VIPS
योगः कर्मसु कौशलम्
IN PURSUIT OF PERFECTION

VIVEKANANDA INSTITUTE OF PROFESSIONAL STUDIES - TECHNICAL CAMPUS

Grade A++ Accredited Institution by NAAC

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Affiliated to GGSIP University, Delhi; Recognized by Bar Council of India and AICTE
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SCHOOL OF ENGINEERING & TECHNOLOGY

BTECH Programme: AI&DS

Course Title: Fundamentals of Deep Learning Lab

Course Code: AIDS304P

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S.No	Experiment Name	Date	Marks			Remark	Updated Marks	Faculty Signature
			Laboratory Assessment (15 Marks)	Class Participation (5 Marks)	Viva (5 Marks)			

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Experiment 1

Aim: To explore the basic features of Tensorflow and Keras packages in Python.

Objectives:

- Understand the foundational functionalities of TensorFlow and Keras for deep learning.
- Explore how to build, compile, and train basic neural network models using Keras.

Theory:

TensorFlow and Keras are powerful libraries in Python that form the backbone of deep learning model implementation. They provide a comprehensive ecosystem for building, training, and deploying machine learning models. These libraries are pivotal for both academic and practical experiments in the field of deep learning.

1. TensorFlow:

TensorFlow, developed by Google, is an open-source machine learning framework designed for high-performance numerical computations. It enables researchers and developers to efficiently create and train machine learning models across various platforms. TensorFlow's core strength lies in its ability to handle tensors, which are multi-dimensional arrays that form the foundation of all computations in deep learning.

Key features of TensorFlow include:

- **Automatic Differentiation**: TensorFlow computes gradients automatically, simplifying the process of backpropagation for complex neural networks.
- **GPU/TPU Acceleration**: TensorFlow optimally utilizes hardware resources like GPUs and TPUs for faster training and inference.
- **Scalability**: Its distributed training capabilities allow it to handle large-scale models and datasets across multiple devices and servers.
- **Versatility**: TensorFlow supports both low-level control for custom operations and high-level APIs like Keras for simplicity.

2. Keras:

Keras is a high-level neural network API integrated with TensorFlow. It is designed to be user-friendly while still providing powerful features for advanced customization. Keras reduces the complexity of building deep learning models by offering intuitive syntax and ready-to-use components for common tasks.

Some of the features of Keras include:

- **Simplified Model Building**: Keras offers Sequential and Functional APIs to define models effortlessly.

- **Ease of Use**: It includes pre-built layers, loss functions, optimizers, and metrics, allowing for rapid prototyping.
- **Modularity**: Every component in Keras is independent, making it easy to adapt and customize.
- **Integration**: Since it is built on TensorFlow, it inherits the performance and scalability benefits of TensorFlow.

3. Core Concepts:

- **Tensors**:
  The primary data structure in TensorFlow, tensors represent multi-dimensional arrays that enable efficient numerical computation. Operations on tensors are highly optimized for both CPU and GPU execution.
- **Layers**:
  Layers are the building blocks of a deep learning model. In Keras, layers perform specific transformations, such as linear computations, activation functions, or normalization, to process input data progressively.
- **Compilation and Training**:
  Keras provides a streamlined workflow for compiling models, training them on datasets, and evaluating their performance. Functions like compile(), fit(), and evaluate() abstract the complexities of training, making the process user-friendly.
- **Backpropagation and Optimization**:
  TensorFlow and Keras automate the process of calculating gradients and updating model parameters using optimizers like SGD, Adam, or RMSprop. This minimizes loss functions and improves model accuracy over successive iterations.

4. Regression and Classification with TensorFlow and Keras

- **Regression**:
  In regression tasks, the model predicts continuous outputs. TensorFlow and Keras simplify the creation of regression models by providing built-in loss functions (e.g., Mean Squared Error) and metrics to evaluate model performance.
- **Classification**:
  For classification tasks, the model predicts categorical outputs, such as labels for data points. TensorFlow and Keras support multi-class and binary classification through layers like Dense, activation functions like softmax or sigmoid, and loss functions like categorical_crossentropy.

By exploring TensorFlow and Keras, learners gain hands-on experience with key deep learning principles. This experiment lays the groundwork for understanding tensor operations, building neural networks, and solving real-world problems through regression and classification tasks. These tools bridge the gap between theoretical concepts and practical applications in the realm of deep learning.

Code:

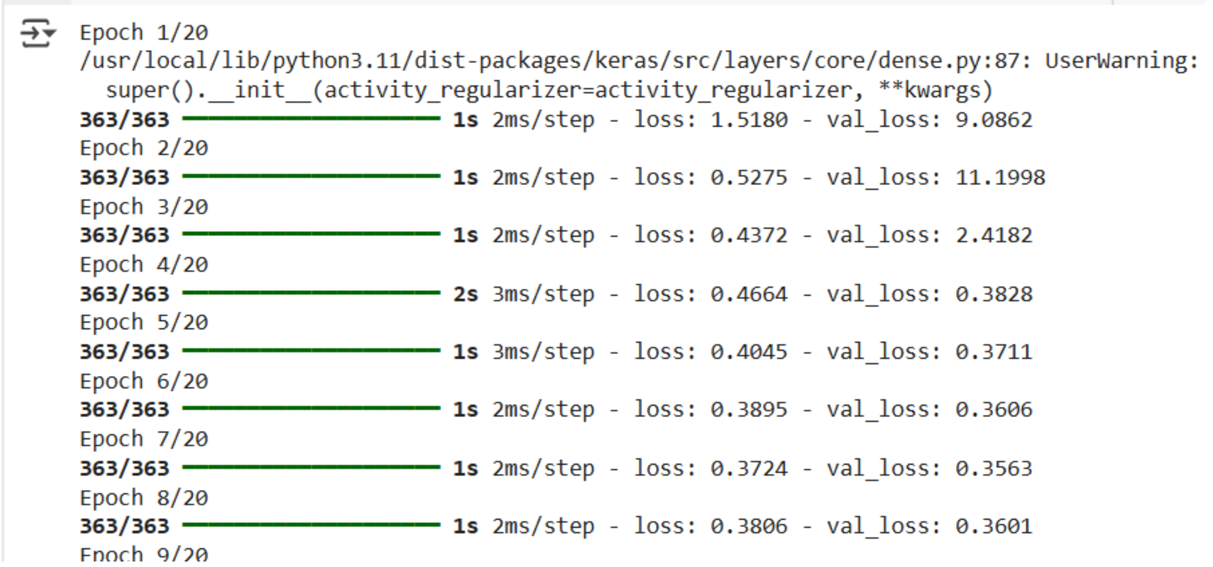
```
# Regression

import tensorflow as tf
import numpy as np
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

housing = fetch_california_housing()
X_train_full, X_test, y_train_full, y_test =
train_test_split(housing.data, housing.target, random_state=42)
X_train, X_valid, y_train, y_valid = train_test_split(X_train_full,
y_train_full, random_state=42)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_valid = scaler.transform(X_valid)
X_test = scaler.transform(X_test)

model = tf.keras.models.Sequential([
    tf.keras.layers.Dense(30, activation='relu',
input_shape=X_train.shape[1:]),
    tf.keras.layers.Dense(1)
])

model.compile(loss='mean_squared_error',
optimizer=tf.keras.optimizers.SGD(learning_rate=0.01))

history = model.fit(X_train, y_train, epochs=20,
validation_data=(X_valid, y_valid))

mse_test = model.evaluate(X_test, y_test)

print(f"Test MSE: {mse_test}")
```

```
# Classification

import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import load_iris

iris = load_iris()
```

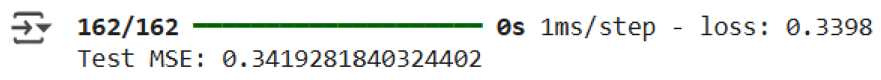
```
X = iris.data
y = iris.target

y = tf.keras.utils.to_categorical(y, num_classes=3)

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

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

model = tf.keras.Sequential([
    tf.keras.layers.Dense(10, activation='relu', input_shape=(4,)),
    tf.keras.layers.Dense(3, activation='softmax')
])

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

model.fit(X_train, y_train, epochs=50, batch_size=32, verbose=1)

loss, accuracy = model.evaluate(X_test, y_test, verbose=0)
print(f"Test Loss: {loss:.4f}")
print(f"Test Accuracy: {accuracy:.4f}")
```

Output:

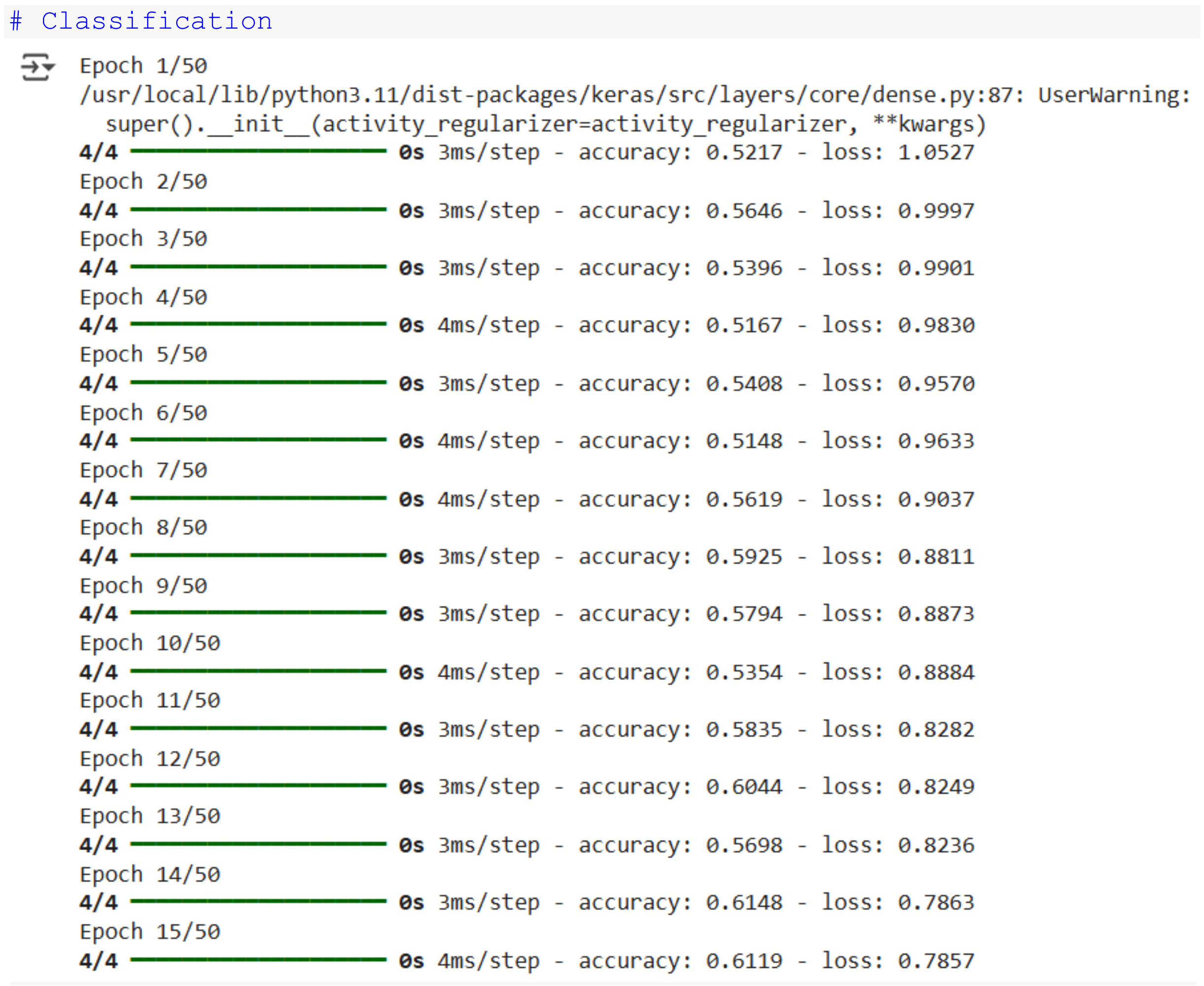
```
# Regression
```



```
Epoch 1/20
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning:
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
363/363 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 1.5180 - val_loss: 9.0862
Epoch 2/20
363/363 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.5275 - val_loss: 11.1998
Epoch 3/20
363/363 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.4372 - val_loss: 2.4182
Epoch 4/20
363/363 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - loss: 0.4664 - val_loss: 0.3828
Epoch 5/20
363/363 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.4045 - val_loss: 0.3711
Epoch 6/20
363/363 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.3895 - val_loss: 0.3606
Epoch 7/20
363/363 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.3724 - val_loss: 0.3563
Epoch 8/20
363/363 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.3806 - val_loss: 0.3601
Epoch 9/20
```

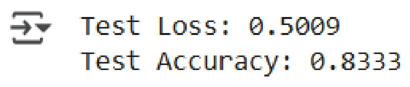


```
162/162 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.3398
Test MSE: 0.3419281840324402
```



```
# Classification
```

```
Epoch 1/50
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning:
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5217 - loss: 1.0527
Epoch 2/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5646 - loss: 0.9997
Epoch 3/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5396 - loss: 0.9901
Epoch 4/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.5167 - loss: 0.9830
Epoch 5/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5408 - loss: 0.9570
Epoch 6/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.5148 - loss: 0.9633
Epoch 7/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.5619 - loss: 0.9037
Epoch 8/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5925 - loss: 0.8811
Epoch 9/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5794 - loss: 0.8873
Epoch 10/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.5354 - loss: 0.8884
Epoch 11/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5835 - loss: 0.8282
Epoch 12/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.6044 - loss: 0.8249
Epoch 13/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.5698 - loss: 0.8236
Epoch 14/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.6148 - loss: 0.7863
Epoch 15/50
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 0.6119 - loss: 0.7857
```



```
Test Loss: 0.5009
Test Accuracy: 0.8333
```

Learning Outcomes:

- Understand how to build and train regression and classification models using TensorFlow and Keras.
- Gain insights into key evaluation metrics like Mean Squared Error (MSE) for regression and Accuracy or F1-Score for classification tasks.
- Develop the ability to preprocess data and apply activation functions, optimizers, and loss functions suitable for different problem domains.

Experiment 2

Aim: Implementation of ANN model for regression and classification problem in Python.

Objectives:

- To implement an ANN model in Python for regression and evaluate its performance using MSE.
- To implement an ANN model in Python for classification and assess its accuracy using performance metrics.

Theory:

Introduction to Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are computational models inspired by the human brain's structure and functioning. They consist of layers of interconnected nodes (neurons) which process and transform input data through various layers to produce an output. The power of ANNs lies in their ability to learn from data, identify patterns, and generalize predictions, making them highly suitable for various tasks such as regression, classification, and time series forecasting.

ANNs are composed of three primary types of layers:

1. **Input Layer**: Receives the raw input data.
2. **Hidden Layers**: Contain neurons that process the data using weights and activation functions.
3. **Output Layer**: Provides the final result or prediction.

Each neuron in the hidden layers and output layer processes inputs from previous layers and passes them through an activation function, which introduces non-linearity into the model. The weights of the connections between neurons are learned during training by using optimization techniques like gradient descent.

Regression Problems with ANN

In regression tasks, the objective is to predict a continuous numerical output based on input features. For example, predicting house prices based on location, size, and other features is a typical regression problem.

The basic architecture of an ANN for regression consists of:

- **Input Layer**: Takes in feature data (e.g., square footage, number of bedrooms).
- **Hidden Layers**: Processes the data through neurons.
- **Output Layer**: Produces a continuous output, which could be a single value (e.g., price).

To train an ANN for regression, the model adjusts its weights to minimize the difference between the predicted output and the actual target value using a loss function like Mean Squared Error (MSE). The training process involves backpropagation, where errors are propagated backward through the network, and weights are updated to reduce the loss.

Key Steps in ANN Regression:

1. **Data Preprocessing**: Normalization and scaling of data are crucial for ensuring efficient learning.
2. **Model Construction**: A neural network model is constructed with appropriate layers and activation functions.
3. **Training the Model**: The model is trained using a dataset, adjusting weights based on the error at each step.
4. **Evaluation**: The model's performance is evaluated using metrics like MSE or Root Mean Squared Error (RMSE).

Python libraries like Keras and TensorFlow are often used to implement ANNs for regression, as they provide simple APIs for defining and training neural networks.

Classification Problems with ANN

In classification tasks, the goal is to categorize data into distinct classes or categories. For example, classifying images as either "cat" or "dog" or predicting whether a customer will buy a product based on their behavior are typical classification problems.

The structure of an ANN for classification is similar to that of regression, but with key differences in the output layer:

- **Input Layer**: Receives features of the data (e.g., image pixels, demographic features).
- **Hidden Layers**: Processes the data through neurons.
- **Output Layer**: Uses a softmax or sigmoid activation function to output class probabilities. In binary classification, the output layer consists of a single neuron with a sigmoid activation function. For multi-class classification, a softmax activation function is used.

For classification tasks, the model is trained using a loss function like **Cross-Entropy Loss**, which measures the difference between predicted probabilities and actual class labels. During training, the model learns to adjust its weights to reduce this loss.

Key Steps in ANN Classification:

1. **Data Preprocessing**: This involves encoding categorical variables (e.g., one-hot encoding for labels) and normalizing input features.
2. **Model Construction**: The model is designed with hidden layers and an output layer with appropriate activation functions (sigmoid for binary classification or softmax for multi-class).
3. **Training the Model**: The neural network is trained using a labeled dataset, and the weights are adjusted through backpropagation.
4. **Evaluation**: The performance is evaluated using accuracy, precision, recall, F1-score, or AUC (for binary classification).

Challenges in ANN Models

While ANNs are powerful, they come with several challenges:

1. **Overfitting**: ANN models, especially deep networks with many layers, can easily overfit the training data, leading to poor generalization. Regularization techniques such as dropout, L2 regularization, or early stopping can help mitigate overfitting.
2. **Data Quality**: ANN models are sensitive to the quality and quantity of data. Proper data preprocessing, including handling missing values, scaling, and feature engineering, is crucial.
3. **Model Tuning**: The performance of an ANN heavily depends on hyperparameters like the number of hidden layers, neurons, learning rate, and batch size. Grid search or random search methods are often employed to optimize these hyperparameters.
4. **Computational Complexity**: Training deep neural networks can be computationally expensive, requiring powerful hardware (e.g., GPUs) and careful resource management.

Python Libraries for Implementing ANN

Several Python libraries make it easy to implement ANN models for both regression and classification:

1. **TensorFlow/Keras**: These are the most popular frameworks for building and training neural networks. Keras provides a high-level API that is user-friendly, while TensorFlow provides more flexibility and control for advanced users.
2. **PyTorch**: Another powerful deep learning framework that offers flexibility and dynamic computation graphs, making it suitable for research and development.
3. **Scikit-learn**: Although primarily used for traditional machine learning algorithms, Scikit-learn provides simple neural network implementations (MLPRegressor and MLPClassifier) that are useful for smaller-scale tasks.

Conclusion

ANNs are versatile tools for both regression and classification tasks in machine learning. By leveraging their ability to model complex relationships and learn from data, they can achieve high accuracy in predicting continuous values and categorizing data into distinct classes. Python, with its rich ecosystem of libraries like Keras and TensorFlow, provides a powerful environment for implementing, training, and evaluating ANN models. However, successful deployment requires careful attention to data quality, model tuning, and computational resources to avoid common pitfalls like overfitting and high computational costs.

Code:

```
#Regression

import tensorflow as tf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

housing = fetch_california_housing()
df = pd.DataFrame(housing.data, columns=housing.feature_names)
df['target'] = housing.target

df.head()
df=df.dropna()

X=df.iloc[:,:-1] ## independent features
y=df.iloc[:,-1] ## dependent features

X.isnull()
y.isnull()

sns.pairplot(df)

df.corr()

corrmat = df.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(20,20))
g=sns.heatmap(df[top_corr_features].corr(),annot=True,cmap="RdYlGn")

corrmat.index

from sklearn.ensemble import ExtraTreesRegressor
import matplotlib.pyplot as plt
model = ExtraTreesRegressor()
model.fit(X,y)

X.head()

print(model.feature_importances_)

feat_importances = pd.Series(model.feature_importances_,
index=X.columns)
```

```
feat_importances.nlargest(5).plot(kind='barh')
plt.show()
sns.distplot(y)

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=0)

import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LeakyReLU,PReLU,ELU
from keras.layers import Dropout

NN_model = Sequential()

# The Input Layer :
NN_model.add(Dense(128, kernel_initializer='normal',input_dim =
X_train.shape[1], activation='relu'))

# The Hidden Layers :
NN_model.add(Dense(256, kernel_initializer='normal',activation='relu'))
NN_model.add(Dense(256, kernel_initializer='normal',activation='relu'))
NN_model.add(Dense(256, kernel_initializer='normal',activation='relu'))

# The Output Layer :
NN_model.add(Dense(1, kernel_initializer='normal',activation='linear'))

# Compile the network :
NN_model.compile(loss='mean_absolute_error', optimizer='adam',
metrics=['mean_absolute_error'])
NN_model.summary()

# Fitting the ANN to the Training set
model_history=NN_model.fit(X_train, y_train,validation_split=0.33,
batch_size = 10, epochs = 100)

prediction=NN_model.predict(X_test)

y_test

sns.distplot(y_test.values.reshape(-1,1)-prediction)
plt.scatter(y_test,prediction)

from sklearn import metrics
print('MAE:', metrics.mean_absolute_error(y_test, prediction))
print('MSE:', metrics.mean_squared_error(y_test, prediction))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, prediction)))
```

```python
# Classification

import numpy as np
import pandas as pd
import tensorflow as tf

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import load_iris

iris = load_iris()
X = iris.data
y = iris.target

y = tf.keras.utils.to_categorical(y, num_classes=3)

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

sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

ann = tf.keras.models.Sequential()

ann.add(tf.keras.layers.Dense(units=6,activation="relu"))
ann.add(tf.keras.layers.Dense(units=6,activation="relu"))
ann.add(tf.keras.layers.Dense(units=3,activation="sigmoid"))

ann.compile(optimizer="adam",loss="categorical_crossentropy",metrics=['
accuracy'])
ann.fit(X_train,y_train,batch_size=32,epochs = 100)

loss, accuracy = ann.evaluate(X_test, y_test, verbose=0)
print(f"Test Loss: {loss:.4f}")
print(f"Test Accuracy: {accuracy:.4f}")
```

Output:

```
#Regression
df.head()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	target
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23	4.526
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22	3.585
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24	3.521
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25	3.413
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25	3.422

```
X.isnull()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
0	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...
20635	False	False	False	False	False	False	False	False
20636	False	False	False	False	False	False	False	False
20637	False	False	False	False	False	False	False	False
20638	False	False	False	False	False	False	False	False
20639	False	False	False	False	False	False	False	False

20640 rows × 8 columns

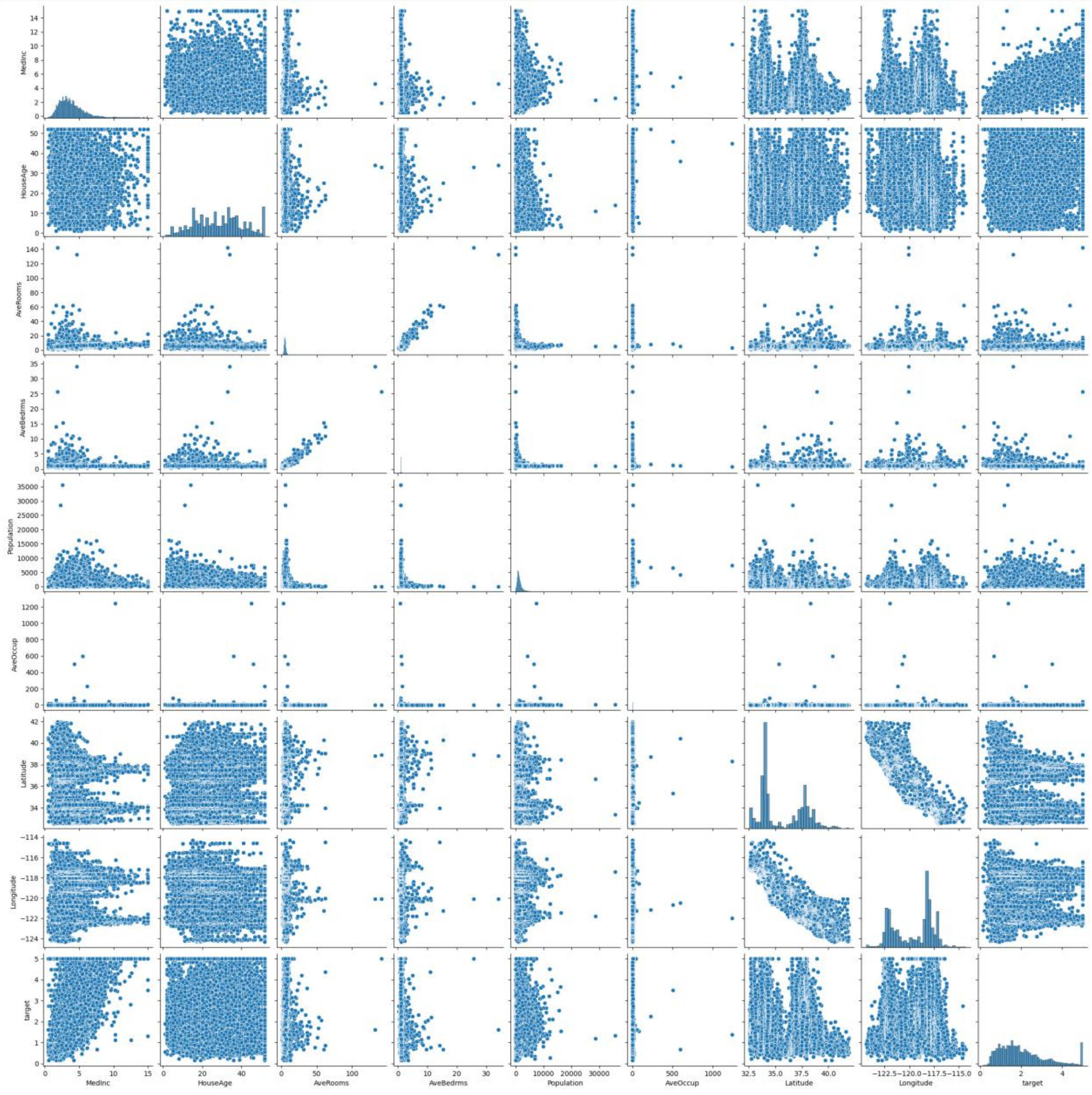
```
y.isnull()
```

	target
0	False
1	False
2	False
3	False
4	False
...	...
20635	False
20636	False
20637	False
20638	False
20639	False

20640 rows × 1 columns

dtype: bool

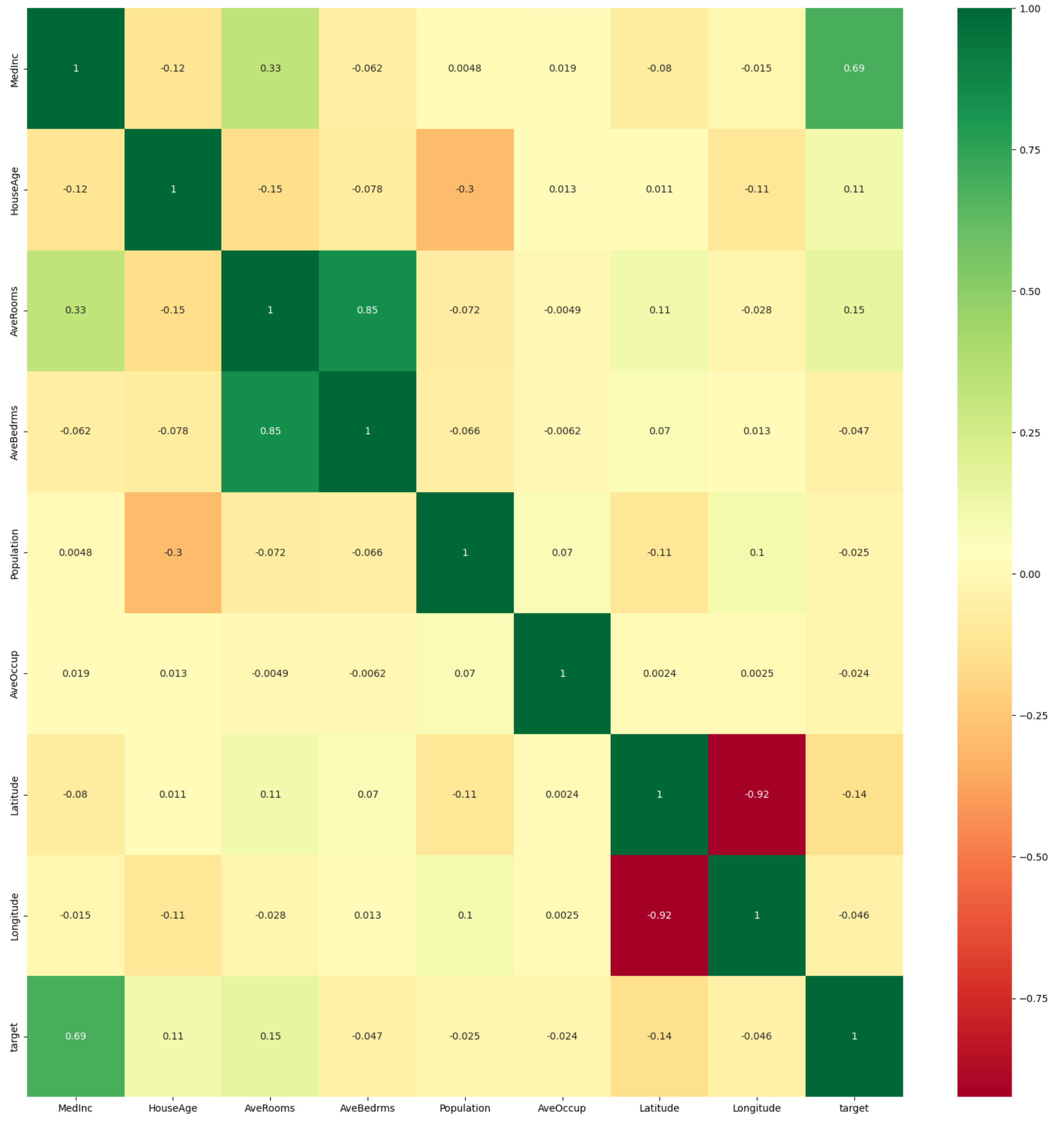
```
sns.pairplot(df)
```



```
df.corr()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	target
MedInc	1.000000	-0.119034	0.326895	-0.062040	0.004834	0.018766	-0.079809	-0.015176	0.688075
HouseAge	-0.119034	1.000000	-0.153277	-0.077747	-0.296244	0.013191	0.011173	-0.108197	0.105623
AveRooms	0.326895	-0.153277	1.000000	0.847621	-0.072213	-0.004852	0.106389	-0.027540	0.151948
AveBedrms	-0.062040	-0.077747	0.847621	1.000000	-0.066197	-0.006181	0.069721	0.013344	-0.046701
Population	0.004834	-0.296244	-0.072213	-0.066197	1.000000	0.069863	-0.108785	0.099773	-0.024650
AveOccup	0.018766	0.013191	-0.004852	-0.006181	0.069863	1.000000	0.002366	0.002476	-0.023737
Latitude	-0.079809	0.011173	0.106389	0.069721	-0.108785	0.002366	1.000000	-0.924664	-0.144160
Longitude	-0.015176	-0.108197	-0.027540	0.013344	0.099773	0.002476	-0.924664	1.000000	-0.045967
target	0.688075	0.105623	0.151948	-0.046701	-0.024650	-0.023737	-0.144160	-0.045967	1.000000

```
sns.heatmap()
```



	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude	target
MedInc	1	-0.12	0.33	-0.062	0.0048	0.019	-0.08	-0.015	0.69
HouseAge	-0.12	1	-0.15	-0.078	-0.3	0.013	0.011	-0.11	0.11
AveRooms	0.33	-0.15	1	0.85	-0.072	-0.0049	0.11	-0.028	0.15
AveBedrms	-0.062	-0.078	0.85	1	-0.066	-0.0062	0.07	0.013	-0.047
Population	0.0048	-0.3	-0.072	-0.066	1	0.07	-0.11	0.1	-0.025
AveOccup	0.019	0.013	-0.0049	-0.0062	0.07	1	0.0024	0.0025	-0.024
Latitude	-0.08	0.011	0.11	0.07	-0.11	0.0024	1	-0.92	-0.14
Longitude	-0.015	-0.11	-0.028	0.013	0.1	0.0025	-0.92	1	-0.046
target	0.69	0.11	0.15	-0.047	-0.025	-0.024	-0.14	-0.046	1

```
corrmat.index
```

```
Index(['MedInc', 'HouseAge', 'AveRooms', 'AveBedrms', 'Population', 'AveOccup',
       'Latitude', 'Longitude', 'target'],
      dtype='object')
```

```
model.fit(X,y)
```

```
▾ ExtraTreesRegressor
ExtraTreesRegressor()
```

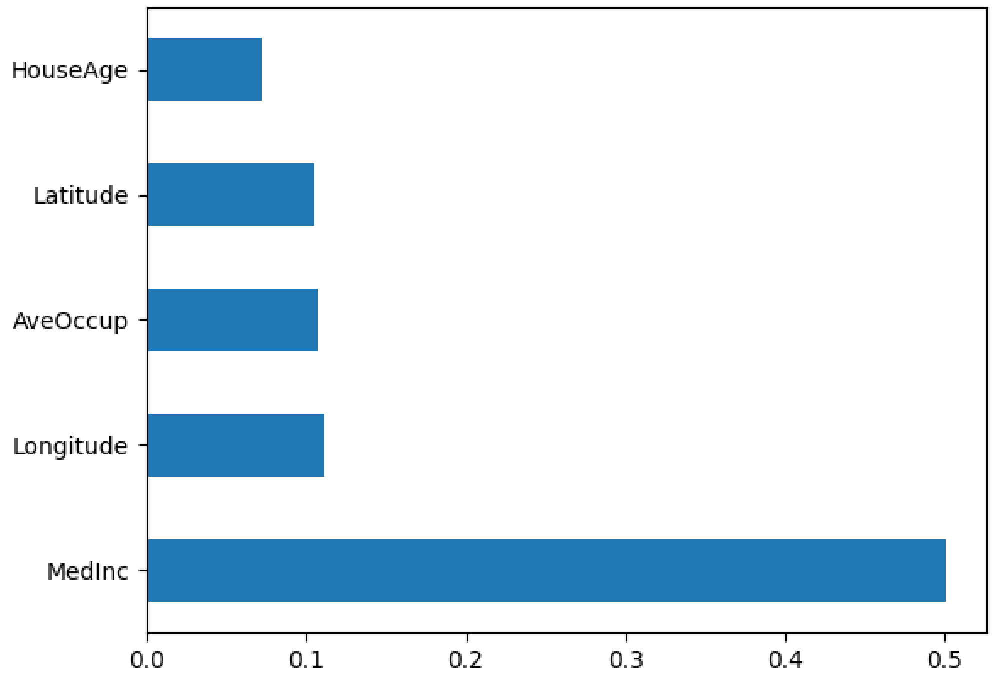
```
X.head()
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24
3	5.6431	52.0	5.817352	1.073059	558.0	2.547945	37.85	-122.25
4	3.8462	52.0	6.281853	1.081081	565.0	2.181467	37.85	-122.25

```
print(model.feature_importances_)
```

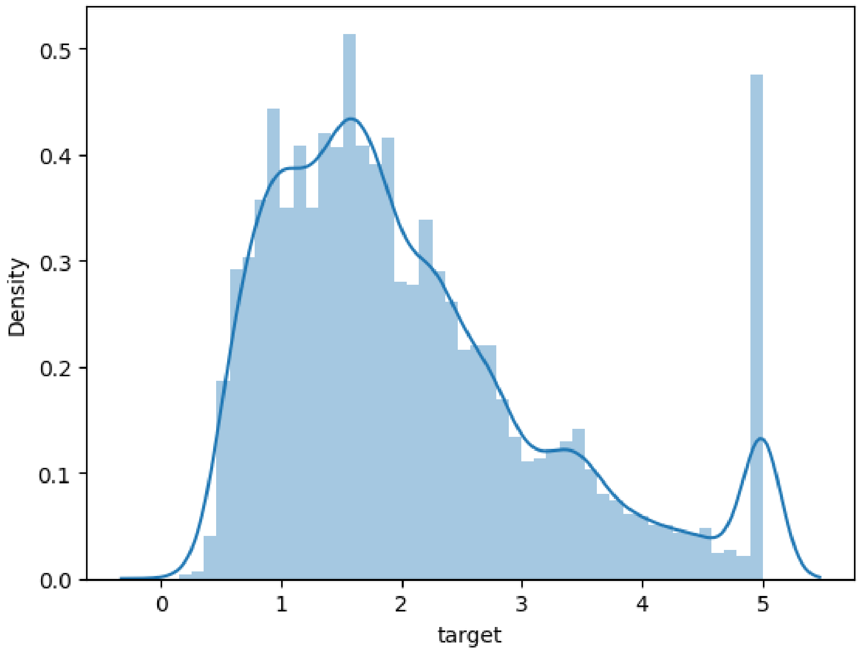
```
[0.50077469 0.07189236 0.04195345 0.03438947 0.0276384  0.10722586
 0.10460644 0.11151933]
```

```
plt.show()
```



```
sns.distplot(y)
```

```
<ipython-input-42-0f415a98584e>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(y)
<Axes: xlabel='target', ylabel='Density'>
```



```
NN_model.fit()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Model: "sequential"
┌─────────────────────────────────┬──────────────────────────────┬─────────────────┐
│ Layer (type)                    │ Output Shape                 │         Param # │
├─────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ dense (Dense)                   │ (None, 128)                  │           1,152 │
├─────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ dense_1 (Dense)                 │ (None, 256)                  │          33,024 │
├─────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ dense_2 (Dense)                 │ (None, 256)                  │          65,792 │
├─────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ dense_3 (Dense)                 │ (None, 256)                  │          65,792 │
├─────────────────────────────────┼──────────────────────────────┼─────────────────┤
│ dense_4 (Dense)                 │ (None, 1)                    │             257 │
└─────────────────────────────────┴──────────────────────────────┴─────────────────┘
 Total params: 166,017 (648.50 KB)
 Trainable params: 166,017 (648.50 KB)
 Non-trainable params: 0 (0.00 B)
Epoch 1/100
968/968 ━━━━━━━━━━━━━━━━━━━━ 10s 7ms/step - loss: 1.3826 - mean_absolute_error: 1.3826 - val_loss: 0.7857 - val_mean_absolute_error: 0.7857
Epoch 2/100
968/968 ━━━━━━━━━━━━━━━━━━━━ 7s 4ms/step - loss: 0.7961 - mean_absolute_error: 0.7961 - val_loss: 0.7636 - val_mean_absolute_error: 0.7636
Epoch 3/100
968/968 ━━━━━━━━━━━━━━━━━━━━ 7s 7ms/step - loss: 0.6541 - mean_absolute_error: 0.6541 - val_loss: 0.6083 - val_mean_absolute_error: 0.6083
Epoch 4/100
968/968 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 0.6483 - mean_absolute_error: 0.6483 - val_loss: 0.5825 - val_mean_absolute_error: 0.5825
Epoch 5/100
968/968 ━━━━━━━━━━━━━━━━━━━━ 8s 8ms/step - loss: 0.6072 - mean_absolute_error: 0.6072 - val_loss: 0.5607 - val_mean_absolute_error: 0.5607
Epoch 6/100
968/968 ━━━━━━━━━━━━━━━━━━━━ 6s 6ms/step - loss: 0.5924 - mean_absolute_error: 0.5924 - val_loss: 0.5867 - val_mean_absolute_error: 0.5867
Epoch 7/100
968/968 ━━━━━━━━━━━━━━━━━━━━ 10s 6ms/step - loss: 0.5857 - mean_absolute_error: 0.5857 - val_loss: 0.5459 - val_mean_absolute_error: 0.5459
Epoch 8/100
968/968 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 0.5931 - mean_absolute_error: 0.5931 - val_loss: 0.5405 - val_mean_absolute_error: 0.5405
Epoch 9/100
968/968 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.5673 - mean_absolute_error: 0.5673 - val_loss: 0.5310 - val_mean_absolute_error: 0.5310
Epoch 10/100
968/968 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 0.5688 - mean_absolute_error: 0.5688 - val_loss: 0.5931 - val_mean_absolute_error: 0.5931
```

```
prediction=NN_model.predict(X_test)
```

```
194/194 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step
```

```
y_test
```

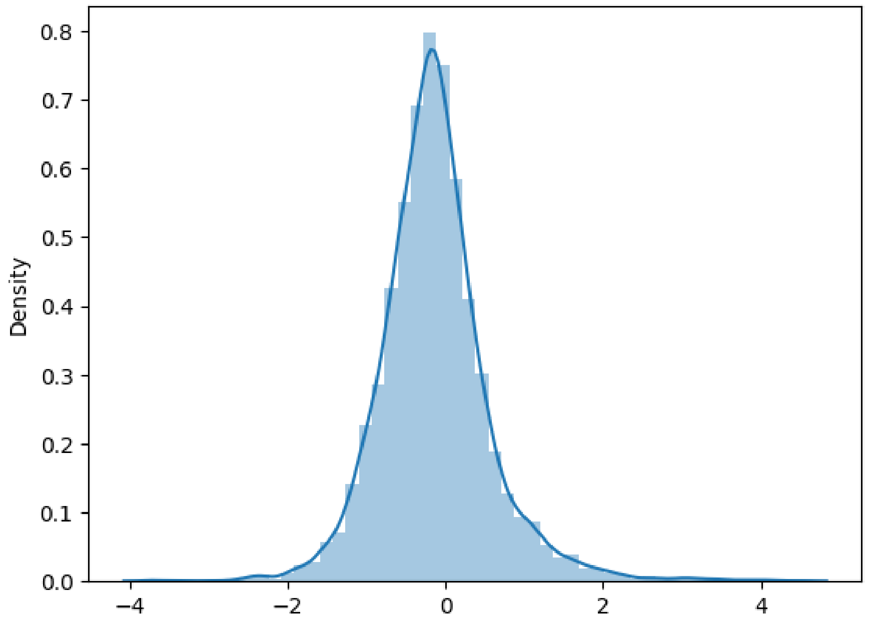
	target
14740	1.369
10101	2.413
20566	2.007
2670	0.725
15709	4.600
...	...
19681	0.740
12156	1.773
10211	3.519
2445	0.925
17914	2.983

6192 rows × 1 columns

dtype: float64

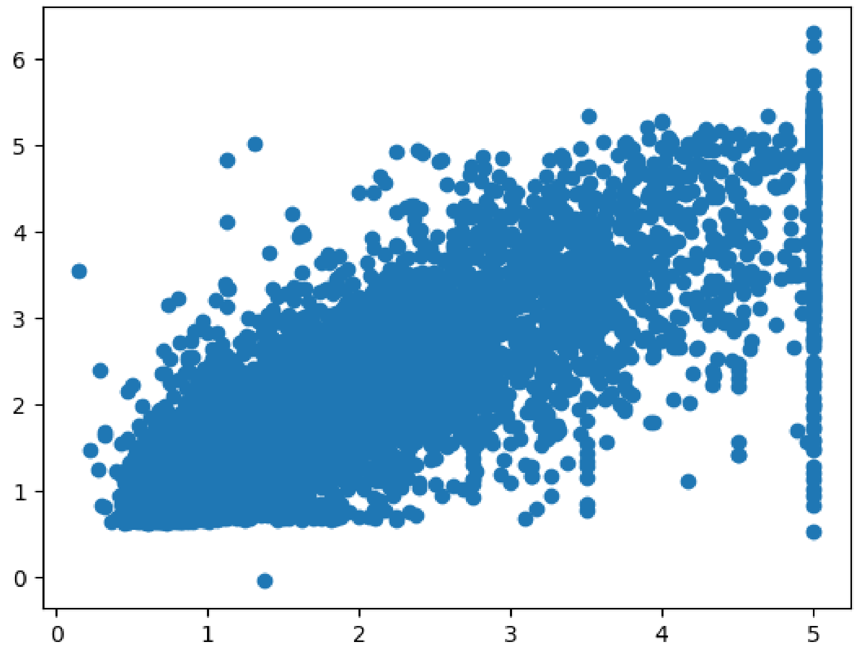
```
sns.distplot(y_test.values.reshape(-1,1)-prediction)
```

```
<ipython-input-50-be70e624d0c6>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(y_test.values.reshape(-1,1)-prediction)
<Axes: ylabel='Density'>
```



```
plt.scatter(y_test,prediction)
```

```
<matplotlib.collections.PathCollection at 0x7e1038f835d0>
```



```
# MAE, MSE and RMSE
```

```
MAE: 0.517750902395806
MSE: 0.50007160344142
RMSE: 0.7071574106529748
```

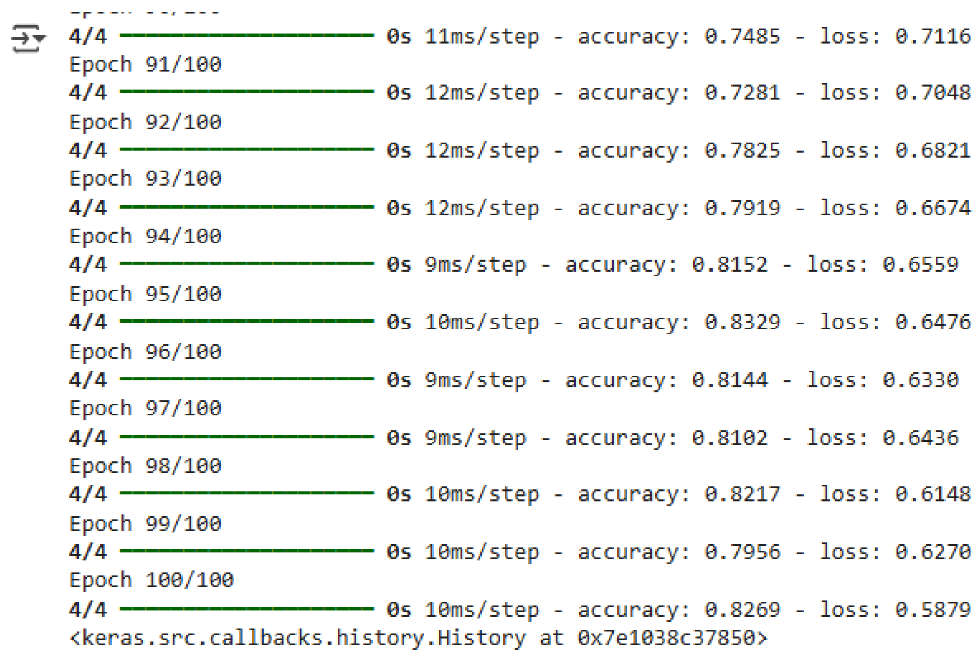
```
#Classification
```

```
Shape of : X_train , y_train
```

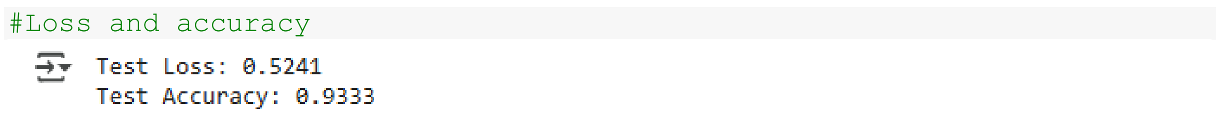
```
(120, 4)
(120, 3)
```

```
ann.fit()
```

```
Epoch 1/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 1s 10ms/step - accuracy: 0.4062 - loss: 1.2876
Epoch 2/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.3973 - loss: 1.2885
Epoch 3/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.3546 - loss: 1.2926
Epoch 4/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.3921 - loss: 1.3113
Epoch 5/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.3696 - loss: 1.2849
Epoch 6/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.4546 - loss: 1.2412
Epoch 7/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.4563 - loss: 1.2322
Epoch 8/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.4862 - loss: 1.2163
Epoch 9/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.4948 - loss: 1.1950
Epoch 10/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy: 0.4448 - loss: 1.2024
```



```
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 0.7485 - loss: 0.7116
Epoch 91/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.7281 - loss: 0.7048
Epoch 92/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.7825 - loss: 0.6821
Epoch 93/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy: 0.7919 - loss: 0.6674
Epoch 94/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.8152 - loss: 0.6559
Epoch 95/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy: 0.8329 - loss: 0.6476
Epoch 96/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.8144 - loss: 0.6330
Epoch 97/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step - accuracy: 0.8102 - loss: 0.6436
Epoch 98/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy: 0.8217 - loss: 0.6148
Epoch 99/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy: 0.7956 - loss: 0.6270
Epoch 100/100
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy: 0.8269 - loss: 0.5879
<keras.src.callbacks.history.History at 0x7e1038c37850>
```



```
#Loss and accuracy
```

```
Test Loss: 0.5241
Test Accuracy: 0.9333
```

Learning Outcomes:

- Gain the ability to build and train ANN models for both regression and classification tasks in Python.
- Learn to preprocess data and evaluate model performance using key metrics like MSE, accuracy, and F1-score.

Experiment 3

Aim: Implementation of Convolution Neural Network for MRI Data Set in Python.

Objectives:

- To implement CNN model in Python on MRI images.
- To implement CNN model for classifying images and evaluate its performance using performance metrics.

Theory:

Introduction to Deep Learning and CNNs

Deep learning is a subset of machine learning that focuses on training artificial neural networks to learn from large amounts of data. Among deep learning architectures, **Convolutional Neural Networks (CNNs)** are particularly effective for analyzing image-based data, making them suitable for medical imaging tasks such as MRI (Magnetic Resonance Imaging) analysis.

MRI scans provide detailed internal body structures, helping in medical diagnosis, treatment planning, and research. However, manually interpreting MRI images is time-consuming and subject to variability. CNNs help automate and improve MRI analysis by detecting patterns, classifying abnormalities, and segmenting regions of interest.

Convolutional Neural Networks (CNNs) in Medical Imaging

CNNs are specialized deep learning models designed for image processing tasks. They use **convolutional layers** to extract spatial features from images, making them efficient in identifying patterns and structures within MRI scans. The fundamental components of a CNN include:

- **Convolutional Layers:** Apply filters to input images to extract features such as edges, textures, and shapes.
- **Pooling Layers:** Reduce the dimensionality of the data while preserving important features, improving computational efficiency.
- **Fully Connected Layers:** Flatten the extracted features and connect them to output neurons for classification or segmentation tasks.
- **Activation Functions (ReLU, Softmax, Sigmoid):** Introduce non-linearity into the model to improve learning capability.

CNNs have significantly advanced medical imaging applications, enabling automated tumor detection, brain segmentation, and disease classification from MRI datasets.

MRI Dataset and Its Importance

MRI datasets contain grayscale images that represent different tissues and structures within the human body. These datasets are crucial for training CNN models in various medical applications, such as:

- **Brain Tumor Classification** (Normal vs. Tumor)
- **Alzheimer's Disease Detection**
- **Organ Segmentation**

MRI datasets usually require preprocessing steps, including normalization, resizing, and augmentation, to improve model performance.

Implementation of CNN for MRI Dataset in Python

Python, with deep learning libraries such as **TensorFlow** and **Keras**, provides an efficient framework for implementing CNNs. The basic steps involved in developing a CNN for MRI image classification include:

1. **Loading the MRI Dataset:** Using libraries like `Pandas`, `NumPy`, or `TensorFlow datasets`.
2. **Preprocessing the Data:** Resizing images, normalizing pixel values, and augmenting the dataset.
3. **Building the CNN Model:** Defining layers such as convolutional, pooling, and fully connected layers.
4. **Compiling and Training the Model:** Using an optimizer (SGD, Adam) and loss function (categorical cross-entropy).
5. **Evaluating the Model:** Testing the model on unseen MRI images and assessing its accuracy.

Applications of CNNs in MRI Analysis

- **Brain Tumor Detection:** CNNs can classify MRI images as normal or containing tumors with high accuracy.
- **Alzheimer's Disease Prediction:** Identifying structural changes in brain MRI scans to diagnose neurodegenerative diseases.
- **Medical Image Segmentation:** Extracting regions of interest, such as tumors or organs, from MRI scans for precise analysis.

Conclusion

The implementation of a Convolutional Neural Network (CNN) for MRI image classification is a powerful deep learning application in medical imaging. CNNs efficiently learn spatial hierarchies of features and can significantly improve disease detection accuracy. With Python-based frameworks like TensorFlow and Keras, researchers and medical professionals can develop robust models to analyze MRI scans, contributing to advancements in medical diagnostics and healthcare.

Code:

```
import pandas as pd
import numpy as np
import cv2
import os
import random
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib.image import imread

import tensorflow as tf
import tensorflow_hub as hub
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'

from keras.models import Sequential
from keras.layers import Conv2D,Activation,MaxPooling2D,Dense,Flatten,
Dropout
from keras.losses import BinaryCrossentropy
try:
    from keras.optimizer import Adam
except:
    from tensorflow.keras.optimizers import Adam

from sklearn.model_selection import train_test_split
from sklearn.metrics import auc, roc_curve, log_loss, roc_auc_score,
auc, roc_curve, accuracy_score, confusion_matrix, cohen_kappa_score


import warnings
warnings.filterwarnings('ignore')


MAIN_DIR = "/content/brain_tumor_dataset/"

# control reproducibility with random seeds
seed_value = 1
np.random.seed(seed_value)
random.seed(seed_value)
tf.random.set_seed(seed_value)

# Define location of dataset
folder_no = MAIN_DIR + '/no'
folder_yes = MAIN_DIR + '/yes'

# Collect image paths
image_paths = []
```

```
for filepath in [folder_no, folder_yes]:
    for f in os.listdir(filepath)[:3]:  # Take the first 3 images per
folder
        image_paths.append(os.path.join(filepath, f))

fig, axes = plt.subplots(1, len(image_paths), figsize=(15, 5))

for ax, img_path in zip(axes, image_paths):
    image = imread(img_path)
    ax.imshow(image)

plt.tight_layout()
plt.show()

filepath = MAIN_DIR
images, labels, filenames = [], [], []

for gt in ['yes','no']:
    filepath_gt = filepath + gt
    for f in os.listdir(filepath_gt):
        filename = filepath_gt + '/' + f
        if '._' not in filename: # metadata files created by macos

            # load image
            photo =
tf.keras.utils.load_img(path=filename,target_size=(200, 200))

            # load image pixels
            image = imread(filename)
            resized_image = cv2.resize(image,dsize=(200,200))

            # in case of grayscale images
            if len(np.shape(resized_image)) > 2:
                # convert the image from COLOR_BGR2GRAY
                resized_image = cv2.cvtColor(resized_image,
cv2.COLOR_BGR2GRAY)

            # store to array
            images.append(resized_image)
            filenames.append(filename)

            if gt=='yes':
                label = 1
                labels.append(label)
            elif gt=='no':
                label = 0
                labels.append(label)
```

```
gtFr =
pd.DataFrame(labels).rename(columns={0:'gt'}).reset_index(drop=False).r
ename(columns={'index':'pID'})
gtFr['filename'] = filenames

# split into training and testing sets, stratifying by gt for equal
representation
trainFr, testFr = train_test_split(gtFr, test_size=0.2,
stratify=gtFr['gt'])

# store training/testing indices
trainFr['set'] = 'train'
testFr['set'] = 'test'

gtFr2 = pd.concat([trainFr,testFr],axis=0)
gtFr2.set_index(['filename']).to_csv('base_model_train_test.csv')

files_train = []
X_train = []
y_train = []


for idx, row in trainFr.iterrows():
    # load image pixels
    image = imread(row['filename'])

    # resize image to standard 200x200
    resized_image = cv2.resize(image,dsize=(200,200))

    # in case of grayscale images
    if len(np.shape(resized_image)) > 2:
        # convert the image from COLOR_BGR2GRAY
        resized_image = cv2.cvtColor(resized_image, cv2.COLOR_BGR2GRAY)

    # store to array
    X_train.append(resized_image)
    y_train.append(row['gt'])
    files_train.append(row['filename'])


# reshape data to fit model
X_train = np.array(X_train).reshape(len(trainFr),200,200,1)
y_train = np.array(y_train)

files_test = []
X_test = []
y_test = []
```

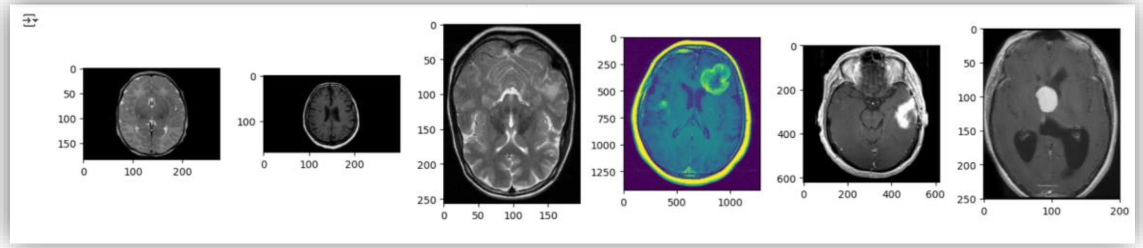
```
for idx, row in testFr.iterrows():
    # load image pixels
    image = imread(row['filename'])

    # resize image to standard 200x200
    resized_image = cv2.resize(image,dsize=(200,200))

    # in case of grayscale images
    if len(np.shape(resized_image)) > 2:
        # convert the image from COLOR_BGR2GRAY
        resized_image = cv2.cvtColor(resized_image, cv2.COLOR_BGR2GRAY)

    # store to array
    X_test.append(resized_image)
    y_test.append(row['gt'])
    files_test.append(row['filename'])

# reshape data to fit model
X_test = np.array(X_test).reshape(len(testFr),200,200,1)
y_test = np.array(y_test)

# create model
model = Sequential()

# add convolutional layer
model.add(Conv2D(64, kernel_size=3, activation='relu',
input_shape=(200,200,1))) # input is of shape (N, C) or (N, C, L) where
N is the batch size as before. However what does the C and L denote
here? It seems that C = number of features, L = number of channels,

# add max pooling layer
model.add(MaxPooling2D(pool_size=(2, 2)))

# add another convolutional layer
model.add(Conv2D(32, kernel_size=3, activation='relu'))

# add another max pooling layer
model.add(MaxPooling2D(pool_size=(2, 2)))

# flatten output (connect convolutional layers and dense layers)
model.add(Flatten())

# add a dense layer with 128 neurons and ReLU activation
model.add(Dense(128, activation='relu'))

# add dense layer
model.add(Dense(1, activation='sigmoid'))
```

```python
# compile model using accuracy to measure model performance
model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])

history = model.fit(X_train, y_train, validation_data=(X_test, y_test),
epochs=30)

# Function to plot loss and accuracy in a single row
def plot_curves(history):
    """
    Returns loss and accuracy curves in a single row.
    """
    loss = history.history["loss"]
    val_loss = history.history["val_loss"]
    accuracy = history.history["accuracy"]
    val_accuracy = history.history["val_accuracy"]
    epochs = range(len(loss))

    # Create a single row with 2 plots (loss and accuracy)
    fig, axes = plt.subplots(1, 2, figsize=(12, 5))

    # Plot loss
    axes[0].plot(epochs, loss, label="training_loss")
    axes[0].plot(epochs, val_loss, label="val_loss")
    axes[0].set_title("Loss")
    axes[0].set_xlabel("Epochs")
    axes[0].legend()

    # Plot accuracy
    axes[1].plot(epochs, accuracy, label="training_accuracy")
    axes[1].plot(epochs, val_accuracy, label="val_accuracy")
    axes[1].set_title("Accuracy")
    axes[1].set_xlabel("Epochs")
    axes[1].legend()

    plt.tight_layout()  # Adjust layout for better spacing
    plt.show()

plot_curves(history)

# make predictions
predictions = model.predict(X_test)

# store as probabilities
probabilities = [p[0] for p in predictions]
testFr['pred'] = probabilities

testFr.set_index(['pID']).to_csv('base_model_predictions.csv')
```

```
dataPos = testFr[testFr['gt']==1]['pred'].values
dataNeg = testFr[testFr['gt']==0]['pred'].values
dataAll = np.concatenate((dataPos, dataNeg))
lblArr = np.zeros(len(dataAll), dtype=bool)
lblArr[0:len(dataPos)] = True

fpr, tpr, thresholds = roc_curve(lblArr, dataAll, pos_label=True)
roc_auc = auc(fpr, tpr)

# invert comparison if (ROC<0.5) required
if roc_auc<0.5:
    lblArr = ~lblArr
    fpr, tpr, thresholds = roc_curve(lblArr, dataAll, pos_label=True)
    roc_auc = auc(fpr, tpr)
    print('inverting labels')

print('ROC AUC: {:0.2f}'.format(roc_auc))

# calculate best cut-off based on distance to top corner of ROC curve
distArr = np.sqrt(np.power(fpr, 2) + np.power((1 - tpr), 2))
cutoffIdx = np.argsort(distArr)[0]
cutoffTh = thresholds[cutoffIdx]

print('Cutoff threshold that maximizes sens/spec:
{:0.2f}'.format(cutoffTh))

lblOut = dataAll >= cutoffTh

acc = accuracy_score(lblArr, lblOut)
print('Accuracy: {:0.2f}'.format(acc))

sens = tpr[cutoffIdx]
print('Sensitivity: {:0.2f}'.format(sens))

spec = 1 - fpr[cutoffIdx]
print('Specificity: {:0.2f}'.format(spec))

kappa = cohen_kappa_score(lblOut, lblArr)
print('Cohen kappa score: {:0.2f}'.format(kappa))
```

Output:

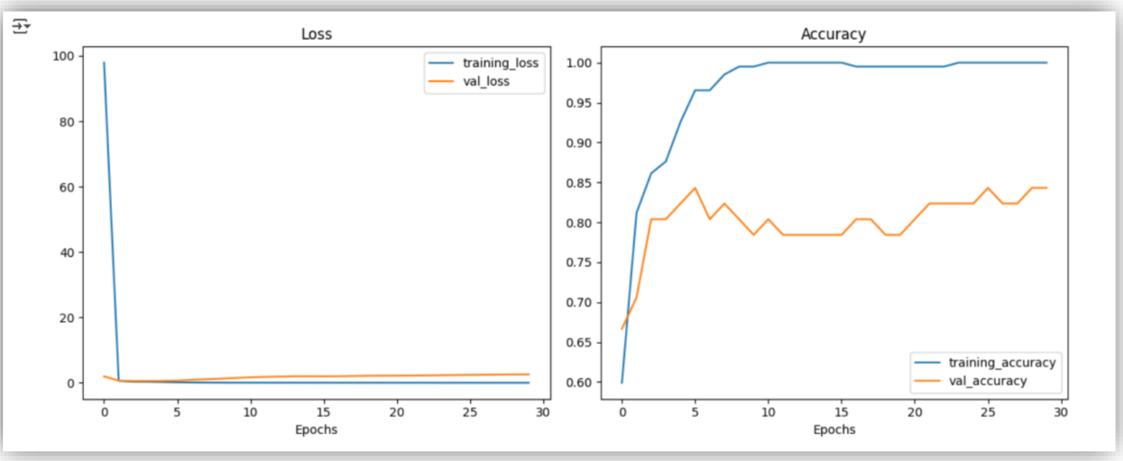
```
# First 3 images per folder
```



```
model.fit()
```

```
Epoch 1/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 23s 3s/step - accuracy: 0.6289 - loss: 109.7322 - val_accuracy: 0.6667 - val_loss: 1.9671
Epoch 2/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 46s 4s/step - accuracy: 0.8392 - loss: 0.5811 - val_accuracy: 0.7059 - val_loss: 0.6620
Epoch 3/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 19s 3s/step - accuracy: 0.8475 - loss: 0.3732 - val_accuracy: 0.8039 - val_loss: 0.5536
Epoch 4/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 21s 3s/step - accuracy: 0.8424 - loss: 0.3469 - val_accuracy: 0.8039 - val_loss: 0.5629
Epoch 5/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 27s 3s/step - accuracy: 0.9068 - loss: 0.2688 - val_accuracy: 0.8235 - val_loss: 0.5739
Epoch 6/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 33s 3s/step - accuracy: 0.9627 - loss: 0.1645 - val_accuracy: 0.8431 - val_loss: 0.6756
Epoch 7/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 20s 3s/step - accuracy: 0.9596 - loss: 0.0938 - val_accuracy: 0.8039 - val_loss: 0.9022
Epoch 8/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 21s 3s/step - accuracy: 0.9855 - loss: 0.0554 - val_accuracy: 0.8235 - val_loss: 1.0873
Epoch 9/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 21s 3s/step - accuracy: 0.9973 - loss: 0.0370 - val_accuracy: 0.8039 - val_loss: 1.2648
Epoch 10/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 20s 2s/step - accuracy: 0.9973 - loss: 0.0269 - val_accuracy: 0.7843 - val_loss: 1.4849
Epoch 11/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 18s 2s/step - accuracy: 1.0000 - loss: 0.0211 - val_accuracy: 0.8039 - val_loss: 1.6774
Epoch 12/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 18s 3s/step - accuracy: 1.0000 - loss: 0.0188 - val_accuracy: 0.7843 - val_loss: 1.8015
Epoch 13/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 21s 3s/step - accuracy: 1.0000 - loss: 0.0178 - val_accuracy: 0.7843 - val_loss: 1.9148
Epoch 14/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 22s 3s/step - accuracy: 1.0000 - loss: 0.0170 - val_accuracy: 0.7843 - val_loss: 1.9916
Epoch 15/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 18s 3s/step - accuracy: 1.0000 - loss: 0.0161 - val_accuracy: 0.7843 - val_loss: 2.0005
Epoch 16/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 20s 3s/step - accuracy: 1.0000 - loss: 0.0142 - val_accuracy: 0.7843 - val_loss: 1.9772
Epoch 17/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 18s 2s/step - accuracy: 0.9951 - loss: 0.0112 - val_accuracy: 0.8039 - val_loss: 2.0106
Epoch 18/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 22s 3s/step - accuracy: 0.9951 - loss: 0.0097 - val_accuracy: 0.8039 - val_loss: 2.0763
Epoch 19/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 20s 3s/step - accuracy: 0.9951 - loss: 0.0093 - val_accuracy: 0.7843 - val_loss: 2.1431
Epoch 20/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 20s 3s/step - accuracy: 0.9951 - loss: 0.0083 - val_accuracy: 0.7843 - val_loss: 2.1772
Epoch 21/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 22s 2s/step - accuracy: 0.9951 - loss: 0.0074 - val_accuracy: 0.8039 - val_loss: 2.1870
Epoch 22/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 20s 3s/step - accuracy: 0.9951 - loss: 0.0065 - val_accuracy: 0.8235 - val_loss: 2.2192
Epoch 23/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 21s 3s/step - accuracy: 0.9951 - loss: 0.0056 - val_accuracy: 0.8235 - val_loss: 2.2601
Epoch 24/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 20s 3s/step - accuracy: 1.0000 - loss: 0.0046 - val_accuracy: 0.8235 - val_loss: 2.3132
Epoch 25/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 20s 2s/step - accuracy: 1.0000 - loss: 0.0037 - val_accuracy: 0.8235 - val_loss: 2.3698
Epoch 26/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 21s 3s/step - accuracy: 1.0000 - loss: 0.0028 - val_accuracy: 0.8431 - val_loss: 2.4179
Epoch 27/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 17s 3s/step - accuracy: 1.0000 - loss: 0.0022 - val_accuracy: 0.8235 - val_loss: 2.4562
Epoch 28/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 19s 3s/step - accuracy: 1.0000 - loss: 0.0016 - val_accuracy: 0.8235 - val_loss: 2.5058
Epoch 29/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 19s 2s/step - accuracy: 1.0000 - loss: 0.0013 - val_accuracy: 0.8431 - val_loss: 2.5441
Epoch 30/30
7/7 ━━━━━━━━━━━━━━━━━━━━ 21s 3s/step - accuracy: 1.0000 - loss: 9.7393e-04 - val_accuracy: 0.8431 - val_loss: 2.5706
```

```
plot_curves(history)
```



```
# Evaluation Metrics
```

```
ROC AUC: 0.84
Cutoff threshold that maximizes sens/spec: 0.75
Accuracy: 0.84
Sensitivity: 0.90
Specificity: 0.75
Cohen kappa score: 0.67
```

Learning Outcomes:

- Gain the ability to build and train CNN models for classification tasks on images in Python.
- Learnt to preprocess and scale image data to train CNN model and evaluate model performance using key metrics like accuracy, sensitivity and kappa score.

Experiment 4

Aim: Implementation of Autoencoders for dimensionality reduction in Python.

Objectives:

- To implement Autoencoders in Python for dimensionality reduction.
- To train an Autoencoder using TensorFlow and Keras and analyze its reconstruction ability.

Theory:

Introduction to Deep Learning and Dimensionality Reduction

Deep learning is a subset of machine learning that enables computers to learn from large datasets using artificial neural networks. One of the critical challenges in machine learning is dealing with **high-dimensional data**, which can lead to increased computational costs and reduced model performance due to the "curse of dimensionality." **Dimensionality reduction** is a technique used to transform high-dimensional data into a lower-dimensional representation while preserving important features.

Among various dimensionality reduction techniques, **Autoencoders** have gained significant importance. Autoencoders are a type of neural network architecture used to learn efficient data representations in an **unsupervised manner**. They compress input data into a **lower-dimensional latent space** and then reconstruct it back, capturing the most critical features of the data.

What are Autoencoders?

An **Autoencoder (AE)** is a neural network designed to encode input data into a lower-dimensional space (encoding) and then reconstruct the original input (decoding). It consists of two main components:

1. **Encoder:** Reduces the input dimensions by learning compressed representations.
2. **Decoder:** Reconstructs the input data from the compressed representation.

The objective of an autoencoder is to minimize the **reconstruction loss**, typically measured using **Mean Squared Error (MSE)** or **Binary Cross-Entropy Loss**.

Applications of Autoencoders in Dimensionality Reduction

Autoencoders are widely used for dimensionality reduction and feature extraction, especially in cases where linear methods like PCA (Principal Component Analysis) are insufficient. Some key applications include:

- **Data Compression:** Efficiently encoding high-dimensional data into a compact representation.
- **Noise Reduction (Denoising Autoencoders):** Removing noise from images or signals by learning a cleaner representation.

- **Anomaly Detection:** Identifying rare patterns by reconstructing normal data patterns and detecting deviations.
- **Feature Extraction:** Learning meaningful representations for downstream machine learning tasks.

Implementation of Autoencoders for Dimensionality Reduction in Python

Autoencoders can be implemented using **TensorFlow** and **Keras** in Python. The basic steps include:

1. **Loading the Dataset:** Common datasets such as **MNIST** or **CIFAR-10** are used to train autoencoders.
2. **Preprocessing the Data:** Normalization and reshaping of input images.
3. **Building the Autoencoder Model:**
    - A simple autoencoder consists of an **encoder (Dense layers)** followed by a **decoder (Dense layers)**.
4. **Training the Autoencoder:** Using an **Adam optimizer** and **Mean Squared Error (MSE) loss**.
5. **Evaluating the Performance:** Checking the quality of reconstructed images and analyzing dimensionality reduction.

Advantages of Autoencoders for Dimensionality Reduction

Compared to traditional techniques like PCA, autoencoders offer several benefits:

- **Non-linearity Handling:** Autoencoders can learn complex, non-linear relationships in data.
- **Better Representation Learning:** Captures hierarchical and meaningful features.
- **Scalability:** Works efficiently on large datasets without significant performance degradation.
- **Feature Learning without Labels:** Unlike supervised learning, autoencoders require no labeled data.

Conclusion

Autoencoders provide an efficient way to perform **dimensionality reduction**, especially for high-dimensional datasets. They are widely used in feature extraction, denoising, and anomaly detection tasks. With deep learning frameworks like **TensorFlow and Keras**, implementing autoencoders in Python has become straightforward. Their ability to learn efficient representations without supervision makes them a powerful tool in modern machine learning and deep learning applications.

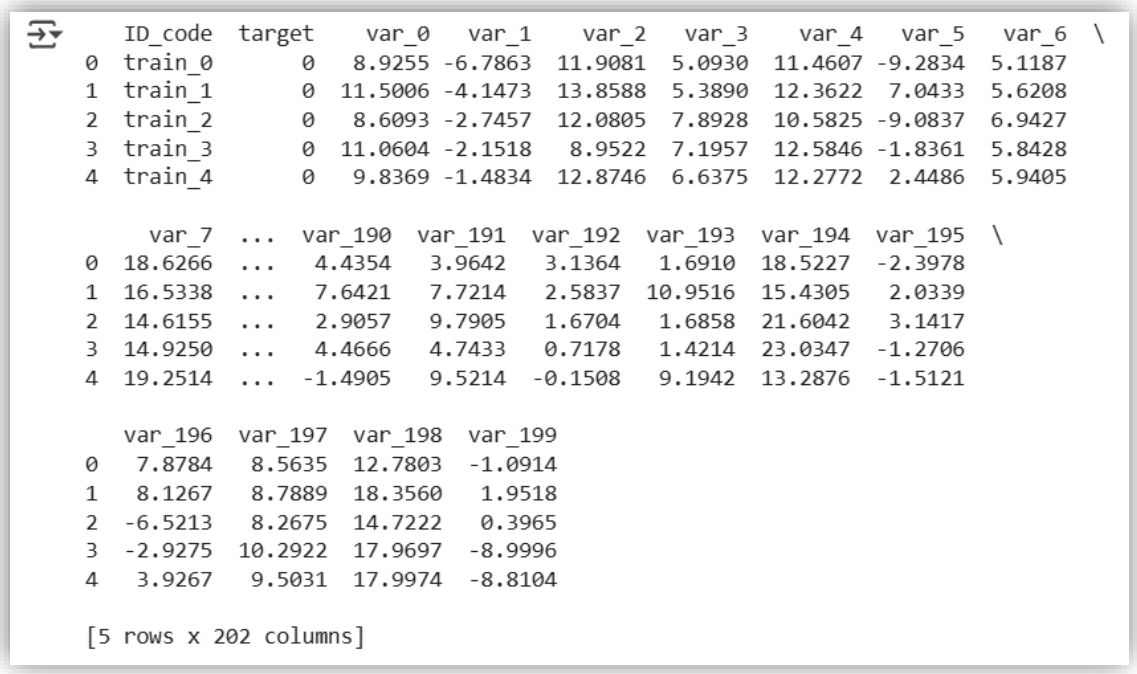
Code:

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense, LeakyReLU
from tensorflow.keras.optimizers import RMSprop
from sklearn.manifold import TSNE

# Load Dataset
file_path = "train.csv"  # Change if needed
df = pd.read_csv(file_path)
print(df.head())

# EDA
print(df.info())
print(df.describe())
print(df.isnull().sum().sum(), "missing values")

# Distribution of Target Variable
sns.histplot(df['target'], bins=30, kde=True)
plt.title("Target Variable Distribution")
plt.show()

# Remove ID and extract features
df.drop(columns=['ID_code'], inplace=True)
X = df.drop(columns=['target']).values  # Features
y = df['target'].values  # Target

# Normalize Data
scaler = StandardScaler()
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Handle NaN or Inf values
X_train = np.nan_to_num(X_train)
X_test = np.nan_to_num(X_test)

# Autoencoder Architecture
encoding_dim = 10  # Dimension reduction size
input_dim = X_train.shape[1]
```

```
input_layer = Input(shape=(input_dim,))
encoded = Dense(64)(input_layer)
encoded = LeakyReLU(alpha=0.1)(encoded)
encoded = Dense(32)(encoded)
encoded = LeakyReLU(alpha=0.1)(encoded)
encoded = Dense(encoding_dim, activation='linear')(encoded)

decoded = Dense(32)(encoded)
decoded = LeakyReLU(alpha=0.1)(decoded)
decoded = Dense(64)(decoded)
decoded = LeakyReLU(alpha=0.1)(decoded)
decoded = Dense(input_dim, activation='linear')(decoded)

# Define Autoencoder
autoencoder = Model(input_layer, decoded)
autoencoder.compile(optimizer=RMSprop(learning_rate=0.0001),
loss='mae')

# Train Autoencoder
autoencoder.fit(X_train, X_train, epochs=50, batch_size=256,
shuffle=True, validation_data=(X_test, X_test))

# Extract Encoder
encoder = Model(input_layer, encoded)
X_train_encoded = encoder.predict(X_train)
X_test_encoded = encoder.predict(X_test)

# t-SNE Visualization
tsne = TSNE(n_components=2, random_state=42)
X_embedded = tsne.fit_transform(X_test_encoded)
plt.scatter(X_embedded[:, 0], X_embedded[:, 1],
c=y_test[:len(X_embedded)], cmap='coolwarm', alpha=0.5)
plt.colorbar()
plt.title("t-SNE Visualization of Encoded Features")
plt.show()

print("Original feature shape:", X_train.shape)
print("Reduced feature shape:", X_train_encoded.shape)
```

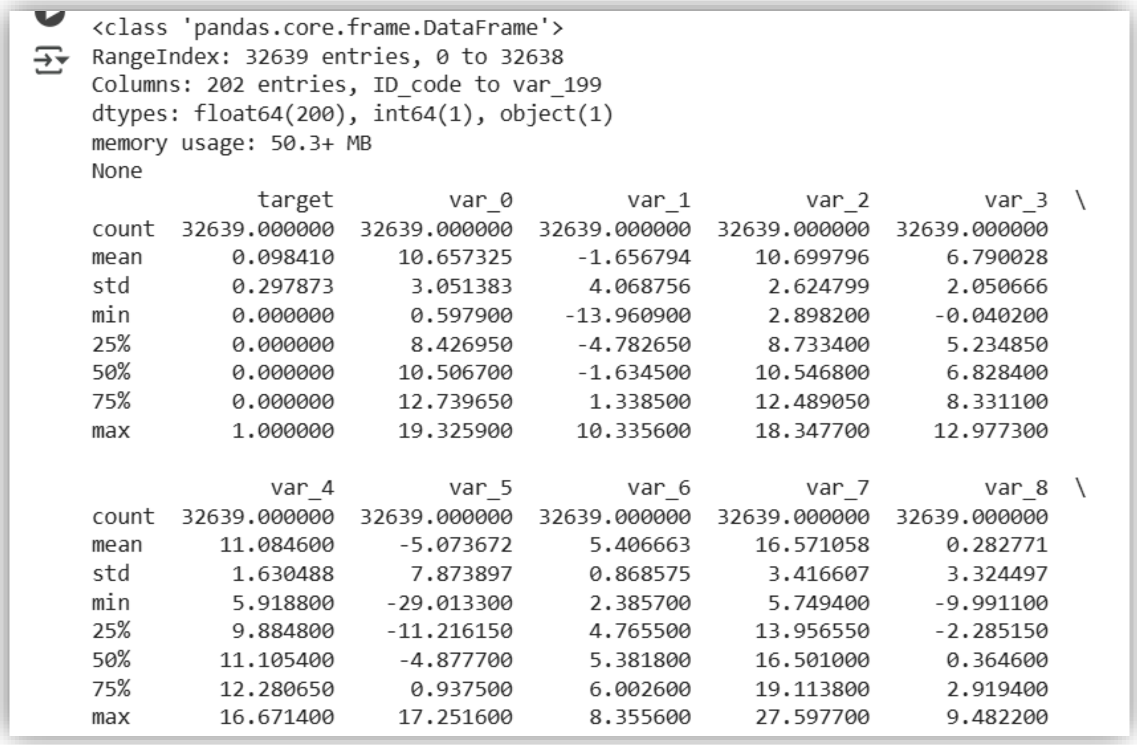
Output:

```
# Load dataset - df.head()
```

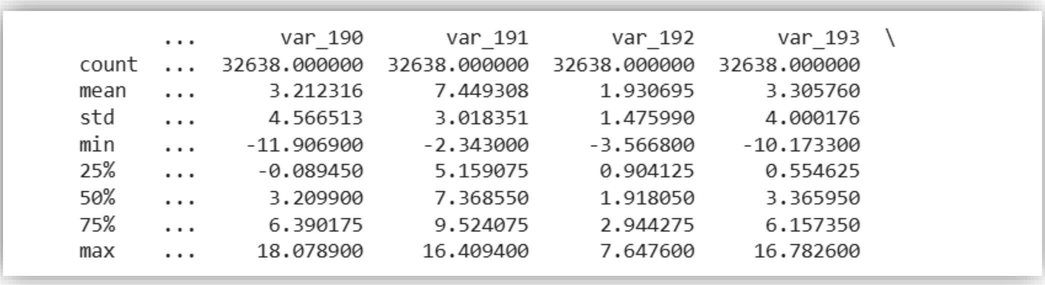


```
  ID_code  target    var_0   var_1    var_2   var_3    var_4   var_5   var_6  \
0  train_0       0   8.9255 -6.7863  11.9081  5.0930  11.4607 -9.2834  5.1187
1  train_1       0  11.5006 -4.1473  13.8588  5.3890  12.3622  7.0433  5.6208
2  train_2       0   8.6093 -2.7457  12.0805  7.8928  10.5825 -9.0837  6.9427
3  train_3       0  11.0604 -2.1518   8.9522  7.1957  12.5846 -1.8361  5.8428
4  train_4       0   9.8369 -1.4834  12.8746  6.6375  12.2772  2.4486  5.9405

     var_7  ...  var_190  var_191  var_192  var_193  var_194  var_195  \
0  18.6266  ...   4.4354   3.9642   3.1364   1.6910  18.5227  -2.3978
1  16.5338  ...   7.6421   7.7214   2.5837  10.9516  15.4305   2.0339
2  14.6155  ...   2.9057   9.7905   1.6704   1.6858  21.6042   3.1417
3  14.9250  ...   4.4666   4.7433   0.7178   1.4214  23.0347  -1.2706
4  19.2514  ...  -1.4905   9.5214  -0.1508   9.1942  13.2876  -1.5121

  var_196  var_197  var_198  var_199
0  7.8784   8.5635  12.7803  -1.0914
1  8.1267   8.7889  18.3560   1.9518
2 -6.5213   8.2675  14.7222   0.3965
3 -2.9275  10.2922  17.9697  -8.9996
4  3.9267   9.5031  17.9974  -8.8104

[5 rows x 202 columns]
```

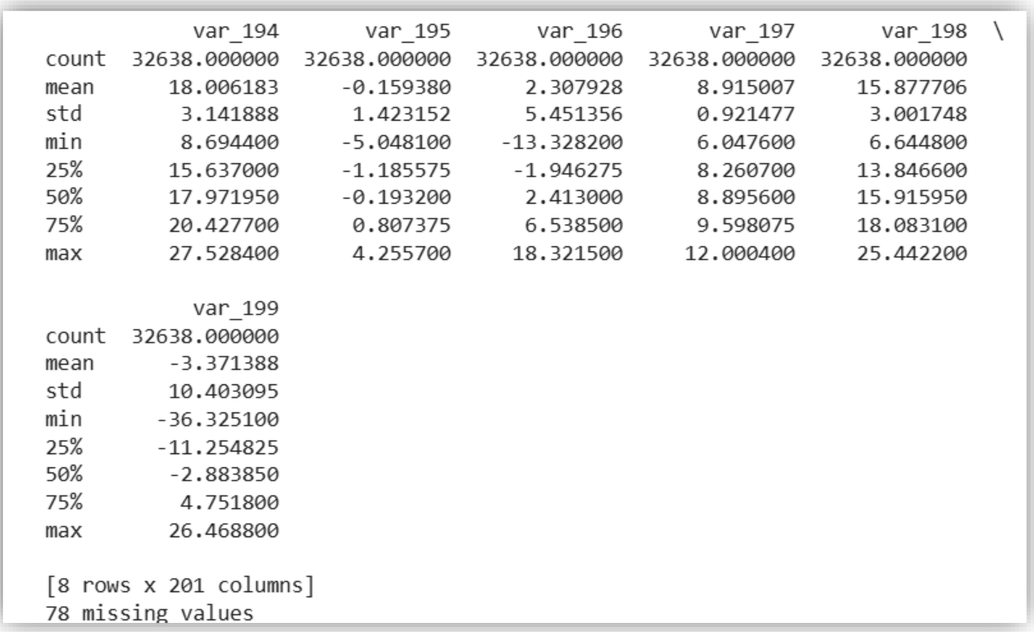
```
# EDA
```



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32639 entries, 0 to 32638
Columns: 202 entries, ID_code to var_199
dtypes: float64(200), int64(1), object(1)
memory usage: 50.3+ MB
None
             target         var_0         var_1         var_2         var_3  \
count  32639.000000  32639.000000  32639.000000  32639.000000  32639.000000
mean       0.098410     10.657325     -1.656794     10.699796      6.790028
std        0.297873      3.051383      4.068756      2.624799      2.050666
min        0.000000      0.597900    -13.960900      2.898200     -0.040200
25%        0.000000      8.426950     -4.782650      8.733400      5.234850
50%        0.000000     10.506700     -1.634500     10.546800      6.828400
75%        0.000000     12.739650      1.338500     12.489050      8.331100
max        1.000000     19.325900     10.335600     18.347700     12.977300

              var_4         var_5         var_6         var_7         var_8  \
count  32639.000000  32639.000000  32639.000000  32639.000000  32639.000000
mean      11.084600     -5.073672      5.406663     16.571058      0.282771
std        1.630488      7.873897      0.868575      3.416607      3.324497
min        5.918800    -29.013300      2.385700      5.749400     -9.991100
25%        9.884800    -11.216150      4.765500     13.956550     -2.285150
50%       11.105400     -4.877700      5.381800     16.501000      0.364600
75%       12.280650      0.937500      6.002600     19.113800      2.919400
max       16.671400     17.251600      8.355600     27.597700      9.482200
```

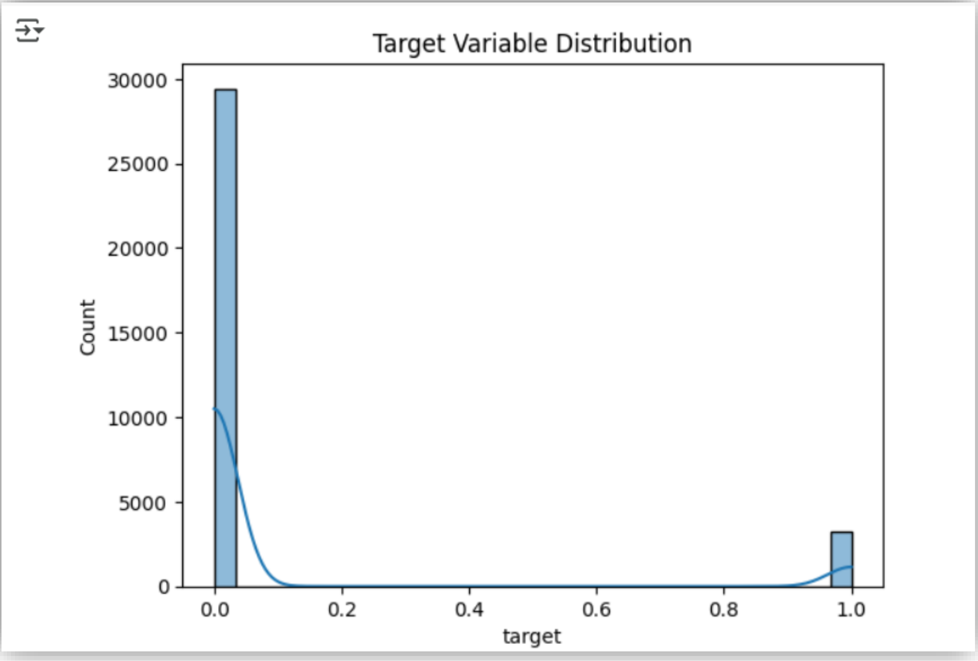


```
       ...        var_190       var_191       var_192       var_193  \
count  ...   32638.000000  32638.000000  32638.000000  32638.000000
mean   ...       3.212316      7.449308      1.930695      3.305760
std    ...       4.566513      3.018351      1.475990      4.000176
min    ...     -11.906900     -2.343000     -3.566800    -10.173300
25%    ...      -0.089450      5.159075      0.904125      0.554625
50%    ...       3.209900      7.368550      1.918050      3.365950
75%    ...       6.390175      9.524075      2.944275      6.157350
max    ...      18.078900     16.409400      7.647600     16.782600
```

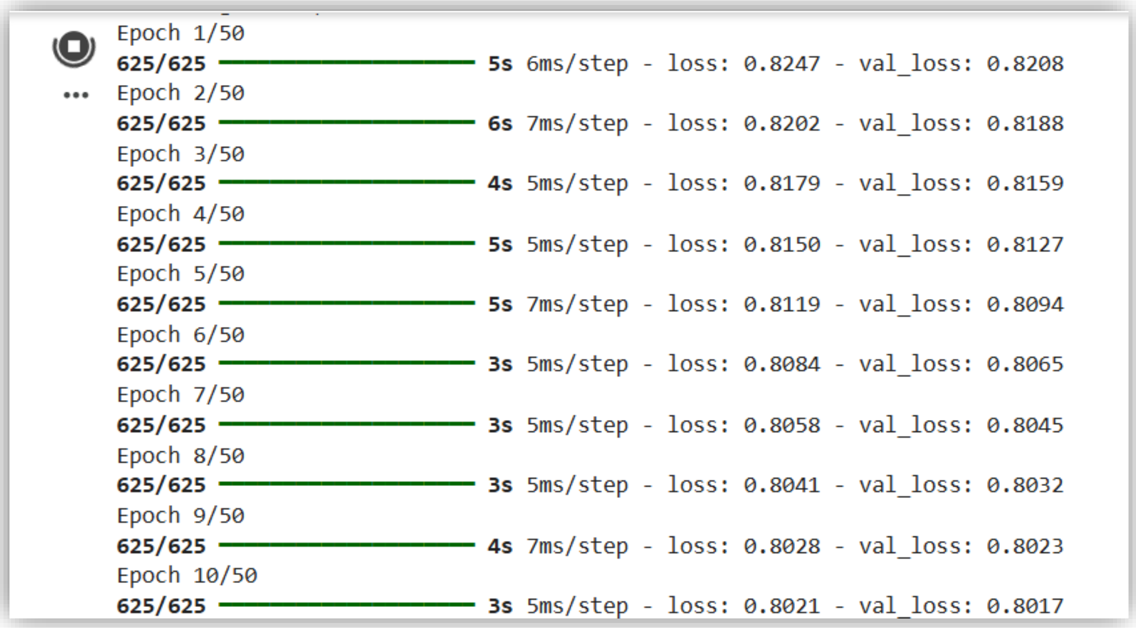


```
            var_194       var_195       var_196       var_197       var_198  \
count  32638.000000  32638.000000  32638.000000  32638.000000  32638.000000
mean      18.006183     -0.159380      2.307928      8.915007     15.877706
std        3.141888      1.423152      5.451356      0.921477      3.001748
min        8.694400     -5.048100    -13.328200      6.047600      6.644800
25%       15.637000     -1.185575     -1.946275      8.260700     13.846600
50%       17.971950     -0.193200      2.413000      8.895600     15.915950
75%       20.427700      0.807375      6.538500      9.598075     18.083100
max       27.528400      4.255700     18.321500     12.000400     25.442200

            var_199
count  32638.000000
mean      -3.371388
std       10.403095
min      -36.325100
25%      -11.254825
50%       -2.883850
75%        4.751800
max       26.468800

[8 rows x 201 columns]
78 missing values
```

```
# Distribution of Target Variable
```

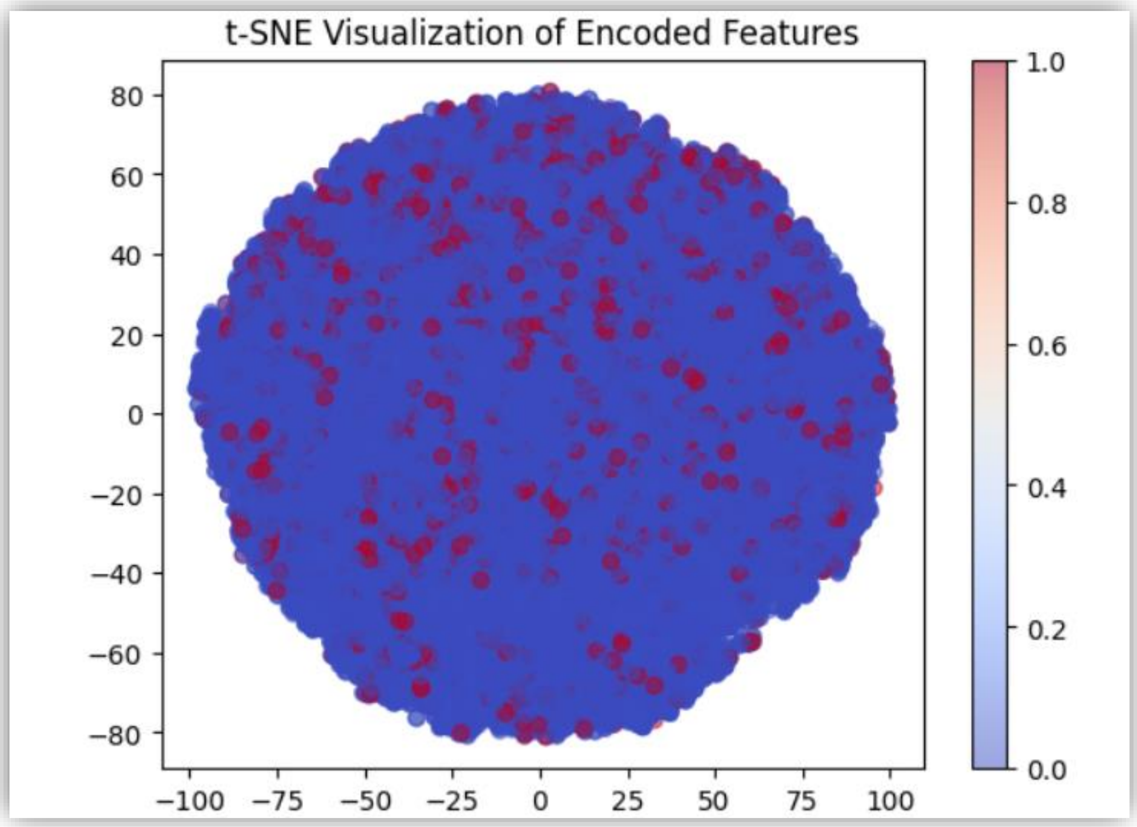


```
# autoencoder.fit()
```

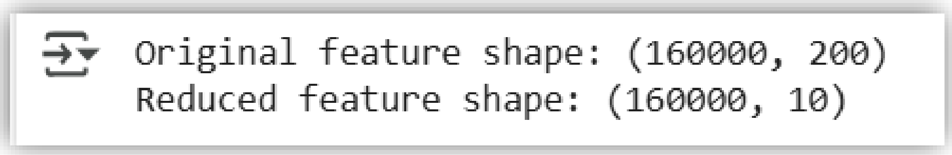


```
Epoch 1/50
625/625 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 0.8247 - val_loss: 0.8208
Epoch 2/50
625/625 ━━━━━━━━━━━━━━━━━━━━ 6s 7ms/step - loss: 0.8202 - val_loss: 0.8188
Epoch 3/50
625/625 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 0.8179 - val_loss: 0.8159
Epoch 4/50
625/625 ━━━━━━━━━━━━━━━━━━━━ 5s 5ms/step - loss: 0.8150 - val_loss: 0.8127
Epoch 5/50
625/625 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - loss: 0.8119 - val_loss: 0.8094
Epoch 6/50
625/625 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - loss: 0.8084 - val_loss: 0.8065
Epoch 7/50
625/625 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - loss: 0.8058 - val_loss: 0.8045
Epoch 8/50
625/625 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - loss: 0.8041 - val_loss: 0.8032
Epoch 9/50
625/625 ━━━━━━━━━━━━━━━━━━━━ 4s 7ms/step - loss: 0.8028 - val_loss: 0.8023
Epoch 10/50
625/625 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - loss: 0.8021 - val_loss: 0.8017
```

```
# t-SNE Visualization
```



```
# Original vs Reduced
```



```
Original feature shape: (160000, 200)
Reduced feature shape: (160000, 10)
```

Learning Outcomes:

- Understand the concept of autoencoders and their role in dimensionality reduction.
- Learn to preprocess and normalize high-dimensional data for efficient training.

Experiment 5

Aim: Improving Autocoder's Performance using convolution layers in Python (MNIST Dataset to be utilized).

Objectives:

- To implement Autoencoders in Python on Image Dataset.
- To train an Autoencoder using TensorFlow and Keras and analyze its reconstruction ability.

Theory:

1. Introduction

Autoencoders are a type of artificial neural network used for unsupervised learning of efficient codings in data. They are primarily utilized for dimensionality reduction, denoising, and feature extraction. In this experiment, we apply autoencoders to the MNIST dataset, a widely used benchmark dataset for handwritten digit recognition. We first implement a basic autoencoder using fully connected layers and later enhance its performance by employing convolutional layers.

2. Autoencoders: Concept and Working Mechanism

Autoencoders consist of two main components:

1. **Encoder**: This part compresses the input data into a lower-dimensional representation (latent space).
2. **Decoder**: This part reconstructs the input data from the compressed representation.

Mathematically, an autoencoder maps an input to a compressed representation using an encoding function , and then reconstructs using a decoding function.

The training objective is to minimize the reconstruction loss between and , usually measured by Mean Squared Error (MSE) or Binary Cross-Entropy (BCE).

3. Application of Autoencoders on MNIST Dataset

3.1 Dataset Preparation

The MNIST dataset consists of 60,000 training images and 10,000 test images of handwritten digits (0-9), each of size 28x28 pixels. The data is normalized to the range to improve training efficiency.

3.2 Fully Connected Autoencoder Implementation

A simple autoencoder with fully connected layers is constructed as follows:

- **Encoder**: Input (784 dimensions) → Dense(128, ReLU) → Dense(64, ReLU) → Latent Space (32 dimensions)
- **Decoder**: Dense(64, ReLU) → Dense(128, ReLU) → Output (784 dimensions, Sigmoid)

After training with Adam optimizer and MSE loss function, the autoencoder is able to reconstruct the input images reasonably well. However, due to the dense architecture, spatial relationships in images are not efficiently captured.

4. Improving Autoencoder Performance with Convolutional Layers

To improve performance, a Convolutional Autoencoder (CAE) is implemented. Unlike fully connected layers, convolutional layers maintain spatial hierarchies, making them better suited for image reconstruction tasks.

4.1 Convolutional Autoencoder Architecture

- **Encoder**: Conv2D(32 filters, 3x3, ReLU) → MaxPooling2D(2x2) → Conv2D(64 filters, 3x3, ReLU) → MaxPooling2D(2x2)
- **Decoder**: Conv2DTranspose(64 filters, 3x3, ReLU) → UpSampling2D(2x2) → Conv2DTranspose(32 filters, 3x3, ReLU) → UpSampling2D(2x2) → Conv2DTranspose(1 filter, 3x3, Sigmoid)

4.2 Performance Comparison

The CAE significantly improves the quality of reconstructed images compared to the fully connected autoencoder. The main advantages include:

- **Preservation of spatial features**, reducing loss of information.
- **Faster convergence** due to fewer trainable parameters.
- **Better generalization** for unseen images.

5. Conclusion

Autoencoders provide a powerful method for image compression and feature extraction. While fully connected autoencoders serve as a baseline, convolutional autoencoders significantly enhance performance by leveraging spatial hierarchies. Future work can include Variational Autoencoders (VAEs) for more structured latent spaces and application of these techniques to real-world datasets beyond MNIST.

Code:

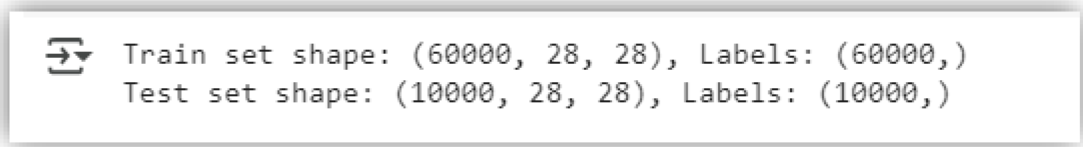
```
import tensorflow as tf
from tensorflow.keras import layers, models
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

(X_train, _), (X_test, _) = tf.keras.datasets.fashion_mnist.load_data()

X_train = X_train.astype('float32') / 255.0
X_test = X_test.astype('float32') / 255.0

X_train_flat = X_train.reshape(-1, 28 * 28)
X_test_flat = X_test.reshape(-1, 28 * 28)

(X_train, y_train), (X_test, y_test) =
tf.keras.datasets.fashion_mnist.load_data()

print(f"Train set shape: {X_train.shape}, Labels: {y_train.shape}")
print(f"Test set shape: {X_test.shape}, Labels: {y_test.shape}")

class_labels = [
    "T-shirt/top", "Trouser", "Pullover", "Dress", "Coat",
    "Sandal", "Shirt", "Sneaker", "Bag", "Ankle boot"
]

plt.figure(figsize=(10, 6))
for i in range(10):
    plt.subplot(2, 5, i+1)
    plt.imshow(X_train[i], cmap="gray")
    plt.title(class_labels[y_train[i]])
    plt.axis("off")
plt.tight_layout()
plt.show()

class_counts = pd.Series(y_train).value_counts().sort_index()

plt.figure(figsize=(8, 5))
sns.barplot(x=class_counts.index, y=class_counts.values,
palette="coolwarm")
plt.xticks(ticks=range(10), labels=class_labels, rotation=45)
plt.xlabel("Class Labels")
plt.ylabel("Count")
plt.title("Distribution of Fashion MNIST Classes")
plt.show()
plt.figure(figsize=(8, 5))
```

```
sns.histplot(X_train.flatten(), bins=50, kde=True, color="purple")
plt.xlabel("Pixel Intensity")
plt.ylabel("Frequency")
plt.title("Pixel Intensity Distribution in Fashion MNIST")
plt.show()
# Convert images to tuples for easy comparison
unique_images = set([tuple(image.flatten()) for image in X_train])

print(f"Total Images: {len(X_train)}")
print(f"Unique Images: {len(unique_images)}")
print(f"Duplicate Images: {len(X_train) - len(unique_images)}")

input_dim = 28 * 28  # 784 pixels
encoding_dim = 64  # Reduced dimension

# Define the autoencoder
input_layer = layers.Input(shape=(input_dim,))
encoded = layers.Dense(128, activation='relu')(input_layer)
encoded = layers.Dense(encoding_dim, activation='relu')(encoded)

decoded = layers.Dense(128, activation='relu')(encoded)
decoded = layers.Dense(input_dim, activation='sigmoid')(decoded)  #
Output same shape as input

autoencoder = models.Model(input_layer, decoded)
encoder = models.Model(input_layer, encoded)  # Encoder for
dimensionality reduction

autoencoder.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
autoencoder.fit(X_train_flat, X_train_flat, epochs=20, batch_size=256,
validation_data=(X_test_flat, X_test_flat))

# Reshape for CNN (add channel dimension)
X_train = X_train.reshape(-1, 28, 28, 1)
X_test = X_test.reshape(-1, 28, 28, 1)

# Convolutional Autoencoder
input_layer = layers.Input(shape=(28, 28, 1))

# Encoder
x = layers.Conv2D(32, (3, 3), activation='relu',
padding='same')(input_layer)
x = layers.MaxPooling2D((2, 2), padding='same')(x)
x = layers.Conv2D(64, (3, 3), activation='relu', padding='same')(x)
x = layers.MaxPooling2D((2, 2), padding='same')(x)
```

```
encoded = layers.Conv2D(128, (3, 3), activation='relu',
padding='same')(x)

# Decoder
x = layers.Conv2DTranspose(64, (3, 3), activation='relu',
padding='same')(encoded)
x = layers.UpSampling2D((2, 2))(x)
x = layers.Conv2DTranspose(32, (3, 3), activation='relu',
padding='same')(x)
x = layers.UpSampling2D((2, 2))(x)

decoded = layers.Conv2DTranspose(1, (3, 3), activation='sigmoid',
padding='same')(x)

# Define model
autoencoder = models.Model(input_layer, decoded)

# Compile and train
autoencoder.compile(optimizer='adam', loss='binary_crossentropy')

autoencoder.fit(X_train, X_train, epochs=20, batch_size=256,
validation_data=(X_test, X_test))

encoder = models.Model(input_layer, encoded)
X_encoded = encoder.predict(X_test)
print("Encoded shape:", X_encoded.shape)

n = 10  # Number of images to display
decoded_imgs = autoencoder.predict(X_test)

plt.figure(figsize=(20, 4))
for i in range(n):
    # Original images
    plt.subplot(2, n, i + 1)
    plt.imshow(X_test[i].reshape(28, 28), cmap='gray')
    plt.axis('off')

    # Reconstructed images
    plt.subplot(2, n, i + 1 + n)
    plt.imshow(decoded_imgs[i].reshape(28, 28), cmap='gray')
    plt.axis('off')

plt.show()
```

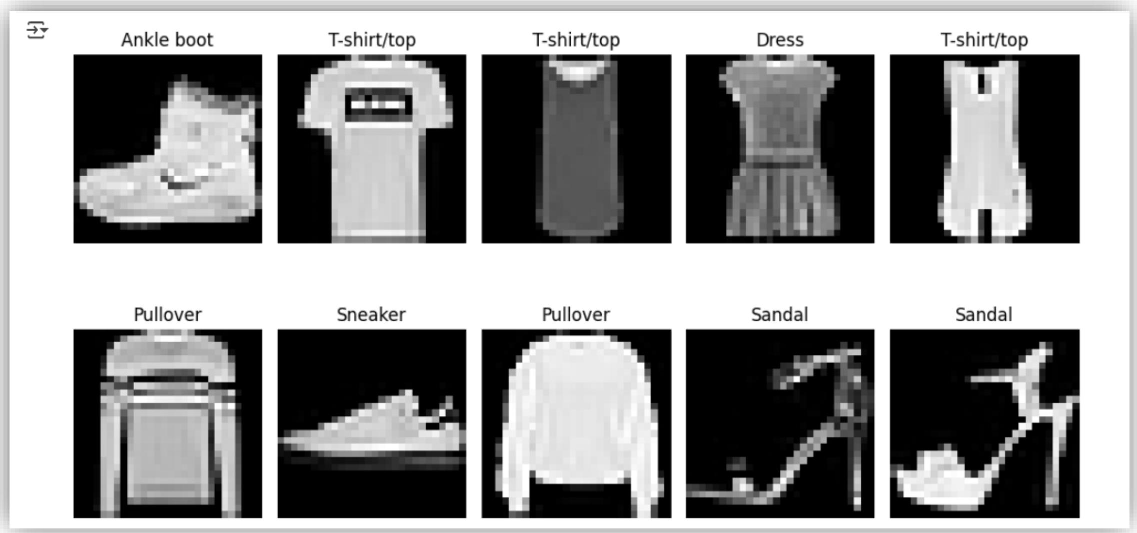
Output:

```
# Check dataset shape
```

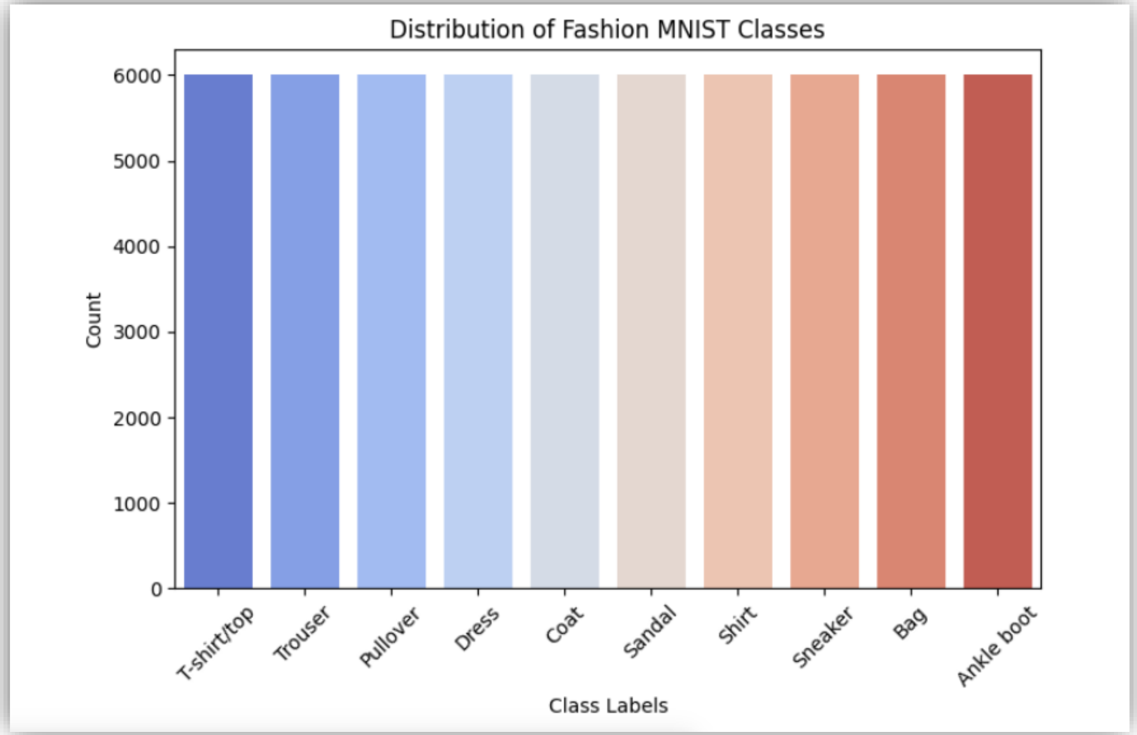


```
Train set shape: (60000, 28, 28), Labels: (60000,)
Test set shape: (10000, 28, 28), Labels: (10000,)
```

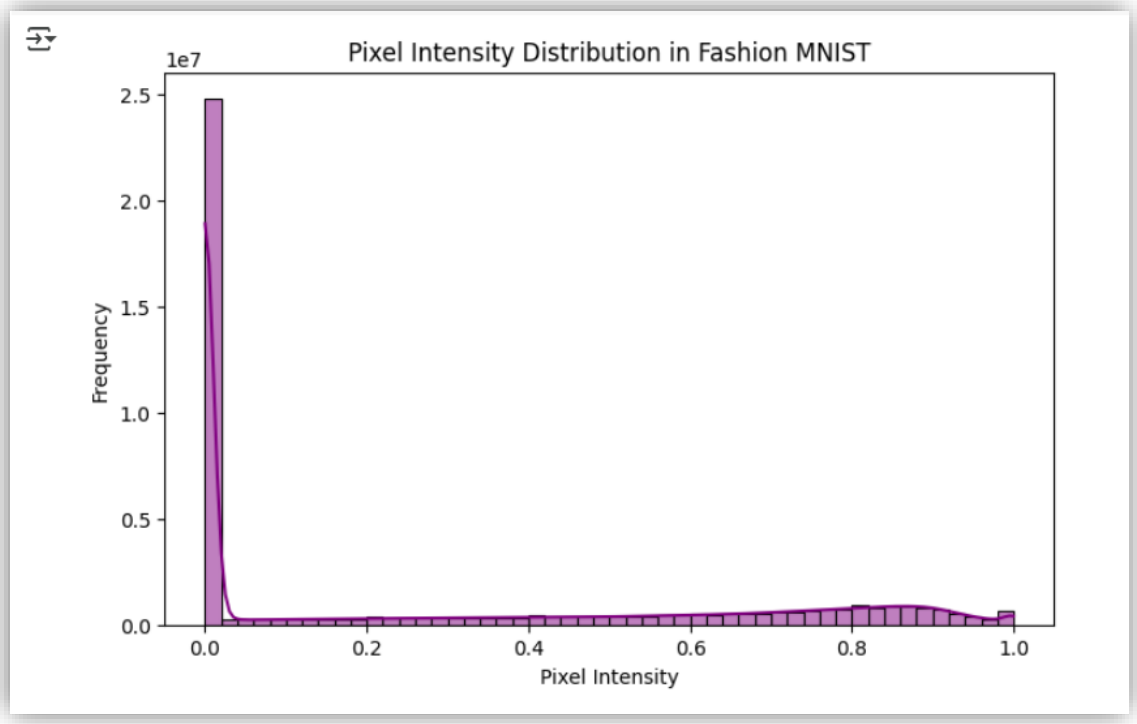
```
# Plot sample images with labels
```



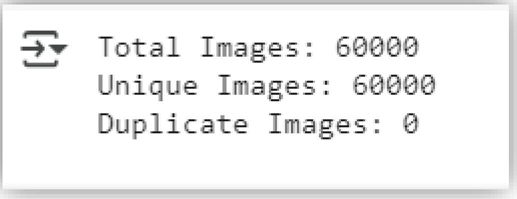
```
# Distribution of Fashion MNIST Classes
```



```
# Pixel Intensity Distribution in Fashion MNIST
```

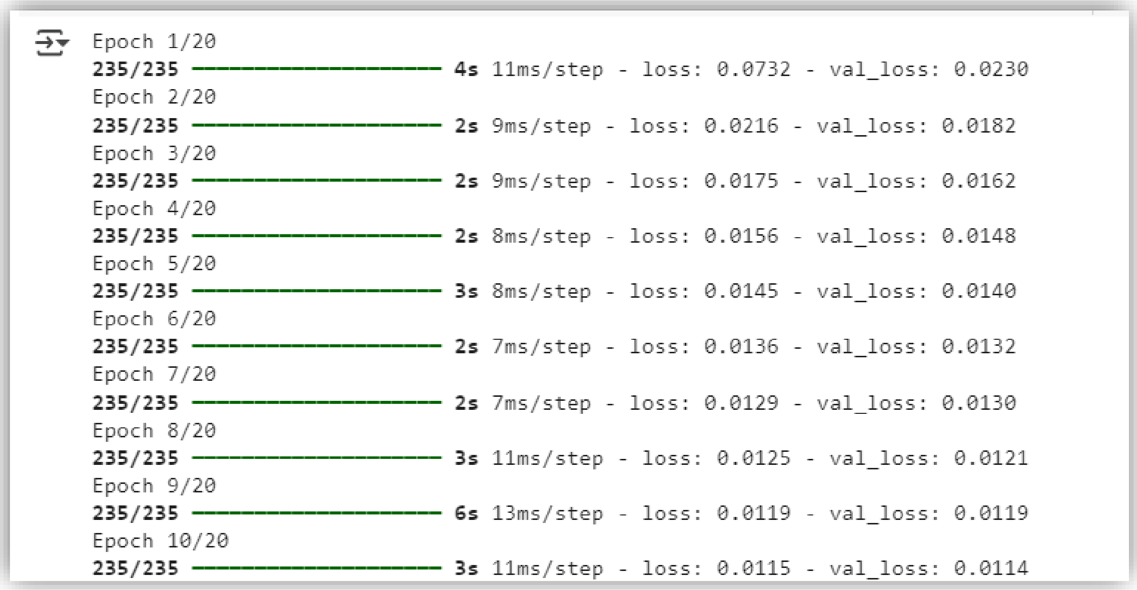


```
# Image count
```



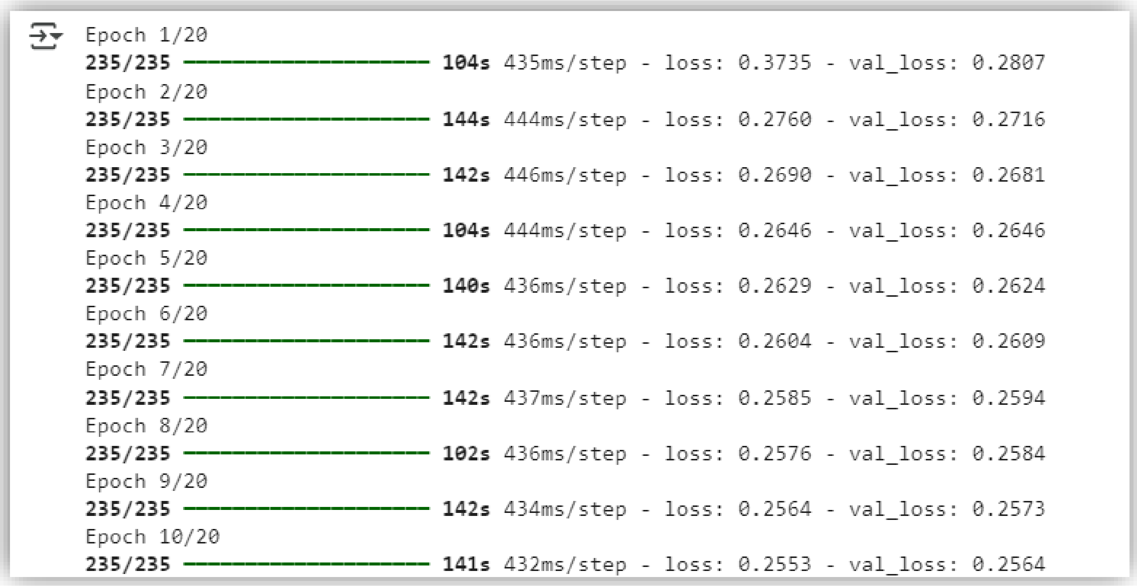
```
Total Images: 60000
Unique Images: 60000
Duplicate Images: 0
```

```
# Train the model
```



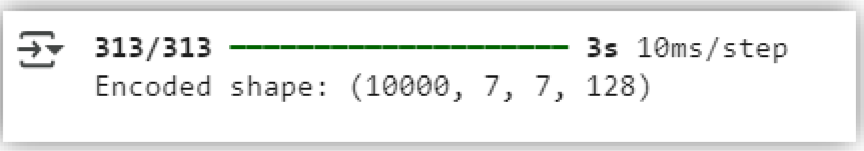
```
Epoch 1/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 4s 11ms/step - loss: 0.0732 - val_loss: 0.0230
Epoch 2/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - loss: 0.0216 - val_loss: 0.0182
Epoch 3/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - loss: 0.0175 - val_loss: 0.0162
Epoch 4/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - loss: 0.0156 - val_loss: 0.0148
Epoch 5/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 3s 8ms/step - loss: 0.0145 - val_loss: 0.0140
Epoch 6/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - loss: 0.0136 - val_loss: 0.0132
Epoch 7/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - loss: 0.0129 - val_loss: 0.0130
Epoch 8/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 3s 11ms/step - loss: 0.0125 - val_loss: 0.0121
Epoch 9/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 6s 13ms/step - loss: 0.0119 - val_loss: 0.0119
Epoch 10/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 3s 11ms/step - loss: 0.0115 - val_loss: 0.0114
```

```
# Convolutional Autoencoder
```



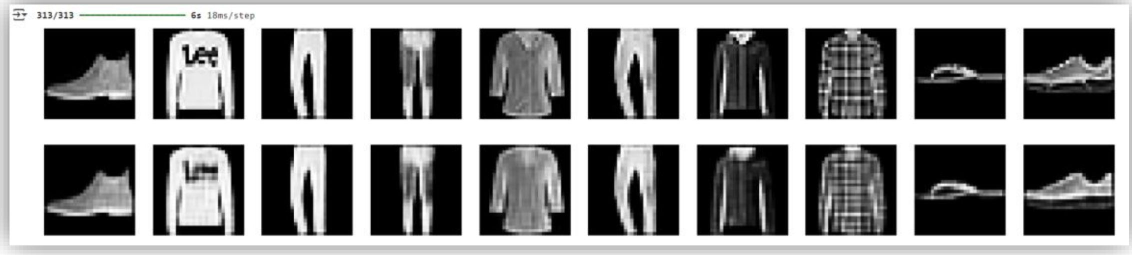
```
Epoch 1/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 104s 435ms/step - loss: 0.3735 - val_loss: 0.2807
Epoch 2/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 144s 444ms/step - loss: 0.2760 - val_loss: 0.2716
Epoch 3/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 142s 446ms/step - loss: 0.2690 - val_loss: 0.2681
Epoch 4/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 104s 444ms/step - loss: 0.2646 - val_loss: 0.2646
Epoch 5/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 140s 436ms/step - loss: 0.2629 - val_loss: 0.2624
Epoch 6/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 142s 436ms/step - loss: 0.2604 - val_loss: 0.2609
Epoch 7/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 142s 437ms/step - loss: 0.2585 - val_loss: 0.2594
Epoch 8/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 102s 436ms/step - loss: 0.2576 - val_loss: 0.2584
Epoch 9/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 142s 434ms/step - loss: 0.2564 - val_loss: 0.2573
Epoch 10/20
235/235 ━━━━━━━━━━━━━━━━━━━━ 141s 432ms/step - loss: 0.2553 - val_loss: 0.2564
```

```
# Encoded shape:
```



```
313/313 ━━━━━━━━━━━━━━━━━━━━ 3s 10ms/step
Encoded shape: (10000, 7, 7, 128)
```

```
# Original vs Reconstructed
```



```
313/313 ━━━━━━━━━━━━━━━━━━━━ 6s 18ms/step
```

Learning Outcomes:

- Understand the concept of autoencoders and their application in image reconstruction.
- Learn to preprocess and normalize the MNIST dataset for improved training efficiency.

Experiment 6

Aim: Application of Autoencoders on Image Dataset.

Objectives:

- To implement Autoencoders in Python for dimensionality reduction.
- To train an Autoencoder using TensorFlow and Keras and analyze its reconstruction ability.

Theory:

Introduction to Deep Learning and Dimensionality Reduction

Deep learning is a subset of machine learning that enables computers to learn from large datasets using artificial neural networks. One of the critical challenges in machine learning is dealing with **high-dimensional data**, which can lead to increased computational costs and reduced model performance due to the "curse of dimensionality." **Dimensionality reduction** is a technique used to transform high-dimensional data into a lower-dimensional representation while preserving important features.

Among various dimensionality reduction techniques, **Autoencoders** have gained significant importance. Autoencoders are a type of neural network architecture used to learn efficient data representations in an **unsupervised manner**. They compress input data into a **lower-dimensional latent space** and then reconstruct it back, capturing the most critical features of the data.

What are Autoencoders?

An **Autoencoder (AE)** is a neural network designed to encode input data into a lower-dimensional space (encoding) and then reconstruct the original input (decoding). It consists of two main components:

3. **Encoder:** Reduces the input dimensions by learning compressed representations.
4. **Decoder:** Reconstructs the input data from the compressed representation.

The objective of an autoencoder is to minimize the **reconstruction loss**, typically measured using **Mean Squared Error (MSE)** or **Binary Cross-Entropy Loss**.

Applications of Autoencoders in Dimensionality Reduction

Autoencoders are widely used for dimensionality reduction and feature extraction, especially in cases where linear methods like PCA (Principal Component Analysis) are insufficient. Some key applications include:

- **Data Compression:** Efficiently encoding high-dimensional data into a compact representation.
- **Noise Reduction (Denoising Autoencoders):** Removing noise from images or signals by learning a cleaner representation.

- **Anomaly Detection:** Identifying rare patterns by reconstructing normal data patterns and detecting deviations.
- **Feature Extraction:** Learning meaningful representations for downstream machine learning tasks.

Implementation of Autoencoders for Dimensionality Reduction in Python

Autoencoders can be implemented using **TensorFlow** and **Keras** in Python. The basic steps include:

6. **Loading the Dataset:** Common datasets such as **MNIST** or **CIFAR-10** are used to train autoencoders.
7. **Preprocessing the Data:** Normalization and reshaping of input images.
8. **Building the Autoencoder Model:**
    - A simple autoencoder consists of an **encoder (Dense layers)** followed by a **decoder (Dense layers)**.
9. **Training the Autoencoder:** Using an **Adam optimizer** and **Mean Squared Error (MSE) loss**.
10. **Evaluating the Performance:** Checking the quality of reconstructed images and analyzing dimensionality reduction.

Advantages of Autoencoders for Dimensionality Reduction

Compared to traditional techniques like PCA, autoencoders offer several benefits:

- **Non-linearity Handling:** Autoencoders can learn complex, non-linear relationships in data.
- **Better Representation Learning:** Captures hierarchical and meaningful features.
- **Scalability:** Works efficiently on large datasets without significant performance degradation.
- **Feature Learning without Labels:** Unlike supervised learning, autoencoders require no labeled data.

Conclusion

Autoencoders provide an efficient way to perform **dimensionality reduction**, especially for high-dimensional datasets. They are widely used in feature extraction, denoising, and anomaly detection tasks. With deep learning frameworks like **TensorFlow and Keras**, implementing autoencoders in Python has become straightforward. Their ability to learn efficient representations without supervision makes them a powerful tool in modern machine learning and deep learning applications.

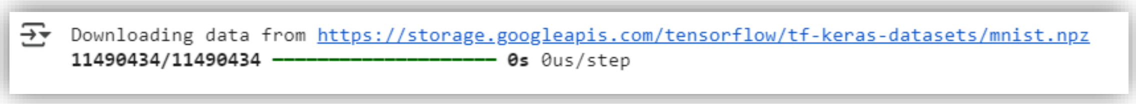
Code:

```python
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.layers import Input, Dense
from tensorflow.keras.models import Model
import numpy as np
import matplotlib.pyplot as plt

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

print("Training set shape:", x_train.shape)
print("Test set shape:", x_test.shape)

print("Pixel Intensity Range: ", np.min(x_train), "to",
np.max(x_train))

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

# Flatten the images (28x28 to 784-dimensional vector)
x_train = x_train.reshape((len(x_train), 784))
x_test = x_test.reshape((len(x_test), 784))

# Display 10 random images from the dataset
n = 10
plt.figure(figsize=(10, 2))
for i in range(n):
    ax = plt.subplot(1, n, i + 1)
    plt.imshow(x_train[i].reshape(28, 28), cmap="gray")
    plt.axis("off")
plt.show()

plt.hist(x_train.flatten(), bins=50, color='blue', alpha=0.7)
plt.xlabel("Pixel Intensity")
plt.ylabel("Frequency")
plt.title("Distribution of Pixel Intensities in MNIST Dataset")
plt.show()

encoding_dim = 32  # Reduce 784 dimensions to 32

# Define the Autoencoder model
input_img = Input(shape=(784,))

# Encoder
encoded = Dense(encoding_dim, activation="relu")(input_img)
```

```python
# Decoder
decoded = Dense(784, activation="sigmoid")(encoded)

# Define Autoencoder Model
autoencoder = Model(input_img, decoded)

# Compile the Autoencoder
autoencoder.compile(optimizer="adam", loss="mse")

# Train the Autoencoder
autoencoder.fit(x_train, x_train,
                epochs=20,
                batch_size=256,
                shuffle=True,
                validation_data=(x_test, x_test))

# Encode and decode images
encoded_imgs = autoencoder.predict(x_test)
decoded_imgs = autoencoder.predict(x_test)

# Display original and reconstructed images
n = 10  # Show 10 images
plt.figure(figsize=(20, 4))
for i in range(n):
    # Original images
    ax = plt.subplot(2, n, i + 1)
    plt.imshow(x_test[i].reshape(28, 28), cmap="gray")
    plt.axis("off")

    # Reconstructed images
    ax = plt.subplot(2, n, i + 1 + n)
    plt.imshow(decoded_imgs[i].reshape(28, 28), cmap="gray")
    plt.axis("off")

plt.show()
```

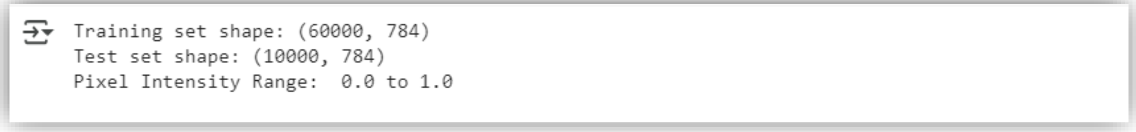
Output:

```
# Load the MNIST dataset
```



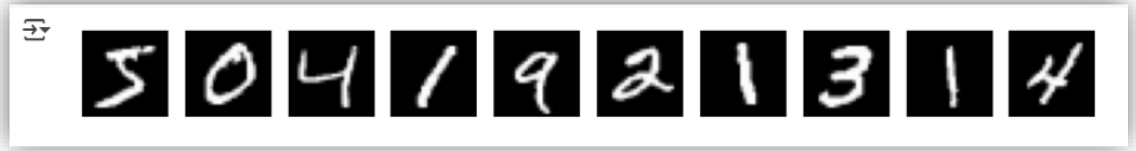
```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz
11490434/11490434 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

```
# Training and Testing Dataset size and Intensity
```

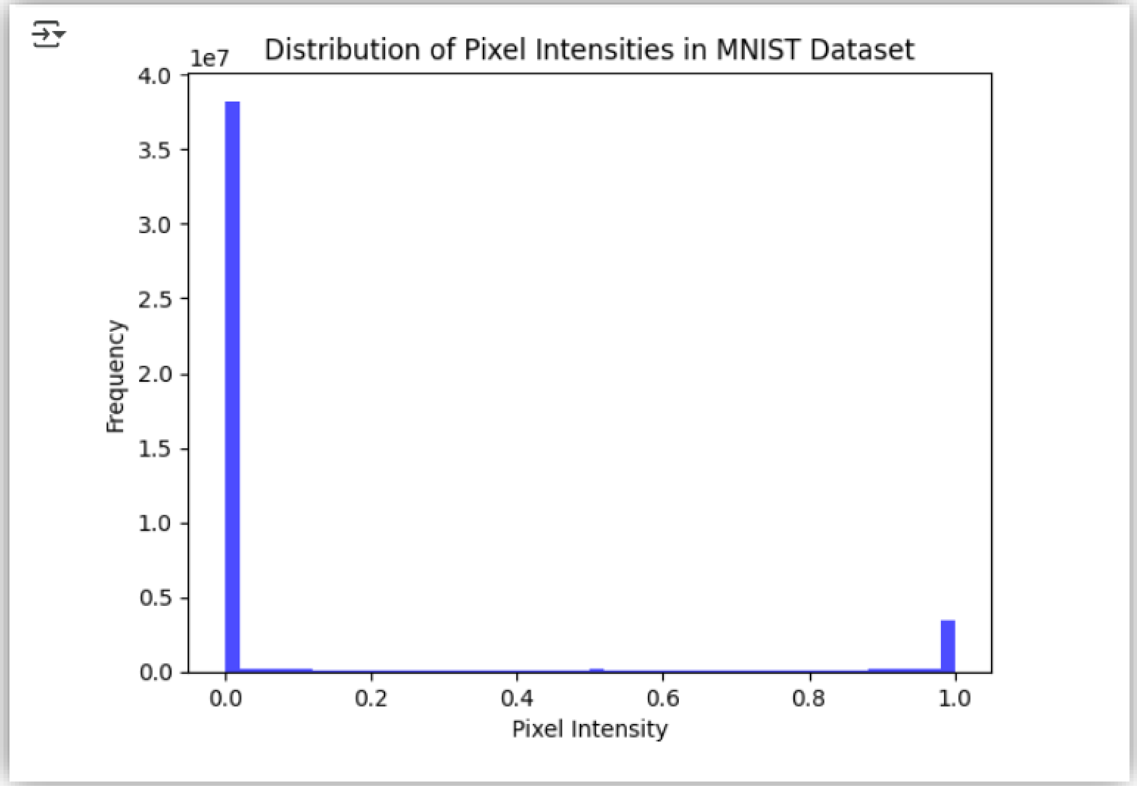


```
Training set shape: (60000, 784)
Test set shape: (10000, 784)
Pixel Intensity Range:  0.0 to 1.0
```

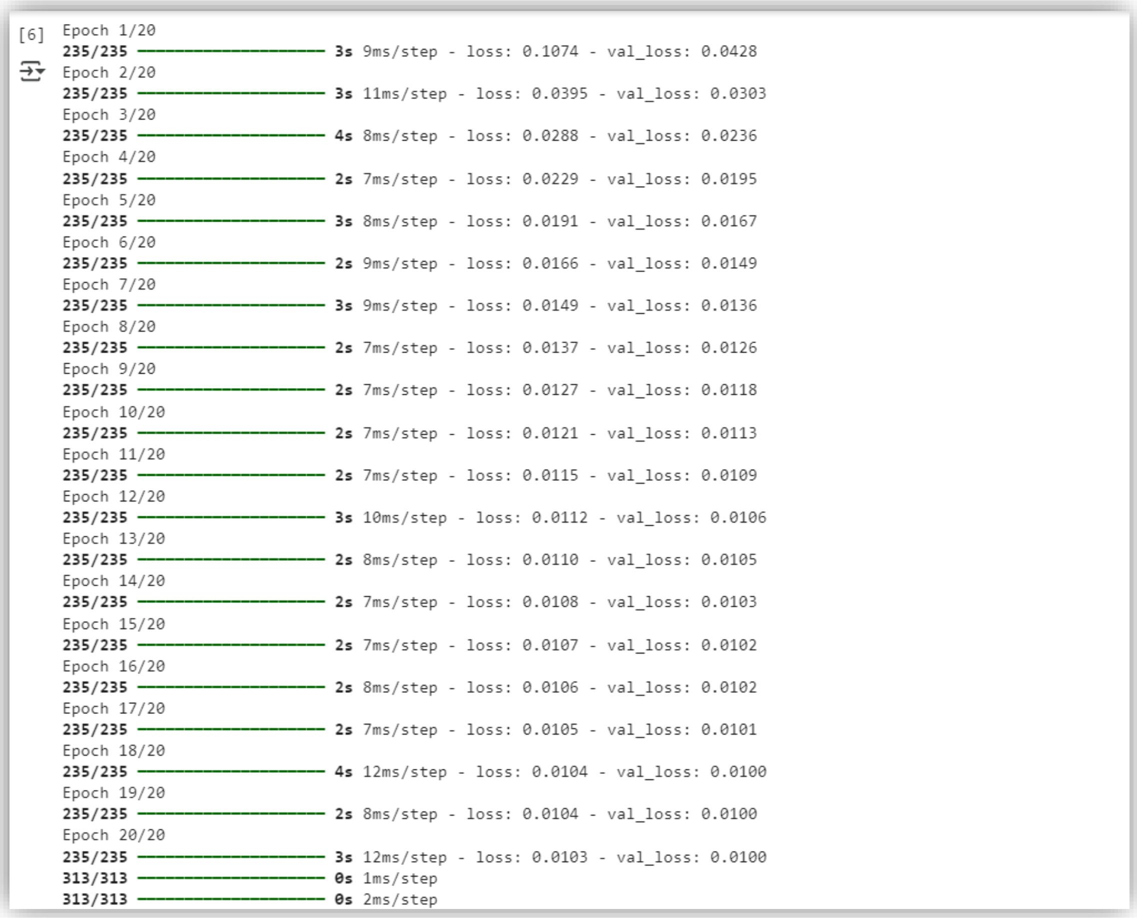
```
# Display 10 random images from the dataset
```



```
# Distribution of Pixel Intensities in MNIST Dataset
```

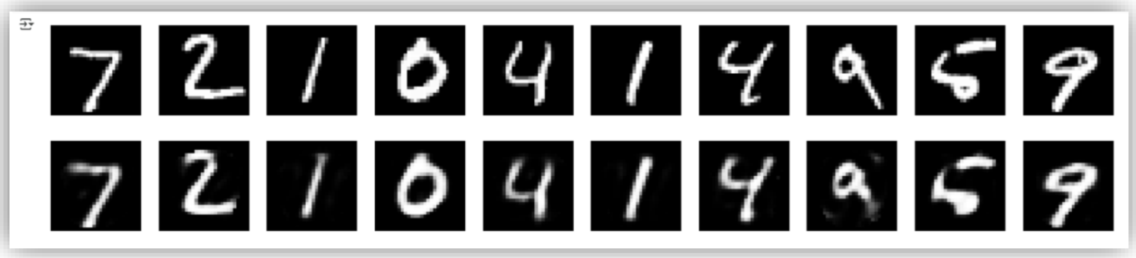


```
# autoencoder.fit()
```



```
[6] Epoch 1/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 3s 9ms/step - loss: 0.1074 - val_loss: 0.0428
    Epoch 2/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 3s 11ms/step - loss: 0.0395 - val_loss: 0.0303
    Epoch 3/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 4s 8ms/step - loss: 0.0288 - val_loss: 0.0236
    Epoch 4/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - loss: 0.0229 - val_loss: 0.0195
    Epoch 5/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 3s 8ms/step - loss: 0.0191 - val_loss: 0.0167
    Epoch 6/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - loss: 0.0166 - val_loss: 0.0149
    Epoch 7/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 3s 9ms/step - loss: 0.0149 - val_loss: 0.0136
    Epoch 8/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - loss: 0.0137 - val_loss: 0.0126
    Epoch 9/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - loss: 0.0127 - val_loss: 0.0118
    Epoch 10/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - loss: 0.0121 - val_loss: 0.0113
    Epoch 11/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - loss: 0.0115 - val_loss: 0.0109
    Epoch 12/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 3s 10ms/step - loss: 0.0112 - val_loss: 0.0106
    Epoch 13/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - loss: 0.0110 - val_loss: 0.0105
    Epoch 14/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - loss: 0.0108 - val_loss: 0.0103
    Epoch 15/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - loss: 0.0107 - val_loss: 0.0102
    Epoch 16/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - loss: 0.0106 - val_loss: 0.0102
    Epoch 17/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - loss: 0.0105 - val_loss: 0.0101
    Epoch 18/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 4s 12ms/step - loss: 0.0104 - val_loss: 0.0100
    Epoch 19/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - loss: 0.0104 - val_loss: 0.0100
    Epoch 20/20
    235/235 ━━━━━━━━━━━━━━━━━━━━ 3s 12ms/step - loss: 0.0103 - val_loss: 0.0100
    313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
    313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

```
# Display original and reconstructed images
```



Learning Outcomes:

- Understand the concept of autoencoders and their role in dimensionality reduction.
- Learn to preprocess and normalize high-dimensional data for efficient training.

Experiment 7

Aim: Implementation of RNN-LSTM model for Stock Price Prediction in Python.

Theory:

Introduction:
Stock price prediction is a crucial task in financial markets, where traders and investors aim to forecast future prices based on historical data. Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) networks, are widely used for time series forecasting due to their ability to learn temporal dependencies. In this experiment, we implement an LSTM-based model for stock price prediction using historical stock data from Yahoo Finance. The model learns patterns from past prices and predicts future values based on these observations.

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)

Concept and Working Mechanism:
Traditional RNNs are designed to process sequential data by maintaining a hidden state that captures information from previous time steps. However, they suffer from the vanishing gradient problem, making it difficult to learn long-term dependencies.
LSTM networks address this issue by introducing memory cells and gating mechanisms, which regulate the flow of information through the network:

- **Forget Gate:** Decides which information from the previous state should be discarded.
- **Input Gate:** Determines which new information should be stored in the cell state.
- **Output Gate:** Controls the output and updates the hidden state.

These mechanisms enable LSTMs to retain long-term dependencies, making them highly effective for time series forecasting.

Application of LSTM in Stock Price Prediction

Dataset Preparation:
The dataset consists of historical stock prices, including Open, High, Low, Close, and Volume data, retrieved using the Yahoo Finance API. For training, we use only the 'Close' price, as it is a key indicator of stock movement. The data is preprocessed by:

- Normalizing prices using MinMax scaling to improve model convergence.
- Creating sequences of past prices to serve as input features for the LSTM model.
- Splitting the data into training and testing sets for model evaluation.

LSTM Model Architecture:
The LSTM model is structured as follows:

- **Input Layer:** Takes sequences of past stock prices as input.
- **LSTM Layer:** Captures temporal dependencies and patterns in the stock price movements.
- **Dense Layer:** Outputs the predicted stock price.

Model architecture:

- LSTM(50 units, ReLU activation, return_sequences=True)

- LSTM(50 units, ReLU activation)
- Dense(25 units, ReLU activation)
- Dense(1 unit, linear activation)

The model is trained using the Adam optimizer and Mean Squared Error (MSE) loss function.

Performance Evaluation and Prediction:

After training, the model is evaluated on unseen test data. The predicted stock prices are compared with actual prices using:

- **Root Mean Squared Error (RMSE):** Measures prediction accuracy.
- **Visualization:** A graph comparing actual and predicted prices to assess performance.

While the model effectively captures trends, it may struggle with sudden market fluctuations caused by external factors (e.g., news events, economic policies).

Conclusion:

LSTM networks provide a robust approach for stock price prediction by learning temporal dependencies in historical data. Despite their effectiveness, challenges such as market volatility and external influences limit their accuracy. Future improvements can include:

- Incorporating additional technical indicators (e.g., moving averages, RSI).
- Using hybrid models combining LSTMs with attention mechanisms.
- Exploring Transformer-based architectures for enhanced forecasting.

This experiment demonstrates the potential of deep learning in financial market analysis, paving the way for more sophisticated predictive models.

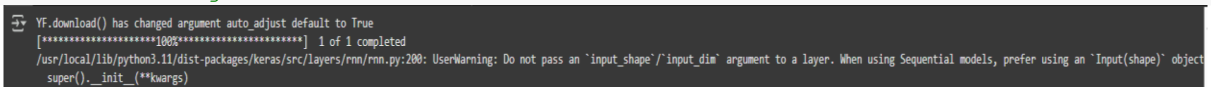
Code:

```
import numpy as np
import pandas as pd
import yfinance as yf
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
# Download stock data
def get_stock_data(ticker, start, end):
    df = yf.download(ticker, start=start, end=end)
    return df[['Close']]

# Prepare data for LSTM
def prepare_data(data, time_steps=60):
    scaler = MinMaxScaler(feature_range=(0, 1))
    data_scaled = scaler.fit_transform(data)

    X, y = [], []
    for i in range(time_steps, len(data_scaled)):
        X.append(data_scaled[i-time_steps:i, 0])
        y.append(data_scaled[i, 0])

    X, y = np.array(X), np.array(y)
    X = np.reshape(X, (X.shape[0], X.shape[1], 1))
    return X, y, scaler
# Build LSTM model
def build_lstm_model(input_shape):
    model = Sequential([
        LSTM(units=50, return_sequences=True, input_shape=input_shape),
        Dropout(0.2),
        LSTM(units=50, return_sequences=True),
        Dropout(0.2),
        LSTM(units=50),
        Dropout(0.2),
        Dense(units=1)
    ])
    model.compile(optimizer='adam', loss='mean_squared_error')
    return model
# Main execution
if __name__ == "__main__":
    ticker = "AAPL"
    start_date = "2020-01-01"
    end_date = "2024-01-01"

    data = get_stock_data(ticker, start_date, end_date)
```

```python
    time_steps = 60
    X, y, scaler = prepare_data(data.values, time_steps)

    train_size = int(len(X) * 0.8)
    X_train, y_train = X[:train_size], y[:train_size]
    X_test, y_test = X[train_size:], y[train_size:]

    model = build_lstm_model((X_train.shape[1], 1))
    model.fit(X_train, y_train, epochs=20, batch_size=32,
validation_data=(X_test, y_test))

    predictions = model.predict(X_test)
    predictions = scaler.inverse_transform(predictions.reshape(-1, 1))

    actual = scaler.inverse_transform(y_test.reshape(-1, 1))

    plt.plot(actual, label='Actual Price')
    plt.plot(predictions, label='Predicted Price')
    plt.legend()
    plt.show()
```

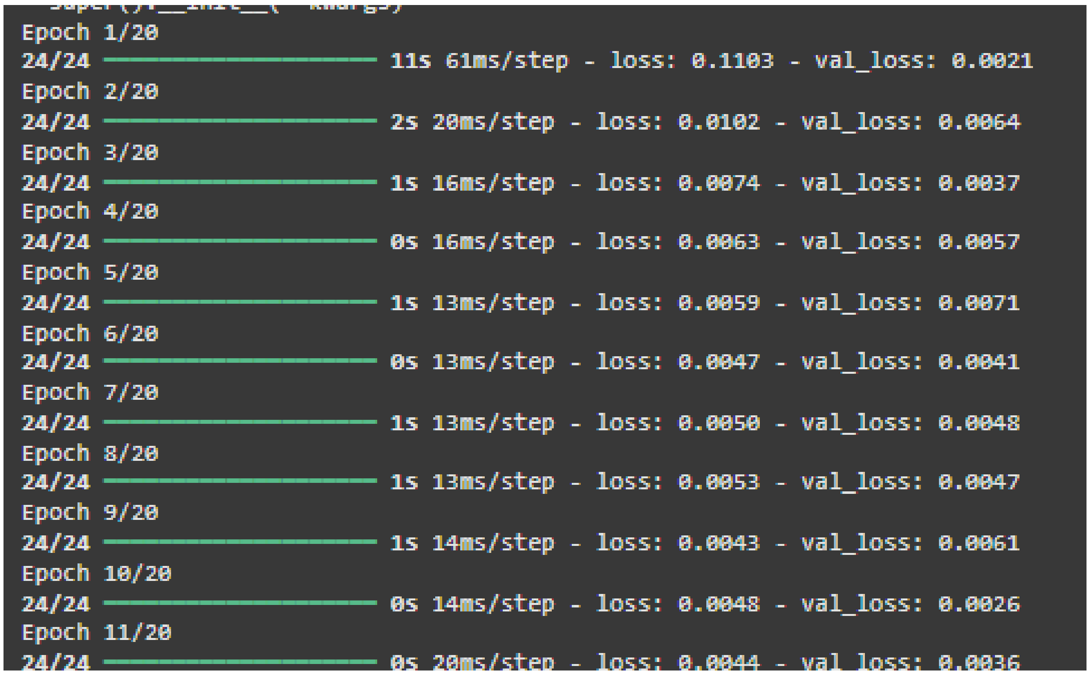
Outputs:

```
# downloading the dataset
```



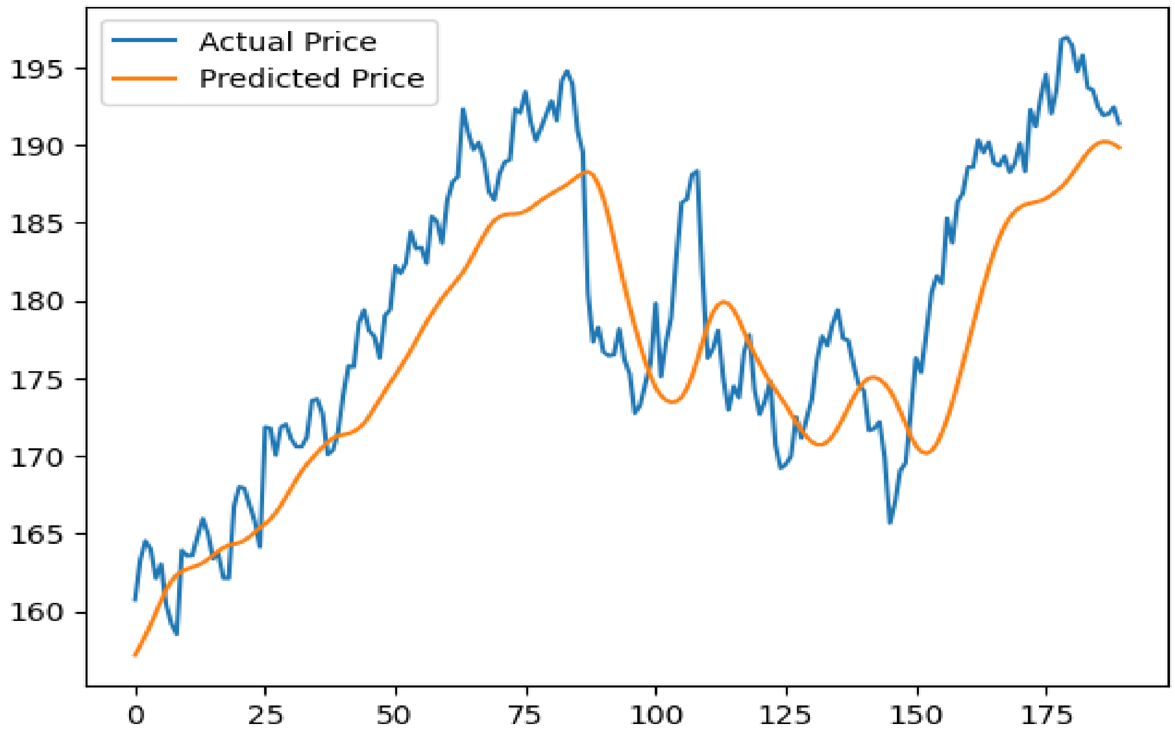
```
YF.download() has changed argument auto_adjust default to True
[*********************100%***********************]  1 of 1 completed
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object
  super().__init__(**kwargs)
```

```
# model training
```



```
Epoch 1/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 11s 61ms/step - loss: 0.1103 - val_loss: 0.0021
Epoch 2/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 20ms/step - loss: 0.0102 - val_loss: 0.0064
Epoch 3/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 1s 16ms/step - loss: 0.0074 - val_loss: 0.0037
Epoch 4/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - loss: 0.0063 - val_loss: 0.0057
Epoch 5/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0059 - val_loss: 0.0071
Epoch 6/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 0.0047 - val_loss: 0.0041
Epoch 7/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0050 - val_loss: 0.0048
Epoch 8/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 1s 13ms/step - loss: 0.0053 - val_loss: 0.0047
Epoch 9/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 1s 14ms/step - loss: 0.0043 - val_loss: 0.0061
Epoch 10/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 0.0048 - val_loss: 0.0026
Epoch 11/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 0s 20ms/step - loss: 0.0044 - val_loss: 0.0036
```

```
# Final Output
```



Learning Outcomes:

- Understand the architecture and working principles of LSTM networks for time-series forecasting.
- Develop a stock price prediction model using Python and TensorFlow.
- Analyze model performance and visualize predictions effectively.

Experiment 8

Aim: Implementation of transfer learning using the pre-trained model (VGG16) on image dataset in Python.

Theory:

Transfer learning using pre-trained VGG16 for image classification
Transfer learning enables the reuse of knowledge gained by a model trained on a large dataset for a different but related task. In image classification, pre-trained models like VGG16, trained on ImageNet with over a million images across 1000 categories, serve as strong foundations for extracting visual features from new datasets. This experiment aims to implement transfer learning using the VGG16 model and evaluate the improvements achieved by leveraging its pre-learned weights instead of training from scratch.
VGG16 Architecture and Role in Transfer Learning
VGG16 is a deep convolutional neural network with 16 weight layers, known for its uniform architecture and strong performance in image classification tasks. It uses small 3x3 convolution filters, arranged in increasing depth, making the network both deep and efficient at capturing hierarchical image features.
Main components of VGG16 include:

- **Input Layer** – Accepts images of size 224x224x3.
- **Convolutional Layers (13 total)** – Use 3x3 filters with stride 1 and 'same' padding; ReLU is applied after each convolution to introduce non-linearity.
- **Max Pooling Layers** – 2x2 max pooling applied after every few convolution layers to reduce spatial dimensions.
- **Fully Connected Layers –** Two dense layers with 4096 neurons each and ReLU activation, followed by a final dense layer with 1000 outputs (for ImageNet) and softmax activation.
- **Dropout Layers –** Applied between fully connected layers to prevent overfitting.
- **Output Layer** – Softmax activation used for classification.

By using the convolutional base of VGG16 as a fixed feature extractor or fine-tuning some of its layers, new image classification models can quickly generalize to novel tasks without needing massive datasets or training time.
Process of Image Classification using Transfer Learning
The classification pipeline involves importing the pre-trained VGG16 model (without the top classifier), attaching custom layers, and training only these new layers while keeping the rest frozen. Alternatively, a few deeper layers of VGG16 can be unfrozen for fine-tuning.

1. **Data Preprocessing -**

Input images are resized (typically to 224x224), normalized, and augmented to increase dataset variability. Data generators are used to handle image loading and transformation in real-time during training.

2. **Model Construction -**

The VGG16 model is loaded with include_top=False and pre-trained ImageNet weights. On top of the frozen convolutional base, custom layers like GlobalAveragePooling2D, Dense, Dropout, and a final softmax Dense layer are added.

3. **Training the Model -**

The model is compiled using optimizers like Adam and the categorical crossentropy loss function for multi-class classification. Training is done in batches using the training set, while performance is monitored on the validation set.

4. **Evaluation and Performance Measurement -**

Once trained, the model is tested on unseen data. The benefit of using VGG16 lies in its ability to quickly generalize using fewer data points. The trained model's accuracy, precision, recall, and F1-score are evaluated and compared to a baseline model trained from scratch.

Model Evaluation and Visualization

Evaluating transfer learning involves observing how well the model generalizes to the target task. Confusion matrices, classification reports, and accuracy/loss curves are plotted to analyze learning behavior.

Performance Metrics:

- **Accuracy** – Measures overall correctness of predictions.
- **Precision & Recall** – Assess model reliability per class.
- **F1-Score** – Harmonic mean of precision and recall.
- **Training Time** – Shorter with transfer learning compared to full training.

Visualization of Results

Visual tools like training/validation accuracy plots and confusion matrices help identify overfitting, misclassifications, and class-wise performance. These insights reveal how efficiently the VGG16 features are reused and adapted.

Conclusion

Transfer learning with VGG16 significantly reduces training time and enhances model performance on small or domain-specific datasets. By utilizing pre-learned visual patterns, the model requires fewer resources while achieving high accuracy. The evaluation confirms that feature reuse through VGG16 is a powerful strategy in image classification tasks.

Code:

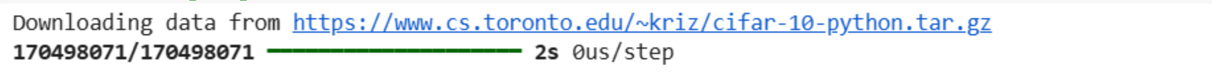
```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
from tensorflow.keras.datasets import cifar10
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.applications import VGG16
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, Flatten, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.applications.vgg16 import preprocess_input

# Load and preprocess the CIFAR-10 dataset
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
x_train = preprocess_input(x_train.astype('float32'))
```

```
x_test = preprocess_input(x_test.astype('float32'))

y_train_cat = to_categorical(y_train, 10)
y_test_cat = to_categorical(y_test, 10)

# Load pre-trained VGG16 without the top layer
base_model = VGG16(weights='imagenet', include_top=False,
input_shape=(32, 32, 3))

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

# Add custom top layers
x = Flatten()(base_model.output)
x = Dense(256, activation='relu')(x)
x = Dropout(0.5)(x)
x = Dense(10, activation='softmax')(x)

# Final model
model = Model(inputs=base_model.input, outputs=x)
model.compile(optimizer=Adam(), loss='categorical_crossentropy',
metrics=['accuracy'])

# Train the model
history = model.fit(x_train, y_train_cat, epochs=10, batch_size=64,
validation_data=(x_test, y_test_cat))

# Evaluate the model
loss, accuracy = model.evaluate(x_test, y_test_cat)
print(f"Test Accuracy: {accuracy:.4f}")

# Predict and generate classification report
y_pred = model.predict(x_test)
y_pred_classes = np.argmax(y_pred, axis=1)
y_true = y_test.flatten()

print("\nClassification Report:")
print(classification_report(y_true, y_pred_classes))

# Confusion Matrix
cm = confusion_matrix(y_true, y_pred_classes)
plt.figure(figsize=(10,7))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title("Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

```python
# Plot accuracy and loss
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.title("Model Accuracy")
plt.xlabel("Epochs")
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='Val Loss')
plt.title("Model Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.tight_layout()
plt.show()
```

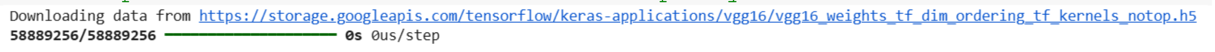
Output:

```
# Load and preprocess the CIFAR-10 dataset
```



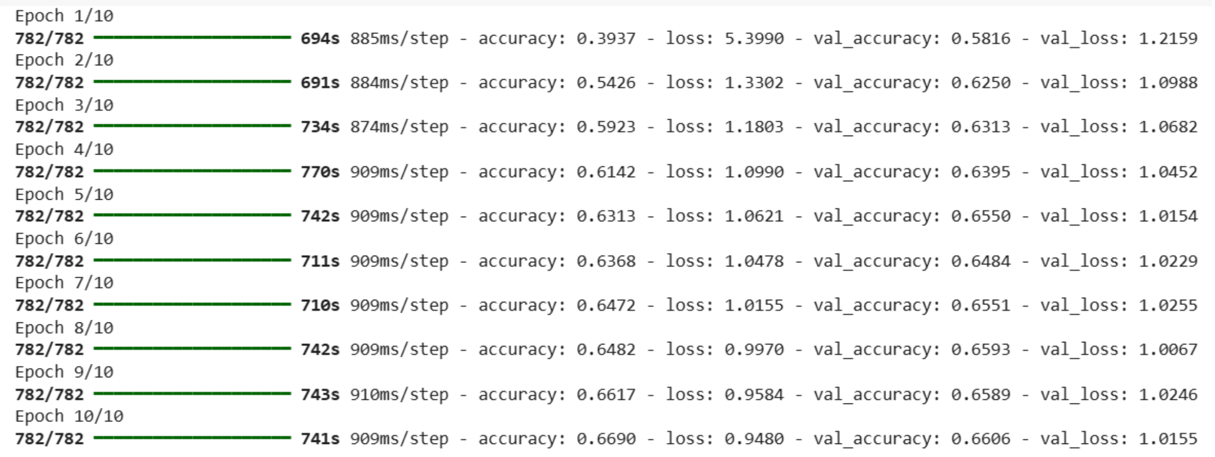
```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 ━━━━━━━━━━━━━━━━━━━━ 2s 0us/step
```

```
# Load pre-trained VGG16 without the top layer
```



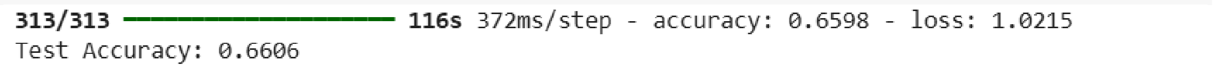
```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.h5
58889256/58889256 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

```
# Train the model
```



```
Epoch 1/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 694s 885ms/step - accuracy: 0.3937 - loss: 5.3990 - val_accuracy: 0.5816 - val_loss: 1.2159
Epoch 2/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 691s 884ms/step - accuracy: 0.5426 - loss: 1.3302 - val_accuracy: 0.6250 - val_loss: 1.0988
Epoch 3/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 734s 874ms/step - accuracy: 0.5923 - loss: 1.1803 - val_accuracy: 0.6313 - val_loss: 1.0682
Epoch 4/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 770s 909ms/step - accuracy: 0.6142 - loss: 1.0990 - val_accuracy: 0.6395 - val_loss: 1.0452
Epoch 5/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 742s 909ms/step - accuracy: 0.6313 - loss: 1.0621 - val_accuracy: 0.6550 - val_loss: 1.0154
Epoch 6/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 711s 909ms/step - accuracy: 0.6368 - loss: 1.0478 - val_accuracy: 0.6484 - val_loss: 1.0229
Epoch 7/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 710s 909ms/step - accuracy: 0.6472 - loss: 1.0155 - val_accuracy: 0.6551 - val_loss: 1.0255
Epoch 8/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 742s 909ms/step - accuracy: 0.6482 - loss: 0.9970 - val_accuracy: 0.6593 - val_loss: 1.0067
Epoch 9/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 743s 910ms/step - accuracy: 0.6617 - loss: 0.9584 - val_accuracy: 0.6589 - val_loss: 1.0246
Epoch 10/10
782/782 ━━━━━━━━━━━━━━━━━━━━ 741s 909ms/step - accuracy: 0.6690 - loss: 0.9480 - val_accuracy: 0.6606 - val_loss: 1.0155
```

```
# Evaluate the model
```

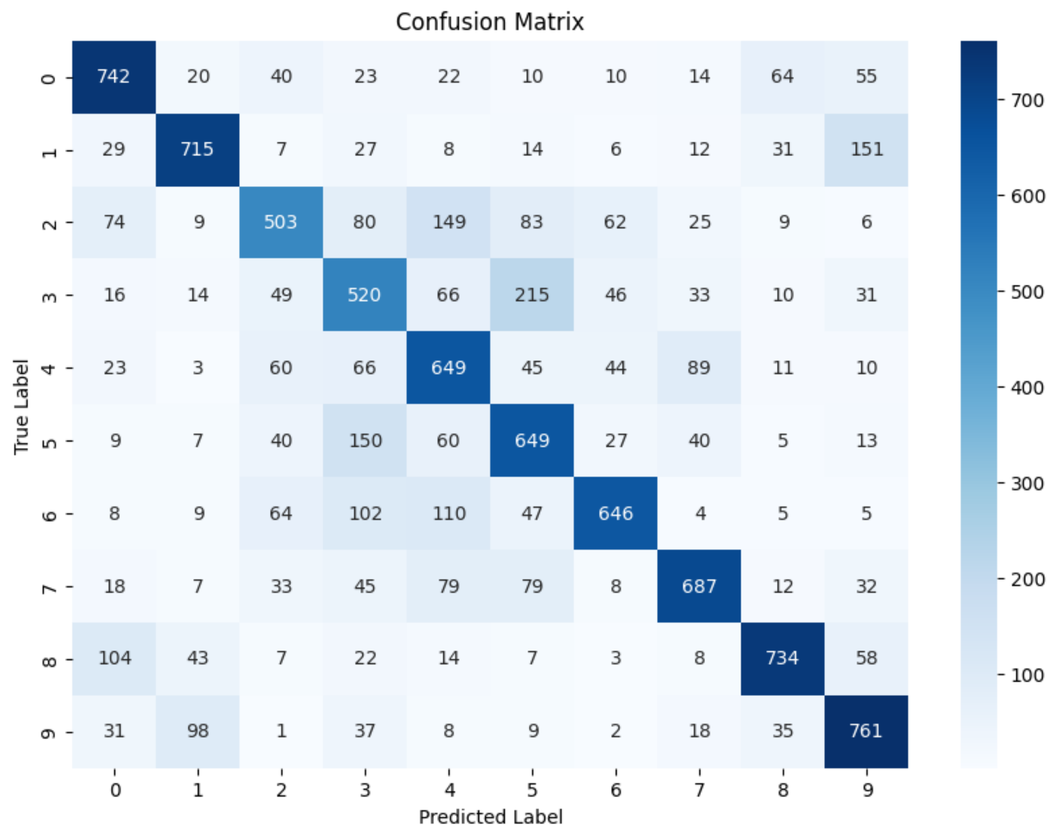


```
313/313 ━━━━━━━━━━━━━━━━━━━━ 116s 372ms/step - accuracy: 0.6598 - loss: 1.0215
Test Accuracy: 0.6606
```

```
# Classification report
```

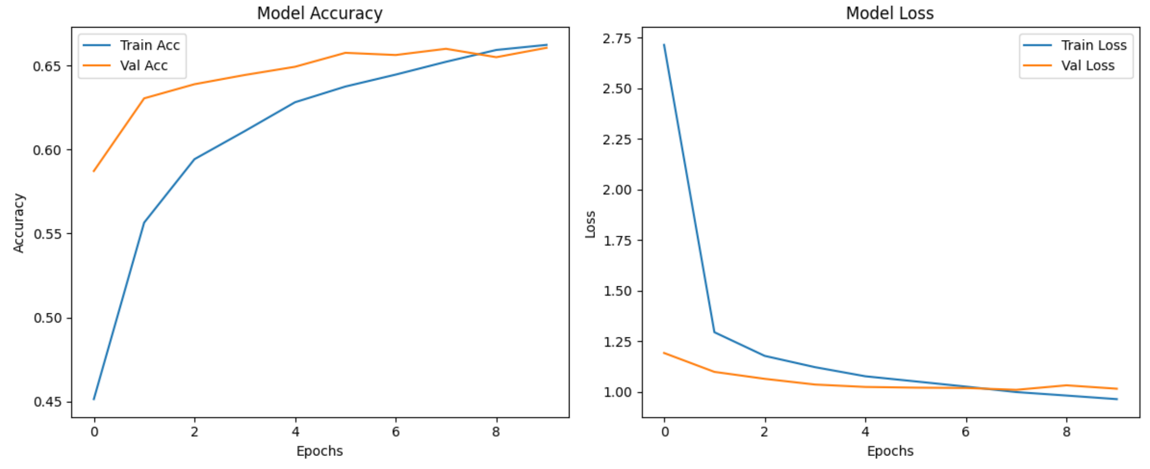
```
313/313 ━━━━━━━━━━━━━━━━━━━━ 120s 384ms/step

Classification Report:
              precision    recall  f1-score   support

           0       0.70      0.74      0.72      1000
           1       0.77      0.71      0.74      1000
           2       0.63      0.50      0.56      1000
           3       0.49      0.52      0.50      1000
           4       0.56      0.65      0.60      1000
           5       0.56      0.65      0.60      1000
           6       0.76      0.65      0.70      1000
           7       0.74      0.69      0.71      1000
           8       0.80      0.73      0.77      1000
           9       0.68      0.76      0.72      1000

    accuracy                           0.66     10000
   macro avg       0.67      0.66      0.66     10000
weighted avg       0.67      0.66      0.66     10000
```

```
# Confusion Matrix
```



	0	1	2	3	4	5	6	7	8	9
0	742	20	40	23	22	10	10	14	64	55
1	29	715	7	27	8	14	6	12	31	151
2	74	9	503	80	149	83	62	25	9	6
3	16	14	49	520	66	215	46	33	10	31
4	23	3	60	66	649	45	44	89	11	10
5	9	7	40	150	60	649	27	40	5	13
6	8	9	64	102	110	47	646	4	5	5
7	18	7	33	45	79	79	8	687	12	32
8	104	43	7	22	14	7	3	8	734	58
9	31	98	1	37	8	9	2	18	35	761

```
# Plot accuracy and loss
```



Learning Outcomes:

1. Understood the application of transfer learning using the pre-trained VGG16 model for efficient image classification.
2. Learned the structure and functionality of VGG16, including its convolutional layers, pooling layers, and fully connected layers.
3. Gained the ability to evaluate and interpret model performance using classification metrics and result visualizations.

SECTION 2

BEYOND THE CURRICULUM

EXPERIMENT-1

Aim: Implement an Inception V3 for image classification.

Objectives:

- To implement the Inception V3 model for efficient and accurate image classification.
- To evaluate the performance benefits of using a deep, multi-scale convolutional architecture.

Theory:

Image Classification using Inception V3
The Inception V3 model is a state-of-the-art convolutional neural network architecture known for its optimized depth, width, and utilization of computational resources. It is specifically designed for large-scale image classification tasks where extracting intricate patterns and multi-scale features is crucial. The primary goal of this experiment is to implement the Inception V3 architecture for accurate image classification while analyzing the improvements gained by its multi-branch, multi-resolution design. This deep model efficiently balances performance and speed, making it suitable for both academic and industrial image classification tasks.

Inception V3 Architecture and Functionality
Inception V3 improves upon earlier versions of the Inception model by integrating advanced concepts like factorized convolutions, label smoothing, batch normalization, and auxiliary classifiers. These enhancements collectively help in accelerating convergence, reducing overfitting, and improving generalization. The architecture is built using a stack of Inception modules, where each module performs multiple convolution operations in parallel using filters of different sizes. This allows the model to learn spatial hierarchies of features efficiently.

Main components of Inception V3:

- **Stem Convolutional Layers –** Initial layers that extract low-level features from raw input images.
- **Inception Modules –** Core blocks that apply multiple types of convolutions and pooling in parallel to capture diverse features.
- **Factorized Convolutions –** Replace large filters (e.g., 5x5) with smaller ones (e.g., two 3x3s) to reduce the number of parameters.
- **Auxiliary Classifiers –** Intermediate output branches used during training to ensure better gradient flow and reduce vanishing gradients.
- **Batch Normalization –** Applied after most layers to speed up training and provide regularization.
- **Global Average Pooling –** Compresses spatial dimensions by averaging feature maps, reducing overfitting.
- **Dropout and Dense Layers –** Dropout helps in regularization, and dense layers map learned features to output class probabilities.

Process of Image Classification using Inception V3

1. **Data Preprocessing -**

Input images are resized to 299x299 pixels, normalized, and optionally augmented using techniques such as horizontal flips, rotations, and zooms. This step enhances the model's robustness to real-world image variations and improves generalization.

2. **Model Construction -**

Inception V3 can be used in two ways: (a) from scratch with randomly initialized weights, or (b) by leveraging a pre-trained version on ImageNet and fine-tuning it for a specific dataset. The top classification layer is modified to match the number of classes in the current task. The model is compiled using categorical crossentropy for multi-class classification and an appropriate optimizer like RMSprop or Adam.

3. **Training the Model -**

The model is trained on training data while validating on a separate validation set. During each epoch, weights are adjusted to minimize the classification error. Callbacks like early stopping and learning rate scheduling may be used to stabilize and optimize training. Auxiliary classifiers assist in faster convergence and deeper learning by injecting gradients into earlier layers.

4. **Evaluation and Prediction -**

Once trained, the model is evaluated on a test set using performance metrics. The predicted labels are compared with actual labels to assess classification accuracy. The final output is a probability distribution over classes, from which the highest-probability class is chosen as the predicted label.

Model Evaluation and Visualization

Evaluation helps determine how effectively the model classifies unseen images and generalizes to new data.

Performance Metrics:

- **Accuracy –** Indicates overall correctness of predictions.
- **Precision and Recall –** Assess classification performance for each class.
- **F1-Score –** Balances precision and recall for better evaluation in imbalanced datasets.
- **Confusion Matrix –** Helps visualize true positives, false positives, and misclassifications across classes.

Visualization of Results:

Plotting training vs. validation loss and accuracy over epochs gives insight into overfitting or underfitting. Class activation maps (CAMs) or Grad-CAMs may also be used to visualize which parts of the image influenced the model's predictions, enhancing interpretability and trust in the model.

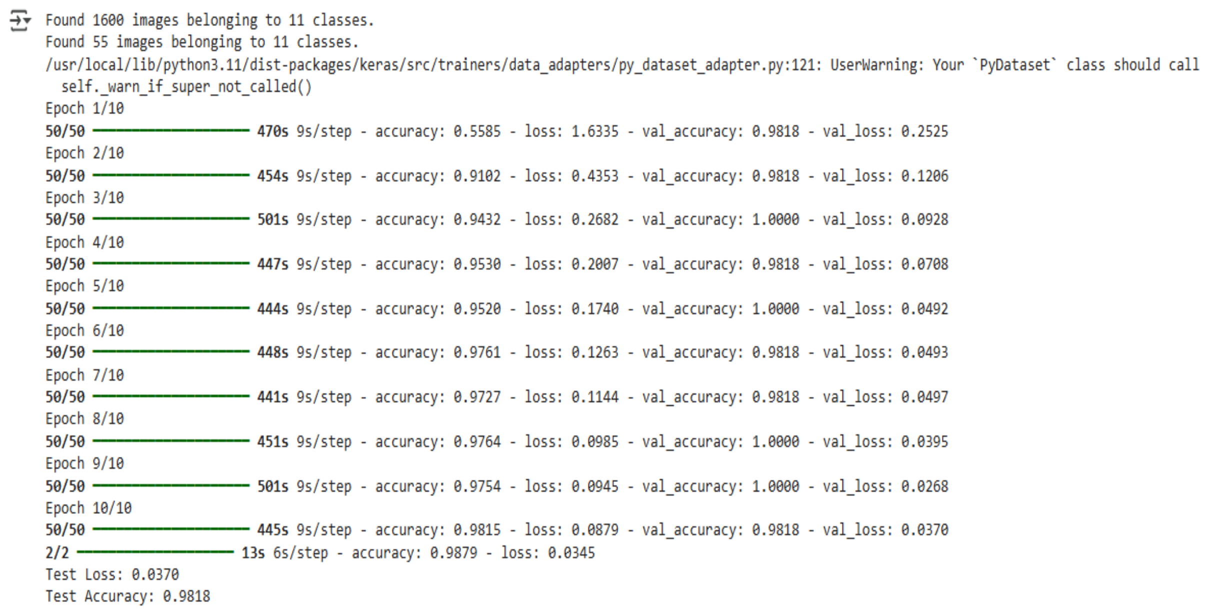
Conclusion

The Inception V3 model is an advanced deep learning architecture that brings significant improvements to image classification through its scalable and efficient design. It effectively captures both local and global patterns within images by combining convolutions of different sizes. Using techniques like factorized convolutions, auxiliary classifiers, and batch normalization, the model achieves a strong balance between performance and computational efficiency. Evaluation with metrics and visualizations confirms its ability to generalize well, making it highly suitable for complex image classification tasks in real-world scenarios.

Code and Outputs:

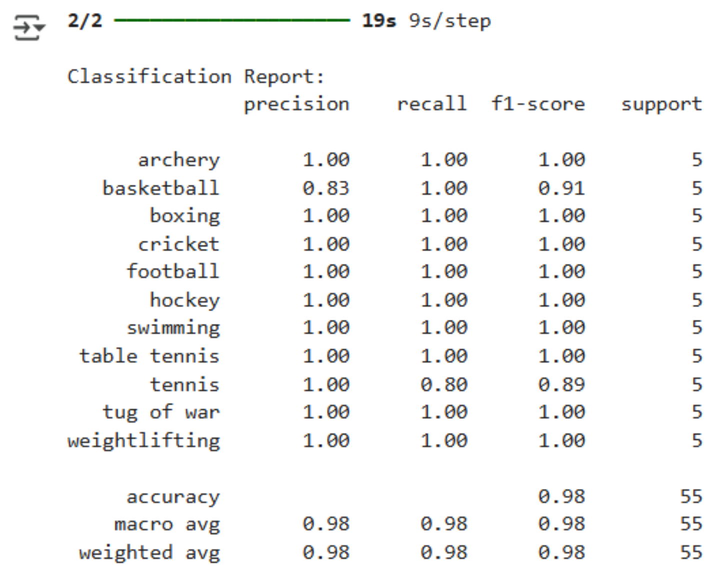
```
import os
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications.inception_v3 import InceptionV3,
preprocess_input
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D
from tensorflow.keras.optimizers import Adam
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns

train_dir = '/content/sports_dataset/sports_dataset/train'
test_dir = '/content/sports_dataset/sports_dataset/test'

train_datagen = ImageDataGenerator(
    preprocessing_function=preprocess_input,
    rotation_range=20,
    zoom_range=0.2,
    horizontal_flip=True
)

test_datagen =
ImageDataGenerator(preprocessing_function=preprocess_input)

train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(299, 299),
    batch_size=32,
    class_mode='categorical'
)

test_generator = test_datagen.flow_from_directory(
    test_dir,
    target_size=(299, 299),
    batch_size=32,
    class_mode='categorical',
    shuffle=False
)
```

```python
# Load base model
base_model = InceptionV3(weights='imagenet', include_top=False)
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(1024, activation='relu')(x)
predictions = Dense(train_generator.num_classes,
activation='softmax')(x)

model = Model(inputs=base_model.input, outputs=predictions)

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

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

# Train model
history = model.fit(
    train_generator,
    epochs=10,
    validation_data=test_generator
)

loss, accuracy = model.evaluate(test_generator)
print(f"Test Loss: {loss:.4f}")
print(f"Test Accuracy: {accuracy:.4f}")
```



```
Found 1600 images belonging to 11 classes.
Found 55 images belonging to 11 classes.
/usr/local/lib/python3.11/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class should call
  self._warn_if_super_not_called()
Epoch 1/10
50/50 ━━━━━━━━━━━━━━━━━━━━ 470s 9s/step - accuracy: 0.5585 - loss: 1.6335 - val_accuracy: 0.9818 - val_loss: 0.2525
Epoch 2/10
50/50 ━━━━━━━━━━━━━━━━━━━━ 454s 9s/step - accuracy: 0.9102 - loss: 0.4353 - val_accuracy: 0.9818 - val_loss: 0.1206
Epoch 3/10
50/50 ━━━━━━━━━━━━━━━━━━━━ 501s 9s/step - accuracy: 0.9432 - loss: 0.2682 - val_accuracy: 1.0000 - val_loss: 0.0928
Epoch 4/10
50/50 ━━━━━━━━━━━━━━━━━━━━ 447s 9s/step - accuracy: 0.9530 - loss: 0.2007 - val_accuracy: 0.9818 - val_loss: 0.0708
Epoch 5/10
50/50 ━━━━━━━━━━━━━━━━━━━━ 444s 9s/step - accuracy: 0.9520 - loss: 0.1740 - val_accuracy: 1.0000 - val_loss: 0.0492
Epoch 6/10
50/50 ━━━━━━━━━━━━━━━━━━━━ 448s 9s/step - accuracy: 0.9761 - loss: 0.1263 - val_accuracy: 0.9818 - val_loss: 0.0493
Epoch 7/10
50/50 ━━━━━━━━━━━━━━━━━━━━ 441s 9s/step - accuracy: 0.9727 - loss: 0.1144 - val_accuracy: 0.9818 - val_loss: 0.0497
Epoch 8/10
50/50 ━━━━━━━━━━━━━━━━━━━━ 451s 9s/step - accuracy: 0.9764 - loss: 0.0985 - val_accuracy: 1.0000 - val_loss: 0.0395
Epoch 9/10
50/50 ━━━━━━━━━━━━━━━━━━━━ 501s 9s/step - accuracy: 0.9754 - loss: 0.0945 - val_accuracy: 1.0000 - val_loss: 0.0268
Epoch 10/10
50/50 ━━━━━━━━━━━━━━━━━━━━ 445s 9s/step - accuracy: 0.9815 - loss: 0.0879 - val_accuracy: 0.9818 - val_loss: 0.0370
2/2 ━━━━━━━━━━━━━━━━━━━━ 13s 6s/step - accuracy: 0.9879 - loss: 0.0345
Test Loss: 0.0370
Test Accuracy: 0.9818
```

```
predictions = model.predict(test_generator)
y_pred = np.argmax(predictions, axis=1)
y_true = test_generator.classes

class_labels = list(test_generator.class_indices.keys())

# Classification report
print("\nClassification Report:")
print(classification_report(y_true, y_pred,
target_names=test_generator.class_indices.keys()))
```

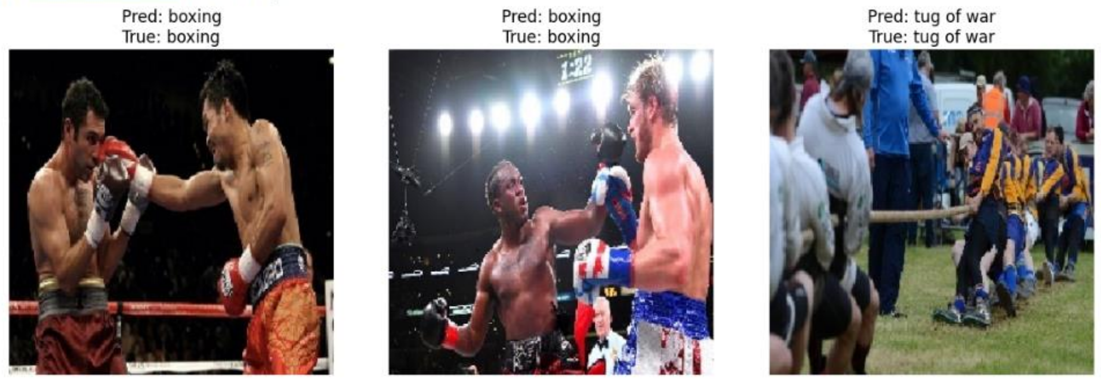


```
2/2 ━━━━━━━━━━━━━━━━━━━━ 19s 9s/step

Classification Report:
              precision    recall  f1-score   support

     archery       1.00      1.00      1.00         5
  basketball       0.83      1.00      0.91         5
      boxing       1.00      1.00      1.00         5
     cricket       1.00      1.00      1.00         5
    football       1.00      1.00      1.00         5
      hockey       1.00      1.00      1.00         5
    swimming       1.00      1.00      1.00         5
table tennis       1.00      1.00      1.00         5
      tennis       1.00      0.80      0.89         5
  tug of war       1.00      1.00      1.00         5
weightlifting      1.00      1.00      1.00         5

    accuracy                           0.98        55
   macro avg       0.98      0.98      0.98        55
weighted avg       0.98      0.98      0.98        55
```

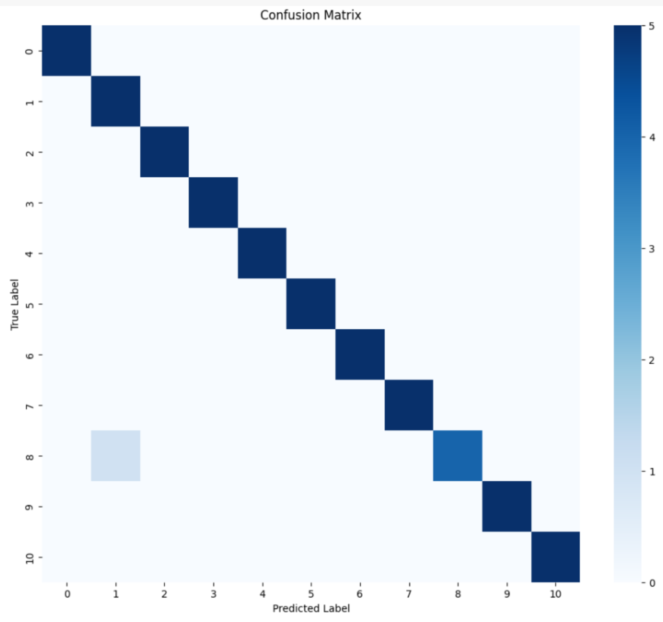
```
def predict_image(img_path, model, class_labels):
    img = image.load_img(img_path, target_size=(299, 299))
    x = image.img_to_array(img)
    x = np.expand_dims(x, axis=0)
    x = preprocess_input(x)
    preds = model.predict(x)
    predicted_class = class_labels[np.argmax(preds)]
    return predicted_class

image_paths_and_labels = []
for class_name in class_labels:
    folder_path = os.path.join(test_dir, class_name)
    for filename in os.listdir(folder_path):
        if filename.endswith(('.jpg', '.jpeg', '.png')):
            image_path = os.path.join(folder_path, filename)
            image_paths_and_labels.append((image_path, class_name))

num_images_to_display = 9
```

```
random_images = random.sample(image_paths_and_labels,
num_images_to_display)

plt.figure(figsize=(12, 12))
for i, (img_path, true_label) in enumerate(random_images):
    predicted_class = predict_image(img_path, model, class_labels)

    plt.subplot(3, 3, i + 1)
    img = image.load_img(img_path, target_size=(299, 299))
    plt.imshow(img)
    plt.title(f"Pred: {predicted_class}\nTrue: {true_label}")
    plt.axis('off')

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

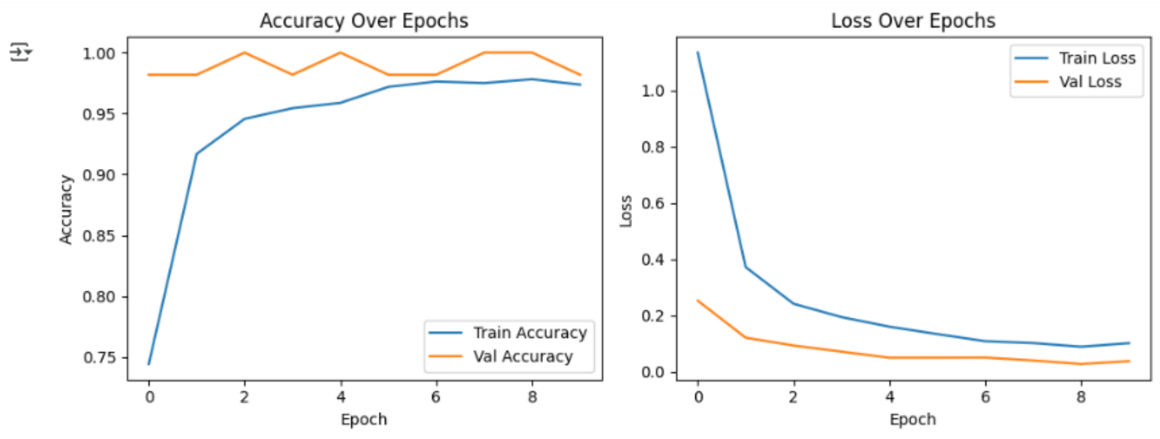
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 711ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 261ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 289ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 279ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 270ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 289ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 313ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 492ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 500ms/step
```



```
# Confusion matrix
cm = confusion_matrix(y_true, y_pred)
plt.figure(figsize=(12,10))
sns.heatmap(cm, annot=False, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
```



```
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='Val Accuracy')
plt.title('Accuracy Over Epochs')
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='Val Loss')
plt.title('Loss Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

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



Learning Outcomes:

1. Gained understanding of Inception V3 architecture and its multi-scale convolutional approach for efficient image classification.
2. Developed skills to preprocess, train, and fine-tune a deep learning model using real-world image datasets.
3. Acquired the ability to evaluate model performance using metrics like accuracy, F1-score, and visualize results for deeper insights.

EXPERIMENT-2

Aim: Implement Bi-directional LSTM for text classification.

Objectives:

- To implement a Bi-directional LSTM model for accurate text classification.
- To analyze the impact of processing text sequences in both forward and backward directions.

Theory:

Text classification using Bi-directional LSTM
Bi-directional Long Short-Term Memory (Bi-LSTM) networks are an advanced deep learning architecture used in Natural Language Processing (NLP), specifically designed to improve the performance of sequence-based tasks like text classification. This experiment aims to implement a Bi-LSTM model to accurately classify text data while analyzing the advantages of processing input sequences in both forward and backward directions. By capturing context from both ends of a sentence, Bi-LSTM models help overcome the limitations of standard LSTM, which can only learn from past information.
Bi-LSTM Architecture and Functionality
In Bi-LSTM, two separate LSTM layers are employed: one reads the input sequence from left to right (forward pass), and the other reads from right to left (backward pass). The outputs of both directions are concatenated at each time step, allowing the model to understand both preceding and succeeding words. This is crucial for tasks where word meaning heavily depends on surrounding context. For example, in the sentence "He **banked** the fire," the meaning of *banked* changes if we don’t consider the full context.
Main components of the Bi-LSTM model include:

- **Embedding Layer –** Transforms input words into dense vector representations that carry semantic meaning. Pre-trained embeddings like Word2Vec or GloVe can enhance this further.

- **Bi-LSTM Layer** – Comprises two LSTM layers operating in opposite directions; they extract both past and future dependencies for deeper context understanding.

- **Dropout Layer** – Randomly drops units to reduce overfitting and improve model generalization.

- **Dense Layer** – Processes the combined outputs of the Bi-LSTM and projects them to the desired output dimension.

- **Output Layer** – Applies softmax or sigmoid activation to produce class probabilities based on binary or multi-class classification setup.

Process of Text Classification using Bi-LSTM
The overall process starts with raw text data and ends with accurate predictions of text categories, typically involving the following steps:

1. **Data Preprocessing-**

The dataset is first cleaned (removing stop words, lowercasing, punctuation, etc.) and tokenized into sequences of integers. These sequences are padded to ensure consistent input length, enabling batch processing.

2. **Model Construction-**

A Sequential model is built starting with an Embedding layer. This is followed by a Bi-LSTM layer that processes each input sequence in both directions. A dropout layer is added for regularization, followed by a dense layer and a softmax/sigmoid output layer for classification.

3. **Training the Model-**

The model is compiled using optimizers like Adam and loss functions such as binary or categorical crossentropy, depending on the task. During training, the model adjusts its internal weights using backpropagation through time to minimize the loss.

4. **Evaluation and Prediction-**

The trained model is tested on a separate validation/test dataset. Predictions are generated and compared with actual labels to calculate performance metrics. The bidirectional architecture typically results in more accurate predictions, especially in context-heavy tasks.

Model Evaluation and Visualization

Performance is assessed using standard classification metrics to ensure that the model generalizes well to unseen data.

Performance Metrics:

- **Accuracy** – Measures the overall percentage of correct predictions.
- **Precision** – Indicates how many of the predicted positives are actually correct.
- **Recall** – Reflects how many actual positives the model correctly identified.
- **F1-Score –** Harmonic mean of precision and recall, useful in cases of class imbalance.

Visualization of Results

Accuracy and loss curves across epochs are plotted to assess learning behavior and convergence. Confusion matrices visualize true vs. predicted labels, making it easier to identify which classes are well-learned and which are misclassified.

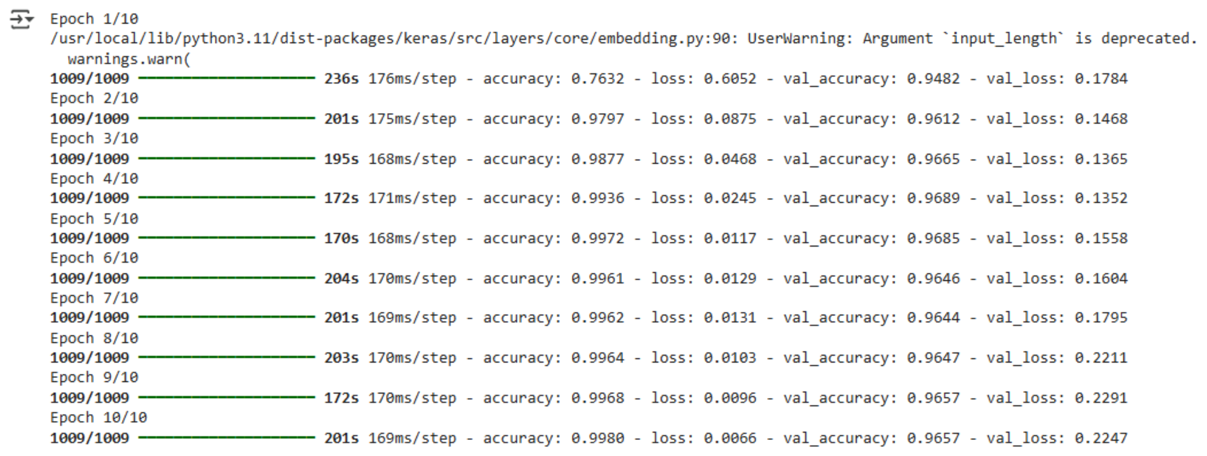
Conclusion

The Bi-directional LSTM architecture effectively enhances model understanding of textual data by capturing both previous and future context, leading to better performance in classification tasks. Its dual-layer setup allows deeper semantic learning, resulting in improved accuracy and generalization. Evaluating through metrics and visual tools confirms the strength of Bi-LSTM over standard unidirectional models in natural language applications.

Code and Outputs:

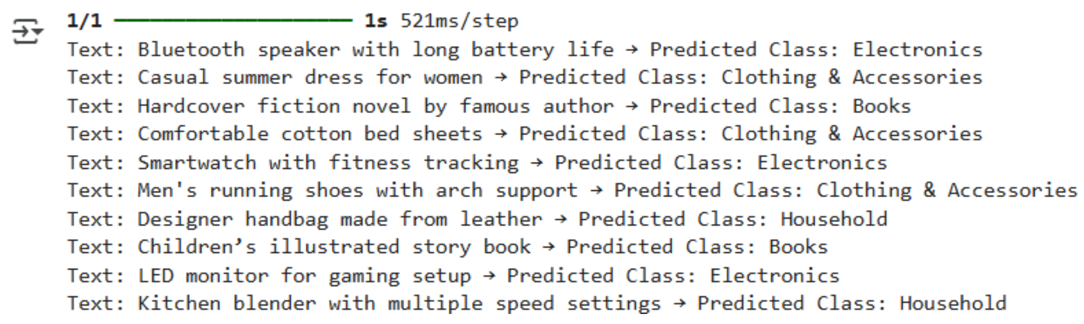
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
```

```python
from sklearn.metrics import classification_report, confusion_matrix
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Bidirectional, LSTM,
Dense, Dropout

df = pd.read_csv('ecommerce_datsaset.csv',usecols=['Text', 'label'])

df['Text'] = df['Text'].astype(str)
label_counts = df['label'].value_counts()
valid_labels = label_counts[label_counts > 1].index
df = df[df['label'].isin(valid_labels)]

label_encoder = LabelEncoder()
df['label_encoded'] = label_encoder.fit_transform(df['label'])

tokenizer = Tokenizer(oov_token='<OOV>')
tokenizer.fit_on_texts(df['Text'])
sequences = tokenizer.texts_to_sequences(df['Text'])
word_index = tokenizer.word_index

max_length = 100
X = pad_sequences(sequences, maxlen=max_length, padding='post')
y = df['label_encoded'].values
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, stratify=y, random_state=42)

# Model
vocab_size = len(word_index) + 1
embedding_dim = 64

model = Sequential([
    Embedding(vocab_size, embedding_dim, input_length=max_length),
    Bidirectional(LSTM(64, return_sequences=False)),
    Dropout(0.5),
    Dense(32, activation='relu'),
    Dense(len(np.unique(y)), activation='softmax')
])

model.compile(loss='sparse_categorical_crossentropy', optimizer='adam',
metrics=['accuracy'])
history = model.fit(X_train, y_train, epochs=10, batch_size=32,
validation_split=0.2)
```



```
Epoch 1/10
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/embedding.py:90: UserWarning: Argument `input_length` is deprecated.
  warnings.warn(
1009/1009 ━━━━━━━━━━━━━━━━━━━━ 236s 176ms/step - accuracy: 0.7632 - loss: 0.6052 - val_accuracy: 0.9482 - val_loss: 0.1784
Epoch 2/10
1009/1009 ━━━━━━━━━━━━━━━━━━━━ 201s 175ms/step - accuracy: 0.9797 - loss: 0.0875 - val_accuracy: 0.9612 - val_loss: 0.1468
Epoch 3/10
1009/1009 ━━━━━━━━━━━━━━━━━━━━ 195s 168ms/step - accuracy: 0.9877 - loss: 0.0468 - val_accuracy: 0.9665 - val_loss: 0.1365
Epoch 4/10
1009/1009 ━━━━━━━━━━━━━━━━━━━━ 172s 171ms/step - accuracy: 0.9936 - loss: 0.0245 - val_accuracy: 0.9689 - val_loss: 0.1352
Epoch 5/10
1009/1009 ━━━━━━━━━━━━━━━━━━━━ 170s 168ms/step - accuracy: 0.9972 - loss: 0.0117 - val_accuracy: 0.9685 - val_loss: 0.1558
Epoch 6/10
1009/1009 ━━━━━━━━━━━━━━━━━━━━ 204s 170ms/step - accuracy: 0.9961 - loss: 0.0129 - val_accuracy: 0.9646 - val_loss: 0.1604
Epoch 7/10
1009/1009 ━━━━━━━━━━━━━━━━━━━━ 201s 169ms/step - accuracy: 0.9962 - loss: 0.0131 - val_accuracy: 0.9644 - val_loss: 0.1795
Epoch 8/10
1009/1009 ━━━━━━━━━━━━━━━━━━━━ 203s 170ms/step - accuracy: 0.9964 - loss: 0.0103 - val_accuracy: 0.9647 - val_loss: 0.2211
Epoch 9/10
1009/1009 ━━━━━━━━━━━━━━━━━━━━ 172s 170ms/step - accuracy: 0.9968 - loss: 0.0096 - val_accuracy: 0.9657 - val_loss: 0.2291
Epoch 10/10
1009/1009 ━━━━━━━━━━━━━━━━━━━━ 201s 169ms/step - accuracy: 0.9980 - loss: 0.0066 - val_accuracy: 0.9657 - val_loss: 0.2247
```

```
# Sample predictions
sample_texts = [
    "Bluetooth speaker with long battery life",
    "Casual summer dress for women",
    "Hardcover fiction novel by famous author",
    "Comfortable cotton bed sheets",
    "Smartwatch with fitness tracking",
    "Men's running shoes with arch support",
    "Designer handbag made from leather",
    "Children’s illustrated story book",
    "LED monitor for gaming setup",
    "Kitchen blender with multiple speed settings"
]
sample_seq = tokenizer.texts_to_sequences(sample_texts)
sample_pad = pad_sequences(sample_seq, maxlen=max_length,
padding='post')
predictions = model.predict(sample_pad)
for i, text in enumerate(sample_texts):
    pred_class =
label_encoder.inverse_transform([np.argmax(predictions[i])])[0]
    print(f"Text: {text} → Predicted Class: {pred_class}")
```



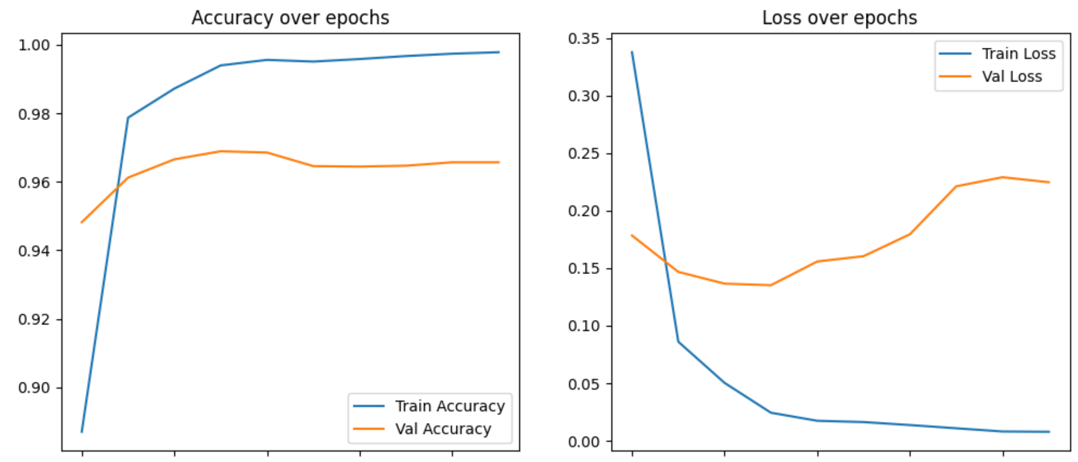
```
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 521ms/step
Text: Bluetooth speaker with long battery life → Predicted Class: Electronics
Text: Casual summer dress for women → Predicted Class: Clothing & Accessories
Text: Hardcover fiction novel by famous author → Predicted Class: Books
Text: Comfortable cotton bed sheets → Predicted Class: Clothing & Accessories
Text: Smartwatch with fitness tracking → Predicted Class: Electronics
Text: Men's running shoes with arch support → Predicted Class: Clothing & Accessories
Text: Designer handbag made from leather → Predicted Class: Household
Text: Children’s illustrated story book → Predicted Class: Books
Text: LED monitor for gaming setup → Predicted Class: Electronics
Text: Kitchen blender with multiple speed settings → Predicted Class: Household
```

```
# Evaluation
y_pred = np.argmax(model.predict(X_test), axis=1)
```

```
print(classification_report(y_test, y_pred,
target_names=label_encoder.classes_))
```

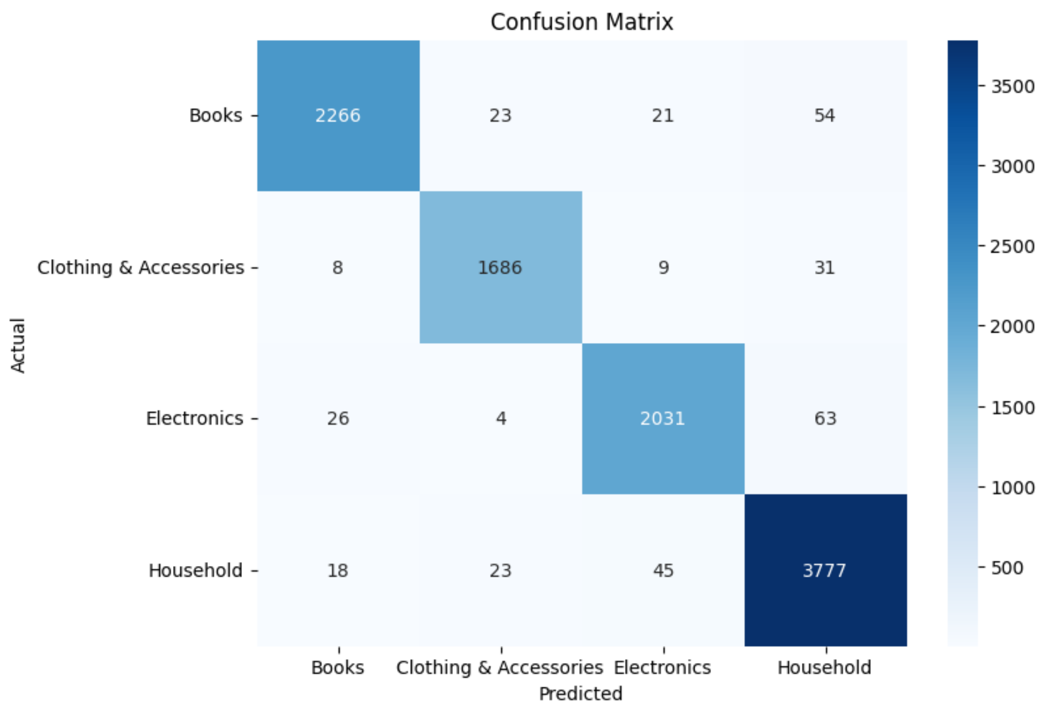
```
316/316 ━━━━━━━━━━━━━━━━━━━━ 10s 30ms/step
                        precision    recall  f1-score   support

                 Books       0.98      0.96      0.97      2364
Clothing & Accessories       0.97      0.97      0.97      1734
           Electronics       0.96      0.96      0.96      2124
             Household       0.96      0.98      0.97      3863

              accuracy                           0.97     10085
             macro avg       0.97      0.97      0.97     10085
          weighted avg       0.97      0.97      0.97     10085
```

```
# Accuracy & loss plot
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='Val Accuracy')
plt.legend()
plt.title('Accuracy over epochs')

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



```
# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8,6))
```

```
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=label_encoder.classes_, yticklabels=label_encoder.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



Learning Outcomes:

1. Understood the working of Bi-directional LSTM and its ability to capture context from both past and future sequences in text data.
2. Gained practical experience in building and training Bi-LSTM models for text classification using Python and deep learning frameworks.
3. Learned to evaluate model performance using metrics like accuracy, precision, recall, and F1-score for reliable classification results.