using_ann.ipynb

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[58]
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

[59]
```
df = pd.read_csv('/content/^NSEI.csv')
df
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	2014-01-02	6301.250000	6358.299805	6211.299805	6221.149902	6221.149902	158100.0
1	2014-01-03	6194.549805	6221.700195	6171.250000	6211.149902	6211.149902	139000.0
2	2014-01-06	6220.850098	6224.700195	6170.250000	6191.450195	6191.450195	118300.0
3	2014-01-07	6203.899902	6221.500000	6144.750000	6162.250000	6162.250000	138600.0
4	2014-01-08	6178.049805	6192.100098	6160.350098	6174.600098	6174.600098	146900.0
...	...	...	...	...	...	...	...
1225	2018-12-21	10944.250000	10963.650391	10738.650391	10754.000000	10754.000000	377500.0
1226	2018-12-24	10780.900391	10782.299805	10649.250000	10663.500000	10663.500000	223400.0
1227	2018-12-26	10635.450195	10747.500000	10534.549805	10729.849609	10729.849609	263700.0
1228	2018-12-27	10817.900391	10834.200195	10764.450195	10779.799805	10779.799805	456100.0
1229	2018-12-28	10820.950195	10893.599609	10817.150391	10859.900391	10859.900391	245500.0

1230 rows × 7 columns

[60]
```
df.head(10)
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	2014-01-02	6301.250000	6358.299805	6211.299805	6221.149902	6221.149902	158100.0
1	2014-01-03	6194.549805	6221.700195	6171.250000	6211.149902	6211.149902	139000.0
2	2014-01-06	6220.850098	6224.700195	6170.250000	6191.450195	6191.450195	118300.0
3	2014-01-07	6203.899902	6221.500000	6144.750000	6162.250000	6162.250000	138600.0
4	2014-01-08	6178.049805	6192.100098	6160.350098	6174.600098	6174.600098	146900.0
5	2014-01-09	6181.700195	6188.049805	6148.250000	6168.350098	6168.350098	150100.0
6	2014-01-10	6178.850098	6239.100098	6139.600098	6171.450195	6171.450195	159900.0
7	2014-01-13	6189.549805	6288.200195	6189.549805	6272.750000	6272.750000	135000.0
8	2014-01-14	6260.250000	6280.350098	6234.149902	6241.850098	6241.850098	110200.0
9	2014-01-15	6265.950195	6325.200195	6265.299805	6320.899902	6320.899902	145900.0

[61]
```
df.shape
```

```
(1230, 7)
```

[62]
```
df.describe()
```

	Open	High	Low	Close	Adj Close	Volume
count	1220.000000	1220.000000	1220.000000	1220.000000	1220.000000	1220.000000
mean	8830.689674	8868.214392	8779.043764	8823.964922	8823.964922	192950.327869
std	1322.591089	1322.044772	1318.170646	1320.040623	1320.040623	74509.699915
min	5947.600098	6017.799805	5933.299805	6000.899902	6000.899902	0.000000
25%	7910.900024	7944.324951	7871.025025	7911.999878	7911.999878	147475.000000
50%	8541.625000	8587.724609	8504.750000	8535.250000	8535.250000	178300.000000
75%	10069.962158	10114.924805	10022.274658	10079.849854	10079.849854	221025.000000
max	11751.799805	11760.200195	11710.500000	11738.500000	11738.500000	719000.000000

[63]
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1230 entries, 0 to 1229
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       1230 non-null   object
 1   Open       1220 non-null   float64
 2   High       1220 non-null   float64
 3   Low        1220 non-null   float64
 4   Close      1220 non-null   float64
 5   Adj Close  1220 non-null   float64
 6   Volume     1220 non-null   float64
dtypes: float64(6), object(1)
```

```
memory usage: 67.4+ KB
```

[64]
```
df.nunique()
#This Implies that each Data is numerical and not categorical
```

```
Date         1230
Open         1212
High         1211
Low          1214
Close        1211
Adj Close    1211
Volume        871
dtype: int64
```

[65]
```
total_null = df.isnull().sum().sort_values(ascending = False)
percent = ((df.isnull().sum()/df.isnull().count())*100).sort_values(ascending = False)
print("Total records = ", df.shape[0])

missing_data = pd.concat([total_null,percent.round(2)],axis=1,keys=['Total Missing','In Percent'])
missing_data
```

```
Total records =  1230
```

	Total Missing	In Percent
Open	10	0.81
High	10	0.81
Low	10	0.81
Close	10	0.81
Adj Close	10	0.81
Volume	10	0.81
Date	0	0.00

[66]
```
df.dropna(inplace=True)
```

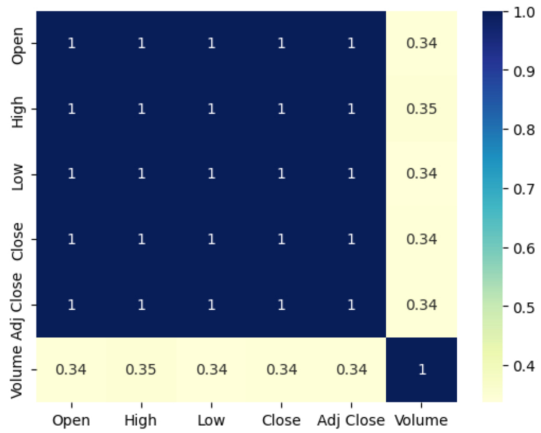
[67]
```
total_null = df.isnull().sum().sort_values(ascending = False)
percent = ((df.isnull().sum()/df.isnull().count())*100).sort_values(ascending = False)
print("Total records = ", df.shape[0])

missing_data = pd.concat([total_null,percent.round(2)],axis=1,keys=['Total Missing','In Percent'])
missing_data
```

```
Total records =  1220
```

	Total Missing	In Percent
Date	0	0.0
Open	0	0.0
High	0	0.0
Low	0	0.0
Close	0	0.0
Adj Close	0	0.0
Volume	0	0.0

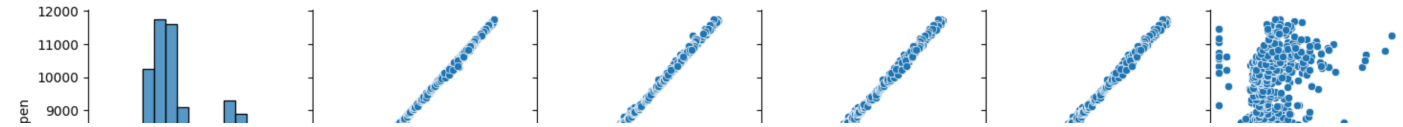
[68]
```
corr = df.corr()
sns.heatmap(corr,annot=True,cmap="YlGnBu")
```

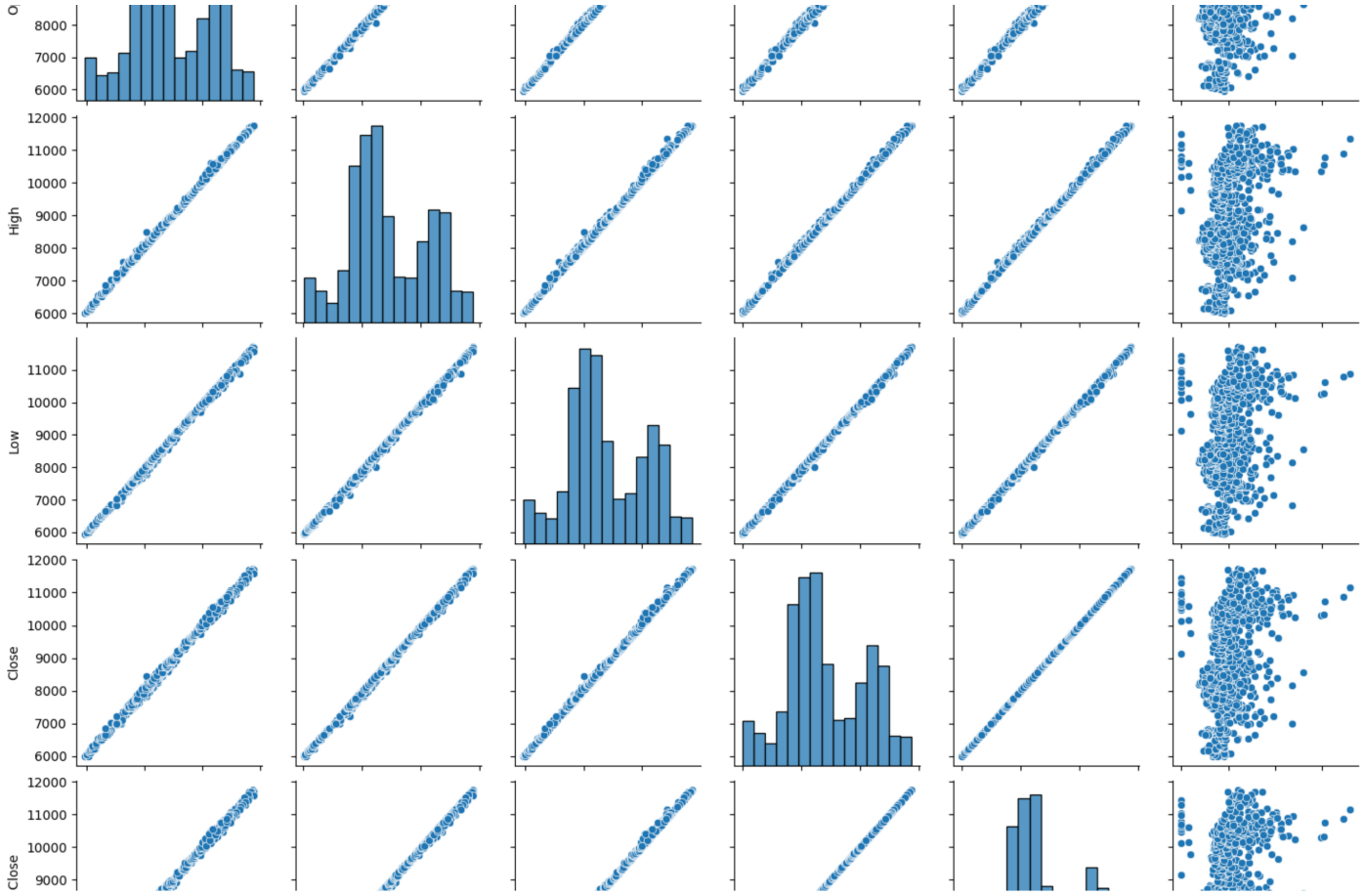
```
<Axes: >
```



[69]
```
sns.pairplot(df)
```

```
<seaborn.axisgrid.PairGrid at 0x7a1a2ab44580>
```





[70]
```
target_column = 'Close'
features = ['Open', 'High', 'Low', 'Adj Close', 'Volume']  # Add other relevant columns
X = df[features]
y = df[target_column]
```

[71]
```
from sklearn.ensemble import ExtraTreesRegressor
import matplotlib.pyplot as plt
model = ExtraTreesRegressor()
model.fit(X,y)
```

```
ExtraTreesRegressor
ExtraTreesRegressor()
```

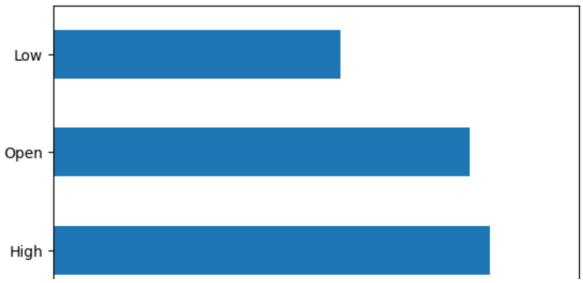
[72]
```
X.head()
```

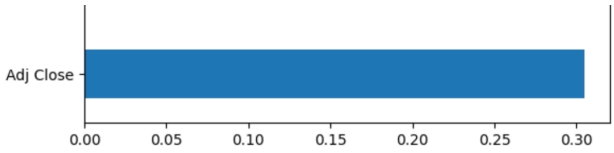
	Open	High	Low	Adj Close	Volume
0	6301.250000	6358.299805	6211.299805	6221.149902	158100.0
1	6194.549805	6221.700195	6171.250000	6211.149902	139000.0
2	6220.850098	6224.700195	6170.250000	6191.450195	118300.0
3	6203.899902	6221.500000	6144.750000	6162.250000	138600.0
4	6178.049805	6192.100098	6160.350098	6174.600098	146900.0

[73]
```
model.feature_importances_
```

```
array([2.54005573e-01, 2.66060817e-01, 1.74818709e-01, 3.05098311e-01,
       1.65908135e-05])
```

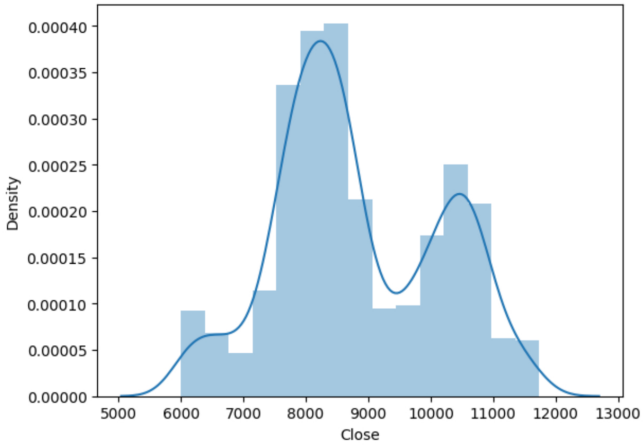
[74]
```
#plot graph of feature importances for better visualization
feat_importances = pd.Series(model.feature_importances_, index=X.columns)
feat_importances.nlargest(4).plot(kind='barh')
plt.show()
```



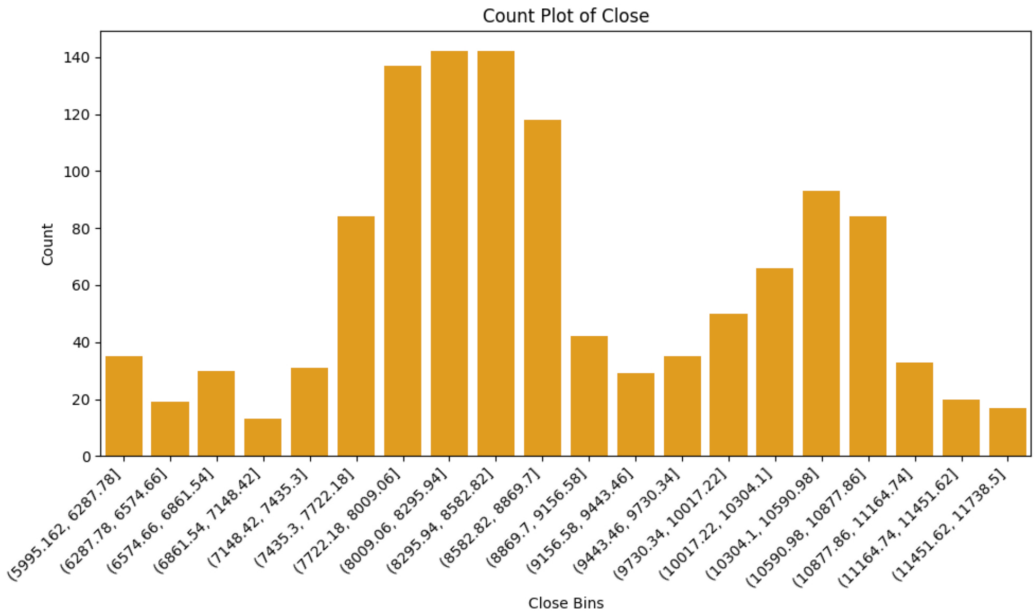


[75]
```
sns.distplot(y)
```

```
<Axes: xlabel='Close', ylabel='Density'>
```



[76]
```
y = df['Close']

# Number of bins for binning the 'PM 2.5' values
num_bins = 20

# Binning the 'PM 2.5' values into discrete categories
binned_pm25 = pd.cut(y, bins=num_bins)

# Create the count plot
plt.figure(figsize=(10, 6))
sns.countplot(x=binned_pm25, color='orange')
plt.xlabel('Close Bins')
plt.ylabel('Count')
plt.title('Count Plot of Close')
plt.xticks(rotation=45, ha='right')  # Rotate the x-axis labels for better visibility
plt.tight_layout()
plt.show()
```



[77]
```
# Calculate the first quartile (Q1) and third quartile (Q3)
Q1 = y.quantile(0.25)
Q3 = y.quantile(0.75)

# Calculate the interquartile range (IQR)
IQR = Q3 - Q1

# Define the outlier boundaries
lower_outlier_boundary = Q1 - 1.5 * IQR
upper_outlier_boundary = Q3 + 1.5 * IQR

# Identify the outliers
```

```
outliers = y[(y < lower_outlier_boundary) | (y > upper_outlier_boundary)]

# Display the outliers
print("Outliers:")
print(outliers)
```

```
Outliers:
Series([], Name: Close, dtype: float64)
```

[78]
```
import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LeakyReLU,PReLU,ELU
from keras.layers import Dropout
```

[79]
```
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()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 128)               768

 dense_1 (Dense)             (None, 256)               33024

 dense_2 (Dense)             (None, 256)               65792

 dense_3 (Dense)             (None, 256)               65792

 dense_4 (Dense)             (None, 1)                 257

=================================================================
Total params: 165633 (647.00 KB)
Trainable params: 165633 (647.00 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[81]
```
model_history=NN_model.fit(X_train, y_train,validation_split=0.33, batch_size = 10, epochs = 300)

```

```
Epoch 272/300
58/58 [==============================] - 0s 4ms/step - loss: 88.0127 - mean_absolute_error: 88.0127 - val_loss: 222.4802 - val_mean_absolute_error: 222.4802
Epoch 273/300
58/58 [==============================] - 0s 4ms/step - loss: 57.7729 - mean_absolute_error: 57.7729 - val_loss: 37.9432 - val_mean_absolute_error: 37.9432
Epoch 274/300
58/58 [==============================] - 0s 4ms/step - loss: 68.2774 - mean_absolute_error: 68.2774 - val_loss: 45.4164 - val_mean_absolute_error: 45.4164
Epoch 275/300
58/58 [==============================] - 0s 3ms/step - loss: 64.4102 - mean_absolute_error: 64.4102 - val_loss: 99.5076 - val_mean_absolute_error: 99.5076
Epoch 276/300
58/58 [==============================] - 0s 4ms/step - loss: 71.4662 - mean_absolute_error: 71.4662 - val_loss: 109.3794 - val_mean_absolute_error: 109.3794
Epoch 277/300
58/58 [==============================] - 0s 4ms/step - loss: 47.7661 - mean_absolute_error: 47.7661 - val_loss: 53.5503 - val_mean_absolute_error: 53.5503
Epoch 278/300
58/58 [==============================] - 0s 4ms/step - loss: 57.3768 - mean_absolute_error: 57.3768 - val_loss: 157.4800 - val_mean_absolute_error: 157.4800
Epoch 279/300
58/58 [==============================] - 0s 3ms/step - loss: 83.7197 - mean_absolute_error: 83.7197 - val_loss: 74.5523 - val_mean_absolute_error: 74.5523
Epoch 280/300
58/58 [==============================] - 0s 4ms/step - loss: 78.5854 - mean_absolute_error: 78.5854 - val_loss: 36.9296 - val_mean_absolute_error: 36.9296
Epoch 281/300
58/58 [==============================] - 0s 4ms/step - loss: 123.8331 - mean_absolute_error: 123.8331 - val_loss: 101.4884 - val_mean_absolute_error: 101.4884
Epoch 282/300
58/58 [==============================] - 0s 4ms/step - loss: 70.4704 - mean_absolute_error: 70.4704 - val_loss: 77.1337 - val_mean_absolute_error: 77.1337
Epoch 283/300
58/58 [==============================] - 0s 4ms/step - loss: 88.7368 - mean_absolute_error: 88.7368 - val_loss: 73.9328 - val_mean_absolute_error: 73.9328
Epoch 284/300
58/58 [==============================] - 0s 3ms/step - loss: 48.9814 - mean_absolute_error: 48.9814 - val_loss: 30.3045 - val_mean_absolute_error: 30.3045
Epoch 285/300
58/58 [==============================] - 0s 4ms/step - loss: 62.5891 - mean_absolute_error: 62.5891 - val_loss: 57.7780 - val_mean_absolute_error: 57.7780
Epoch 286/300
58/58 [==============================] - 0s 5ms/step - loss: 75.5722 - mean_absolute_error: 75.5722 - val_loss: 70.1325 - val_mean_absolute_error: 70.1325
Epoch 287/300
58/58 [==============================] - 0s 5ms/step - loss: 130.5069 - mean_absolute_error: 130.5069 - val_loss: 353.6583 - val_mean_absolute_error: 353.6583
Epoch 288/300
58/58 [==============================] - 0s 5ms/step - loss: 83.4650 - mean_absolute_error: 83.4650 - val_loss: 62.7536 - val_mean_absolute_error: 62.7536
Epoch 289/300
58/58 [==============================] - 0s 5ms/step - loss: 38.9951 - mean_absolute_error: 38.9951 - val_loss: 48.2460 - val_mean_absolute_error: 48.2460
Epoch 290/300
58/58 [==============================] - 0s 5ms/step - loss: 49.2118 - mean_absolute_error: 49.2118 - val_loss: 60.9846 - val_mean_absolute_error: 60.9846
Epoch 291/300
58/58 [==============================] - 0s 6ms/step - loss: 80.6996 - mean_absolute_error: 80.6996 - val_loss: 111.8704 - val_mean_absolute_error: 111.8704
Epoch 292/300
58/58 [==============================] - 0s 5ms/step - loss: 51.6345 - mean_absolute_error: 51.6345 - val_loss: 67.7599 - val_mean_absolute_error: 67.7599
Epoch 293/300
58/58 [==============================] - 0s 4ms/step - loss: 57.8564 - mean_absolute_error: 57.8564 - val_loss: 27.2426 - val_mean_absolute_error: 27.2426
Epoch 294/300
58/58 [==============================] - 0s 5ms/step - loss: 124.8719 - mean_absolute_error: 124.8719 - val_loss: 90.1162 - val_mean_absolute_error: 90.1162
Epoch 295/300
58/58 [==============================] - 0s 5ms/step - loss: 51.4129 - mean_absolute_error: 51.4129 - val_loss: 64.5148 - val_mean_absolute_error: 64.5148
Epoch 296/300
58/58 [==============================] - 0s 5ms/step - loss: 70.3950 - mean_absolute_error: 70.3950 - val_loss: 25.1779 - val_mean_absolute_error: 25.1779
```

```
Epoch 297/300
58/58 [==============================] - 0s 4ms/step - loss: 61.7518 - mean_absolute_error: 61.7518 - val_loss: 216.4065 - val_mean_absolute_error: 216.4065
Epoch 298/300
58/58 [==============================] - 0s 4ms/step - loss: 91.0999 - mean_absolute_error: 91.0999 - val_loss: 119.0340 - val_mean_absolute_error: 119.0340
Epoch 299/300
58/58 [==============================] - 0s 4ms/step - loss: 48.1803 - mean_absolute_error: 48.1803 - val_loss: 206.7226 - val_mean_absolute_error: 206.7226
Epoch 300/300
58/58 [==============================] - 0s 3ms/step - loss: 104.7047 - mean_absolute_error: 104.7047 - val_loss: 170.3306 - val_mean_absolute_error: 170.3306
```

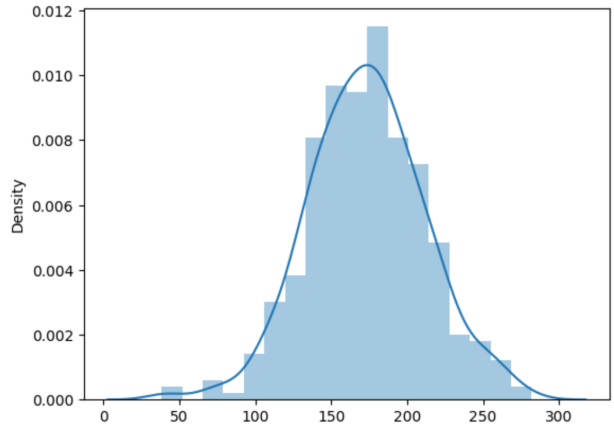
[82]
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
# Predict on the test set
y_pred11 = NN_model.predict(X_test)

# Calculate evaluation metrics
mae = mean_absolute_error(y_test, y_pred11)
mse = mean_squared_error(y_test, y_pred11)
rmse = mean_squared_error(y_test, y_pred11, squared=False)
r2 = r2_score(y_test, y_pred11)

print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"R-squared (R2) Score: {r2:.2f}")
```

```
12/12 [==============================] - 0s 2ms/step
Mean Absolute Error (MAE): 173.25
Mean Squared Error (MSE): 31493.92
Root Mean Squared Error (RMSE): 177.47
R-squared (R2) Score: 0.98
```

The r2 score measures the proportion of the variance in the dependent variable (the target) that is predictable from the independent variables (the features) in a regression model.

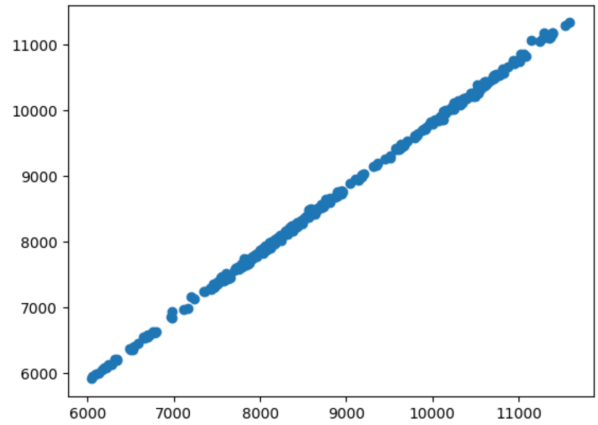
[83]
```
sns.distplot(y_test.values.reshape(-1,1)-y_pred11)

```

```
<Axes: ylabel='Density'>
```



[84]
```
plt.scatter(y_test,y_pred11)

```

```
<matplotlib.collections.PathCollection at 0x7a1a202bd9f0>
```




```
1
```

✓ 0s completed at 3:56 PM