

## ▼ Datasets

```

1 #Price

1 import pandas as pd
2
3 # URL to the raw CSV file
4 url = 'https://raw.githubusercontent.com/Amarpreet3/CIND-820-CAPSTONE/main/Sentimental%20Analysis/BitcoinPricePreprocessed.csv'
5
6 # Read the CSV file from the URL
7 crypto_usd = pd.read_csv(url)
8
9 # Display the first few rows of the data
10 print(crypto_usd.head())
11
12

```

		time	close	high	low	open	volume	from \
0	2023-02-19	13:00:00	24682.03	24715.82	24682.03	24707.39	903.97	
1	2023-02-19	14:00:00	24765.79	24792.85	24679.21	24682.03	1220.29	
2	2023-02-19	15:00:00	24928.21	25022.49	24751.96	24765.79	5074.50	
3	2023-02-19	16:00:00	24786.44	25175.28	24704.53	24928.21	7094.72	
4	2023-02-19	17:00:00	24364.95	24806.64	24346.17	24786.44	6896.84	

	volume	to	Date	Time	volume	marketcap	price_delta
0	2.233594e+07		2023-02-19	13:00:00	2.233504e+07	5.512964e+11	NaN
1	3.020300e+07		2023-02-19	14:00:00	3.020178e+07	7.480012e+11	83.76
2	1.263085e+08		2023-02-19	15:00:00	1.263034e+08	3.148644e+12	162.42
3	1.770671e+08		2023-02-19	16:00:00	1.770600e+08	4.388863e+12	-141.77
4	1.693379e+08		2023-02-19	17:00:00	1.693310e+08	4.125910e+12	-421.49

```

1 import pandas as pd
2
3 file_urls = [
4     'https://github.com/Amarpreet3/CIND-820-CAPSTONE/raw/main/Sentimental%20Analysis/BitcoinTweetsPreprocessed_1.csv',
5     'https://github.com/Amarpreet3/CIND-820-CAPSTONE/raw/main/Sentimental%20Analysis/BitcoinTweetsPreprocessed_2.csv',
6     'https://github.com/Amarpreet3/CIND-820-CAPSTONE/raw/main/Sentimental%20Analysis/BitcoinTweetsPreprocessed_3.csv',
7     'https://github.com/Amarpreet3/CIND-820-CAPSTONE/raw/main/Sentimental%20Analysis/BitcoinTweetsPreprocessed_4.csv',
8     'https://github.com/Amarpreet3/CIND-820-CAPSTONE/raw/main/Sentimental%20Analysis/BitcoinTweetsPreprocessed_5.csv',
9     'https://github.com/Amarpreet3/CIND-820-CAPSTONE/raw/main/Sentimental%20Analysis/BitcoinTweetsPreprocessed_6.csv'
10 ]
11
12 dfs = []
13
14 for url in file_urls:
15     # Read the CSV file
16     df = pd.read_csv(url)
17
18     # Append the DataFrame to the list
19     dfs.append(df)
20
21 # Combine all DataFrames into a single DataFrame
22 combined_df = pd.concat(dfs)
23
24 # Display the first few rows of the combined DataFrame
25 print(combined_df.head())
26

```

	user_name	user_location	\
0	Irk	Vancouver, WA	
1	Xiang Zhang	NaN	
2	Rhizoo	NaN	
3	Hari Marquez	Las Vegas, NV	
4	Bitcoin Candle Bot	Brazil	

	user_description	user_created	\
0	Irk started investing in the stock market in 1...	2018-08-11 03:17:00	
1	Professional Software Engineer 00000000Crypto ...	2011-01-11 01:37:00	
2	researcher. local maxima dunning&kruger spec...	2019-04-03 18:09:00	
3	Don't trust, verify. #Bitcoin   El Salvador ...	2014-01-17 23:04:00	
4	Robot that posts the closure of the bitcoin da...	2021-01-06 01:36:00	

	user_followers	user_friends	user_favourites	user_verified	\
0	116.0	8.0	4580.0	False	

1	42.0	22.0	5.0	False
2	778.0	627.0	32005.0	False
3	222.0	521.0	13052.0	False
4	40.0	4.0	1.0	False

	date	text \
0	2023-02-25 23:59:00	bitcoin btc rest crypto ye bitcoin cryptocurr ...
1	2023-02-25 23:59:00	retriev invest fund current ongo tidexcoin kic...
2	2023-02-25 23:59:00	bull save monthli thread today good shit bitco...
3	2023-02-25 23:59:00	el salvador shape futur bitcoin membv32cn
4	2023-02-25 23:59:00	candl day 25022023 close open 2319406 high 232...

	hashtags	source \
0	['Bitcoin', 'crypto', 'NeedsMoreCrash']	Twitter Web App
1	['Tidexcoin', 'Kicurrency', 'LMY', 'GMK', 'SYR...]	Twitter for iPhone
2	['bitcoin']	Twitter Web App
3	['Bitcoin']	Twitter Web App
4	['Bitcoin', 'Candle', 'BearMarket']	Bitcoin Candle Bot

	is_retweet	compound	score	sentiment_level	polarity	subjectivity
0	0.0	-0.4019	-2.154092e+05	Negative	0.000000	0.000000
1	0.0	0.0000	0.000000e+00	Neutral	0.000000	0.400000
2	0.0	0.3612	9.005682e+06	Positive	0.250000	0.700000
3	0.0	0.0000	0.000000e+00	Neutral	0.000000	0.000000
4	0.0	-0.2732	-2.240240e+01	Negative	0.053333	0.446667

```
1 tweets = combined_df.copy()
```

```
1 tweets.head()
```

	user_name	user_location	user_description	user_created	user_followers	user_friends	u:
0	Irk	Vancouver, WA	Irk started investing in the stock market in 1...	2018-08-11 03:17:00	116.0	8.0	
1	Xiang Zhang	NaN	Professional Software Engineer ðŸŒŸ»ðŸŒŸCrypto ...	2011-01-11 01:37:00	42.0	22.0	
2	Rhizoo	NaN	researcher. local maxima dunningâŸŸkruger spec...	2019-04-03 18:09:00	778.0	627.0	
3	Hari Marquez	Las Vegas, NV	DonâŸŸt trust, verify. #Bitcoin   El Salvador ...	2014-01-17 23:04:00	222.0	521.0	
4	Bitcoin Candle Bot	Brazil	Robot that posts the closure of the bitcoin da...	2021-01-06 01:36:00	40.0	4.0	



```
1 print(tweets.columns)
```

```
Index(['user_name', 'user_location', 'user_description', 'user_created',  
      'user_followers', 'user_friends', 'user_favourites', 'user_verified',  
      'date', 'text', 'hashtags', 'source', 'is_retweet', 'compound', 'score',  
      'sentiment_level', 'polarity', 'subjectivity'],  
      dtype='object')  
  
1 import pandas as pd  
2  
3  
4 # Check the shape of the dataset  
5 print("Shape of the dataset:", tweets.shape)  
6  
7 # Check the size of the dataset
```

```
8 print("Size of the dataset (number of elements):", tweets.size)
9
```

```
Shape of the dataset: (167652, 18)
Size of the dataset (number of elements): 3017736
```

```
1 import pandas as pd
2 import os
3
4
5 # Check the shape of the data
6 print("Shape of the data:", tweets.shape)
7
8
```

```
Shape of the data: (167652, 18)
```

```
1 label_counts = tweets['sentiment_level'].value_counts()
2 print(label_counts)
```

```
Neutral          93169
Positive         35921
Extreme Positive  17343
Negative         15903
Extreme Negative   5316
Name: sentiment_level, dtype: int64
```

## ▾ Combining both datasets

```
1 # Create a copy of the bitcoin price DataFrame
2 crypto_usd.head(2)
```

	time	close	high	low	open	volumefrom	volumeto	Date	Time
0	2023-02-19 13:00:00	24682.03	24715.82	24682.03	24707.39	903.97	22335943.28	2023-02-19	13:00:00 22

```
1 print(crypto_usd.columns)

Index(['time', 'close', 'high', 'low', 'open', 'volumefrom', 'volumeto',
      'Date', 'Time', 'volume', 'marketcap', 'price_delta'],
      dtype='object')

1 df_score = tweets.copy()
```

## ▾ Classification on Price Prediction based on sentiment

```
1 import pandas as pd
2 import numpy as np
3
4 # Define custom bin edges based on quantiles
5 bin_edges = np.linspace(df_score['compound'].min(), df_score['compound'].max(), num=6) # Adjust the 'num' parameter as needed
6
7 # Define labels
8 labels = ['Extreme Negative', 'Negative', 'Neutral', 'Positive', 'Extreme Positive']
9
10 # Calculate average compound score for each sentiment level
11 sentiment_scores = []
12 for i in range(len(bin_edges)-1):
13     lower_bound = bin_edges[i]
14     upper_bound = bin_edges[i+1]
15     scores_in_range = df_score[(df_score['compound'] >= lower_bound) & (df_score['compound'] < upper_bound)]['compound']
16     sentiment_scores.append(scores_in_range.mean())
17
18 # Map sentiment levels to numerical values with scores
19 sentiment_mapping = {label: score for label, score in zip(labels, sentiment_scores)}
20 df_score['sentiment_score'] = df_score['sentiment_level'].map(sentiment_mapping)
21
```

```
22 # Save the updated dataframe as a new CSV file
23 df_score.to_csv('updated_sentiment_data.csv', index=False)
24

1 # Create a copy of the bitcoin tweets DataFrame
2 df_tweets = pd.read_csv('/content/updated_sentiment_data.csv')
3 df_tweets.head(2)
```

	user_name	user_location	user_description	user_created	user_followers	user_friends	u:
0	Irk	Vancouver, WA	Irk started investing in the stock market in 1...	2018-08-11 03:17:00	116.0	8.0	
1	Xiang Zhang	NaN	Professional Software Engineer ðŸ’€»ðŸ’€Crypto ...	2011-01-11 01:37:00	42.0	22.0	



```
1 # Merge the tweet data with the Bitcoin price data
2 tweets_df = pd.merge(df_tweets, crypto_usd, left_on='date', right_on='time', how='inner')
```

```
1 print(tweets_df.columns)
2
```

```
Index(['user_name', 'user_location', 'user_description', 'user_created',
       'user_followers', 'user_friends', 'user_favourites', 'user_verified',
       'date', 'text', 'hashtags', 'source', 'is_retweet', 'compound', 'score',
       'sentiment_level', 'polarity', 'subjectivity', 'sentiment_score',
       'time', 'close', 'high', 'low', 'open', 'volumefrom', 'volumeto',
       'Date', 'Time', 'volume', 'marketcap', 'price_delta'],
      dtype='object')
```

```
1 tweets_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7898 entries, 0 to 7897
Data columns (total 31 columns):
#   Column                Non-Null Count  Dtype
---  -
0   user_name              7898 non-null   object
1   user_location          3898 non-null   object
2   user_description       7620 non-null   object
3   user_created           7898 non-null   object
4   user_followers         7898 non-null   float64
5   user_friends           7898 non-null   float64
6   user_favourites        7898 non-null   float64
7   user_verified          7898 non-null   bool
8   date                   7898 non-null   object
9   text                   7898 non-null   object
10  hashtags               7891 non-null   object
11  source                 7891 non-null   object
12  is_retweet             7891 non-null   float64
13  compound               7898 non-null   float64
14  score                  7898 non-null   float64
15  sentiment_level        7898 non-null   object
16  polarity               7898 non-null   float64
17  subjectivity           7898 non-null   float64
18  sentiment_score        7898 non-null   float64
19  time                   7898 non-null   object
20  close                  7898 non-null   float64
21  high                   7898 non-null   float64
22  low                    7898 non-null   float64
23  open                   7898 non-null   float64
24  volumefrom             7898 non-null   float64
25  volumeto               7898 non-null   float64
26  Date                   7898 non-null   object
27  Time                   7898 non-null   object
28  volume                 7898 non-null   float64
```

```

29 marketcap          7898 non-null    float64
30 price_delta         7898 non-null    float64
dtypes: bool(1), float64(18), object(12)
memory usage: 1.9+ MB

```

```

1 import pandas as pd
2 from sklearn.feature_extraction.text import CountVectorizer
3 from sklearn.model_selection import train_test_split
4 from sklearn.linear_model import LinearRegression
5 from sklearn.metrics import mean_squared_error, classification_report
6 from scipy.sparse import hstack
7
8 # Feature Extraction: Unigrams
9 unigram_vectorizer = CountVectorizer(ngram_range=(1, 1))
10 unigram_features = unigram_vectorizer.fit_transform(tweets_df['text'])
11
12 # Feature Extraction: Bigrams
13 bigram_vectorizer = CountVectorizer(ngram_range=(2, 2))
14 bigram_features = bigram_vectorizer.fit_transform(tweets_df['text'])
15
16 # Combining Features
17 combined_features = hstack([unigram_features, bigram_features])
18
19 # Additional Input Features
20 additional_features = tweets_df[['compound', 'score', 'polarity', 'subjectivity', 'sentiment_score']].values
21
22 # Concatenate Additional Features with Combined Features
23 X = hstack([combined_features, additional_features])
24
25 # Target Variable
26 y = tweets_df['close']
27
28 # Split the data into training and testing sets
29 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
30
31
32

```

```

1 import numpy as np
2
3 # Print the first 10 rows of the term frequency matrix
4 print(combined_features[:10].toarray())
5

```

```

[[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]

```

```

1 from sklearn.metrics import mean_squared_error, accuracy_score, precision_score, recall_score, f1_score
2 import numpy as np
3 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
4 from scipy.sparse import hstack
5 import time

```

## ▼ Linear Regression

```

1 from sklearn.linear_model import LinearRegression
2 from sklearn.metrics import mean_squared_error, accuracy_score, precision_score, recall_score, f1_score
3 start_time = time.time()
4 # Train the linear regression model
5 model = LinearRegression()
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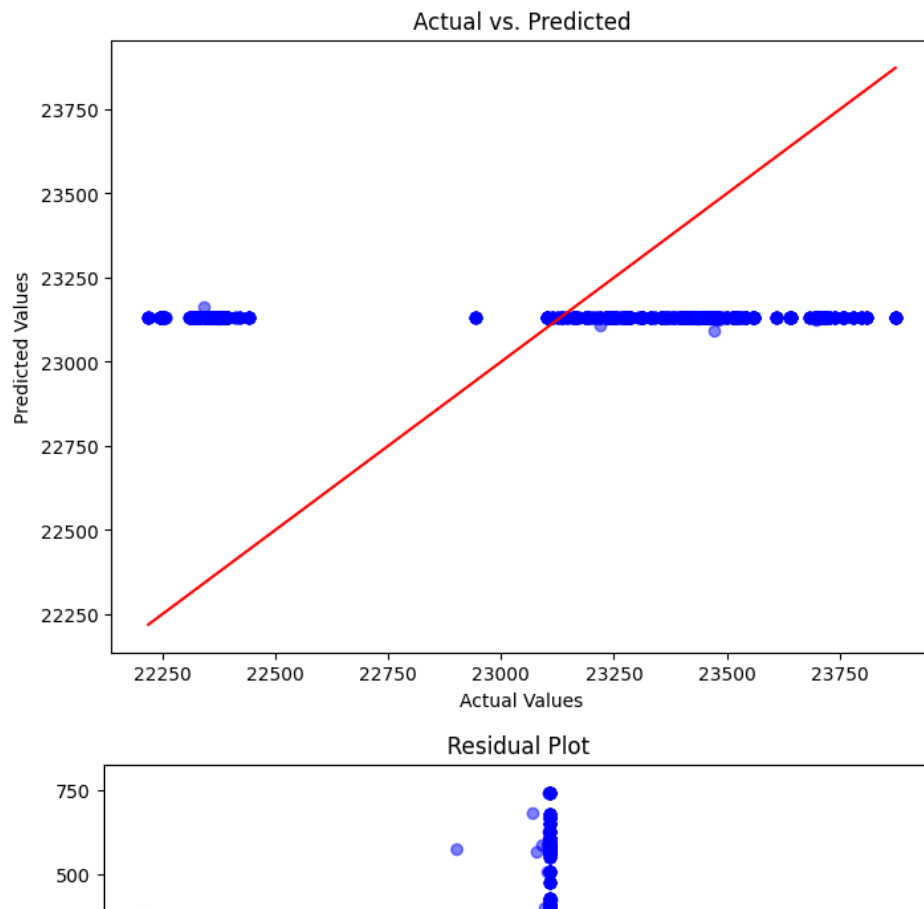
```

6
7 # Evaluate the model
8 mse = mean_squared_error(y_test, y_pred)
9 r2 = r2_score(y_test, y_pred)
10 mae = mean_absolute_error(y_test, y_pred)
11 rmse = np.sqrt(mse)
12
13 print("Mean Squared Error:", mse)
14 print("R-squared:", r2)
15 print("Mean Absolute Error:", mae)
16 print("Root Mean Squared Error:", rmse)
17
18 # Use the trained model for future predictions
19 new_tweet = ["New tweet about Bitcoin"]
20 new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:len(new_tweet)]])
21 predicted_close = model.predict(new_tweet_features)
22
23 print("Predicted Close Price:", predicted_close)
24 end_time = time.time()
25 # Calculate the execution time
26 execution_time = end_time - start_time
27
28 # Print the execution time
29 print(f"Execution time: {execution_time} seconds")

    Mean Squared Error: 263642.15720830334
    R-squared: -0.00027683995676786033
    Mean Absolute Error: 434.52422429092474
    Root Mean Squared Error: 513.460959770364
    Predicted Close Price: [23131.47449878]
    Execution time: 0.04199504852294922 seconds

1 import matplotlib.pyplot as plt
2 import numpy as np
3
4 # Scatter plot
5 plt.figure(figsize=(8, 6))
6 plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
7 plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')
8 plt.xlabel('Actual Values')
9 plt.ylabel('Predicted Values')
10 plt.title('Actual vs. Predicted')
11 plt.show()
12
13 # Residual plot
14 plt.figure(figsize=(8, 6))
15 residuals = y_test - y_pred
16 plt.scatter(y_pred, residuals, color='blue', alpha=0.5)
17 plt.axhline(y=0, color='red', linestyle='--')
18 plt.xlabel('Predicted Values')
19 plt.ylabel('Residuals')
20 plt.title('Residual Plot')
21 plt.show()
22

```



## Decision Tree Regressor

```

1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
3 start_time = time.time()
4 # Train the decision tree regressor model
5 model = DecisionTreeRegressor()
6
7
8
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16
17 # Use the trained model for future predictions
18 new_tweet = ["New tweet about Bitcoin"]
19 new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:len(new_tweet)]])
20 predicted_close = model.predict(new_tweet_features)
21
22 print("Predicted Close Price:", predicted_close)
23 end_time = time.time()
24 # Calculate the execution time
25 execution_time = end_time - start_time
26

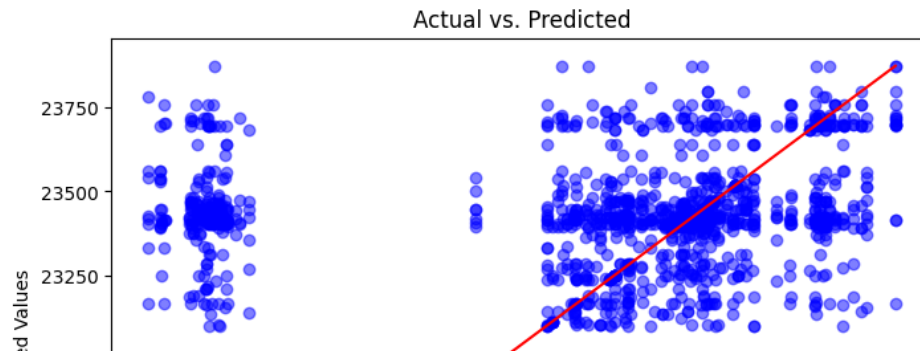
```

```
27 # Print the execution time
28 print(f"Execution time: {execution_time} seconds")

Model: DecisionTreeRegressor()
Mean Squared Error: 330171.6101172941
R-squared: -0.25269425158975833
Mean Absolute Error: 372.79546518987394
Root Mean Squared Error: 574.6056126747233
Predicted Close Price: [23457.06]
Execution time: 7.175631284713745 seconds

1 import matplotlib.pyplot as plt
2 import numpy as np
3
4 # Scatter plot
5 plt.figure(figsize=(8, 6))
6 plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
7 plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')
8 plt.xlabel('Actual Values')
9 plt.ylabel('Predicted Values')
10 plt.title('Actual vs. Predicted')
11 plt.show()
12
13 # Residual plot
14 plt.figure(figsize=(8, 6))
15 residuals = y_test - y_pred
16 plt.scatter(y_pred, residuals, color='blue', alpha=0.5)
17 plt.axhline(y=0, color='red', linestyle='--')
18 plt.xlabel('Predicted Values')
19 plt.ylabel('Residuals')
20 plt.title('Residual Plot')
21 plt.show()
```





## ▼ Random Forest Regressor

```

1 from sklearn.ensemble import RandomForestRegressor
2 start_time = time.time()
3 # Rest of the code is the same as above
4 model = RandomForestRegressor()
5
6
7
8
9
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14
15
16
17 # Use the trained model for future predictions
18 new_tweet = ["New tweet about Bitcoin"]
19 new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:len(new_tweet)]])
20 predicted_close = model.predict(new_tweet_features)
21
22 print("Predicted Close Price:", predicted_close)
23 end_time = time.time()
24 # Calculate the execution time
25 execution_time = end_time - start_time
26
27 # Print the execution time
28 print(f"Execution time: {execution_time} seconds")

```

Model: RandomForestRegressor()  
Mean Squared Error: 229402.74962978673  
R-squared: 0.12962987442188278  
Mean Absolute Error: 332.16736972573915  
Root Mean Squared Error: 478.96007101822875  
Predicted Close Price: [22660.31346667]  
Execution time: 433.4518885612488 seconds

```

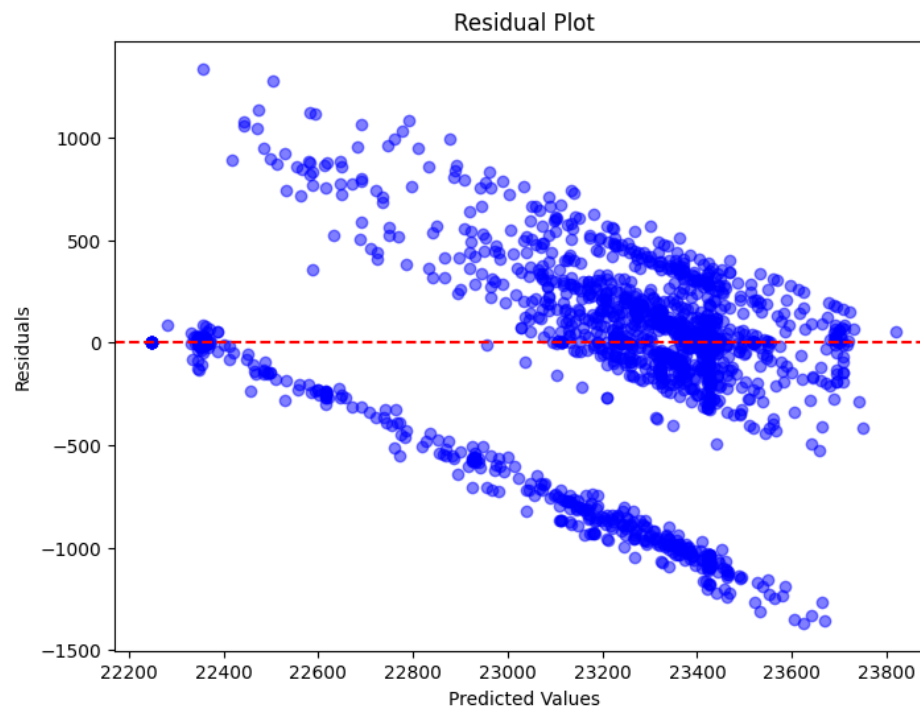
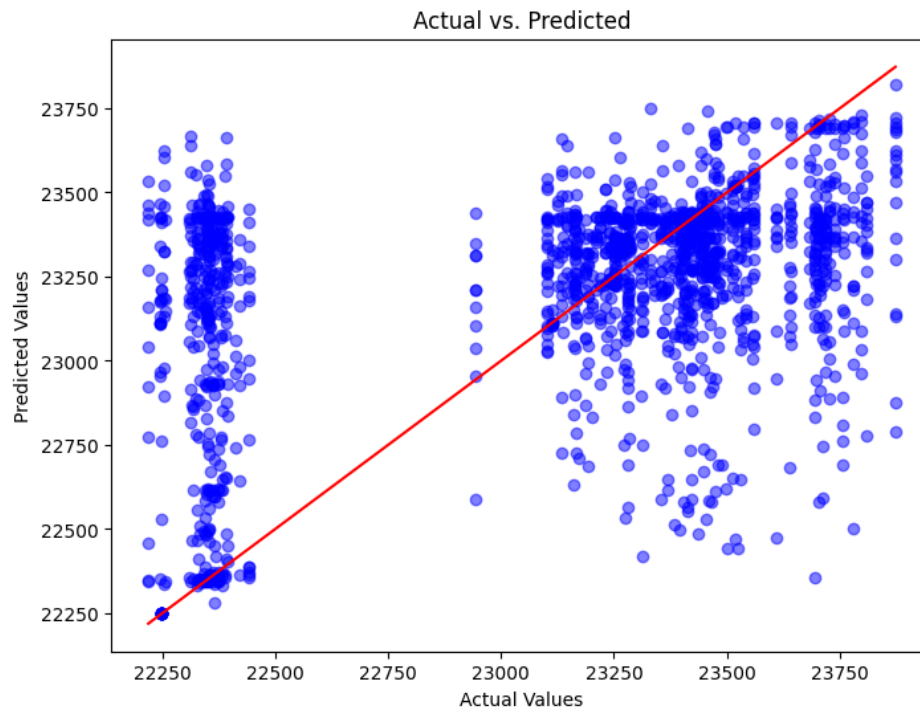
1 import matplotlib.pyplot as plt
2 import numpy as np
3
4 # Scatter plot
5 plt.figure(figsize=(8, 6))
6 plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
7 plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')
8 plt.xlabel('Actual Values')
9 plt.ylabel('Predicted Values')
10 plt.title('Actual vs. Predicted')
11 plt.show()
12
13 # Residual plot

```

```

14 plt.figure(figsize=(8, 6))
15 residuals = y_test - y_pred
16 plt.scatter(y_pred, residuals, color='blue', alpha=0.5)
17 plt.axhline(y=0, color='red', linestyle='--')
18 plt.xlabel('Predicted Values')
19 plt.ylabel('Residuals')
20 plt.title('Residual Plot')
21 plt.show()

```



## ▼ Support Vector Regressor

```

1 from sklearn.svm import SVR
2 start_time = time.time()
3 model = SVR()

```

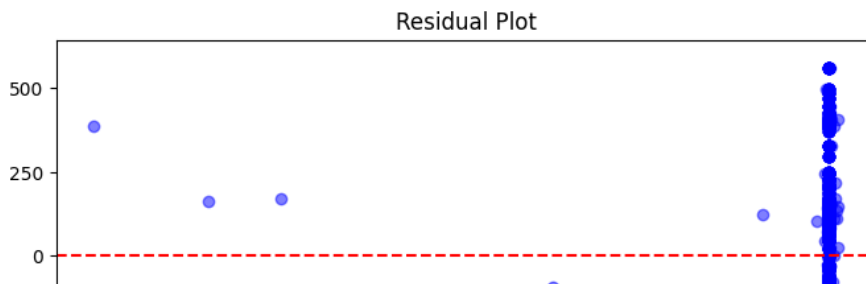
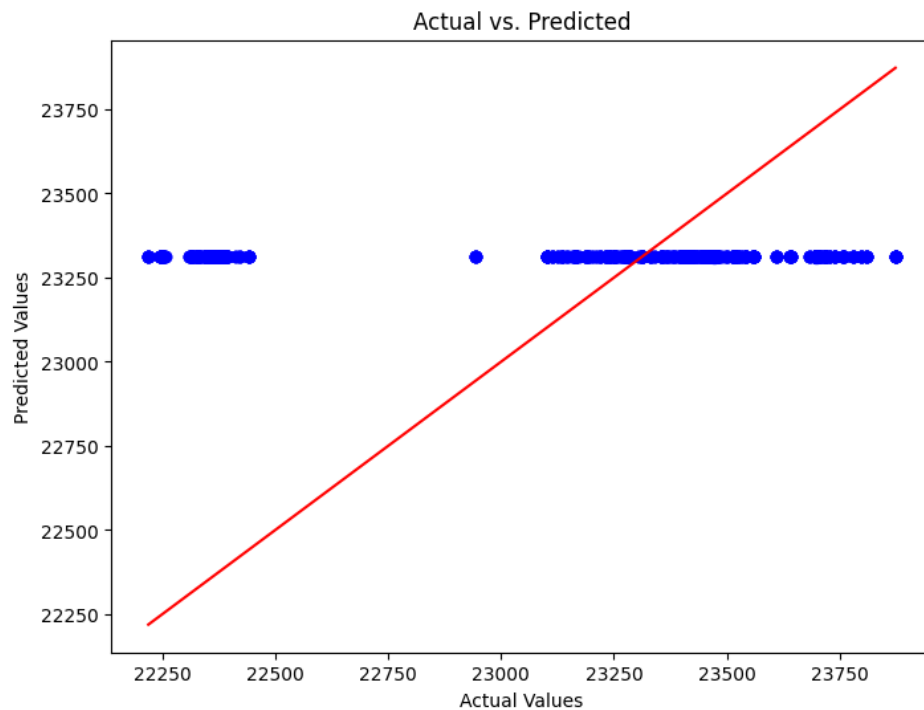
```

1 model.fit(X_train, y_train)
2
3 # Make predictions on the test set
4 y_pred = model.predict(X_test)
5
6 # Evaluate the model
7 mse = mean_squared_error(y_test, y_pred)
8 r2 = r2_score(y_test, y_pred)
9 mae = mean_absolute_error(y_test, y_pred)
10 rmse = np.sqrt(mse)
11 print("Model:", model)
12 print("Mean Squared Error:", mse)
13 print("R-squared:", r2)
14 print("Mean Absolute Error:", mae)
15 print("Root Mean Squared Error:", rmse)
16
17 # Use the trained model for future predictions
18 new_tweet = ["New tweet about Bitcoin"]
19 new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:len(new_tweet)]])
20 predicted_close = model.predict(new_tweet_features)
21
22 print("Predicted Close Price:", predicted_close)
23 end_time = time.time()
24 # Calculate the execution time
25 execution_time = end_time - start_time
26
27 # Print the execution time
28 print(f"Execution time: {execution_time} seconds")

Model: SVR()
Mean Squared Error: 297238.96105083235
R-squared: -0.12774547067996522
Mean Absolute Error: 399.9472665866779
Root Mean Squared Error: 545.1962592047311
Predicted Close Price: [23312.32985827]
Execution time: 11.594075202941895 seconds

1 import matplotlib.pyplot as plt
2 import numpy as np
3
4 # Scatter plot
5 plt.figure(figsize=(8, 6))
6 plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
7 plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')
8 plt.xlabel('Actual Values')
9 plt.ylabel('Predicted Values')
10 plt.title('Actual vs. Predicted')
11 plt.show()
12
13 # Residual plot
14 plt.figure(figsize=(8, 6))
15 residuals = y_test - y_pred
16 plt.scatter(y_pred, residuals, color='blue', alpha=0.5)
17 plt.axhline(y=0, color='red', linestyle='--')
18 plt.xlabel('Predicted Values')
19 plt.ylabel('Residuals')
20 plt.title('Residual Plot')
21 plt.show()

```



## ▼ Gradient Boosting Regressor

```

1 from sklearn.ensemble import GradientBoostingRegressor
2 start_time = time.time()
3 model = GradientBoostingRegressor()

-750 ↓

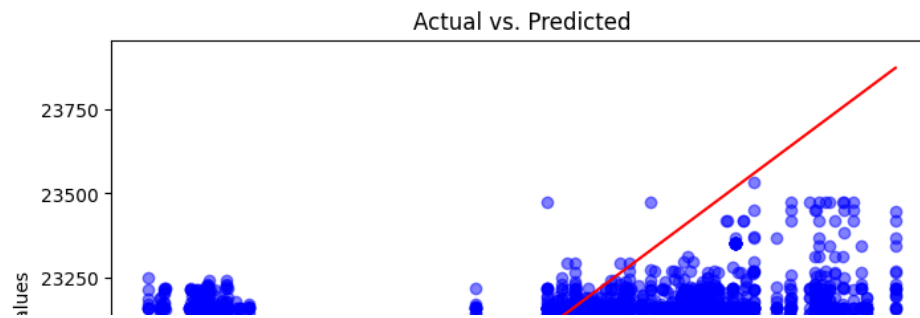
1 model.fit(X_train, y_train)
2
3 # Make predictions on the test set
4 y_pred = model.predict(X_test)
5
6 # Evaluate the model
7 mse = mean_squared_error(y_test, y_pred)
8 r2 = r2_score(y_test, y_pred)
9 mae = mean_absolute_error(y_test, y_pred)
10 rmse = np.sqrt(mse)
11 print("Model:", model)
12 print("Mean Squared Error:", mse)
13 print("R-squared:", r2)
14 print("Mean Absolute Error:", mae)
15 print("Root Mean Squared Error:", rmse)
16
17 # Use the trained model for future predictions
18 new_tweet = ["New tweet about Bitcoin"]
19 new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:len(new_tweet)]])
20 predicted_close = model.predict(new_tweet_features)
21
22 print("Predicted Close Price:", predicted_close)
23 end_time = time.time()
24 # Calculate the execution time
25 execution_time = end_time - start_time
26
27 # Print the execution time
28 print(f"Execution time: {execution_time} seconds")

```

```
20 print('Execution time: {execution_time} seconds')
```

```
Model: GradientBoostingRegressor()  
Mean Squared Error: 218755.55046442378  
R-squared: 0.17002609499712606  
Mean Absolute Error: 378.03401143678497  
Root Mean Squared Error: 467.71310700516375  
Predicted Close Price: [23144.45192473]  
Execution time: 40.16045880317688 seconds
```

```
1 import matplotlib.pyplot as plt  
2 import numpy as np  
3  
4 # Scatter plot  
5 plt.figure(figsize=(8, 6))  
6 plt.scatter(y_test, y_pred, color='blue', alpha=0.5)  
7 plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')  
8 plt.xlabel('Actual Values')  
9 plt.ylabel('Predicted Values')  
10 plt.title('Actual vs. Predicted')  
11 plt.show()  
12  
13 # Residual plot  
14 plt.figure(figsize=(8, 6))  
15 residuals = y_test - y_pred  
16 plt.scatter(y_pred, residuals, color='blue', alpha=0.5)  
17 plt.axhline(y=0, color='red', linestyle='--')  
18 plt.xlabel('Predicted Values')  
19 plt.ylabel('Residuals')  
20 plt.title('Residual Plot')  
21 plt.show()
```



## Neural Network Regressor (MLP)

```

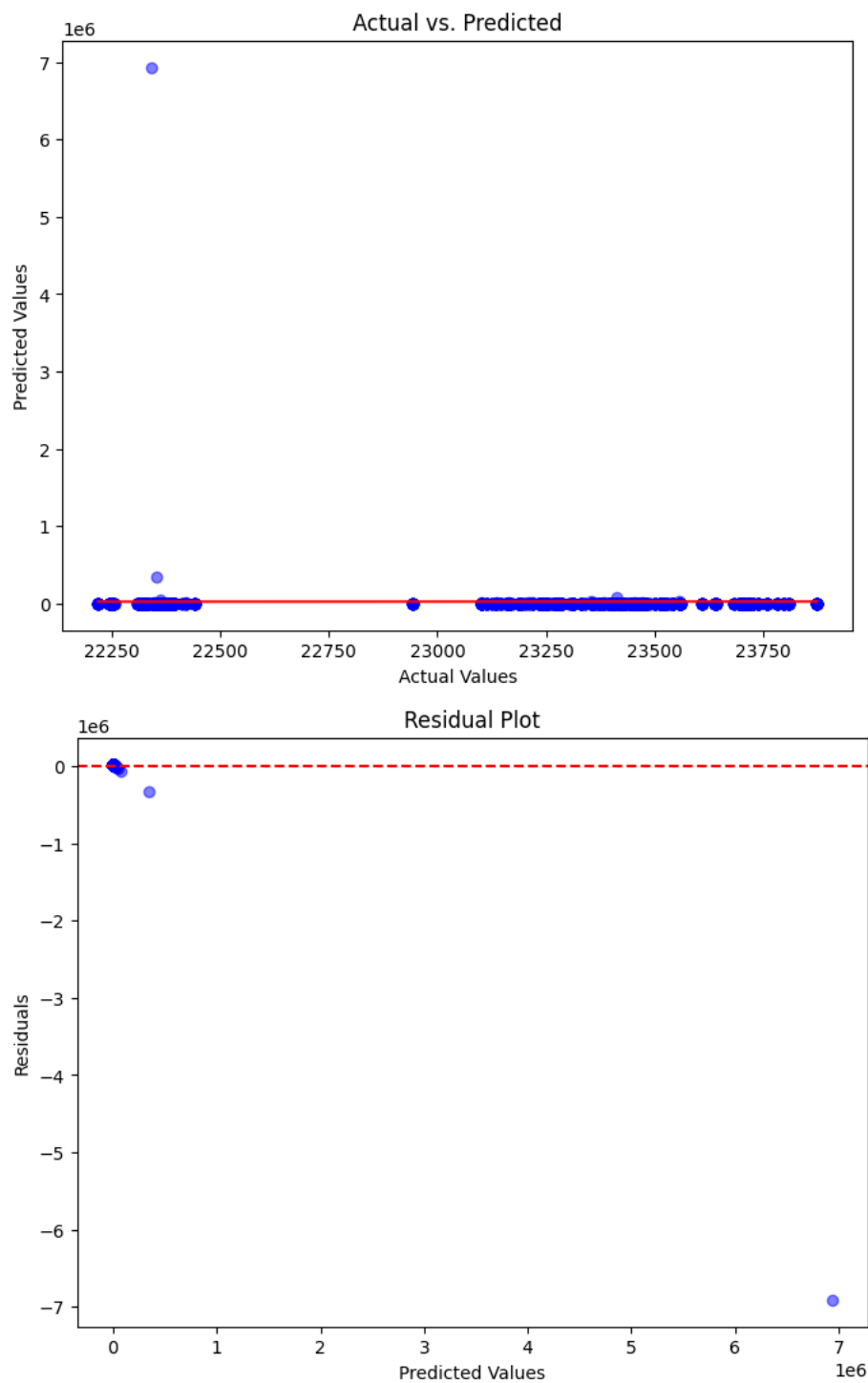
1 from sklearn.neural_network import MLPRegressor
2 start_time = time.time()
3 model = MLPRegressor()
4
5
6
7
8
9
10
11 model.fit(X_train, y_train)
12
13
14 # Make predictions on the test set
15 y_pred = model.predict(X_test)
16
17 # Evaluate the model
18 mse = mean_squared_error(y_test, y_pred)
19 r2 = r2_score(y_test, y_pred)
20 mae = mean_absolute_error(y_test, y_pred)
21 rmse = np.sqrt(mse)
22 print("Model:", model)
23 print("Mean Squared Error:", mse)
24 print("R-squared:", r2)
25 print("Mean Absolute Error:", mae)
26 print("Root Mean Squared Error:", rmse)
27
28 # Use the trained model for future predictions
29 new_tweet = ["New tweet about Bitcoin"]
30 new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:len(new_tweet)]])
31 predicted_close = model.predict(new_tweet_features)
32
33 print("Predicted Close Price:", predicted_close)
34 end_time = time.time()
35 # Calculate the execution time
36 execution_time = end_time - start_time
37
38 # Print the execution time
39 print(f"Execution time: {execution_time} seconds")
40
41
42 Model: MLPRegressor()
43 Mean Squared Error: 312875279304.78375
44 R-squared: -1187069.7590831518
45 Mean Absolute Error: 51811.649418078436
46 Root Mean Squared Error: 559352.5536768235
47 Predicted Close Price: [2.23164465]
48 Execution time: 144.90826535224915 seconds
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```

```

19 plt.ylabel('Residuals')
20 plt.title('Residual Plot')
21 plt.show()

```



## ▼ Cross Validation of Models

## ▼ Linear Regression

```

1 from sklearn.linear_model import LinearRegression
2 from sklearn.metrics import mean_squared_error, accuracy_score, precision_score, recall_score, f1_score
3
4 # Train the linear regression model

```

```

5 model = LinearRegression()
6

1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.model_selection import cross_val_score
3 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
4
5
6 # Perform cross-validation
7 cv_scores = cross_val_score(model, X, y, cv=5, scoring='neg_mean_squared_error')
8
9 # Convert the negative mean squared error scores to positive
10 mse_scores = -cv_scores
11
12 # Calculate the mean and standard deviation of the MSE scores
13 mean_mse = np.mean(mse_scores)
14 std_mse = np.std(mse_scores)
15
16 # Print the mean and standard deviation of the MSE scores
17 print("Mean MSE:", mean_mse)
18 print("Std MSE:", std_mse)
19

Mean MSE: 369821.0979640644
Std MSE: 306106.77056563296

```

## ▼ Decision Tree Regressor

```

1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
3
4 # Train the decision tree regressor model
5 model = DecisionTreeRegressor()
6
7

1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.model_selection import cross_val_score
3 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
4
5
6 # Perform cross-validation
7 cv_scores = cross_val_score(model, X, y, cv=5, scoring='neg_mean_squared_error')
8
9 # Convert the negative mean squared error scores to positive
10 mse_scores = -cv_scores
11
12 # Calculate the mean and standard deviation of the MSE scores
13 mean_mse = np.mean(mse_scores)
14 std_mse = np.std(mse_scores)
15
16 # Print the mean and standard deviation of the MSE scores
17 print("Mean MSE:", mean_mse)
18 print("Std MSE:", std_mse)
19

Mean MSE: 465009.6395099891
Std MSE: 335780.0275937437

```

## ▼ Random Forest Regressor

```

1 from sklearn.ensemble import RandomForestRegressor
2
3 model = RandomForestRegressor()

1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.model_selection import cross_val_score
3 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
4
5

```



```

6 # Perform cross-validation
7 cv_scores = cross_val_score(model, X, y, cv=5, scoring='neg_mean_squared_error')
8
9 # Convert the negative mean squared error scores to positive
10 mse_scores = -cv_scores
11
12 # Calculate the mean and standard deviation of the MSE scores
13 mean_mse = np.mean(mse_scores)
14 std_mse = np.std(mse_scores)
15
16 # Print the mean and standard deviation of the MSE scores
17 print("Mean MSE:", mean_mse)
18 print("Std MSE:", std_mse)
19

```

Mean MSE: 358518.1748665846  
Std MSE: 372697.4355903579

## ▼ Support Vector Regressor

```

1 from sklearn.svm import SVR
2
3 model = SVR()


```

```

1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.model_selection import cross_val_score
3 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
4
5
6 # Perform cross-validation
7 cv_scores = cross_val_score(model, X, y, cv=5, scoring='neg_mean_squared_error')
8
9 # Convert the negative mean squared error scores to positive
10 mse_scores = -cv_scores
11
12 # Calculate the mean and standard deviation of the MSE scores
13 mean_mse = np.mean(mse_scores)
14 std_mse = np.std(mse_scores)
15
16 # Print the mean and standard deviation of the MSE scores
17 print("Mean MSE:", mean_mse)
18 print("Std MSE:", std_mse)
19

```

Mean MSE: 347812.1745007644  
Std MSE: 401289.31804972445

## ▼ Gradient Boosting Regressor

```

1 from sklearn.ensemble import GradientBoostingRegressor
2
3 model = GradientBoostingRegressor()


```

```

1


```

```

1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.model_selection import cross_val_score
3 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
4
5
6 # Perform cross-validation
7 cv_scores = cross_val_score(model, X, y, cv=5, scoring='neg_mean_squared_error')
8
9 # Convert the negative mean squared error scores to positive
10 mse_scores = -cv_scores
11
12 # Calculate the mean and standard deviation of the MSE scores
13 mean_mse = np.mean(mse_scores)
14 std_mse = np.std(mse_scores)
15

```

```

16 # Print the mean and standard deviation of the MSE scores
17 print("Mean MSE:", mean_mse)
18 print("Std MSE:", std_mse)
19

```

```

Mean MSE: 348887.6854683334
Std MSE: 310402.66705840186

```

## ▼ Neural Network Regressor (MLP)

```

1 from sklearn.neural_network import MLPRegressor
2
3 model = MLPRegressor()

1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.model_selection import cross_val_score
3 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
4
5
6 # Perform cross-validation
7 cv_scores = cross_val_score(model, X, y, cv=5, scoring='neg_mean_squared_error')
8
9 # Convert the negative mean squared error scores to positive
10 mse_scores = -cv_scores
11
12 # Calculate the mean and standard deviation of the MSE scores
13 mean_mse = np.mean(mse_scores)
14 std_mse = np.std(mse_scores)
15
16 # Print the mean and standard deviation of the MSE scores
17 print("Mean MSE:", mean_mse)
18 print("Std MSE:", std_mse)
19

```

```

Mean MSE: 31205126756566.926
Std MSE: 47041070509094.12

```

## ▼ Hyperparameter Tuning for Price

```

1 #Hyperparameter Tuning

1 import pandas as pd
2 from sklearn.feature_extraction.text import CountVectorizer
3 from sklearn.model_selection import train_test_split
4 from sklearn.linear_model import LinearRegression
5 from sklearn.metrics import mean_squared_error, classification_report
6 from scipy.sparse import hstack
7
8 # Feature Extraction: Unigrams
9 unigram_vectorizer = CountVectorizer(ngram_range=(1, 1))
10 unigram_features = unigram_vectorizer.fit_transform(tweets_df['text'])
11
12 # Feature Extraction: Bigrams
13 bigram_vectorizer = CountVectorizer(ngram_range=(2, 2))
14 bigram_features = bigram_vectorizer.fit_transform(tweets_df['text'])
15
16 # Combining Features
17 combined_features = hstack([unigram_features, bigram_features])
18
19 # Additional Input Features
20 additional_features = tweets_df[['compound', 'score', 'polarity', 'subjectivity', 'sentiment_score']].values
21
22 # Concatenate Additional Features with Combined Features
23 X = hstack([combined_features, additional_features])
24
25 # Target Variable
26 y = tweets_df['close']
27
28 # Split the data into training and testing sets
29 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

```

```

30
31
32

1 from sklearn.model_selection import GridSearchCV
2 from sklearn.feature_selection import SelectKBest
3 from sklearn.linear_model import LinearRegression
4 from sklearn.metrics import mean_squared_error
5
6 # Define the models
7 models = {
8     "Decision Tree Regressor": DecisionTreeRegressor(),
9     "Random Forest Regressor": RandomForestRegressor(),
10    "Support Vector Regressor": SVR(),
11    "Gradient Boosting Regressor": GradientBoostingRegressor(),
12    "Neural Network Regressor": MLPRegressor(),
13    "Linear Regression": LinearRegression()
14 }
15
16 # Define the parameter grids for hyperparameter tuning
17 param_grids = {
18     "Decision Tree Regressor": {
19         "max_depth": [3, 5, 7],
20         "min_samples_split": [2, 5, 10],
21         "min_samples_leaf": [1, 3, 5]
22     },
23     "Random Forest Regressor": {
24         "n_estimators": [50, 100, 200],
25         "max_depth": [3, 5, 7],
26         "min_samples_split": [2, 5, 10],
27         "min_samples_leaf": [1, 3, 5]
28     },
29     "Support Vector Regressor": {
30         "C": [0.1, 1, 10],
31         "epsilon": [0.1, 0.01, 0.001]
32     },
33     "Gradient Boosting Regressor": {
34         "n_estimators": [50, 100, 200],
35         "learning_rate": [0.1, 0.01, 0.001],
36         "max_depth": [3, 5, 7]
37     },
38     "Neural Network Regressor": {
39         "hidden_layer_sizes": [(100,), (100, 50), (200, 100)],
40         "alpha": [0.1, 0.01, 0.001]
41     },
42     "Linear Regression": {}
43 }
44
45 # Initialize an empty dictionary to store the results
46 results = {}
47
48 # Iterate over the models
49 for model_name, model in models.items():
50     print("Model:", model_name)
51
52     # Perform feature selection
53     feature_selector = SelectKBest()
54     X_selected = feature_selector.fit_transform(X, y)
55
56     # Perform grid search cross-validation
57     param_grid = param_grids[model_name]
58     grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=5, scoring='neg_mean_squared_error')
59     grid_search.fit(X_selected, y)
60
61     # Get the best model and its corresponding hyperparameters
62     best_model = grid_search.best_estimator_
63     best_params = grid_search.best_params_
64
65     # Train the best model on the entire dataset
66     best_model.fit(X_selected, y)
67
68     # Make predictions on the test set
69     X_test_selected = feature_selector.transform(X_test)
70     y_pred = best_model.predict(X_test_selected)
71
72     # Evaluate the best model

```

```
Model: Decision Tree Regressor
Best Model: DecisionTreeRegressor(max_depth=7, min_samples_leaf=3, min_samples_split=5)
Best Parameters: {'max_depth': 7, 'min_samples_leaf': 3, 'min_samples_split': 5}
Mean Squared Error: 249886.37207620614
R-squared: 0.05191357385549278
Mean Absolute Error: 413.05794247618445
Root Mean Squared Error: 499.8863591619661

Model: Random Forest Regressor
Best Model: RandomForestRegressor(max_depth=7, min_samples_split=5, n_estimators=50)
Best Parameters: {'max_depth': 7, 'min_samples_leaf': 1, 'min_samples_split': 5, 'n_estimators': 50}
Mean Squared Error: 249886.91762665412
R-squared: 0.05191150399882072
Mean Absolute Error: 412.8730317998603
Root Mean Squared Error: 499.886904836138

Model: Support Vector Regressor
Best Model: SVR(C=0.1, epsilon=0.001)
Best Parameters: {'C': 0.1, 'epsilon': 0.001}
Mean Squared Error: 296035.0250691949
R-squared: -0.12317765310490625
Mean Absolute Error: 399.4075468116839
Root Mean Squared Error: 544.091008076034

Model: Gradient Boosting Regressor
Best Model: GradientBoostingRegressor(n_estimators=50)
Best Parameters: {'learning_rate': 0.1, 'max_depth': 3, 'n_estimators': 50}
Mean Squared Error: 249884.83969784752
R-squared: 0.05191938780648764
Mean Absolute Error: 413.1128964010035
Root Mean Squared Error: 499.88482643289694
```

[illegible]

```

1 from sklearn.tree import DecisionTreeRegressor
2 from sklearn.model_selection import cross_val_score
3 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
4
5
6 # Perform cross-validation
7 cv_scores = cross_val_score(model, X, y, cv=5, scoring='neg_mean_squared_error')
8
9 # Convert the negative mean squared error scores to positive
10 mse_scores = -cv_scores
11
12 # Calculate the mean and standard deviation of the MSE scores
13 mean_mse = np.mean(mse_scores)
14 std_mse = np.std(mse_scores)
15
16 # Print the mean and standard deviation of the MSE scores
17 print("Mean MSE:", mean_mse)
18 print("Std MSE:", std_mse)
19

```

```

Mean MSE: 31205126756566.926
Std MSE: 47041070509094.12

```

## ▼ All Models Together for comparison with price [close]

```

1 import pandas as pd
2 from sklearn.feature_extraction.text import CountVectorizer
3 from sklearn.model_selection import train_test_split
4 from sklearn.linear_model import LinearRegression
5 from sklearn.metrics import mean_squared_error, classification_report
6 from scipy.sparse import hstack
7
8 # Feature Extraction: Unigrams
9 unigram_vectorizer = CountVectorizer(ngram_range=(1, 1))
10 unigram_features = unigram_vectorizer.fit_transform(tweets_df['text'])
11
12 # Feature Extraction: Bigrams
13 bigram_vectorizer = CountVectorizer(ngram_range=(2, 2))
14 bigram_features = bigram_vectorizer.fit_transform(tweets_df['text'])
15
16 # Combining Features
17 combined_features = hstack([unigram_features, bigram_features])
18
19 # Additional Input Features
20 additional_features = tweets_df[['compound', 'score', 'polarity', 'subjectivity', 'sentiment_score']].values
21
22 # Concatenate Additional Features with Combined Features
23 X = hstack([combined_features, additional_features])
24
25 # Target Variable
26 y = tweets_df['close']
27
28 # Split the data into training and testing sets
29 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
30
31
32

```

```

1 import pandas as pd
2 from sklearn.linear_model import LinearRegression
3 from sklearn.tree import DecisionTreeRegressor
4 from sklearn.ensemble import RandomForestRegressor
5 from sklearn.svm import SVR
6 from sklearn.ensemble import GradientBoostingRegressor
7 from sklearn.neural_network import MLPRegressor
8 from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
9 from scipy.sparse import hstack
10
11 # Define the models
12 models = {
13     "Linear Regression": LinearRegression(),

```

```

14 "Decision Tree Regressor": DecisionTreeRegressor(),
15 "Random Forest Regressor": RandomForestRegressor(),
16 "Support Vector Regressor": SVR(),
17 "Gradient Boosting Regressor": GradientBoostingRegressor(),
18 "Neural Network Regressor": MLPRegressor()
19 }
20
21 # Initialize an empty dictionary to store the results
22 results = {}
23
24 # Iterate over the models
25 for model_name, model in models.items():
26     # Train the model
27     model.fit(X_train, y_train)
28
29     # Make predictions on the test set
30     y_pred = model.predict(X_test)
31
32     # Evaluate the model
33     mse = mean_squared_error(y_test, y_pred)
34     r2 = r2_score(y_test, y_pred)
35     mae = mean_absolute_error(y_test, y_pred)
36     rmse = np.sqrt(mse)
37
38     # Store the results in the dictionary
39     results[model_name] = {
40         "Mean Squared Error": mse,
41         "R-squared": r2,
42         "Mean Absolute Error": mae,
43         "Root Mean Squared Error": rmse
44     }
45
46 # Use the trained model for future predictions
47 new_tweet = ["New tweet about Bitcoin"]
48 new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:1]
49 predicted_close = model.predict(new_tweet_features)
50
51 results[model_name]["Predicted Close Price"] = predicted_close
52
53 # Convert the results to a pandas DataFrame for tabular representation
54 results_df = pd.DataFrame.from_dict(results, orient="index")
55
56 # Print the results
57 print(results_df)
58

```

	Mean Squared Error	R-squared \
Linear Regression	2.636422e+05	-2.768400e-04
Decision Tree Regressor	3.345694e+05	-2.693799e-01
Random Forest Regressor	2.315119e+05	1.216275e-01
Support Vector Regressor	2.972390e+05	-1.277455e-01
Gradient Boosting Regressor	2.188733e+05	1.695795e-01
Neural Network Regressor	4.803038e+11	-1.822305e+06

	Mean Absolute Error	Root Mean Squared Error \
Linear Regression	434.524224	513.460960
Decision Tree Regressor	374.074494	578.419766
Random Forest Regressor	334.207529	481.156859
Support Vector Regressor	399.947267	545.196259
Gradient Boosting Regressor	378.111052	467.838936
Neural Network Regressor	58711.619235	693039.555859

	Predicted Close Price
Linear Regression	[23131.47449878233]
Decision Tree Regressor	[23447.51]
Random Forest Regressor	[22580.549866666664]
Support Vector Regressor	[23312.329858272555]
Gradient Boosting Regressor	[23144.45192472882]
Neural Network Regressor	[4.349573192223386]

```

1
2 # Transpose the DataFrame
3 transposed_df = results_df.transpose()
4
5 # Print the transposed DataFrame
6 print(transposed_df)

```

	Linear Regression	Decision Tree Regressor	\
Mean Squared Error	263642.157208	334569.425348	
R-squared	-0.000277	-0.26938	
Mean Absolute Error	434.524224	374.074494	
Root Mean Squared Error	513.46096	578.419766	
Predicted Close Price	[23131.47449878233]	[23447.51]	

	Random Forest Regressor	Support Vector Regressor	\
Mean Squared Error	231511.922529	297238.961051	
R-squared	0.121628	-0.127745	
Mean Absolute Error	334.207529	399.947267	
Root Mean Squared Error	481.156859	545.196259	
Predicted Close Price	[22580.549866666664]	[23312.329858272555]	

	Gradient Boosting Regressor	Neural Network Regressor
Mean Squared Error	218873.270426	480303825985.190186
R-squared	0.169579	-1822305.410943
Mean Absolute Error	378.111052	58711.619235
Root Mean Squared Error	467.838936	693039.555859
Predicted Close Price	[23144.45192472882]	[4.349573192223386]

1 #Linear Regression and Decision Tree Regressor have low R-squared values and high mean squared error, indicating poor fit and high predict  
2 #Random Forest Regressor and Gradient Boosting Regressor show relatively better performance with higher R-squared values, lower mean squar  
3 #The Neural Network Regressor seems to have highly inaccurate predictions, as indicated by the extremely high mean squared error and mean

1 #Based on the provided evaluation metrics, the Random Forest Regressor and Gradient Boosting Regressor perform relatively better compared

## ▼ All Models Together for comparison with price\_delta

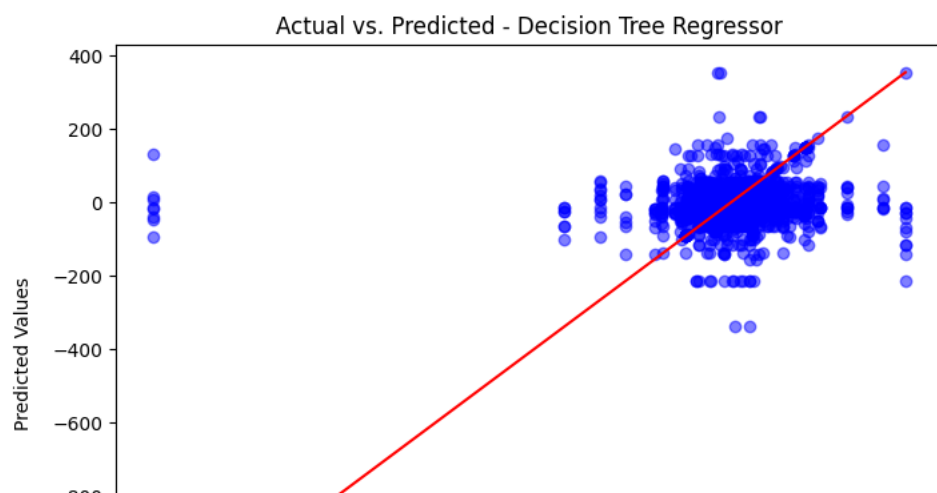
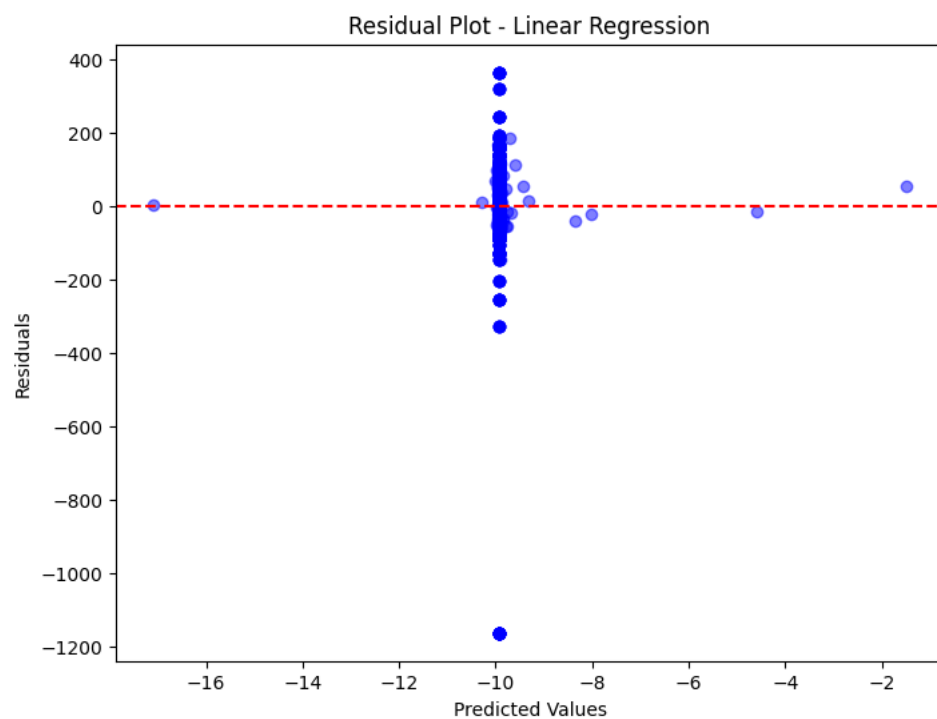
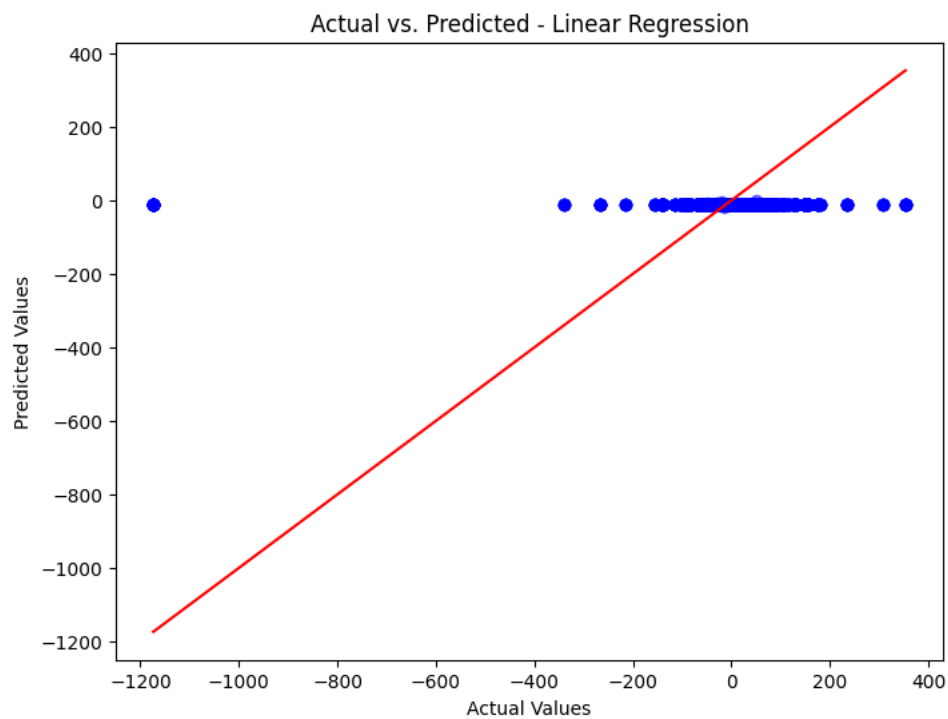
```

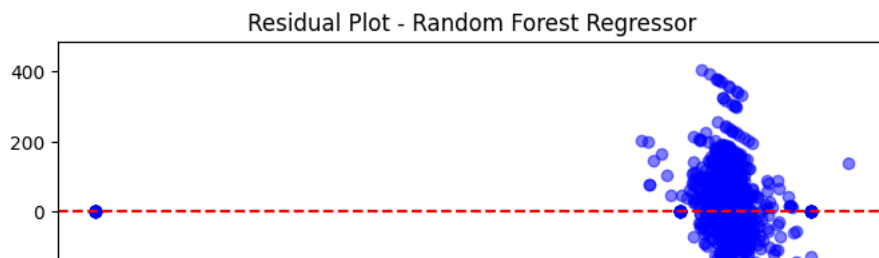
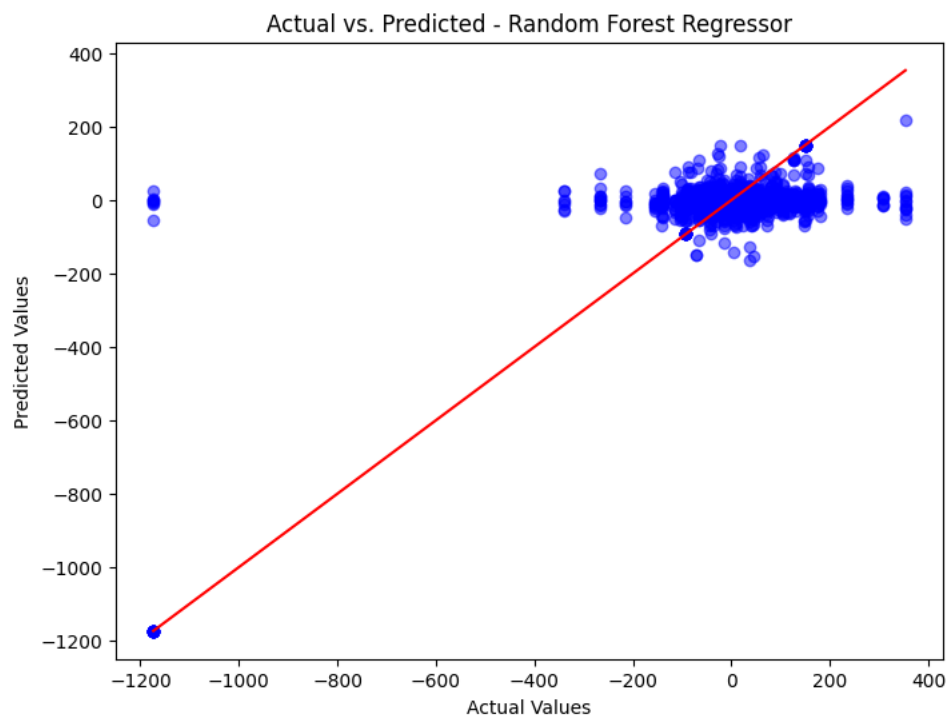
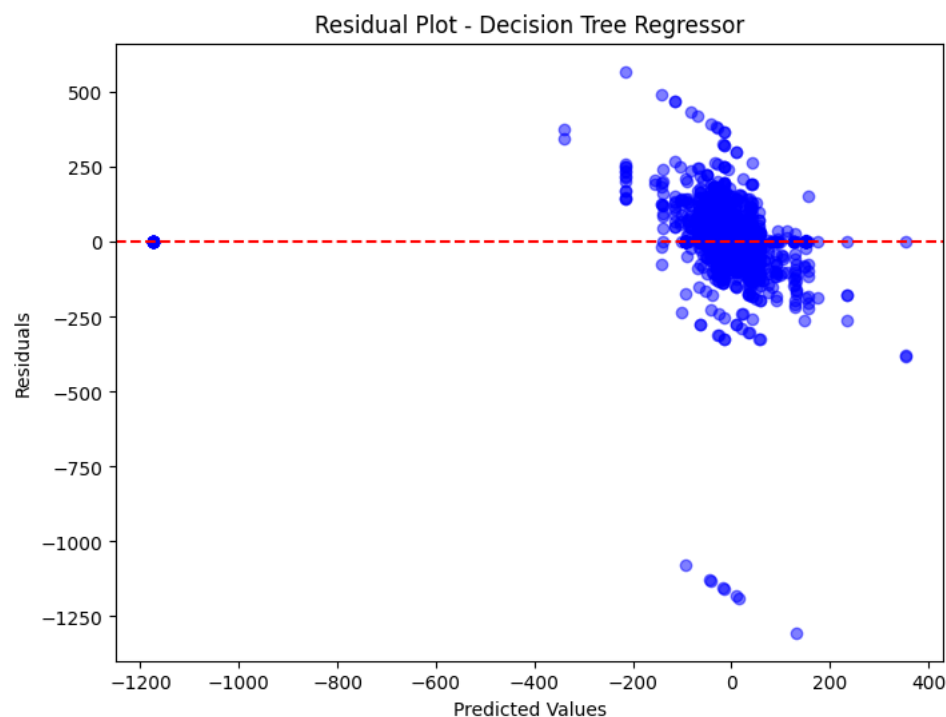
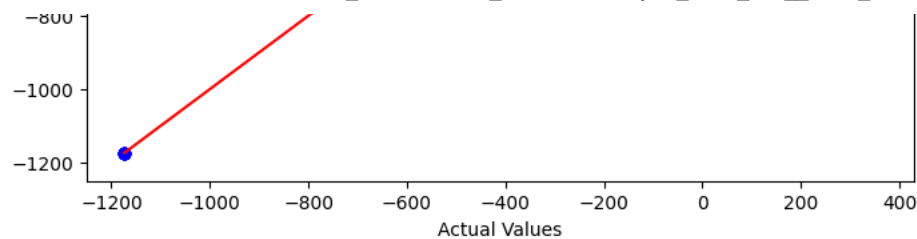
1 import pandas as pd
2 from sklearn.feature_extraction.text import CountVectorizer
3 from sklearn.model_selection import train_test_split
4 from sklearn.linear_model import LinearRegression
5 from sklearn.metrics import mean_squared_error, classification_report
6 from scipy.sparse import hstack
7
8 # Feature Extraction: Unigrams
9 unigram_vectorizer = CountVectorizer(ngram_range=(1, 1))
10 unigram_features = unigram_vectorizer.fit_transform(tweets_df['text'])
11
12 # Feature Extraction: Bigrams
13 bigram_vectorizer = CountVectorizer(ngram_range=(2, 2))
14 bigram_features = bigram_vectorizer.fit_transform(tweets_df['text'])
15
16 # Combining Features
17 combined_features = hstack([unigram_features, bigram_features])
18
19 # Additional Input Features
20 additional_features = tweets_df[['compound', 'score', 'polarity', 'subjectivity', 'sentiment_score']].values
21
22 # Concatenate Additional Features with Combined Features
23 X = hstack([combined_features, additional_features])
24
25 # Target Variable
26 y = tweets_df['price_delta']
27
28 # Split the data into training and testing sets
29 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
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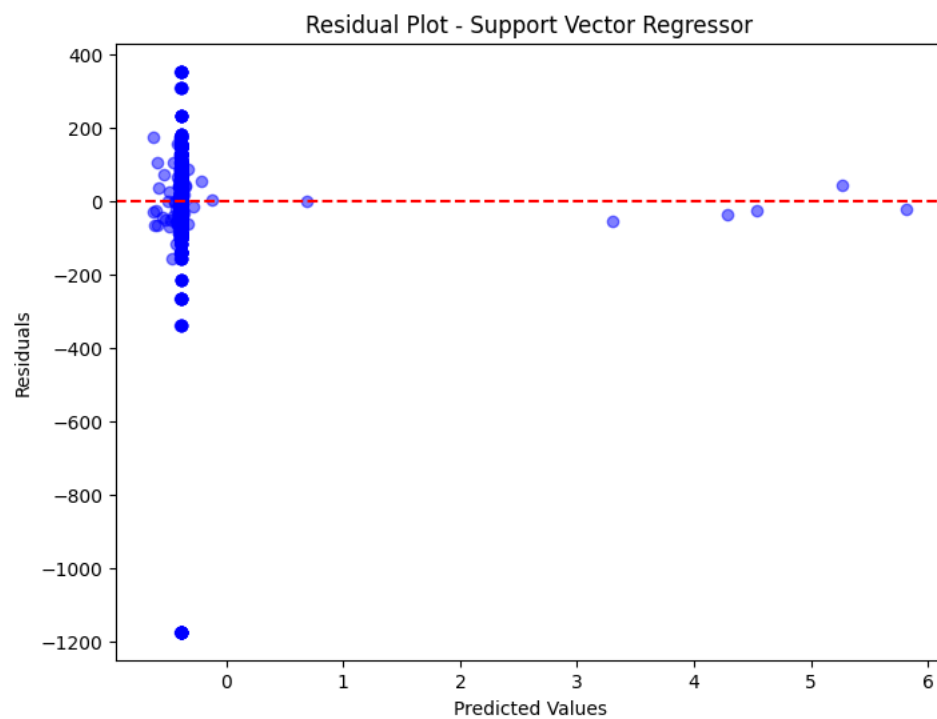
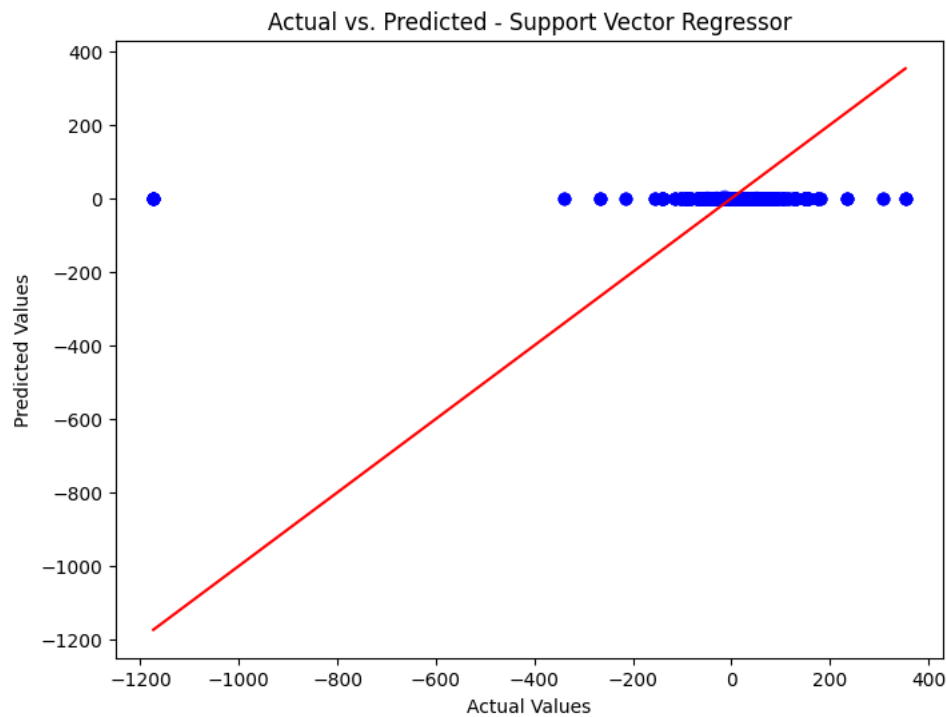
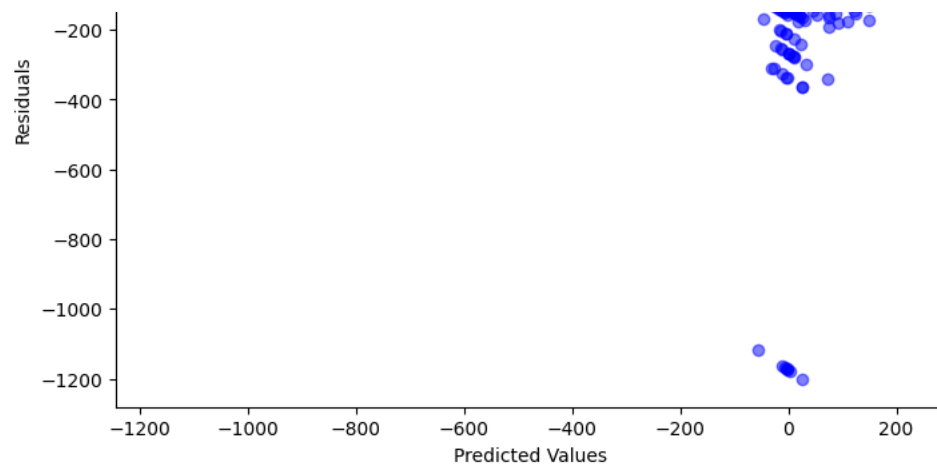
```

```
12
13 # Define the models
14 models = {
15     "Linear Regression": LinearRegression(),
16     "Decision Tree Regressor": DecisionTreeRegressor(),
17     "Random Forest Regressor": RandomForestRegressor(),
18     "Support Vector Regressor": SVR(),
19     "Gradient Boosting Regressor": GradientBoostingRegressor(),
20     "Neural Network Regressor": MLPRegressor()
21 }
22
23 # Initialize an empty dictionary to store the results
24 results = {}
25
26 # Iterate over the models
27 for model_name, model in models.items():
28     # Train the model
29     model.fit(X_train, y_train)
30
31     # Make predictions on the test set
32     y_pred = model.predict(X_test)
33
34     # Evaluate the model
35     mse = mean_squared_error(y_test, y_pred)
36     r2 = r2_score(y_test, y_pred)
37     mae = mean_absolute_error(y_test, y_pred)
38     rmse = np.sqrt(mse)
39
40     # Store the results in the dictionary
41     results[model_name] = {
42         "Mean Squared Error": mse,
43         "R-squared": r2,
44         "Mean Absolute Error": mae,
45         "Root Mean Squared Error": rmse
46     }
47
48     # Use the trained model for future predictions
49     new_tweet = ["New tweet about Bitcoin"]
50     new_tweet_features = hstack([unigram_vectorizer.transform(new_tweet), bigram_vectorizer.transform(new_tweet), additional_features[:1]
51     predicted_close = model.predict(new_tweet_features)
52
53     results[model_name]["Predicted Close Price"] = predicted_close
54
55     # Scatter plot
56     plt.figure(figsize=(8, 6))
57     plt.scatter(y_test, y_pred, color='blue', alpha=0.5)
58     plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red')
59     plt.xlabel('Actual Values')
60     plt.ylabel('Predicted Values')
61     plt.title(f'Actual vs. Predicted - {model_name}')
62     plt.show()
63
64     # Residual plot
65     plt.figure(figsize=(8, 6))
66     residuals = y_test - y_pred
67     plt.scatter(y_pred, residuals, color='blue', alpha=0.5)
68     plt.axhline(y=0, color='red', linestyle='--')
69     plt.xlabel('Predicted Values')
70     plt.ylabel('Residuals')
71     plt.title(f'Residual Plot - {model_name}')
72     plt.show()
73
74 # Convert the results to a pandas DataFrame for tabular representation
75 results_df = pd.DataFrame.from_dict(results, orient="index")
76
77 # Print the results
78 print(results_df)
79
```

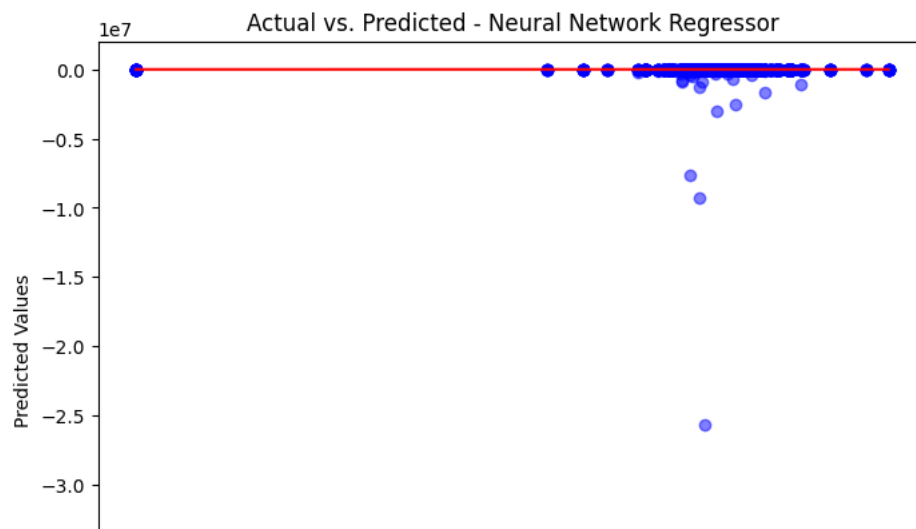
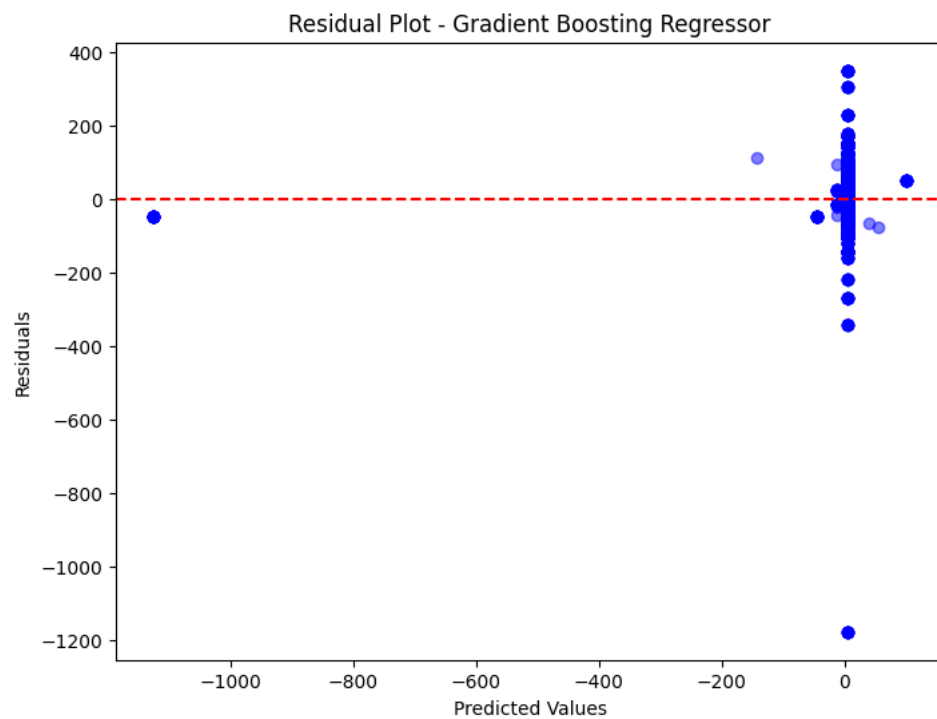
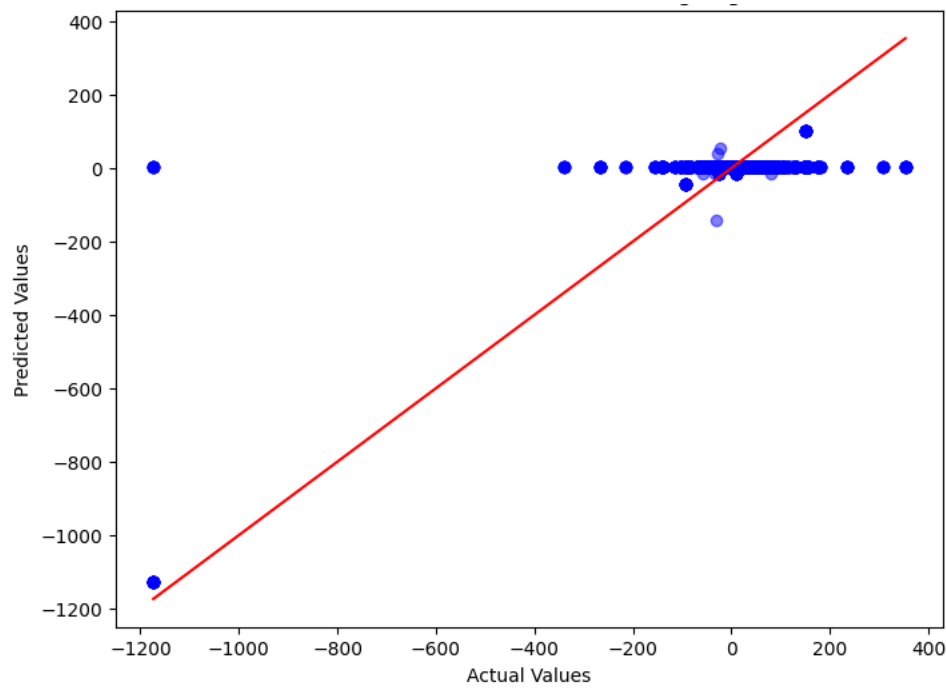


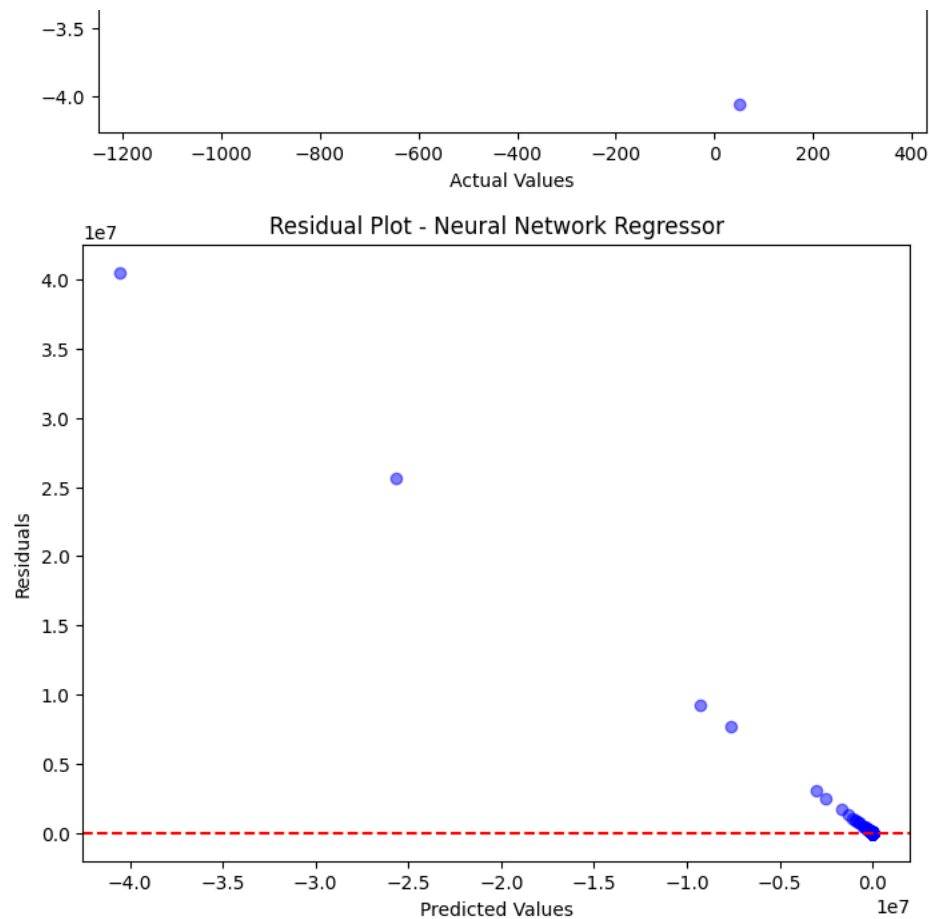






Actual vs. Predicted - Gradient Boosting Regressor





	Mean Squared Error	R-squared \
Linear Regression	2.719533e+04	1.690131e-05
Decision Tree Regressor	1.629985e+04	4.006479e-01
Random Forest Regressor	1.426430e+04	4.754961e-01
Support Vector Regressor	2.728427e+04	-3.253527e-03
Gradient Boosting Regressor	1.402917e+04	4.841418e-01
Neural Network Regressor	1.561907e+12	-5.743195e+07

	Mean Absolute Error	Root Mean Squared Error \
Linear Regression	77.295484	1.649101e+02
Decision Tree Regressor	72.397503	1.276709e+02
Random Forest Regressor	65.215510	1.194332e+02
Support Vector Regressor	76.810227	1.651795e+02
Gradient Boosting Regressor	64.989379	1.184448e+02
Neural Network Regressor	64229.120665	1.249763e+06

1 #The Decision Tree Regressor, Random Forest Regressor, and Gradient Boosting Regressor perform relatively better with higher R-squared val  
 2 #The Neural Network Regressor has a significantly negative R-squared value and extremely high mean squared error and mean absolute error,  
 3 #Among the three better-performing models, the Random Forest Regressor has the lowest mean squared error and mean absolute error, followed  
 4 #Based on these metrics, both the Random Forest Regressor and Gradient Boosting Regressor show promise in predicting price change, with th  
 Gradient Boosting Regressor [3.0043414199153072]

```
1
2 # Transpose the DataFrame
3 transposed_df = results_df.transpose()
4
5 # Print the transposed DataFrame
6 print(transposed_df)
```

## ▼ Cross Validation for price\_delta

1

## ▼ Linear Regression

```

1 from sklearn.linear_model import LinearRegression
2 from sklearn.metrics import mean_squared_error, accuracy_score, precision_score, recall_score, f1_score
3
4 # Train the linear regression model
5 model = LinearRegression()
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