import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from keras.models import Sequential
from keras.layers import Dense

df = pd.read_csv('/content/fusiondataset.csv')

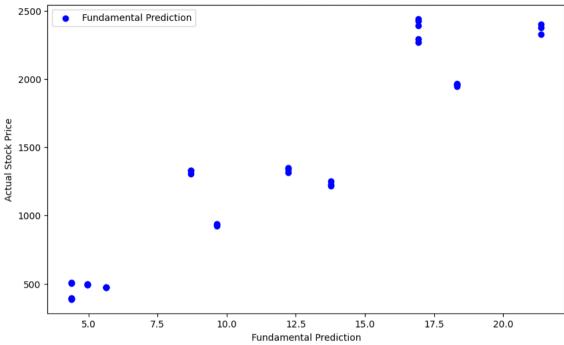
	EPS Prediction	Closing Price Predicted	Actual stock price
0	9.631759	919.67	921.812134
1	9.631759	931.62	932.015442
2	9.631759	939.16	938.751587
3	12.224196	1339.67	1347.427734
4	12.224196	1348.04	1338.958008
5	12.224196	1322.02	1314.886230
6	13.757649	1219.61	1214.537354
7	13.757649	1222.72	1226.028442
8	13.757649	1250.39	1252.923584
9	4.389111	519.13	509.767914
10	4.389111	501.49	501.917328
11	4.389111	505.19	505.161560
12	21.375632	2381.94	2398.550049
13	21.375632	2384.83	2378.300049
14	21.375632	2340.09	2325.550049
15	8.699729	1342.30	1303.791382
16	8.699729	1328.10	1330.240601
17	8.699729	1325.92	1327.120239
18	5.646127	473.94	472.322845

```
import matplotlib.pyplot as plt
# Assuming 'Fundamental_Prediction', 'Technical_Prediction', and 'Actual_Stock_Price' are column names
fundamental_predictions = df['EPS Prediction']
technical predictions = df['Closing Price Predicted']
actual_stock_price = df['Actual stock price']
# Scatter plot for Fundamental Prediction vs Actual Stock Price
plt.figure(figsize=(10, 6))
plt.scatter(fundamental_predictions, actual_stock_price, color='blue', label='Fundamental Prediction')
plt.xlabel('Fundamental Prediction')
plt.ylabel('Actual Stock Price')
plt.title('Fundamental Prediction vs Actual Stock Price')
plt.legend()
plt.show()
# Scatter plot for Technical Prediction vs Actual Stock Price
plt.figure(figsize=(10, 6))
plt.scatter(technical_predictions, actual_stock_price, color='red', label='Technical Prediction')
plt.xlabel('Technical Prediction')
plt.ylabel('Actual Stock Price')
plt.title('Technical Prediction vs Actual Stock Price')
```

```
plt.legend()
plt.show()

# Line plot for Fundamental Prediction, Technical Prediction, and Actual Stock Price
plt.figure(figsize=(10, 6))
plt.plot(fundamental_predictions, label='Fundamental Prediction')
plt.plot(technical_predictions, label='Technical Prediction')
plt.plot(actual_stock_price, label='Actual Stock Price')
plt.xlabel('Data Point')
plt.ylabel('Price')
plt.title('Predictions vs Actual Stock Price')
plt.legend()
plt.show()
```

Fundamental Prediction vs Actual Stock Price



Technical Prediction vs Actual Stock Price



```
# Assuming 'Fundamental_Prediction' and 'Technical_Prediction' are column names in the CSV fundamental_predictions = df['EPS Prediction'].values.reshape(-1, 1) technical_predictions = df['Closing Price Predicted'].values.reshape(-1, 1) actual_targets = df['Actual stock price'].values.reshape(-1, 1) # Replace with your actual target column name
```

```
X = df[['EPS Prediction', 'Closing Price Predicted']]
y = df['Actual stock price']
```

```
# Split the data into train and test sets
X train, X test, y train, y test = train test split(
    np.column stack((fundamental predictions, technical predictions)),
    actual_targets, test_size=0.2, random_state=42)
# Train base models
fundamental model = RandomForestRegressor()
fundamental model.fit(fundamental predictions, actual targets)
technical_model = MLPRegressor(hidden_layer_sizes=(10,10)) # Adjust hidden layer sizes as needed
technical model.fit(technical predictions, actual targets)
     <ipython-input-23-4e190c5fadfe>:3: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n samples,), for example using ravel().
       fundamental model.fit(fundamental predictions, actual targets)
     /usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:1623: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the s
       y = column or 1d(y, warn=True)
                     MLPRegressor
     MLPRegressor(hidden_layer_sizes=(10, 10))
# Obtain predictions from base models
fundamental predictions train = fundamental model.predict(fundamental predictions)
technical_predictions_train = technical_model.predict(technical_predictions)
# Stack the predictions for training the meta-model
stacked features train = np.column stack((fundamental predictions train, technical predictions train))
                                                            Data Point
# Train the meta-model (Neural Network)
meta model = Sequential([
    Dense(10, activation='relu', input_dim=2), # Adjust the number of neurons as needed
    Dense(1) # Output layer
])
meta model.compile(optimizer='adam', loss='mean squared error')
meta_model.fit(stacked_features_train, actual_targets, epochs=1000, batch_size=32)
```

```
Epoch 741/1000
   Epoch 742/1000
   Fnoch 743/1000
   Epoch 744/1000
   2/2 [============ ] - 0s 9ms/step - loss: 334.6840
   Epoch 745/1000
   2/2 [======] - 0s 7ms/step - loss: 334.6488
   Epoch 746/1000
   2/2 [=========== ] - 0s 11ms/step - loss: 334.8601
   Epoch 747/1000
   2/2 [=======] - 0s 6ms/step - loss: 336.4365
   Epoch 748/1000
   2/2 [============ ] - 0s 6ms/step - loss: 337.3625
   Epoch 749/1000
   2/2 [============= ] - 0s 6ms/step - loss: 332.3364
   Epoch 750/1000
   2/2 [=========== ] - 0s 6ms/step - loss: 330.1559
   Epoch 751/1000
   2/2 [========== ] - 0s 14ms/step - loss: 349.9369
   Epoch 752/1000
   Epoch 753/1000
   2/2 [========= ] - 0s 7ms/step - loss: 339.0022
   Epoch 754/1000
   2/2 [======== ] - 0s 5ms/step - loss: 349.4843
   Epoch 755/1000
   2/2 [========= ] - 0s 7ms/step - loss: 334.5739
   Epoch 756/1000
   2/2 [========= ] - 0s 9ms/step - loss: 332.8574
   Epoch 757/1000
   2/2 [========== ] - 0s 10ms/step - loss: 336.2375
   Epoch 758/1000
   2/2 [========== ] - 0s 12ms/step - loss: 332.9759
   Epoch 759/1000
   2/2 [======== ] - 0s 8ms/step - loss: 337.2145
# Obtain predictions from base models on the test set
fundamental_predictions_test = fundamental_model.predict(X_test[:, 0].reshape(-1, 1))
technical_predictions_test = technical_model.predict(X_test[:, 1].reshape(-1, 1))
# Stack the predictions for the test set
stacked_features_test = np.column_stack((fundamental_predictions_test, technical_predictions_test))
# Predict using the meta-model (Neural Network)
combined predictions test = meta model.predict(stacked features test)
```

from sklearn.metrics import mean_squared_error, r2_score # Evaluate the performance of the combined predictions

4.950175

18.328121

12.224196

21.375632

5

493.38

1957.98

1348.04

2381.94

495.416504

1966.129028

1338.340088

2368.240967

```
mse combined = mean squared error(y test, combined predictions test)
print('Mean Squared Error for combined predictions:', mse_combined)
r2 combined = r2 score(y test, combined predictions test)
print('R-squared for combined predictions:', r2 combined)
     Mean Squared Error for combined predictions: 116.27612800721651
     R-squared for combined predictions: 0.9997701038081679
print('Combined Prediction: ',combined predictions test)
print('Actual :',y_test)
     Combined Prediction: [[ 496.353 ]
      [ 392.00418]
      [ 393.11484]
       496.3143
      [ 495.4165 ]
      Γ1966.129
      [1338.3401]
      [2368.241
      [1250.9573]]
     Actual : [[ 494.884003]
      [ 386.436951]
      [ 397.234619]
       497.880585]
       492.704651]
      [1958.150024]
      [1338.958008]
      [2398.550049]
      [1252.923584]]
# Predict using the meta-model (Neural Network)
combined predictions test = meta model.predict(stacked features test)
# Convert the predictions and actual inputs to a DataFrame for easy visualization
combined predictions df = pd.DataFrame({
    'Fundamental_Prediction': X_test[:, 0], # Assuming 0 is the index for EPS prediction
    'Technical_Prediction': X_test[:, 1], # Assuming 1 is the index for closing price prediction
    'Combined Prediction': combined predictions test.flatten(),
    'Actual_Stock_Price': y_test.flatten()
})
# Print the DataFrame to view the predictions and actual inputs
print(combined_predictions_df)
     1/1 [======] - Os 21ms/step
        Fundamental_Prediction Technical_Prediction Combined_Prediction \
                                             495.80
                                                              496.352997
                     4.950175
                     4.371347
                                             388.20
                                                              392.004181
                     4.371347
                                             391.07
                                                              393.114838
                                             495.70
                     4.950175
                                                              496.314301
```

```
8
                13.757649
                                        1250.39
                                                        1250.957275
   Actual_Stock_Price
          494.884003
           386.436951
          397.234619
2
3
          497.880585
          492.704651
          1958.150024
          1338.958008
          2398.550049
8
          1252.923584
```

```
import matplotlib.pyplot as plt
# Convert the predictions and actual inputs to a DataFrame for easy visualization
combined_predictions_df = pd.DataFrame({
    'Fundamental_Prediction': X_test[:, 0].flatten(), # Assuming 0 is the index for EPS prediction
    'Technical_Prediction': X_test[:, 1].flatten(), # Assuming 1 is the index for closing price prediction
    'Combined_Prediction': combined_predictions_test.flatten(),
    'Actual_Stock_Price': y_test.flatten()
})
# Plot the predictions
plt.figure(figsize=(12, 6))
plt.plot(combined_predictions_df['Fundamental_Prediction'], label='Fundamental Prediction')
plt.plot(combined_predictions_df['Technical_Prediction'], label='Technical Prediction')
plt.plot(combined_predictions_df['Combined_Prediction'], label='Combined Prediction')
plt.plot(combined_predictions_df['Actual_Stock_Price'], label='Actual Stock Price')
plt.xlabel('Data Point')
plt.ylabel('Price/Prediction')
plt.title('Stock Price Predictions')
plt.legend()
plt.show()
```

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4 Data Point

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