```
                                                 DATASCI 3ML3 FINAL
PROJECT.
```

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```
import pandas as pd
import os

file_name = "Food Delivery Time Prediction Case Study.xlsx"
directory_path = "/Users/apple/Desktop/DATASCI FINAL PROJECT/"

file_path = os.path.join(directory_path, file_name)

# Load the dataset into a pandas DataFrame
df = pd.read_excel(file_path)

# Display the first few rows of the DataFrame
df.head(11)

      ID Delivery_person_ID  Delivery_person_Age
Delivery_person_Ratings  \
0   4607     INDORES13DEL02                   37
4.9
1   B379     BANGRES18DEL02                   34
4.5
2   5D6D     BANGRES19DEL01                   23
4.4
3   7A6A    COIMBRES13DEL02                   38
4.7
4   70A2     CHENRES12DEL01                   32
4.6
5   9BB4      HYDRES09DEL03                   22
4.8
6   95B4   RANCHIRES15DEL01                   33
4.7
7   9EB2      MYSRES15DEL02                   35
4.6
8   1102      HYDRES05DEL02                   22
4.8
9   CDCD      DEHRES17DEL01                   36
4.2
10  D987      KOCRES16DEL01                   21
4.7

    Restaurant_latitude  Restaurant_longitude
Delivery_location_latitude  \
0             22.745049             75.892471
22.765049
```

```
1              12.913041              77.683237
13.043041
2              12.914264              77.678400
12.924264
3              11.003669              76.976494
11.053669
4              12.972793              80.249982
13.012793
5              17.431668              78.408321
17.461668
6              23.369746              85.339820
23.479746
7              12.352058              76.606650
12.482058
8              17.433809              78.386744
17.563809
9              30.327968              78.046106
30.397968
10             10.003064              76.307589
10.043064

    Delivery_location_longitude Type_of_order Type_of_vehicle
Time_taken(min)
0                     75.912471        Snack      motorcycle
24
1                     77.813237        Snack         scooter
33
2                     77.688400       Drinks      motorcycle
26
3                     77.026494       Buffet      motorcycle
21
4                     80.289982        Snack         scooter
30
5                     78.438321       Buffet      motorcycle
26
6                     85.449820         Meal         scooter
40
7                     76.736650         Meal      motorcycle
32
8                     78.516744       Buffet      motorcycle
34
9                     78.116106        Snack      motorcycle
46
10                    76.347589         Meal      motorcycle
23

#droping unnecessary columns.
df = df.drop(['ID', 'Delivery_person_ID'], axis=1)
```

```python
from sklearn.preprocessing import OneHotEncoder

encoder = OneHotEncoder(drop='if_binary')

encoded_features = encoder.fit_transform(df[['Type_of_order',
'Type_of_vehicle']])

# Convert the encoded features into a DataFrame
encoded_df = pd.DataFrame(encoded_features.toarray(),
columns=encoder.get_feature_names_out(['Type_of_order',
'Type_of_vehicle']))

df = pd.concat([df, encoded_df], axis=1)

# Drop the original categorical columns
df = df.drop(['Type_of_order', 'Type_of_vehicle'], axis=1)

#Getting an idea of the shape fo the dataset
print("Shape of DataFrame:", df.shape)
df.head(11)
```

```
Shape of DataFrame: (45593, 15)
```

```
    Delivery_person_Age  Delivery_person_Ratings  Restaurant_latitude  
\
0                    37                      4.9            22.745049

1                    34                      4.5            12.913041

2                    23                      4.4            12.914264

3                    38                      4.7            11.003669

4                    32                      4.6            12.972793

5                    22                      4.8            17.431668

6                    33                      4.7            23.369746

7                    35                      4.6            12.352058

8                    22                      4.8            17.433809

9                    36                      4.2            30.327968

10                   21                      4.7            10.003064


    Restaurant_longitude  Delivery_location_latitude  \
0              75.892471                   22.765049
1              77.683237                   13.043041
```

```
2              77.678400                           12.924264
3              76.976494                           11.053669
4              80.249982                           13.012793
5              78.408321                           17.461668
6              85.339820                           23.479746
7              76.606650                           12.482058
8              78.386744                           17.563809
9              78.046106                           30.397968
10             76.307589                           10.043064

    Delivery_location_longitude  Time_taken(min)  Type_of_order_Buffet  
\
0                     75.912471               24                   
0.0
1                     77.813237               33                   
0.0
2                     77.688400               26                   
0.0
3                     77.026494               21                   
1.0
4                     80.289982               30                   
0.0
5                     78.438321               26                   
1.0
6                     85.449820               40                   
0.0
7                     76.736650               32                   
0.0
8                     78.516744               34                   
1.0
9                     78.116106               46                   
0.0
10                    76.347589               23                   
0.0

    Type_of_order_Drinks   Type_of_order_Meal  
Type_of_order_Snack   \
0                     0.0                 0.0                   1.0   

1                     0.0                 0.0                   1.0   

2                     1.0                 0.0                   0.0   

3                     0.0                 0.0                   0.0   

4                     0.0                 0.0                   1.0   

5                     0.0                 0.0                   0.0   

6                     0.0                 1.0                   0.0   
```

```
7                      0.0                    1.0                     0.0

8                      0.0                    0.0                     0.0

9                      0.0                    0.0                     1.0

10                     0.0                    1.0                     0.0


    Type_of_vehicle_bicycle   Type_of_vehicle_electric_scooter   \
0                       0.0                                0.0
1                       0.0                                0.0
2                       0.0                                0.0
3                       0.0                                0.0
4                       0.0                                0.0
5                       0.0                                0.0
6                       0.0                                0.0
7                       0.0                                0.0
8                       0.0                                0.0
9                       0.0                                0.0
10                      0.0                                0.0

    Type_of_vehicle_motorcycle   Type_of_vehicle_scooter
0                          1.0                       0.0
1                          0.0                       1.0
2                          1.0                       0.0
3                          1.0                       0.0
4                          0.0                       1.0
5                          1.0                       0.0
6                          0.0                       1.0
7                          1.0                       0.0
8                          1.0                       0.0
9                          1.0                       0.0
10                         1.0                       0.0
```

```
#Finding the basic statistics of the dataset
df.describe()
```

```
       Delivery_person_Age  Delivery_person_Ratings
Restaurant_latitude  \
count         45593.000000             45593.000000
45593.000000
mean             29.544075                 4.632367
17.017729
std               5.696793                 0.327708
8.185109
min              15.000000                 1.000000            -
30.905562
25%              25.000000                 4.600000
```

```
12.933284
50%              29.000000                         4.700000
18.546947
75%              34.000000                         4.800000
22.728163
max              50.000000                         6.000000
30.914057

       Restaurant_longitude  Delivery_location_latitude  \
count          45593.000000                45593.000000
mean              70.231332                   17.465186
std               22.883647                    7.335122
min              -88.366217                    0.010000
25%               73.170000                   12.988453
50%               75.898497                   18.633934
75%               78.044095                   22.785049
max               88.433452                   31.054057

       Delivery_location_longitude  Time_taken(min)
Type_of_order_Buffet   \
count                 45593.000000     45593.000000
45593.000000
mean                     70.845702        26.294607
0.247406
std                      21.118812         9.383806
0.431510
min                       0.010000        10.000000
0.000000
25%                      73.280000        19.000000
0.000000
50%                      76.002574        26.000000
0.000000
75%                      78.107044        32.000000
0.000000
max                      88.563452        54.000000
1.000000

       Type_of_order_Drinks   Type_of_order_Meal   Type_of_order_Snack
\
count          45593.000000         45593.000000
45593.000000
mean               0.248328             0.251311
0.252955
std                0.432048             0.433771
0.434710
min                0.000000             0.000000
0.000000
25%                0.000000             0.000000
0.000000
50%                0.000000             0.000000
```

```
0.000000
75%                    0.000000             1.000000
1.000000
max                    1.000000             1.000000
1.000000

       Type_of_vehicle_bicycle   Type_of_vehicle_electric_scooter   \
count             45593.000000                       45593.000000
mean                  0.001491                           0.083653
std                   0.038591                           0.276870
min                   0.000000                           0.000000
25%                   0.000000                           0.000000
50%                   0.000000                           0.000000
75%                   0.000000                           0.000000
max                   1.000000                           1.000000

       Type_of_vehicle_motorcycle   Type_of_vehicle_scooter
count                45593.000000              45593.000000
mean                     0.579804                  0.335051
std                      0.493596                  0.472014
min                      0.000000                  0.000000
25%                      0.000000                  0.000000
50%                      1.000000                  0.000000
75%                      1.000000                  1.000000
max                      1.000000                  1.000000

#checking for null values
df.isnull().sum()

Delivery_person_Age                    0
Delivery_person_Ratings                0
Restaurant_latitude                    0
Restaurant_longitude                   0
Delivery_location_latitude             0
Delivery_location_longitude            0
Time_taken(min)                        0
Type_of_order_Buffet                   0
Type_of_order_Drinks                   0
Type_of_order_Meal                     0
Type_of_order_Snack                    0
Type_of_vehicle_bicycle                0
Type_of_vehicle_electric_scooter       0
Type_of_vehicle_motorcycle             0
Type_of_vehicle_scooter                0
dtype: int64

# Import necessary libraries
from geopy.distance import geodesic
import pandas as pd
```

```python
# EDA: for deriving the distance, we use Vincenty Formula.
# Define function to calculate distance between two points in miles
def get_distance(row):
    point1 = (row['Restaurant_latitude'], row['Restaurant_longitude'])
    point2 = (row['Delivery_location_latitude'],
row['Delivery_location_longitude'])
    return geodesic(point1, point2).miles

# Calculate distance for all points and store in a new column
'Distance_miles'
df['Distance_miles'] = df.apply(get_distance, axis=1)

# Display the first few rows of the DataFrame with the Distance_miles
column
print(df.head())
```

```
   Delivery_person_Age  Delivery_person_Ratings
Restaurant_latitude  \
0                   37                      4.9            22.745049

1                   34                      4.5            12.913041

2                   23                      4.4            12.914264

3                   38                      4.7            11.003669

4                   32                      4.6            12.972793


   Restaurant_longitude  Delivery_location_latitude  \
0             75.892471                   22.765049
1             77.683237                   13.043041
2             77.678400                   12.924264
3             76.976494                   11.053669
4             80.249982                   13.012793

   Delivery_location_longitude  Time_taken(min)  Type_of_order_Buffet
\
0                    75.912471               24                   0.0

1                    77.813237               33                   0.0

2                    77.688400               26                   0.0

3                    77.026494               21                   1.0

4                    80.289982               30                   0.0


   Type_of_order_Drinks   Type_of_order_Meal   Type_of_order_Snack   \
0                   0.0                  0.0                   1.0
```

```
1                     0.0                     0.0                        1.0
2                     1.0                     0.0                        0.0
3                     0.0                     0.0                        0.0
4                     0.0                     0.0                        1.0

   Type_of_vehicle_bicycle   Type_of_vehicle_electric_scooter   \
0                     0.0                                0.0
1                     0.0                                0.0
2                     0.0                                0.0
3                     0.0                                0.0
4                     0.0                                0.0

   Type_of_vehicle_motorcycle   Type_of_vehicle_scooter
Distance_miles
0                        1.0                        0.0
1.876999
1                        0.0                        1.0
12.516738
2                        1.0                        0.0
0.962935
3                        1.0                        0.0
4.830848
4                        0.0                        1.0
3.851195

#observe the statistics for the distance_miles column
df.head(11)

    Delivery_person_Age  Delivery_person_Ratings  Restaurant_latitude
\
0                    37                      4.9            22.745049

1                    34                      4.5            12.913041

2                    23                      4.4            12.914264

3                    38                      4.7            11.003669

4                    32                      4.6            12.972793

5                    22                      4.8            17.431668

6                    33                      4.7            23.369746

7                    35                      4.6            12.352058

8                    22                      4.8            17.433809

9                    36                      4.2            30.327968

10                   21                      4.7            10.003064
```

```
    Restaurant_longitude  Delivery_location_latitude  \
0              75.892471                   22.765049
1              77.683237                   13.043041
2              77.678400                   12.924264
3              76.976494                   11.053669
4              80.249982                   13.012793
5              78.408321                   17.461668
6              85.339820                   23.479746
7              76.606650                   12.482058
8              78.386744                   17.563809
9              78.046106                   30.397968
10             76.307589                   10.043064

    Delivery_location_longitude  Time_taken(min)  Type_of_order_Buffet
\
0                     75.912471               24
0.0
1                     77.813237               33
0.0
2                     77.688400               26
0.0
3                     77.026494               21
1.0
4                     80.289982               30
0.0
5                     78.438321               26
1.0
6                     85.449820               40
0.0
7                     76.736650               32
0.0
8                     78.516744               34
1.0
9                     78.116106               46
0.0
10                    76.347589               23
0.0

    Type_of_order_Drinks   Type_of_order_Meal
Type_of_order_Snack   \
0                     0.0                  0.0                    1.0

1                     0.0                  0.0                    1.0

2                     1.0                  0.0                    0.0

3                     0.0                  0.0                    0.0
```

```
4                      0.0                   0.0                     1.0

5                      0.0                   0.0                     0.0

6                      0.0                   1.0                     0.0

7                      0.0                   1.0                     0.0

8                      0.0                   0.0                     0.0

9                      0.0                   0.0                     1.0

10                     0.0                   1.0                     0.0


    Type_of_vehicle_bicycle   Type_of_vehicle_electric_scooter   \
0                       0.0                                0.0
1                       0.0                                0.0
2                       0.0                                0.0
3                       0.0                                0.0
4                       0.0                                0.0
5                       0.0                                0.0
6                       0.0                                0.0
7                       0.0                                0.0
8                       0.0                                0.0
9                       0.0                                0.0
10                      0.0                                0.0

    Type_of_vehicle_motorcycle   Type_of_vehicle_scooter
Distance_miles
0                          1.0                        0.0
1.876999
1                          0.0                        1.0
12.516738
2                          1.0                        0.0
0.962935
3                          1.0                        0.0
4.830848
4                          0.0                        1.0
3.851195
5                          1.0                        0.0
2.859678
6                          0.0                        1.0
10.300400
7                          1.0                        0.0
12.529942
8                          1.0                        0.0
12.390278
9                          1.0                        0.0
6.382392
```

```
10                            1.0                        0.0
3.870755
```

```python
from sklearn.preprocessing import MinMaxScaler

# Define the columns to scale
columns_to_scale = ['Delivery_person_Age', 'Delivery_person_Ratings',
                    'Restaurant_latitude', 'Restaurant_longitude',
                    'Delivery_location_latitude',
'Delivery_location_longitude',
                    'Distance_miles', 'Time_taken(min)']

# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Fit and transform the data
df_scaled = df.copy()
df_scaled[columns_to_scale] =
scaler.fit_transform(df_scaled[columns_to_scale])

df_scaled.head(11)
```

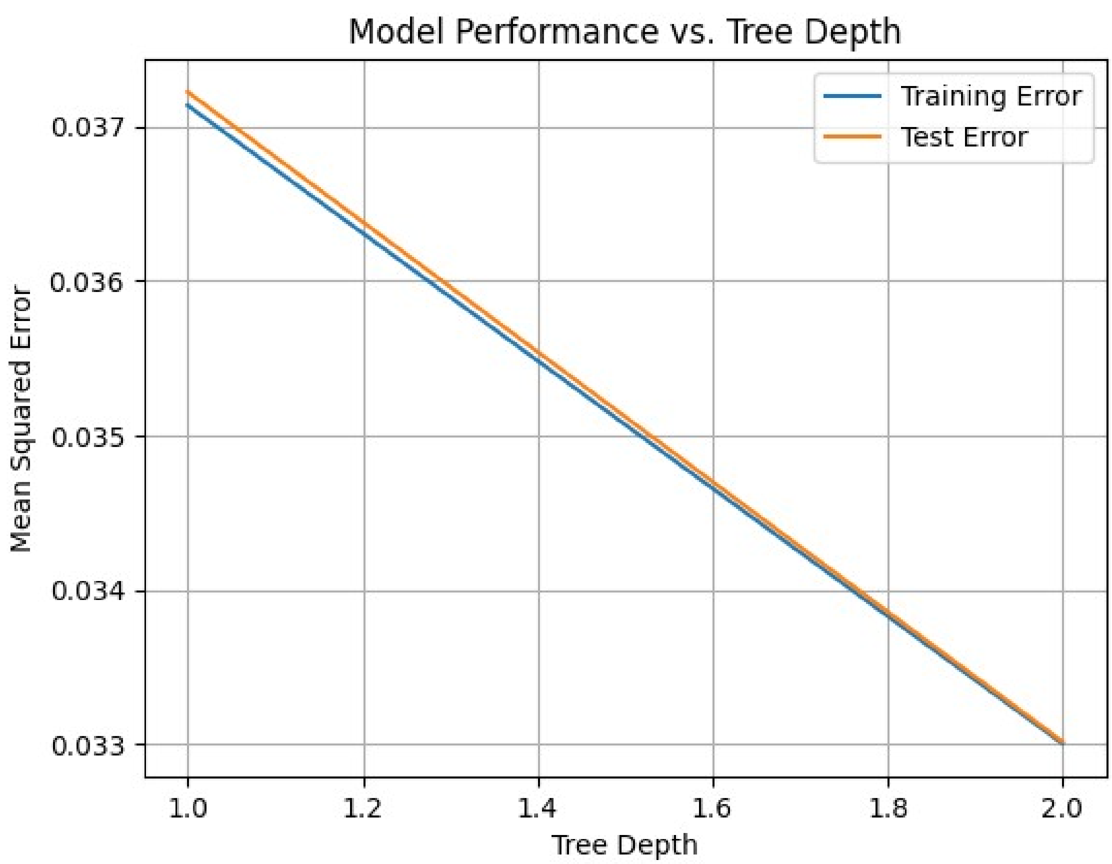
```
    Delivery_person_Age  Delivery_person_Ratings  Restaurant_latitude
\
0              0.628571                     0.78             0.867857

1              0.542857                     0.70             0.708814

2              0.228571                     0.68             0.708834

3              0.657143                     0.74             0.677928

4              0.485714                     0.72             0.709780

5              0.200000                     0.76             0.781908

6              0.514286                     0.74             0.877963

7              0.571429                     0.72             0.699739

8              0.200000                     0.76             0.781942

9              0.600000                     0.64             0.990519

10             0.171429                     0.74             0.661742


    Restaurant_longitude  Delivery_location_latitude  \
0               0.929067                    0.732992
1               0.939196                    0.419824
2               0.939168                    0.415998
```

```
3               0.935198                           0.355742
4               0.953713                           0.418850
5               0.943297                           0.562158
6               0.982502                           0.756014
7               0.933106                           0.401753
8               0.943175                           0.565448
9               0.941248                           0.978866
10              0.931415                           0.323188

    Delivery_location_longitude  Time_taken(min)  Type_of_order_Buffet  
\
0                      0.857137         0.318182                       
0.0
1                      0.878602         0.522727                       
0.0
2                      0.877192         0.363636                       
0.0
3                      0.869718         0.250000                       
1.0
4                      0.906571         0.454545                       
0.0
5                      0.885661         0.363636                       
1.0
6                      0.964839         0.681818                       
0.0
7                      0.866444         0.500000                       
0.0
8                      0.886546         0.545455                       
1.0
9                      0.882022         0.818182                       
0.0
10                     0.862051         0.295455                       
0.0

    Type_of_order_Drinks   Type_of_order_Meal  
Type_of_order_Snack   \
0                      0.0                  0.0                    1.0   

1                      0.0                  0.0                    1.0   

2                      1.0                  0.0                    0.0   

3                      0.0                  0.0                    0.0   

4                      0.0                  0.0                    1.0   

5                      0.0                  0.0                    0.0   

6                      0.0                  1.0                    0.0   
```

```
7                     0.0                    1.0                     0.0

8                     0.0                    0.0                     0.0

9                     0.0                    0.0                     1.0

10                    0.0                    1.0                     0.0


    Type_of_vehicle_bicycle   Type_of_vehicle_electric_scooter   \
0                        0.0                                0.0
1                        0.0                                0.0
2                        0.0                                0.0
3                        0.0                                0.0
4                        0.0                                0.0
5                        0.0                                0.0
6                        0.0                                0.0
7                        0.0                                0.0
8                        0.0                                0.0
9                        0.0                                0.0
10                       0.0                                0.0

    Type_of_vehicle_motorcycle   Type_of_vehicle_scooter
Distance_miles
0                           1.0                         0.0
0.000079
1                           0.0                         1.0
0.000948
2                           1.0                         0.0
0.000004
3                           1.0                         0.0
0.000320
4                           0.0                         1.0
0.000240
5                           1.0                         0.0
0.000159
6                           0.0                         1.0
0.000767
7                           1.0                         0.0
0.000949
8                           1.0                         0.0
0.000938
9                           1.0                         0.0
0.000447
10                          1.0                         0.0
0.000242

from sklearn.model_selection import train_test_split

# Split the data into features (X) and target variable (y)
```

```python
X = df_scaled.drop('Time_taken(min)', axis=1)  # Features
y = df_scaled['Time_taken(min)']  # Target variable

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

#base model for dt and gb
import pandas as pd
import numpy as np
from sklearn.metrics import mean_squared_error, mean_absolute_error

def model_01(model, X_train, y_train, X_test, y_test):
    # Let's calculate some metric MSE
    ypredict_train = model.predict(X_train)
    ypredict_test = model.predict(X_test)

    metric = []

    # Mean Squared Error (MSE)
    mse_train = mean_squared_error(y_train, ypredict_train)
    mse_test = mean_squared_error(y_test, ypredict_test)

    # Create a DataFrame to store the metrics
    df = pd.DataFrame({
        'Metric': ['MSE (Mean Squared Error)'],
        'Train': [mse_train],
        'Test': [mse_test]
    })

    return df, ypredict_train, ypredict_test

#decision tree (1,3)

import numpy as np
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error

dt_model = DecisionTreeRegressor()
dt_model.fit(X_train, y_train)

metric_df_dt, ypredict_train_dt, ypredict_test_dt = model_01(dt_model,
X_train, y_train, X_test, y_test)
print("Decision Tree Model:")
print(metric_df_dt)

depths = range(1,3)  # Adjust the range of depths as needed

train_errors = [mean_squared_error(y_train,
DecisionTreeRegressor(max_depth=depth, random_state=42).fit(X_train,
```

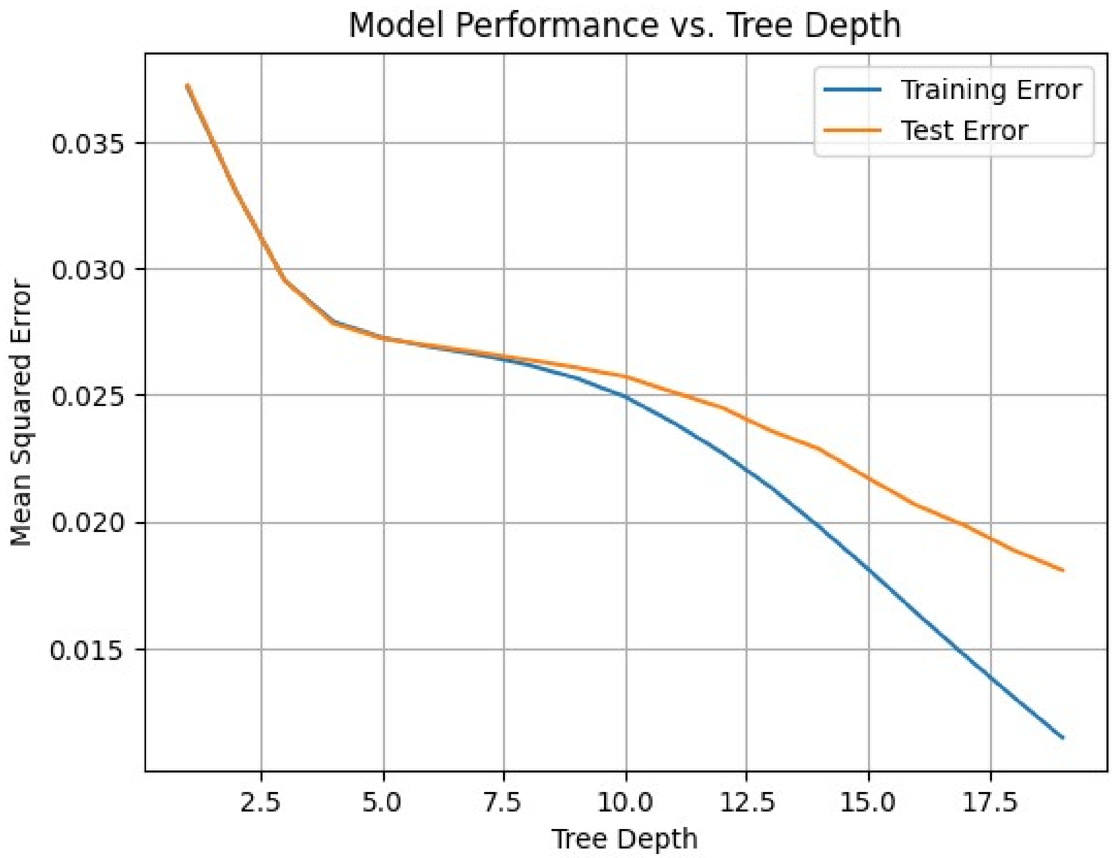
```
y_train).predict(X_train)) for depth in depths]
test_errors = [mean_squared_error(y_test,
DecisionTreeRegressor(max_depth=depth, random_state=42).fit(X_train,
y_train).predict(X_test)) for depth in depths]

plt.plot(depths, train_errors, label='Training Error')
plt.plot(depths, test_errors, label='Test Error')
plt.xlabel('Tree Depth')
plt.ylabel('Mean Squared Error')
plt.title('Model Performance vs. Tree Depth')
plt.legend()
plt.grid(True)
plt.show()

# Find the depths with the lowest training and test errors
best_train_depth = depths[np.argmin(train_errors)]
best_test_depth = depths[np.argmin(test_errors)]
print(f"Best Depth for Training Error: {best_train_depth}")
print(f"Best Depth for Test Error: {best_test_depth}")

Decision Tree Model:
                     Metric     Train      Test
0  MSE (Mean Squared Error)  0.000377  0.011473
```



```
Best Depth for Training Error: 2
Best Depth for Test Error: 2
```

```python
#decision tree (1,20)
import numpy as np
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error

dt_model = DecisionTreeRegressor()
dt_model.fit(X_train, y_train)

metric_df_dt, ypredict_train_dt, ypredict_test_dt = model_01(dt_model,
X_train, y_train, X_test, y_test)
print("Decision Tree Model:")
print(metric_df_dt)

depths = range(1,20)  # Adjust the range of depths as needed

train_errors = [mean_squared_error(y_train,
DecisionTreeRegressor(max_depth=depth, random_state=42).fit(X_train,
y_train).predict(X_train)) for depth in depths]
test_errors = [mean_squared_error(y_test,
DecisionTreeRegressor(max_depth=depth, random_state=42).fit(X_train,
y_train).predict(X_test)) for depth in depths]

plt.plot(depths, train_errors, label='Training Error')
plt.plot(depths, test_errors, label='Test Error')
plt.xlabel('Tree Depth')
plt.ylabel('Mean Squared Error')
plt.title('Model Performance vs. Tree Depth')
plt.legend()
plt.grid(True)
plt.show()

# Find the depths with the lowest training and test errors
best_train_depth = depths[np.argmin(train_errors)]
best_test_depth = depths[np.argmin(test_errors)]
print(f"Best Depth for Training Error: {best_train_depth}")
print(f"Best Depth for Test Error: {best_test_depth}")
```

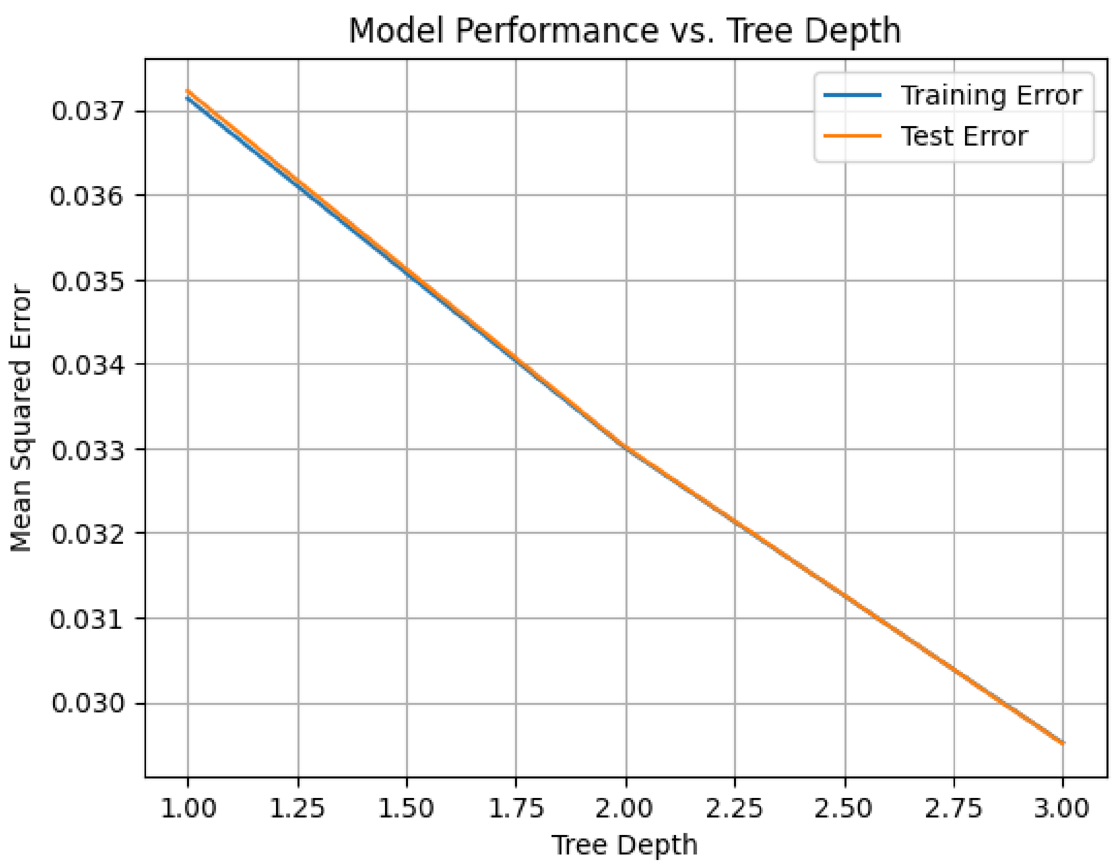
```
Decision Tree Model:
                     Metric     Train      Test
0  MSE (Mean Squared Error)  0.000377  0.011454
```




```
Best Depth for Training Error: 19
Best Depth for Test Error: 19

#decision tree (1,4)
import numpy as np
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error

dt_model = DecisionTreeRegressor()
dt_model.fit(X_train, y_train)

metric_df_dt, ypredict_train_dt, ypredict_test_dt = model_01(dt_model,
X_train, y_train, X_test, y_test)
print("Decision Tree Model:")
print(metric_df_dt)

depths = range(1,4)  # Adjust the range of depths as needed

train_errors = [mean_squared_error(y_train,
DecisionTreeRegressor(max_depth=depth, random_state=42).fit(X_train,
y_train).predict(X_train)) for depth in depths]
test_errors = [mean_squared_error(y_test,
```

```
DecisionTreeRegressor(max_depth=depth, random_state=42).fit(X_train,
y_train).predict(X_test)) for depth in depths]

plt.plot(depths, train_errors, label='Training Error')
plt.plot(depths, test_errors, label='Test Error')
plt.xlabel('Tree Depth')
plt.ylabel('Mean Squared Error')
plt.title('Model Performance vs. Tree Depth')
plt.legend()
plt.grid(True)
plt.show()

# Find the depths with the lowest training and test errors
best_train_depth = depths[np.argmin(train_errors)]
best_test_depth = depths[np.argmin(test_errors)]
print(f"Best Depth for Training Error: {best_train_depth}")
print(f"Best Depth for Test Error: {best_test_depth}")
```

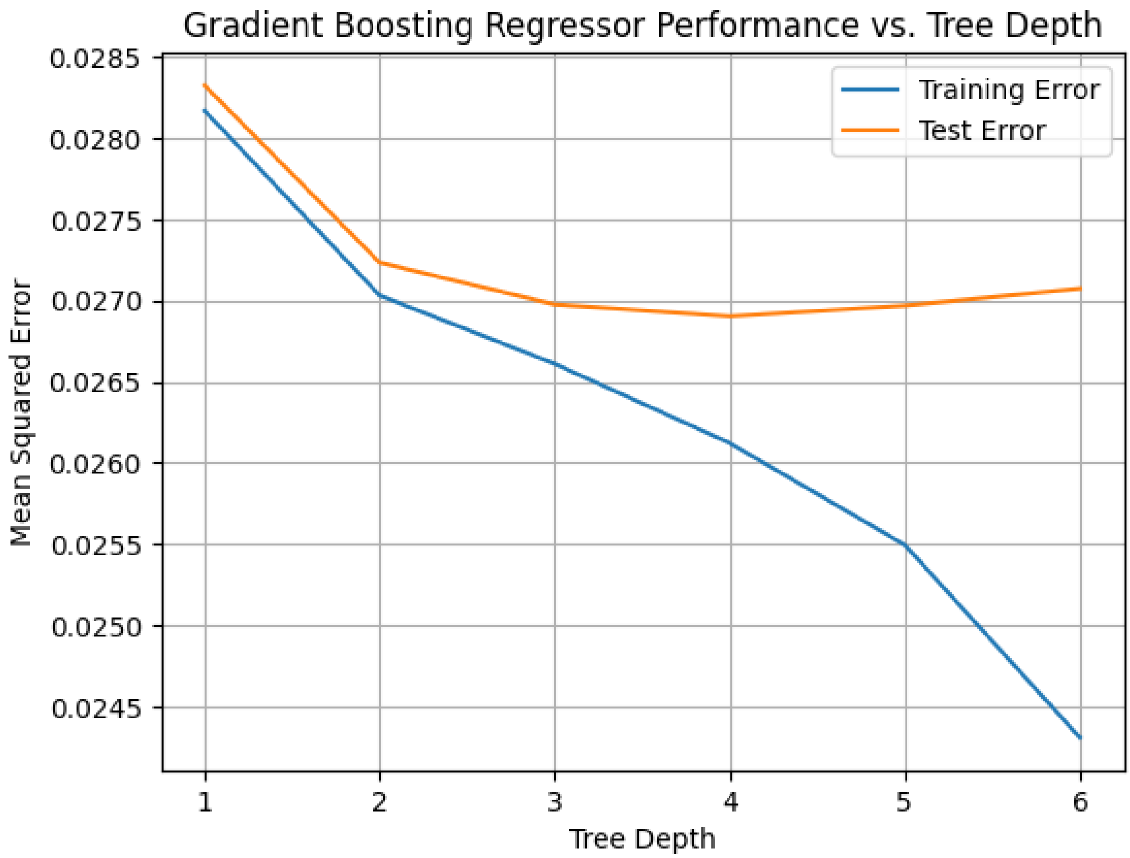
```
Decision Tree Model:
                     Metric     Train      Test
0  MSE (Mean Squared Error)  0.000377  0.011377
```



```
Best Depth for Training Error: 3
Best Depth for Test Error: 3
```

```python
# Gradient boosting (1,7)
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error
import numpy as np

gb_model = GradientBoostingRegressor()
gb_model.fit(X_train, y_train)

metric_df_gb, ypredict_train_gb, ypredict_test_gb = model_01(gb_model,
X_train, y_train, X_test, y_test)
print("Gradient Boosting Model:")
print(metric_df_gb)

depths = range(1, 7)  # Adjust the range of depths as needed

train_errors = [mean_squared_error(y_train,
GradientBoostingRegressor(max_depth=depth).fit(X_train,
y_train).predict(X_train)) for depth in depths]
test_errors = [mean_squared_error(y_test,
GradientBoostingRegressor(max_depth=depth).fit(X_train,
y_train).predict(X_test)) for depth in depths]

plt.plot(depths, train_errors, label='Training Error')
plt.plot(depths, test_errors, label='Test Error')
plt.xlabel('Tree Depth')
plt.ylabel('Mean Squared Error')
plt.title('Gradient Boosting Regressor Performance vs. Tree Depth')
plt.legend()
plt.grid(True)
plt.show()

# Find the depths with the lowest training and test errors
best_train_depth = depths[np.argmin(train_errors)]
best_test_depth = depths[np.argmin(test_errors)]
print(f"Best Depth for Training Error: {best_train_depth}")
print(f"Best Depth for Test Error: {best_test_depth}")
```

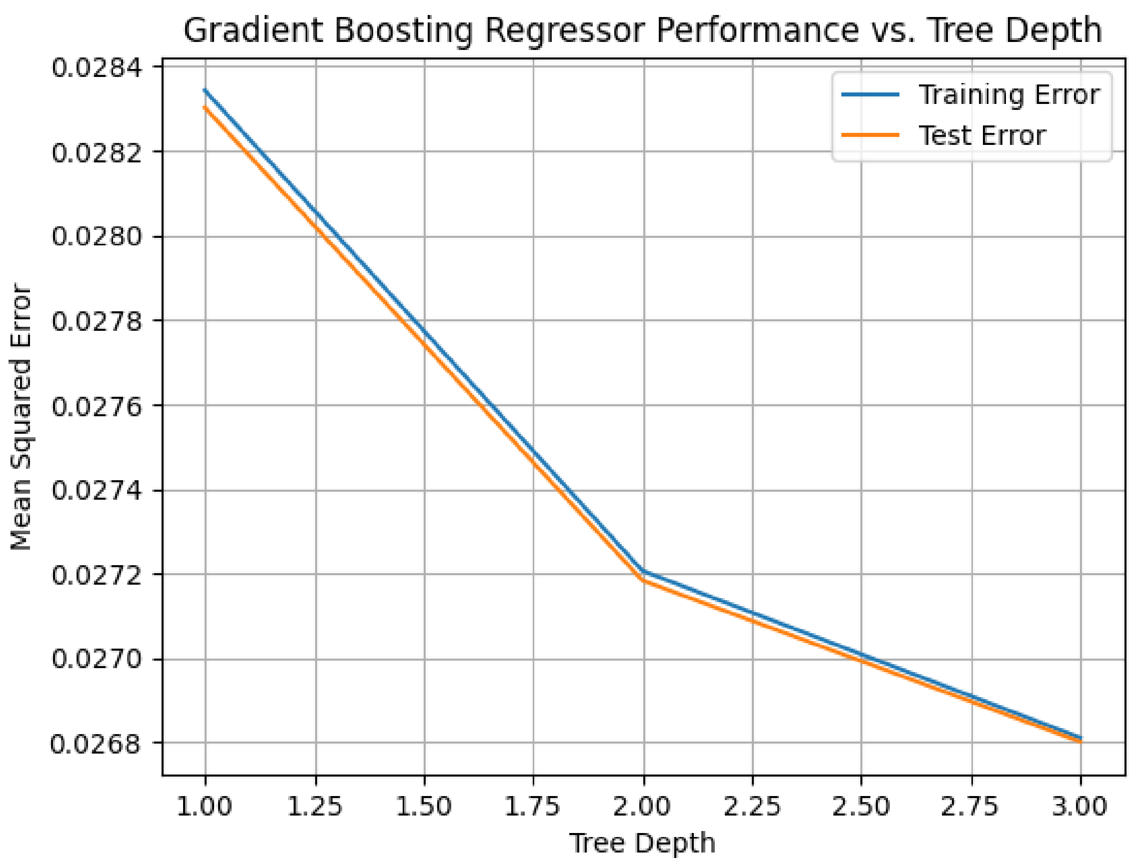
```
Gradient Boosting Model:
                     Metric    Train      Test
0  MSE (Mean Squared Error)  0.02661  0.026978
```




```
Best Depth for Training Error: 6
Best Depth for Test Error: 4

# Gradient boosting (1,4)
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error
import numpy as np

gb_model = GradientBoostingRegressor()
gb_model.fit(X_train, y_train)

metric_df_gb, ypredict_train_gb, ypredict_test_gb = model_01(gb_model,
X_train, y_train, X_test, y_test)
print("Gradient Boosting Model:")
print(metric_df_gb)

depths = range(1, 4)  # Adjust the range of depths as needed

train_errors = [mean_squared_error(y_train,
GradientBoostingRegressor(max_depth=depth).fit(X_train,
y_train).predict(X_train)) for depth in depths]
test_errors = [mean_squared_error(y_test,
GradientBoostingRegressor(max_depth=depth).fit(X_train,
```

```
y_train).predict(X_test)) for depth in depths]

plt.plot(depths, train_errors, label='Training Error')
plt.plot(depths, test_errors, label='Test Error')
plt.xlabel('Tree Depth')
plt.ylabel('Mean Squared Error')
plt.title('Gradient Boosting Regressor Performance vs. Tree Depth')
plt.legend()
plt.grid(True)
plt.show()

# Find the depths with the lowest training and test errors
best_train_depth = depths[np.argmin(train_errors)]
best_test_depth = depths[np.argmin(test_errors)]
print(f"Best Depth for Training Error: {best_train_depth}")
print(f"Best Depth for Test Error: {best_test_depth}")
```

```
Gradient Boosting Model:
                     Metric     Train      Test
0  MSE (Mean Squared Error)  0.026812  0.026802
```




```
Best Depth for Training Error: 3
Best Depth for Test Error: 3
```

```
# Small neural network model
model_04 = Sequential([
    Dense(10, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(1)
])

# Compile the model
model_04.compile(optimizer='rmsprop', loss='mean_squared_error')

# Train the model
history_small_model = model_04.fit(X_train, y_train, epochs=50,
batch_size=128, validation_split=0.2)
```

```
Epoch 1/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0766 - val_loss:
0.0439
Epoch 2/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0418 - val_loss:
0.0419
Epoch 3/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0399 - val_loss:
0.0402
Epoch 4/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0387 - val_loss:
0.0396
Epoch 5/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0390 - val_loss:
0.0389
Epoch 6/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0376 - val_loss:
0.0385
Epoch 7/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0375 - val_loss:
0.0383
Epoch 8/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0373 - val_loss:
0.0380
Epoch 9/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0366 - val_loss:
0.0378
Epoch 10/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0368 - val_loss:
0.0375
Epoch 11/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0370 - val_loss:
0.0376
Epoch 12/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0364 - val_loss:
0.0374
Epoch 13/50
```

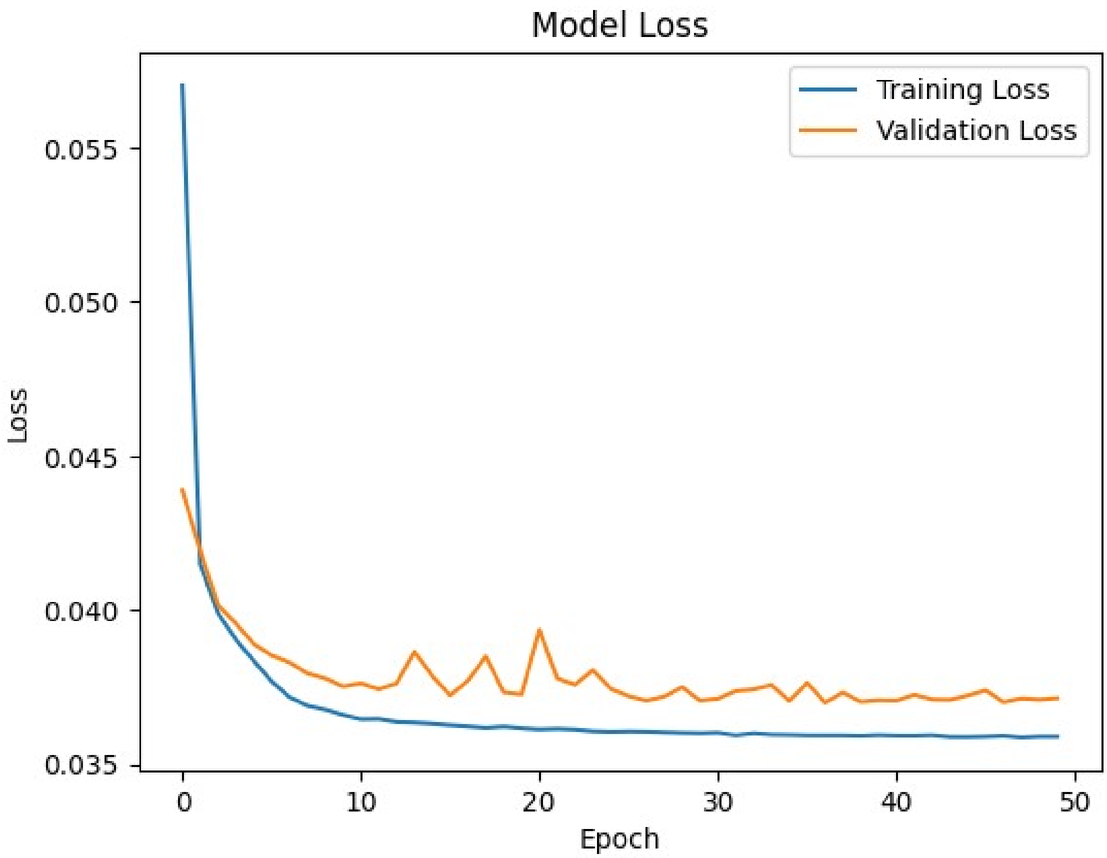
```
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0365 - val_loss:
0.0376
Epoch 14/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0362 - val_loss:
0.0387
Epoch 15/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0362 - val_loss:
0.0379
Epoch 16/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0357 - val_loss:
0.0372
Epoch 17/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0360 - val_loss:
0.0377
Epoch 18/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0364 - val_loss:
0.0385
Epoch 19/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0362 - val_loss:
0.0373
Epoch 20/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0361 - val_loss:
0.0373
Epoch 21/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0360 - val_loss:
0.0394
Epoch 22/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0360 - val_loss:
0.0378
Epoch 23/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0359 - val_loss:
0.0376
Epoch 24/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0361 - val_loss:
0.0381
Epoch 25/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0364 - val_loss:
0.0374
Epoch 26/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0360 - val_loss:
0.0372
Epoch 27/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0362 - val_loss:
0.0371
Epoch 28/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0361 - val_loss:
0.0372
Epoch 29/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0355 - val_loss:
```

```
0.0375
Epoch 30/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0359 - val_loss:
0.0371
Epoch 31/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0364 - val_loss:
0.0371
Epoch 32/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0355 - val_loss:
0.0374
Epoch 33/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0362 - val_loss:
0.0374
Epoch 34/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0360 - val_loss:
0.0376
Epoch 35/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0364 - val_loss:
0.0371
Epoch 36/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0367 - val_loss:
0.0376
Epoch 37/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0357 - val_loss:
0.0370
Epoch 38/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0359 - val_loss:
0.0373
Epoch 39/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0363 - val_loss:
0.0370
Epoch 40/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0363 - val_loss:
0.0371
Epoch 41/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0356 - val_loss:
0.0371
Epoch 42/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0359 - val_loss:
0.0373
Epoch 43/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0361 - val_loss:
0.0371
Epoch 44/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0351 - val_loss:
0.0371
Epoch 45/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0353 - val_loss:
0.0372
```

```
Epoch 46/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0360 - val_loss:
0.0374
Epoch 47/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0360 - val_loss:
0.0370
Epoch 48/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0359 - val_loss:
0.0371
Epoch 49/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0361 - val_loss:
0.0371
Epoch 50/50
228/228 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0360 - val_loss:
0.0371
```

```python
import matplotlib.pyplot as plt
# Calculate test loss
test_loss = model_04.evaluate(X_test, y_test)
print("Test Loss:", test_loss)
# Calculate MSE for training data
mse_train = mean_squared_error(y_train, model_04.predict(X_train))
print("Mean Squared Error (MSE) for training data:", mse_train)
# Calculate MSE for test data
mse_test = mean_squared_error(y_test, model_04.predict(X_test))
print("Mean Squared Error (MSE) for test data:", mse_test)


# Plot training loss
plt.plot(history_small_model.history['loss'], label='Training Loss')
# Plot validation loss
plt.plot(history_small_model.history['val_loss'], label='Validation
Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

```
428/428 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0360
Test Loss: 0.03607228398323059
1140/1140 ━━━━━━━━━━━━━━━━━━━━ 1s 981us/step
Mean Squared Error (MSE) for training data: 0.03607497909798289
428/428 ━━━━━━━━━━━━━━━━━━━━ 0s 968us/step
Mean Squared Error (MSE) for test data: 0.03609767022159636
```




```
#neural network model
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
import numpy as np


num_features = X_train.shape[1]

# Define the model architecture
model_02 = Sequential([
    Dense(128, activation='relu', input_shape=(num_features,)),
    Dense(64, activation='relu'),
    Dense(1)
])

# Compile the model
model_02.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
history = model_02.fit(X_train, y_train,
```

```
                    validation_data=(X_test, y_test),
                    batch_size=64,
                    epochs=50,
                    verbose=1,
                    shuffle=True)
```

```
2024-04-26 11:29:06.512277: I
tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow
binary is optimized to use available CPU instructions in performance-
critical operations.
To enable the following instructions: AVX2 FMA, in other operations,
rebuild TensorFlow with the appropriate compiler flags.

Epoch 1/50

/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages/keras/src/layers/core/dense.py:85: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using
Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer,
**kwargs)

499/499 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.0524 - val_loss:
0.0375
Epoch 2/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0369 - val_loss:
0.0367
Epoch 3/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0376 - val_loss:
0.0367
Epoch 4/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0366 - val_loss:
0.0358
Epoch 5/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0355 - val_loss:
0.0359
Epoch 6/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0362 - val_loss:
0.0353
Epoch 7/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0352 - val_loss:
0.0352
Epoch 8/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0350 - val_loss:
0.0348
Epoch 9/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0346 - val_loss:
0.0384
Epoch 10/50
```

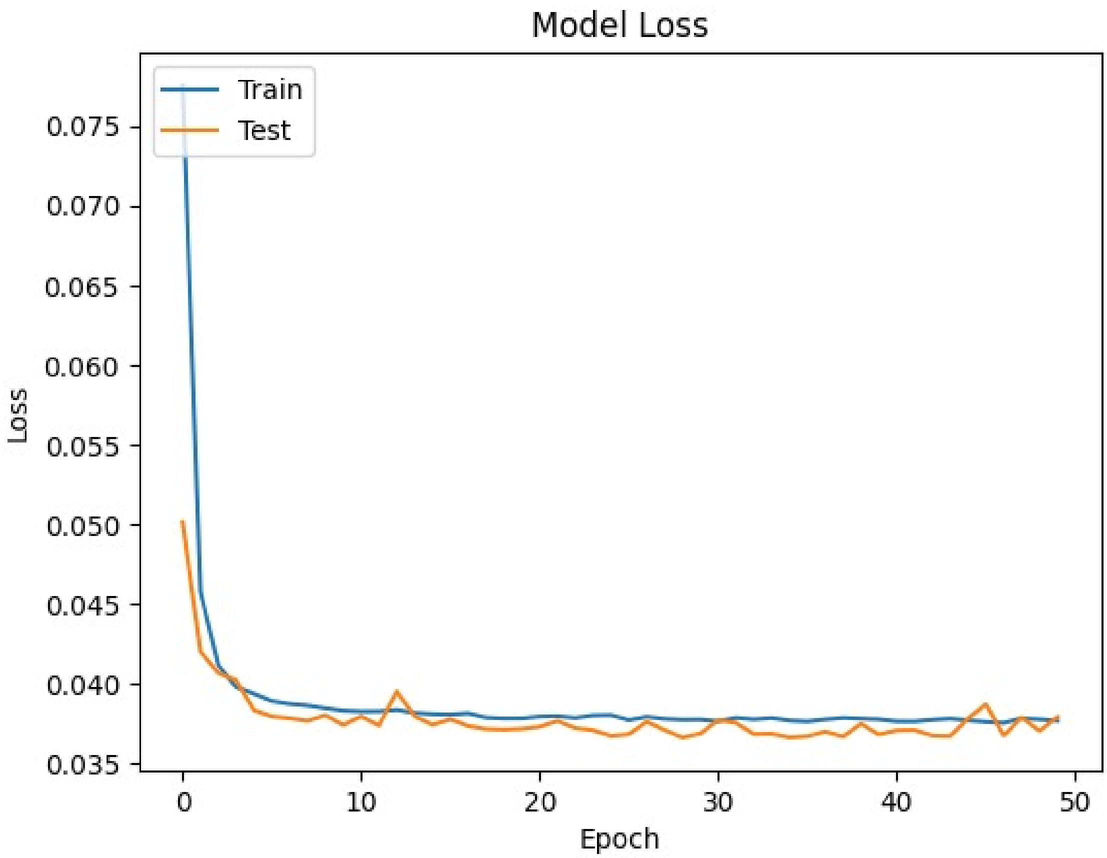
```
499/499 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - loss: 0.0353 - val_loss: 
0.0351
Epoch 11/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0343 - val_loss: 
0.0352
Epoch 12/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0344 - val_loss: 
0.0352
Epoch 13/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0346 - val_loss: 
0.0344
Epoch 14/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0343 - val_loss: 
0.0348
Epoch 15/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0344 - val_loss: 
0.0342
Epoch 16/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0343 - val_loss: 
0.0355
Epoch 17/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0342 - val_loss: 
0.0341
Epoch 18/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0338 - val_loss: 
0.0345
Epoch 19/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0338 - val_loss: 
0.0341
Epoch 20/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0343 - val_loss: 
0.0342
Epoch 21/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0334 - val_loss: 
0.0340
Epoch 22/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0338 - val_loss: 
0.0344
Epoch 23/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0341 - val_loss: 
0.0338
Epoch 24/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0338 - val_loss: 
0.0336
Epoch 25/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0331 - val_loss: 
0.0341
Epoch 26/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0330 - val_loss: 
```

```
0.0340
Epoch 27/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0334 - val_loss:
0.0344
Epoch 28/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0337 - val_loss:
0.0336
Epoch 29/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0327 - val_loss:
0.0338
Epoch 30/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0332 - val_loss:
0.0340
Epoch 31/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0333 - val_loss:
0.0336
Epoch 32/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0332 - val_loss:
0.0335
Epoch 33/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0334 - val_loss:
0.0333
Epoch 34/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0335 - val_loss:
0.0340
Epoch 35/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0331 - val_loss:
0.0334
Epoch 36/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0332 - val_loss:
0.0333
Epoch 37/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - loss: 0.0330 - val_loss:
0.0332
Epoch 38/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0330 - val_loss:
0.0331
Epoch 39/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0326 - val_loss:
0.0336
Epoch 40/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0328 - val_loss:
0.0340
Epoch 41/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0332 - val_loss:
0.0335
Epoch 42/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0332 - val_loss:
0.0332
```

```
Epoch 43/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0327 - val_loss:
0.0335
Epoch 44/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0327 - val_loss:
0.0330
Epoch 45/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0328 - val_loss:
0.0331
Epoch 46/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0328 - val_loss:
0.0330
Epoch 47/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0326 - val_loss:
0.0332
Epoch 48/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0328 - val_loss:
0.0341
Epoch 49/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0333 - val_loss:
0.0331
Epoch 50/50
499/499 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0330 - val_loss:
0.0340
```

```python
#test loss and plot for nn
# calculate test loss
loss = model_02.evaluate(X_test, y_test, verbose=0)
print("Test Loss:", loss)
# Calculate MSE for training data
mse_train = mean_squared_error(y_train, model_02.predict(X_train))
print("Mean Squared Error (MSE) for training data:", mse_train)
# Calculate MSE for test data
mse_test = mean_squared_error(y_test, model_02.predict(X_test))
print("Mean Squared Error (MSE) for test data:", mse_test)

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
```

```
Test Loss: 0.03255172073841095
1140/1140 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step
Mean Squared Error (MSE) for training data: 0.03238161095349632
428/428 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
Mean Squared Error (MSE) for test data: 0.03257640276547331

<matplotlib.legend.Legend at 0x13a6dc170>
```




```
#nn model with regularization
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras import regularizers


num_features = X_train.shape[1]

# Define the model architecture with regularization
model_03 = Sequential([
    Dense(128, activation='relu',
kernel_regularizer=regularizers.l2(0.001),
input_shape=(num_features,)),
    Dropout(0.2),  # Dropout layer with a dropout rate of 20%
    Dense(64, activation='relu',
kernel_regularizer=regularizers.l2(0.001)),
    Dropout(0.2),  # Dropout layer with a dropout rate of 20%
    Dense(1)
])

# Compile the model
model_03.compile(optimizer='adam', loss='mse')
```

```
# Train the model
history = model_03.fit(X_train, y_train, validation_data=(X_test,
y_test), epochs=50, batch_size=64, verbose=1)
```

```
Epoch 1/50

/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages/keras/src/layers/core/dense.py:85: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using
Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer,
**kwargs)

570/570 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.1060 - val_loss:
0.0501
Epoch 2/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0485 - val_loss:
0.0420
Epoch 3/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0417 - val_loss:
0.0407
Epoch 4/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0402 - val_loss:
0.0402
Epoch 5/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0395 - val_loss:
0.0383
Epoch 6/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0394 - val_loss:
0.0379
Epoch 7/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - loss: 0.0384 - val_loss:
0.0378
Epoch 8/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0385 - val_loss:
0.0377
Epoch 9/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0383 - val_loss:
0.0380
Epoch 10/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step - loss: 0.0384 - val_loss:
0.0374
Epoch 11/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0384 - val_loss:
0.0380
Epoch 12/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0384 - val_loss:
0.0374
```

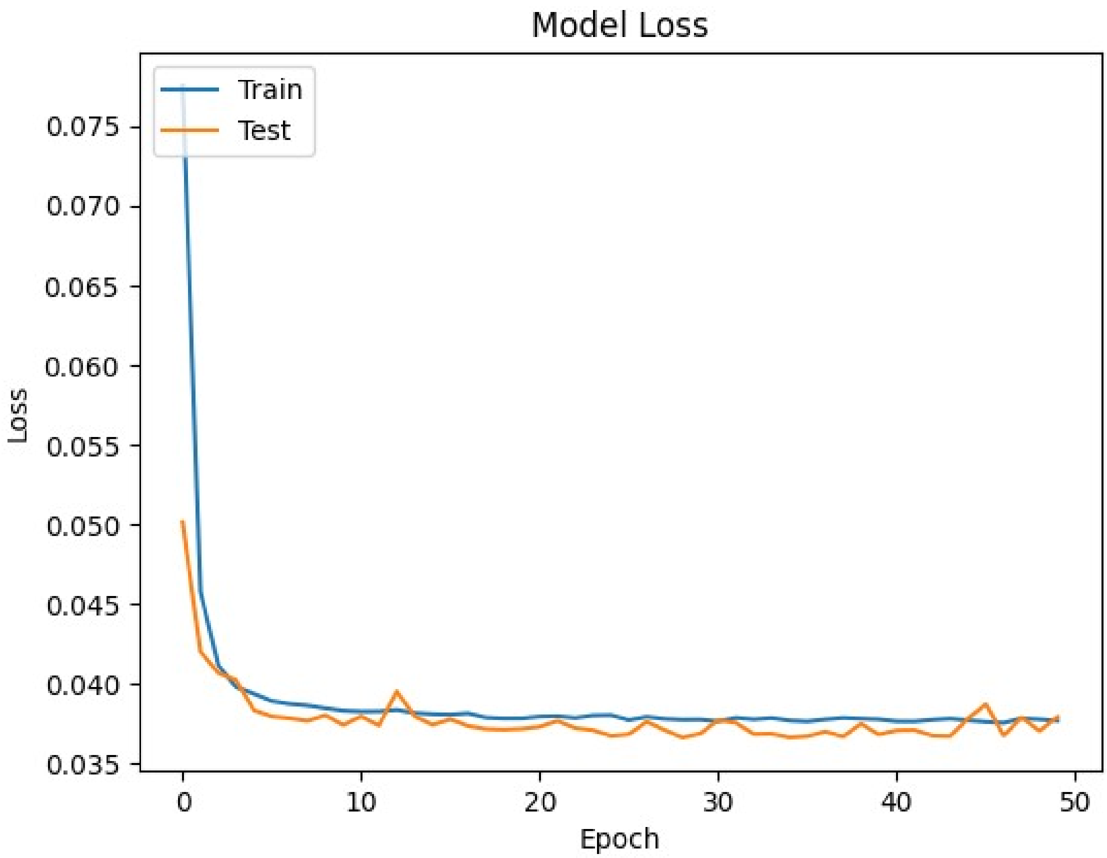
```
Epoch 13/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0386 - val_loss:
0.0395
Epoch 14/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - loss: 0.0383 - val_loss:
0.0380
Epoch 15/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0378 - val_loss:
0.0374
Epoch 16/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0386 - val_loss:
0.0378
Epoch 17/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0381 - val_loss:
0.0374
Epoch 18/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0380 - val_loss:
0.0372
Epoch 19/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - loss: 0.0379 - val_loss:
0.0371
Epoch 20/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0377 - val_loss:
0.0372
Epoch 21/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - loss: 0.0381 - val_loss:
0.0373
Epoch 22/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0380 - val_loss:
0.0377
Epoch 23/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0377 - val_loss:
0.0372
Epoch 24/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0381 - val_loss:
0.0371
Epoch 25/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0387 - val_loss:
0.0367
Epoch 26/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0377 - val_loss:
0.0368
Epoch 27/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0377 - val_loss:
0.0376
Epoch 28/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0383 - val_loss:
0.0371
Epoch 29/50
```

```
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0375 - val_loss:
0.0366
Epoch 30/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0377 - val_loss:
0.0369
Epoch 31/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0378 - val_loss:
0.0377
Epoch 32/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0381 - val_loss:
0.0376
Epoch 33/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0377 - val_loss:
0.0368
Epoch 34/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0378 - val_loss:
0.0369
Epoch 35/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0380 - val_loss:
0.0366
Epoch 36/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0376 - val_loss:
0.0367
Epoch 37/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0377 - val_loss:
0.0370
Epoch 38/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0387 - val_loss:
0.0367
Epoch 39/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0382 - val_loss:
0.0375
Epoch 40/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0377 - val_loss:
0.0368
Epoch 41/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0374 - val_loss:
0.0371
Epoch 42/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0376 - val_loss:
0.0371
Epoch 43/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0378 - val_loss:
0.0367
Epoch 44/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0376 - val_loss:
0.0367
Epoch 45/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0381 - val_loss:
```

```
0.0378
Epoch 46/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0379 - val_loss:
0.0387
Epoch 47/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - loss: 0.0381 - val_loss:
0.0368
Epoch 48/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0373 - val_loss:
0.0379
Epoch 49/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0381 - val_loss:
0.0370
Epoch 50/50
570/570 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - loss: 0.0379 - val_loss:
0.0379
```

```
# test loss and plot for nn modoel with regularization
loss = model_03.evaluate(X_test, y_test, verbose=0)
print("Test Loss:", loss)
# Calculate MSE for train data
mse_train = mean_squared_error(y_train, model_03.predict(X_train))
print("Mean Squared Error (MSE) for training data:", mse_train)
# Calculate MSE for test data
mse_test = mean_squared_error(y_test, model_03.predict(X_test))
print("Mean Squared Error (MSE) for test data:", mse_test)

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```

```
Test Loss: 0.0379117876291275
1140/1140 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step
Mean Squared Error (MSE) for training data: 0.03676896880396006
428/428 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
Mean Squared Error (MSE) for test data: 0.036910547859390866
```




```
from sklearn.ensemble import BaggingRegressor

# Combine predictions using Bagging
bagging_models = [dt_model, gb_model, model_02, model_04]
bagging_predictions = np.mean(np.stack([model.predict(X_test) for
model in bagging_models], axis=0), axis=0)


# Evaluate Bagging performance
bagging_mse = mean_squared_error(y_test, bagging_predictions)

print("Bagging Model:")
print("Mean Squared Error (MSE):", bagging_mse)

428/428 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
428/428 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step

-----------------------------------------------------------------------
-----
ValueError                                Traceback (most recent call
last)
Cell In[74], line 5
      3 # Combine predictions using Bagging
      4 bagging_models = [dt_model, gb_model, model_02, model_04]
```

```
----> 5 bagging_predictions = np.mean(np.stack([model.predict(X_test)
for model in bagging_models], axis=0), axis=0)
      8 # Evaluate Bagging performance
      9 bagging_mse = mean_squared_error(y_test, bagging_predictions)

File
/Library/Frameworks/Python.framework/Versions/3.12/lib/python3.12/
site-packages/numpy/core/shape_base.py:449, in stack(arrays, axis,
out, dtype, casting)
    447 shapes = {arr.shape for arr in arrays}
    448 if len(shapes) != 1:
--> 449     raise ValueError('all input arrays must have the same
shape')
    451 result_ndim = arrays[0].ndim + 1
    452 axis = normalize_axis_index(axis, result_ndim)

ValueError: all input arrays must have the same shape
```

```
print("Shape of predictions from model_02:",
model_02.predict(X_test).shape)
print("Shape of predictions from model_04:",
model_04.predict(X_test).shape)
print("Shape of predictions from DecisionTreeRegressor:",
dt_model.predict(X_test).shape)
print("Shape of predictions from GradientBoostingRegressor:",
gb_model.predict(X_test).shape)
```

```
428/428 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
Shape of predictions from model_02: (13678, 1)
428/428 ━━━━━━━━━━━━━━━━━━━━ 0s 980us/step
Shape of predictions from model_04: (13678, 1)
Shape of predictions from DecisionTreeRegressor: (13678,)
Shape of predictions from GradientBoostingRegressor: (13678,)
```

```
# Stack predictions from all models
all_predictions = [model.predict(X_test).flatten() for model in
[model_02, model_04, dt_model, gb_model]]

# Calculate mean predictions
bagging_predictions = np.mean(np.stack(all_predictions, axis=0),
axis=0)

# Evaluate Bagging performance
bagging_mse = mean_squared_error(y_test, bagging_predictions)
print("Bagging Mean Squared Error (MSE):", bagging_mse)
```

```
428/428 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
428/428 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
Bagging Mean Squared Error (MSE): 0.030721526234414275
```