNN model
model = tf.keras.Sequential([
    tf.keras.layers.Conv2D(32, (3,3), activation='relu', input_shape=(32,32,3)),
    tf.keras.layers.MaxPooling2D((2,2)),
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D((2,2)),
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(10, activation='softmax')
])

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

# Train the model
model.fit(x_train, y_train, epochs=10, batch_size=64, validation_split=0.2)

# CIFAR-10 class names
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer',
               'dog', 'frog', 'horse', 'ship', 'truck']

# Ask for a test image index
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

# Get the test image and true label
test_image = x_test[index]
true_label = np.argmax(y_test[index])

# Predict
prediction = model.predict(np.expand_dims(test_image, axis=0))
predicted_label = np.argmax(prediction)

# Display the image
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
```

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:01/08/2025

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

Procedure:

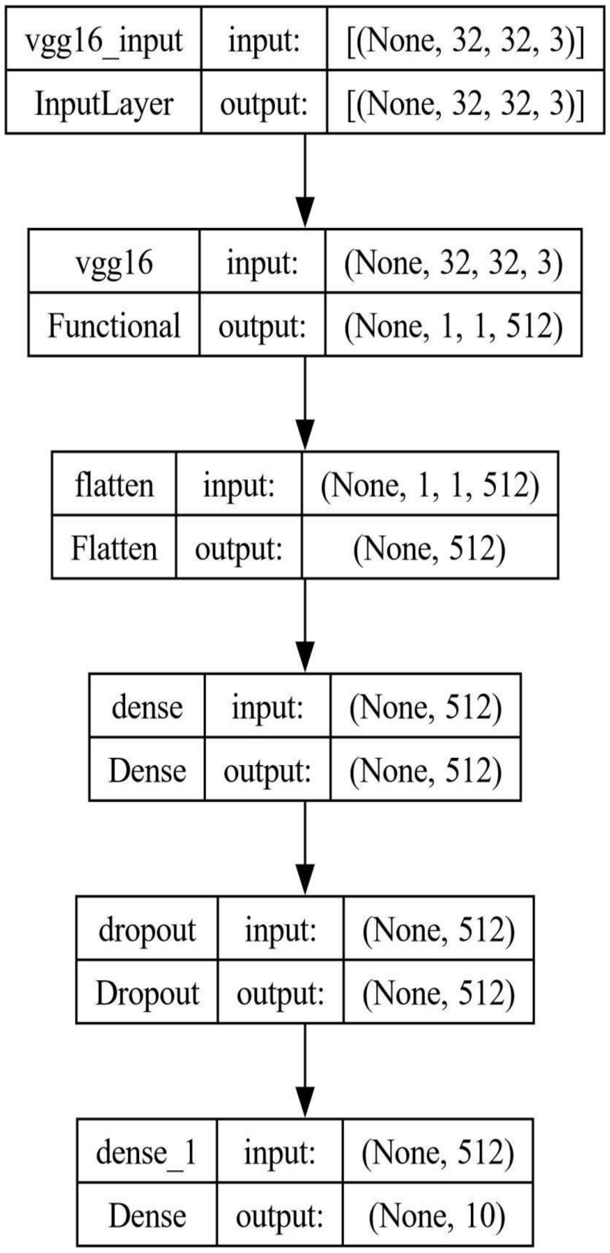
1. Download and load the dataset.
2. Perform analysis and preprocessing of the dataset.
3. Build a simple neural network model using Keras/TensorFlow.
4. Compile and fit the model.
5. Perform prediction with the test dataset.
6. Calculate performance metrics.

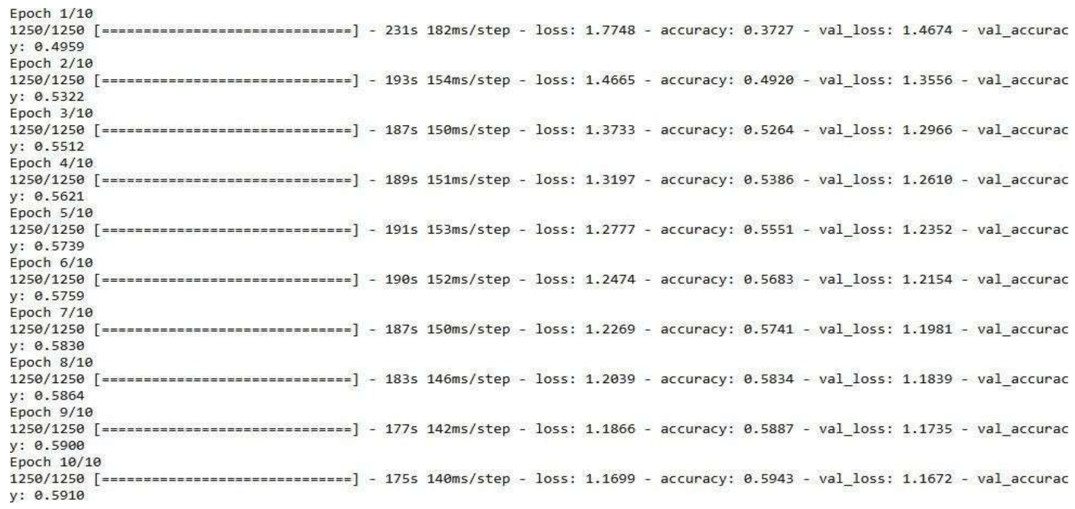
Code:

```
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

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

# Normalize pixel values between 0 and 1
x_train = x_train / 255.0
x_test = x_test / 255.0

# Load pretrained VGG16 without top layers (fully connected layers)
vgg_base = VGG16(weights='imagenet', include_top=False, input_shape=(32, 32, 3))

# Freeze the base layers (don’t train them)
for layer in vgg_base.layers:
    layer.trainable = False

# Build the new model on top of VGG16
model = Sequential([
    vgg_base,
    Flatten(),
    Dense(512, activation='relu'),
    Dropout(0.5),
    Dense(10, activation='softmax')
])

# Compile the model
model.compile(optimizer=Adam(learning_rate=0.0001),
            loss='sparse_categorical_crossentropy',
            metrics=['accuracy'])

# Visualize model architecture
plot_model(model, to_file='cnn.png', show_shapes=True, show_layer_names=True, dpi=300)

# Display the architecture image
plt.figure(figsize=(20, 20))
img = plt.imread('cnn.png')
plt.imshow(img)
plt.axis('off')
plt.show()

# Train the model
history = model.fit(x_train, y_train, epochs=10, batch_size=32, validation_split=0.2)

# Evaluate on test data
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}%')

# Plot Accuracy and Loss
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 for CIFAR-10
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer',
             'dog', 'frog', 'horse', 'ship', 'truck']
```

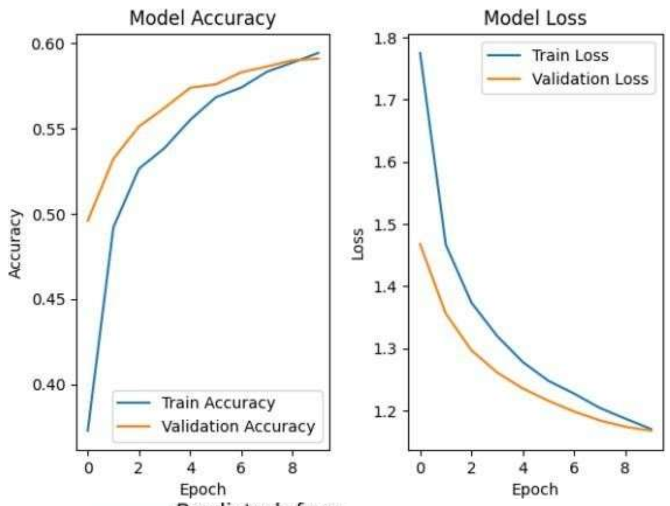
```
# Test a single image
sample = x_test[0].reshape(1, 32, 32, 3)
prediction = model.predict(sample)
predicted_class = class_names[np.argmax(prediction)]

# Show test image with prediction
plt.imshow(x_test[0])
plt.title(f"Predicted: {predicted_class}")
plt.axis('off')
plt.show()
```

Output:





```
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

EX NO: 5 BUILD A RECURRENT NEURAL NETWORK (RNN) USING
DATE:27/08/2025 KERAS/TENSORFLOW

Aim:

To build a recurrent neural network with Keras/TensorFlow.

Procedure:

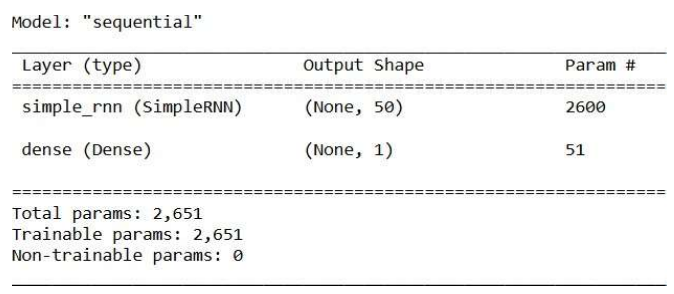
1. Download and load the dataset.
2. Perform analysis and preprocessing of the dataset.
3. Build a simple neural network model using Keras/TensorFlow.
4. Compile and fit the model.
5. Perform prediction with the test dataset.
6. Calculate performance metrics.

Code:

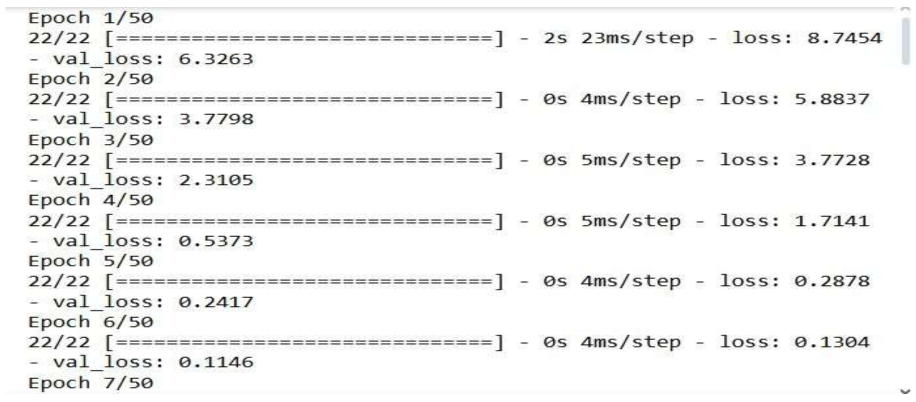
```
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import SimpleRNN, Dense
from sklearn.metrics import r2_score

# Set random seed for reproducibility
np.random.seed(0)

# Generate synthetic sequential data
seq_length = 10       # each sample has 10 time steps
num_samples = 1000    # total samples

# Random input data (time series)
X = np.random.randn(num_samples, seq_length, 1)

# Target: sum of each sequence + small random noise
y = X.sum(axis=1) + 0.1 * np.random.randn(num_samples, 1)

# Split into training and test sets (80%-20%)
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:]

# Define the RNN model
model = Sequential()
model.add(SimpleRNN(units=50, activation='relu', input_shape=(seq_length, 1)))
model.add(Dense(units=1))
```

```
# Compile model
model.compile(optimizer='adam', loss='mean_squared_error')

# Show model summary
model.summary()

# Train the model
batch_size = 30
epochs = 50  # reduced for faster demonstration
history = model.fit(
    X_train, y_train,
    batch_size=batch_size,
    epochs=epochs,
    validation_split=0.2
)

# Evaluate on test data
test_loss = model.evaluate(X_test, y_test)
print(f'Test Loss: {test_loss:.4f}')

# Predict and evaluate performance using R² score
y_pred = model.predict(X_test)
r2 = r2_score(y_test, y_pred)
print(f'Test Accuracy (R^2): {r2:.4f}')

# Predict new unseen data
new_data = np.random.randn(5, seq_length,
```

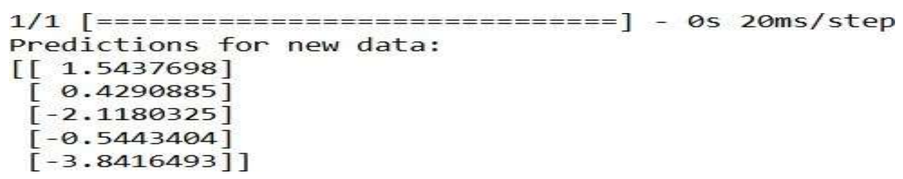
Output:



```
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:

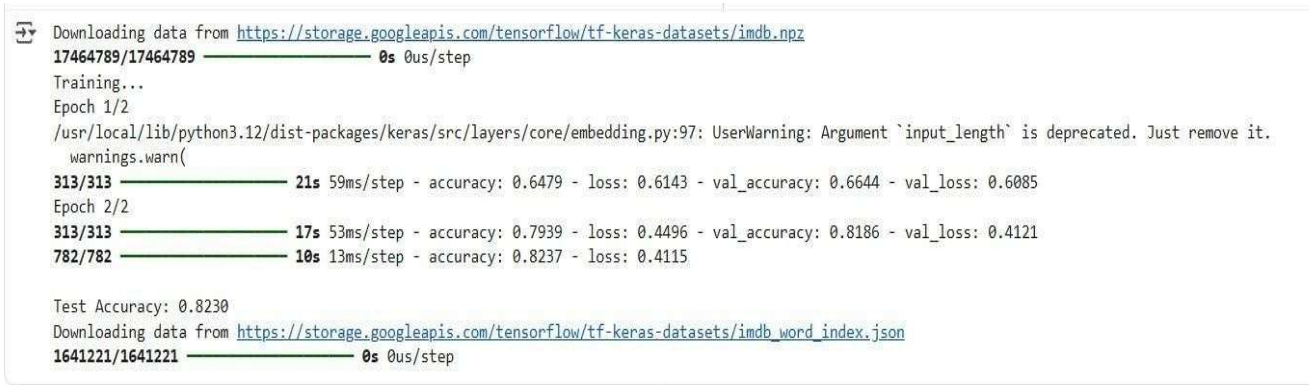
1. Import necessary libraries.
2. Load and preprocess the text dataset (e.g., IMDb).
3. Pad sequences and prepare labels.
4. Build an RNN model with Embedding and SimpleRNN layers.
5. Compile the model with loss and optimizer.
6. Train the model on training data.
7. Evaluate the model on test data.
8.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

Code:

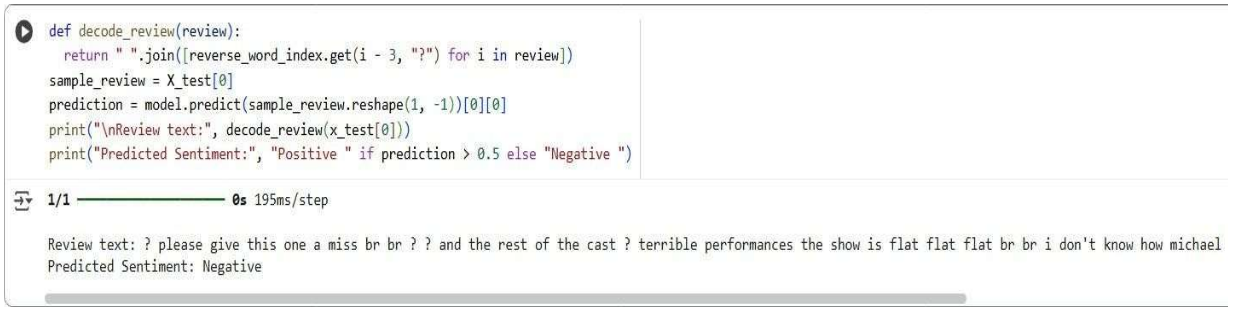
```
import numpy as np
from tensorflow.keras.datasets import imdb
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, SimpleRNN, Dense

# Limit vocabulary size
max_words = 5000
max_len = 200

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

# Pad/truncate reviews to same length
X_train = pad_sequences(x_train, maxlen=max_len)
X_test = pad_sequences(x_test, maxlen=max_len)

# Build RNN model
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'))
```

```
# Compile model
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)

# Evaluate the model
loss, acc = model.evaluate(X_test, y_test)
print(f"\nTest Accuracy: {acc:.4f}")

# Decode integer sequence back to words
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])

# Make a prediction on one test 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:

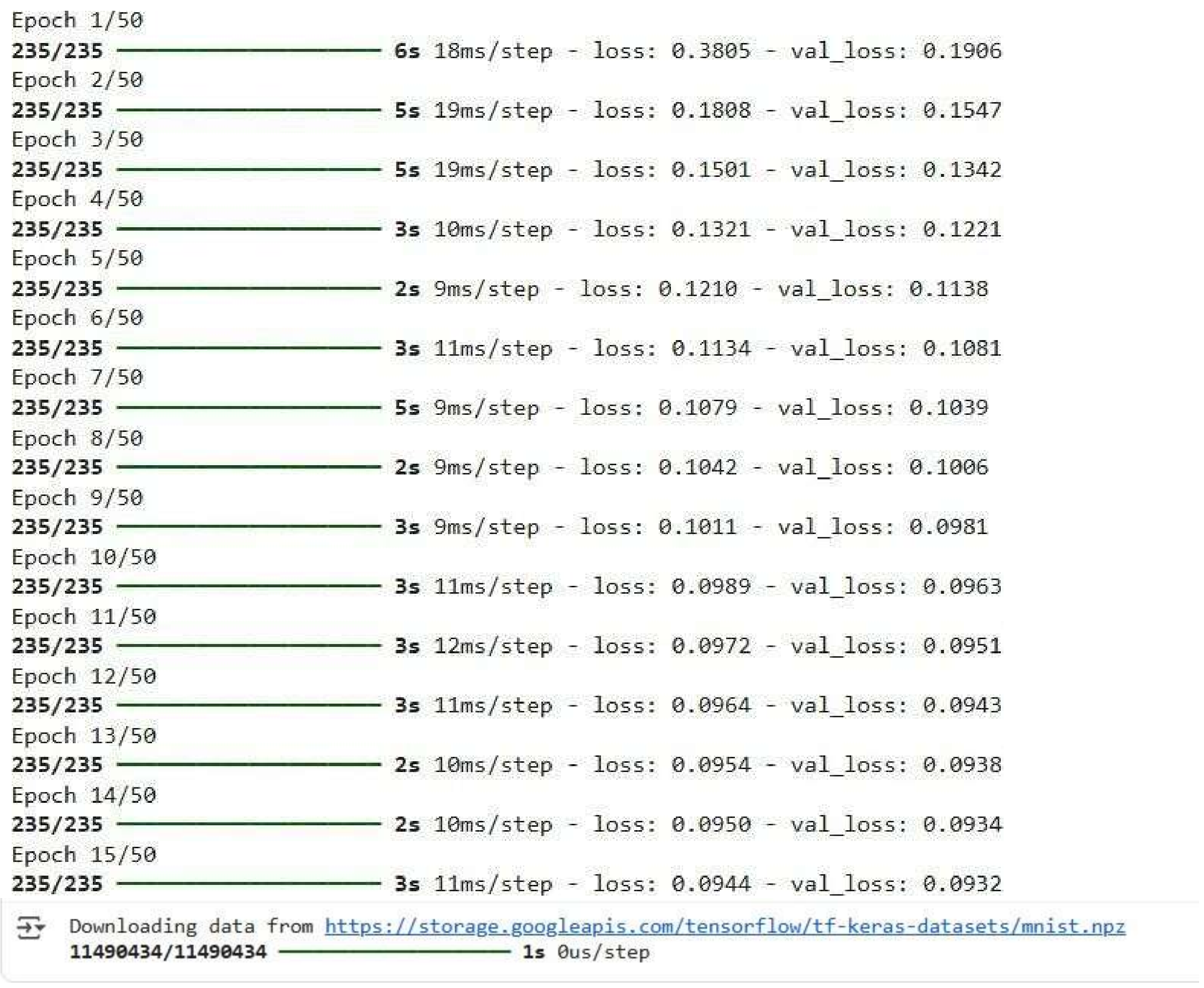
1. Download and load the dataset.
2. Perform analysis and preprocessing of the dataset.
3. Build a simple neural network model using Keras/TensorFlow.
4. Compile and fit the model.
5. Perform prediction with the test dataset.
6. Calculate performance metrics.

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

# Load MNIST dataset
(x_train, _), (x_test, _) = mnist.load_data()

# Normalize and flatten the 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:])))

# Build Autoencoder model
input_img = Input(shape=(784,))
encoded = Dense(32, activation='relu')(input_img)
decoded = Dense(784, activation='sigmoid')(encoded)
autoencoder = Model(input_img, decoded)

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

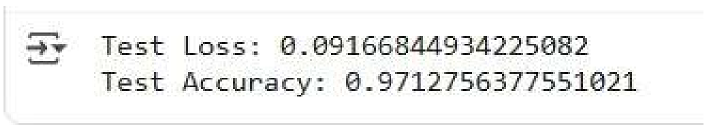
```
# Train model
autoencoder.fit(
    x_train, x_train,
    epochs=50,
    batch_size=256,
    shuffle=True,
    validation_data=(x_test, x_test)
)

# Evaluate the model
test_loss = autoencoder.evaluate(x_test, x_test)

# Predict reconstructed images
decoded_imgs = autoencoder.predict(x_test)

# Calculate test accuracy manually
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)

# Display original and reconstructed images
n = 10  # number of digits to display
plt.figure(figsize=(20, 4))
for i in range(n):
    # 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)

    # Reconstructed (thresholded)
    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:

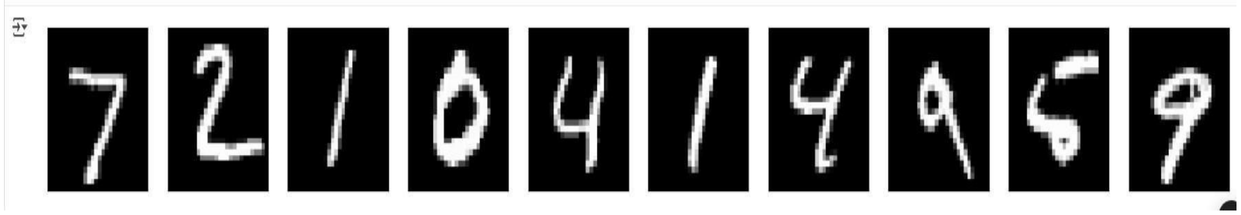


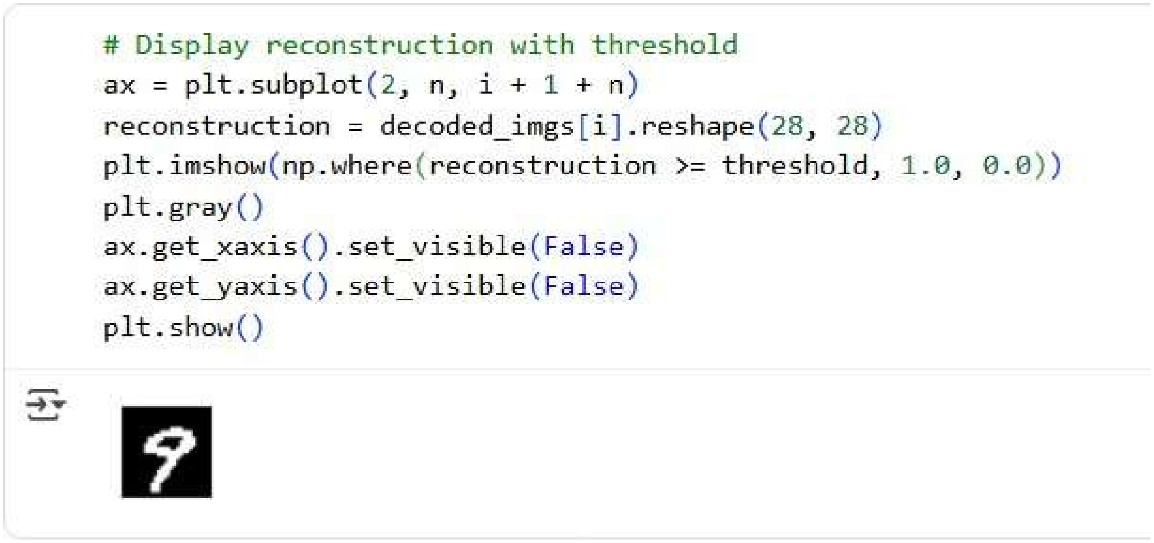
```
Epoch 1/50
235/235 ━━━━━━━━━━━━━━━━━━━━ 6s 18ms/step - loss: 0.3805 - val_loss: 0.1906
Epoch 2/50
235/235 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.1808 - val_loss: 0.1547
Epoch 3/50
235/235 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step - loss: 0.1501 - val_loss: 0.1342
Epoch 4/50
235/235 ━━━━━━━━━━━━━━━━━━━━ 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:06/10/2025

Aim:

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

Procedure:

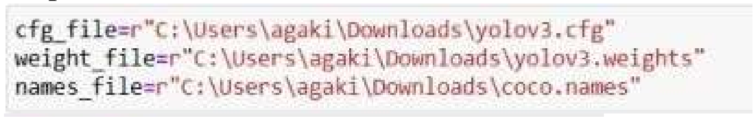
1. Download and load the dataset.
2. Perform analysis and preprocessing of the dataset.
3. Build a simple neural network model using Keras/TensorFlow.
4. Compile and fit the model.
5. Perform prediction with the test dataset.
6. Calculate performance metrics.

Code:

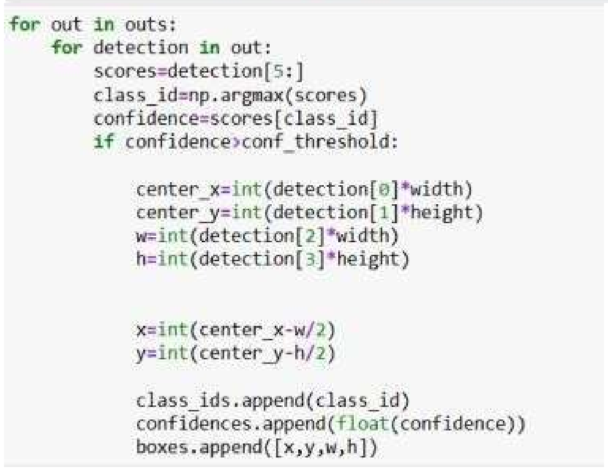
```
import cv2 import
matplotlib.pyplot as plt
import numpy as np

# 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 passouts = 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()
```

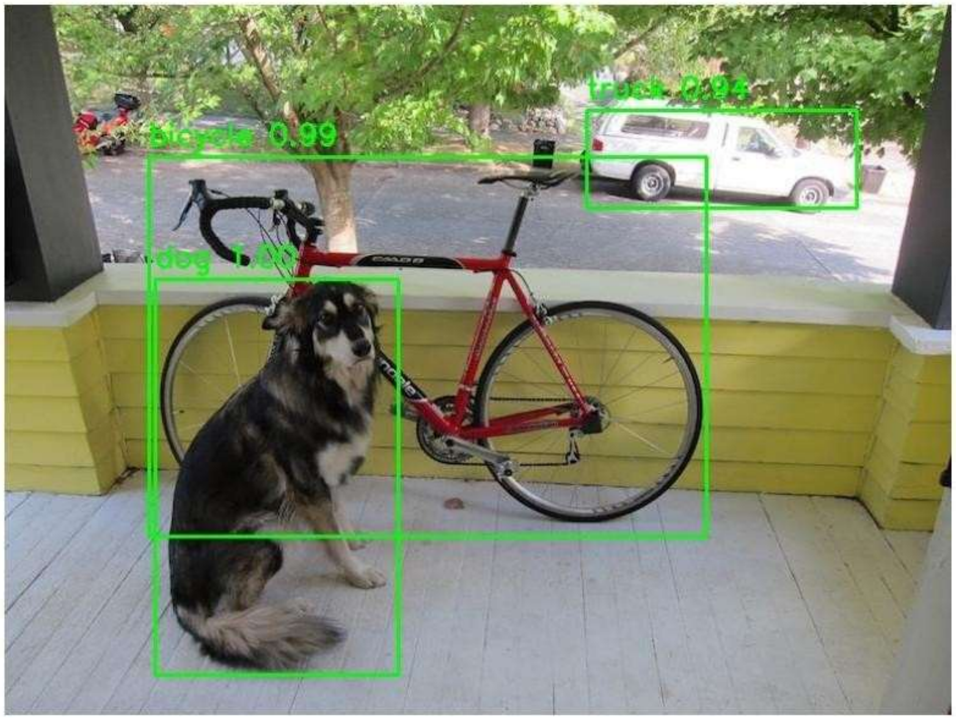
Output:



```
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:06/10/2025

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
```

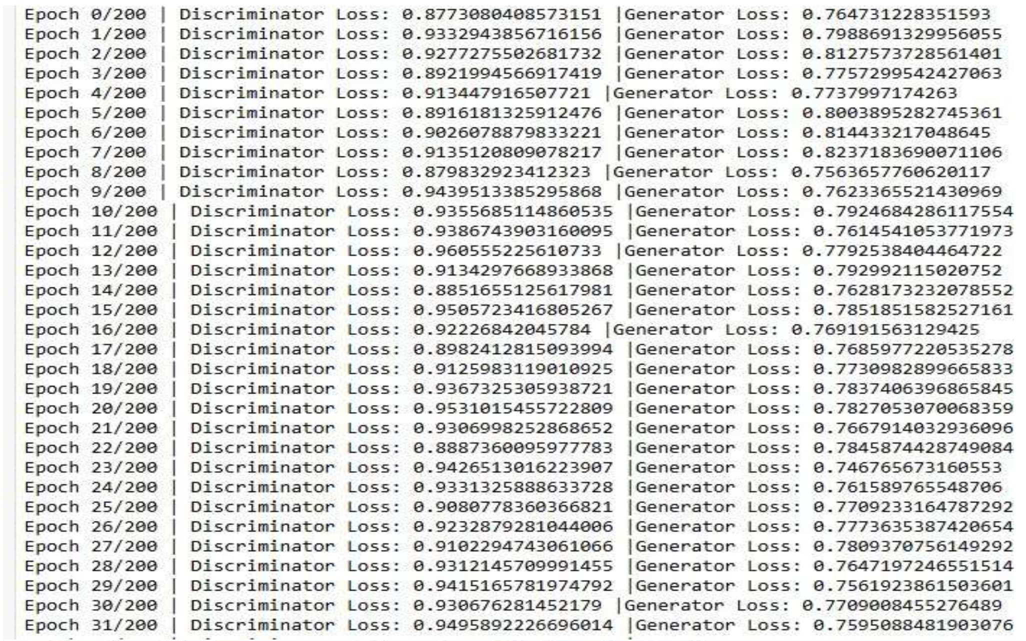
```
generator = build_generator()
discriminator = build_discriminator() gan
= build_gan(generator, discriminator)

# 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

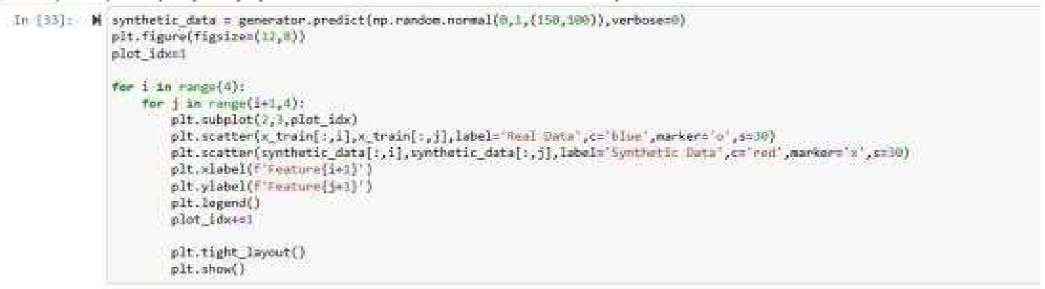
plt.tight_layout()

plt.show()

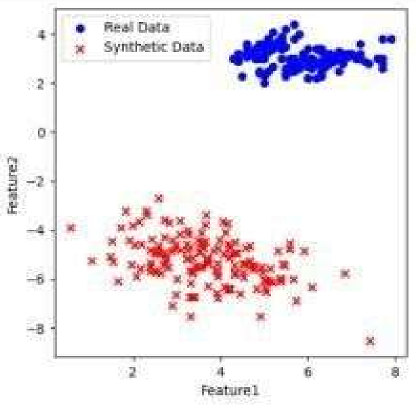
Output:

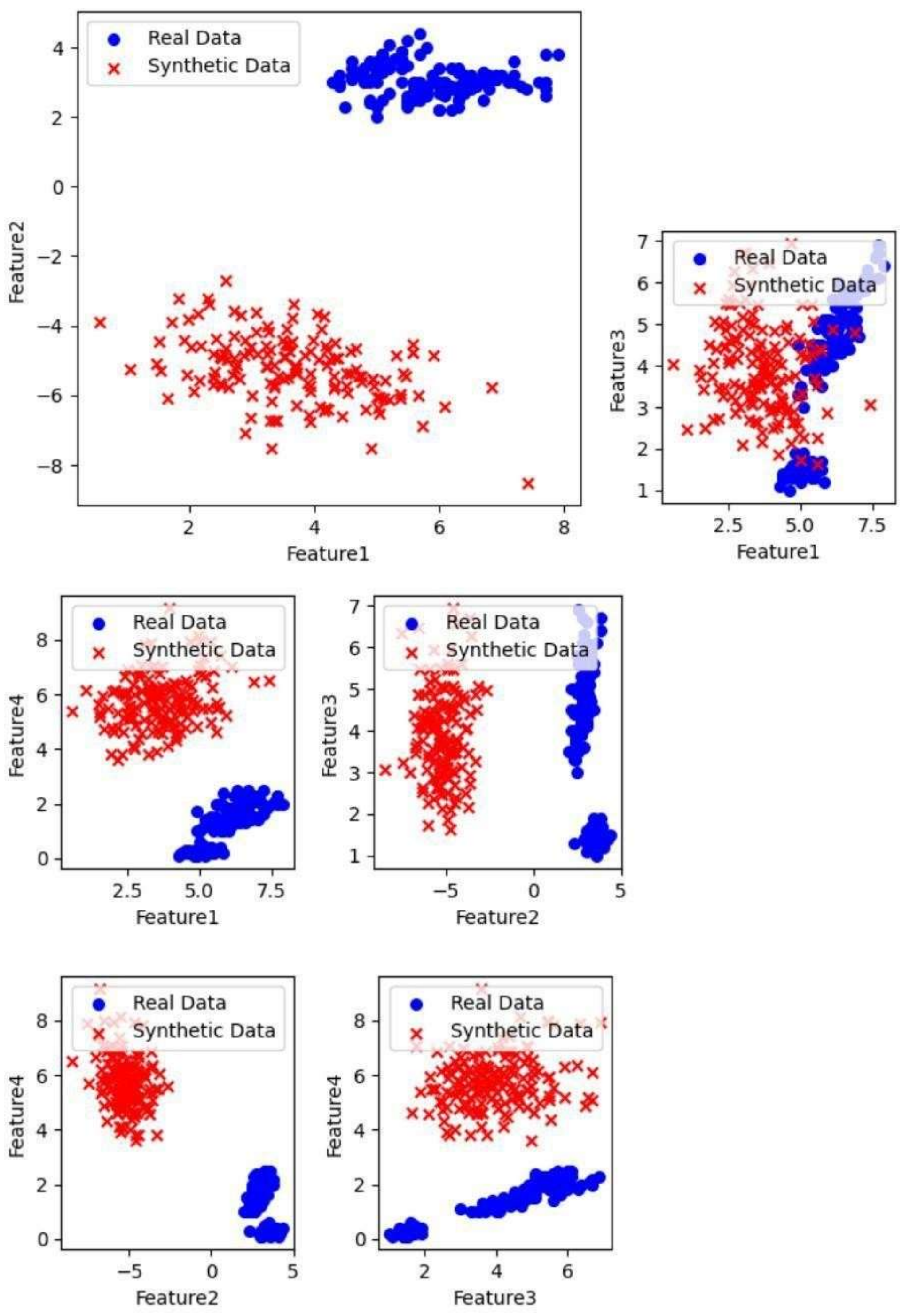


```
Epoch 0/200 | Discriminator Loss: 0.8773080408573151 |Generator Loss: 0.764731228351593
Epoch 1/200 | Discriminator Loss: 0.9332943856716156 |Generator Loss: 0.7988691329956055
Epoch 2/200 | Discriminator Loss: 0.9277275502681732 |Generator Loss: 0.8127573728561401
Epoch 3/200 | Discriminator Loss: 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',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()
```





Result

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

Ex No:10 **MINI PROJECT**
DATE:14/10/2025

Image Colorization Using Convolutional Autoencoder

Aim:

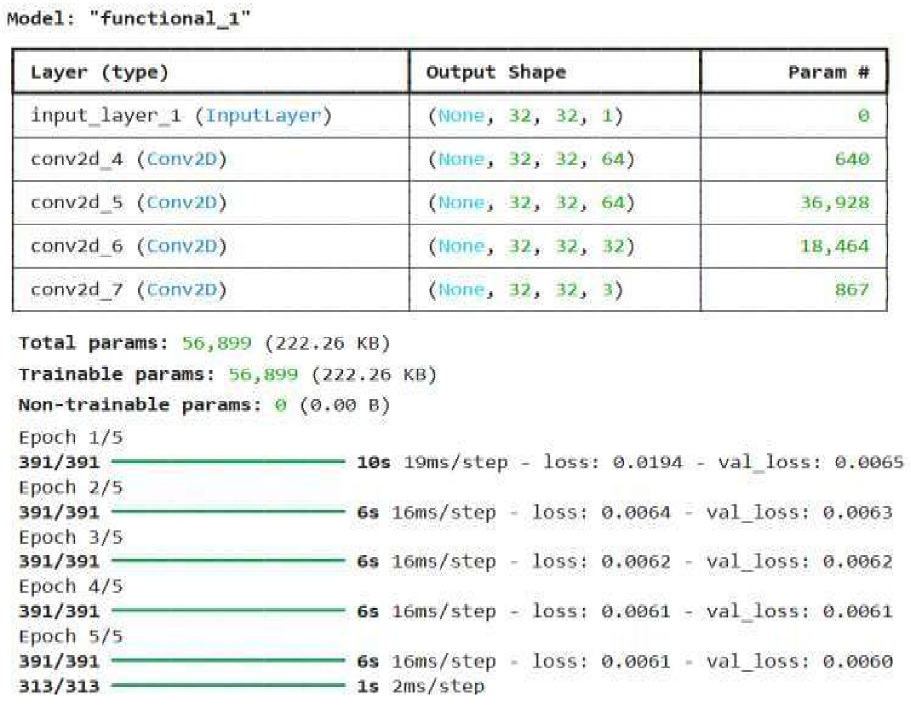
The aim of this project is to build a convolutional autoencoder that learns to colorize grayscale images automatically. Using the CIFAR-10 dataset, the model takes grayscale images as input and predicts their corresponding color versions, demonstrating how convolutional neural networks can learn feature representations for image restoration and colorization tasks.

Program:

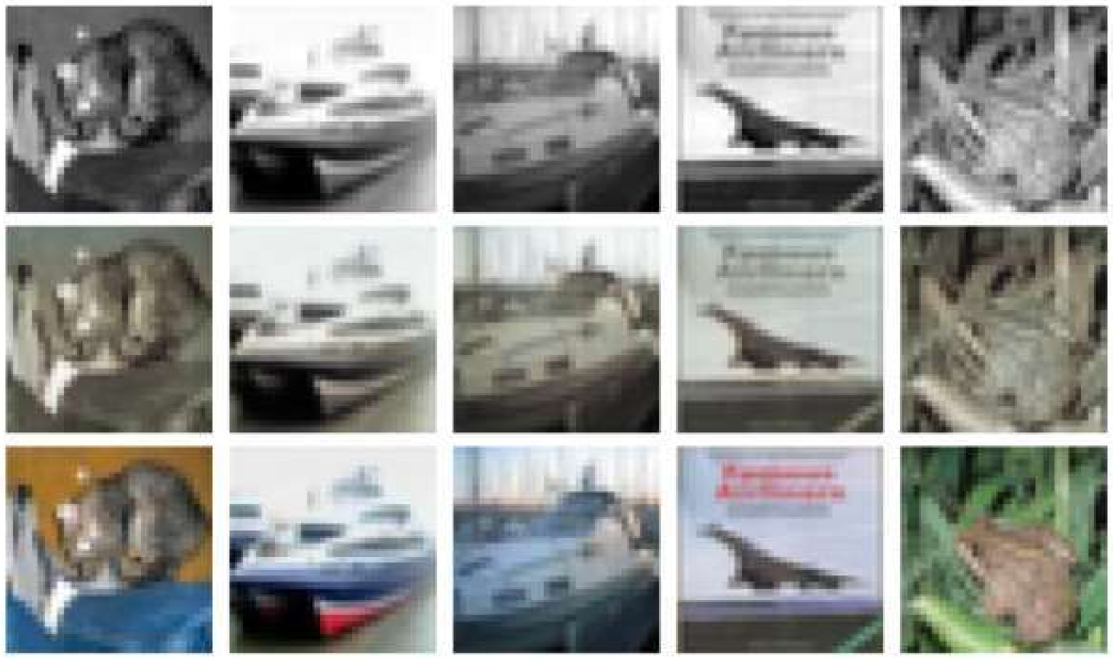
```
import numpy as np import matplotlib.pyplot as plt from tensorflow.keras.models import Model
from tensorflow.keras.layers import Conv2D, Input from tensorflow.keras.preprocessing.image
import img_to_array, load_img from sklearn.model_selection import train_test_split import
tensorflow as tf
import cifar10
(X_train, _), (X_test, _) = cifar10.load_data()

# --- Convert to grayscale and normalize ---
X_train_gray = np.dot(X_train[...,:3], [0.299, 0.587, 0.114])
X_test_gray = np.dot(X_test[...,:3], [0.299, 0.587, 0.114])

X_train_gray = X_train_gray / 255.
X_test_gray = X_test_gray / 255.
X_train = X_train / 255.
X_test = X_test / 255.

# Add channel dimension
X_train_gray = X_train_gray.reshape(X_train_gray.shape + (1,))
X_test_gray = X_test_gray.reshape(X_test_gray.shape + (1,))


# --- Define CNN Autoencoder Model --- input_img = Input(shape=(32, 32, 1)) # Encoder
+ simple decoder without upsampling x = Conv2D(64, (3,3), activation='relu',
padding='same')(input_img) x = Conv2D(64, (3,3), activation='relu', padding='same')(x)
x = Conv2D(32, (3,3), activation='relu', padding='same')(x) x = Conv2D(3, (3,3),
activation='sigmoid', padding='same')(x) autoencoder = Model(input_img, x)
autoencoder.compile(optimizer='adam', loss='mse') autoencoder.summary() # --- Train the
model --- autoencoder.fit(X_train_gray, X_train,          validation_data=(X_test_gray,
X_test),          epochs=5,          batch_size=128)
```

```
# --- Predict and visualize --- output =
autoencoder.predict(X_test_gray)

plt.figure(figsize=(10,6)) for i in range(5):     # grayscale input     ax =
plt.subplot(3, 5, i+1)     plt.imshow(X_test_gray[i].reshape(32,32),
cmap='gray')     plt.axis('off')

    # colorized (predicted)     ax =
plt.subplot(3, 5, i+6)     plt.imshow(output[i])
plt.axis('off')

    # original     ax = plt.subplot(3, 5, i+11)
plt.imshow(X_test[i])     plt.axis('off')

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

Output:



```
Model: "functional_1"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━┓
┃ Layer (type)                    ┃ Output Shape           ┃       Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━┩
│ input_layer_1 (InputLayer)      │ (None, 32, 32, 1)      │             0 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ conv2d_4 (Conv2D)               │ (None, 32, 32, 64)     │           640 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ conv2d_5 (Conv2D)               │ (None, 32, 32, 64)     │        36,928 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ conv2d_6 (Conv2D)               │ (None, 32, 32, 32)     │        18,464 │
├─────────────────────────────────┼────────────────────────┼───────────────┤
│ conv2d_7 (Conv2D)               │ (None, 32, 32, 3)      │           867 │
└─────────────────────────────────┴────────────────────────┴───────────────┘
 Total params: 56,899 (222.26 KB)
 Trainable params: 56,899 (222.26 KB)
 Non-trainable params: 0 (0.00 B)
 Epoch 1/5
 391/391 ━━━━━━━━━━━━━━━━━━━━ 10s 19ms/step - loss: 0.0194 - val_loss: 0.0065
 Epoch 2/5
 391/391 ━━━━━━━━━━━━━━━━━━━━ 6s 16ms/step - loss: 0.0064 - val_loss: 0.0063
 Epoch 3/5
 391/391 ━━━━━━━━━━━━━━━━━━━━ 6s 16ms/step - loss: 0.0062 - val_loss: 0.0062
 Epoch 4/5
 391/391 ━━━━━━━━━━━━━━━━━━━━ 6s 16ms/step - loss: 0.0061 - val_loss: 0.0061
 Epoch 5/5
 391/391 ━━━━━━━━━━━━━━━━━━━━ 6s 16ms/step - loss: 0.0061 - val_loss: 0.0060
 313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```



Result:
Thus, the Image Colorization Using Convolutional Autoencoder model is successfully executed and verified.