DAIP CASE 4

BITCOIN PRICE PREDICTION USING MACHINE LEARNING SUPERVISED ALGORITHMS

BY

GROUP 5

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1.0 INTRODUCTION

Bitcoin, the pioneer of cryptocurrencies, has captivated global attention with its decentralized nature and remarkable price volatility. Its emergence has led to a fervent interest in understanding and predicting its price movements. In response to this, this report embarks on a journey to explore the predictive potential of machine learning, specifically employing Logistic Regression, Random Forest Classifier, Gradient Boosting Classifier and Bagging Classifier, to forecast the direction of Bitcoin's price fluctuations.

While traditional financial markets have established tools for price forecasting, the dynamic and decentralized nature of cryptocurrencies presents unique challenges. Consequently, innovative approaches leveraging machine learning techniques have garnered significant interest within the cryptocurrency community.

By harnessing the power of machine learning, we aim to distil meaningful patterns from the vast troves of historical Bitcoin price data. Our focus lies in classifying whether the closing price of Bitcoin on the next day will exceed or fall below the opening price of the present day. Such classification not only provides insight into short-term price dynamics but also lays the groundwork for informed decision-making in cryptocurrency trading.

Through this endeavour, we seek to contribute to the evolving landscape of cryptocurrency analysis, offering a practical framework for traders, investors, and enthusiasts to navigate the intricate world of Bitcoin price prediction.

2.0 LITERATURE REVIEW

Two notable studies have investigated the predictive capabilities of machine learning models for Bitcoin price movements:

Aggarwal et al. (2019) examined the use of deep learning algorithms, including LSTM (Long Short-Term Memory), CNN (Convolutional Neural Network), and GRU (Gated Recurrent Unit), to predict Bitcoin prices based on gold prices. While LSTM demonstrated the highest accuracy, the study's reliance solely on gold prices may overlook other influential factors impacting Bitcoin prices.

McNally et al. (2018) incorporated Bitcoin attributes such as difficulty and hash rate into their LSTM model, outperforming traditional methods like RNN (Recurrent Neural Network) and ARIMA (Autoregressive Integrated Moving Average). However, their study could benefit from considering additional external variables to enhance predictive accuracy further.

Both studies highlight the potential of machine learning in predicting Bitcoin prices. Nevertheless, they underscore the importance of incorporating a broader range of explanatory variables to develop more robust and accurate predictive models.

3.0 DATA COLLECTION AND PREPROCESSING

Data for Bitcoin and Gold were collected from Yahoo Finance website spanning from January 1, 2015, to February 14, 2024. Both datasets included features such as close, open, high, low, Adjusted close, and volume. Null values were removed from the Bitcoin dataset in preparation for model building.

Feature engineering was conducted to compute and include new features in the Bitcoin dataframe. These features comprised NextDayClose - which represents the next day's closing price brought to the present day; PriceTrend - a binary feature indicating whether the NextDayClose is higher than the open price of that day; PriceChange - representing the difference between the closing and opening prices; various moving averages (50-days_MA and 200-days_MA), and metrics such as Price_vs_50days_MA and Price_vs_200days_MA, providing insights into short-term and long-term trends and volatility. Moreover, volatility indicators such as RollingStd and UpperBand and LowerBand features representing Bollinger Bands were computed to further characterize price movements.

Following the computation of these new features, feature importance analysis was conducted to identify the most significant features for the classification model. The random forest classifier was utilized for this feature selection, and based on the results of its feature importance, significant features were selected for the model. The selected features are those whose feature importance score ranges from 0.034 to 0.56 and they include: Open, PriceChange, 200days_MA, Price_vs_50days_MA, and RollingStd.

4.0 METHODOLOGY AND EXPERIMENTAL SETUP

The methodology and experimental setup for this study involved a systematic approach to model construction, validation, and evaluation. To begin, the Bitcoin dataframe was partitioned into training and testing sets, with 25% of the data reserved for testing purposes and the remaining 75% allocated to training the models. This splitting strategy ensured that the models were trained on a sufficiently large dataset while allowing for robust evaluation on unseen data.

Four distinct machine learning models were selected for predicting Bitcoin price trends: Logistic Regression, Random Forest Classifier, Bagging Classifier, and Gradient Boosting Classifier. These models were chosen based on their suitability for binary classification tasks and their capability to capture complex relationships within the data.

Cross-validation was employed to assess the performance and generalization ability of each model. This involved partitioning the training data into 10 subsets, training the model on a subset, and validating it on the remaining data. By repeating this process multiple times and averaging the results, cross-validation provided a comprehensive evaluation of each model's predictive performance while mitigating the risk of overfitting.

Following cross-validation, the models were trained on the entirety of the training set and evaluated on the reserved testing set. This allowed for an assessment of how well each model generalized to unseen data and provided insights into their predictive capabilities in real-world scenarios.

Standard evaluation metrics such as accuracy and precision were utilized to assess the performance of the models. Accuracy measures the proportion of correctly classified instances, while precision measures the proportion of true positive predictions among all positive predictions. These metrics provided a quantitative assessment of each model's ability to correctly classify Bitcoin price trends Owusu-Adjei et al., 2023).

Moreover, the accuracy scores obtained from cross-validation for each model were recorded, along with their average accuracy scores. Additionally, the standard deviation of these cross-validation accuracy scores was computed to gauge the variability in model performance across different subsets of the training data.

These models are being considered because they have high accuracy, precision, and they deal with outliers better than others. By employing this comprehensive methodology, the study aimed to rigorously evaluate the performance of different machine learning models in predicting Bitcoin price trends. The experimental setup ensured robust validation and provided valuable insights into the reliability and stability of each model's predictions.

5.0 RESULT AND DISCUSSION

The evaluation of various machine learning models for predicting Bitcoin price trends offers valuable insights into their performance and suitability for real-world applications.

5.1 Logistic Regression:

The mean cross-validation accuracy for Logistic Regression was approximately 69.9%, with a standard deviation of 1.8%. While this model demonstrated moderate performance, achieving an accuracy score of 68.9% on the test set, its precision score of 76.3% indicates a relatively high ability to correctly classify positive instances. However, the confusion matrix shows a notable number of false positives and false negatives, suggesting room for improvement.

5.2 Random Forest Classifier:

The Random Forest Classifier exhibited a slightly higher mean cross-validation accuracy of 75.0%, with a standard deviation of 1.7%. When tested on the test set, the model achieved an accuracy score of 75.0% and a precision score of 76.2%. The confusion matrix illustrates a comparable distribution of true positives and true negatives, indicating balanced performance in classifying Bitcoin price trends.

5.3 Bagging Classifier:

The Bagging Classifier showcased promising results with a mean cross-validation accuracy of 75.2% and a standard deviation of 1.6%. Testing on the holdout set yielded an accuracy score of 75.2% and a precision score of 76.6%. The confusion matrix indicates a relatively balanced distribution of true positives and true negatives, further affirming the model's effectiveness in classifying Bitcoin price movements.

5.4 Gradient Boosting Classifier:

The Gradient Boosting Classifier demonstrated a mean cross-validation accuracy of 75.3%, with a standard deviation of 1.4%. Testing the model on the test set gave an accuracy score of 75.6% and a precision score of 77.1%. The confusion matrix highlights a similar distribution of true positives and true negatives, indicative of the model's robust performance in classifying Bitcoin price trends.

In summary, ensemble classifiers, particularly Bagging Classifier and Gradient Boosting Classifier, exhibit superior performance compared to Logistic Regression and Random Forest Classifier. These models demonstrate relatively high accuracy and precision in predicting Bitcoin price trends, with balanced distributions of true positives and true negatives. However, further optimization and refinement may be warranted to enhance the models' predictive capabilities and mitigate the occurrence of false positives and false negatives.

5.6 Influence of Gold price on the prediction of Bitcoin price:

After augmenting the feature set with the close price of gold, the performance of the Gradient Boosting Classifier in predicting Bitcoin price trends was evaluated. The model underwent both cross-validation and testing phases to assess its robustness and predictive accuracy.

In terms of cross-validation, the model demonstrated a mean accuracy of approximately 76.7%, with a standard deviation of 2.9%. This indicates consistent performance across different subsets of the training data, suggesting that the model generalizes well to unseen instances. The precision score of 79.0% and accuracy score of 79.1% on the test set further confirm the model's effectiveness in correctly classifying Bitcoin price trends.

Comparing these results to previous experiments without the inclusion of gold prices, we observe a slight improvement in both mean cross-validation accuracy and test set performance. Specifically, the addition of gold prices as a feature resulted in a marginal increase in mean cross-validation accuracy and a slight improvement in precision and accuracy scores on the test set. This suggests that incorporating gold prices into the feature set contributes positively to the model's predictive capabilities, potentially capturing additional patterns or correlations in the data.

6.0 RECOMMENDATION

Following the findings of this study, Further exploration and refinement of ensemble learning techniques is recommended, especially the Bagging Classifier and Gradient Boosting Classifier for the prediction of Bitcoin price trend. Additionally, integrating additional features and data sources, such as sentiment analysis from social media and news sources, may enhance the predictive capabilities of the models. Furthermore, ongoing research and development efforts should focus on improving model interpretability and robustness to market fluctuations. Collaborative efforts between researchers, practitioners, and industry stakeholders are essential to advance the field of cryptocurrency price prediction and leverage machine learning innovations for informed decision-making in financial markets.

7.0 REFLECTION

What went well?

- Exploratory Data Analysis
- Slide Structure
- Team work

What challenges were encountered?

- Inability to get sentimental data for inclusion in the analysis
- Time constraint

Future Improvement

- To integrate sentimental analysis, form social media sources as well as news sources into our model building process.
- Adding significant features for better model building.

8.0 CONCLUSSION

In conclusion, our study explored the effectiveness of various machine learning models in predicting Bitcoin price trends. Through rigorous experimentation and evaluation, we found that ensemble classifiers, particularly Bagging Classifier and Gradient Boosting Classifier, demonstrated superior performance compared to Logistic Regression and Random Forest Classifier. These models exhibited relatively high accuracy and precision in classifying Bitcoin price movements, with balanced distributions of true positives and true negatives. However, further optimization and refinement may be necessary to enhance predictive capabilities and mitigate potential shortcomings. Overall, our findings contribute to the growth of cryptocurrency price prediction research body and emphasize the importance of employing advanced machine learning techniques for accurate and reliable forecasting in dynamic financial markets.

9.0 APPENDICES

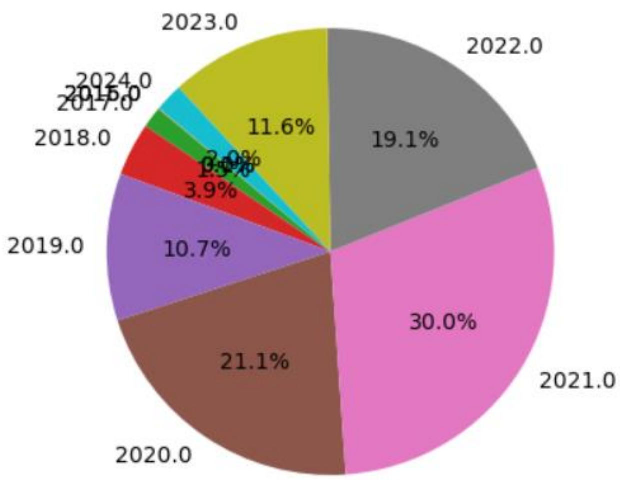


Fig 1: Pie chart showing the volume distribution by year

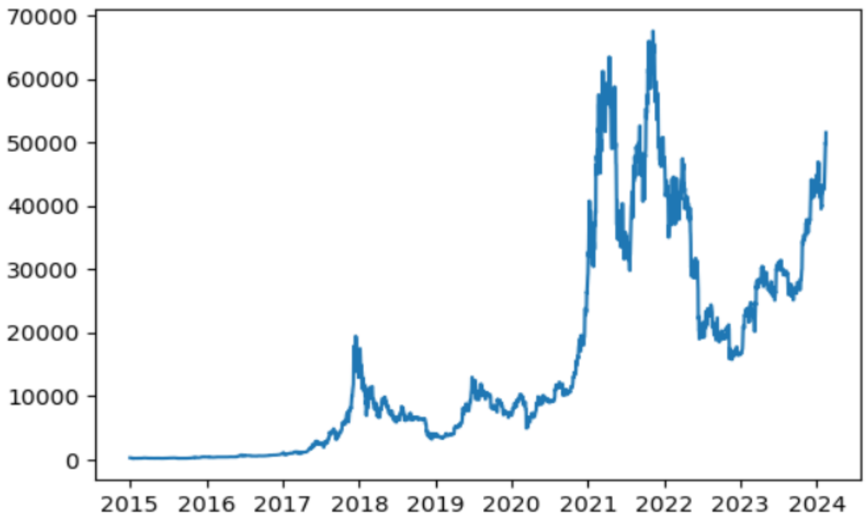


Fig 2: Bitcoin Price Trend

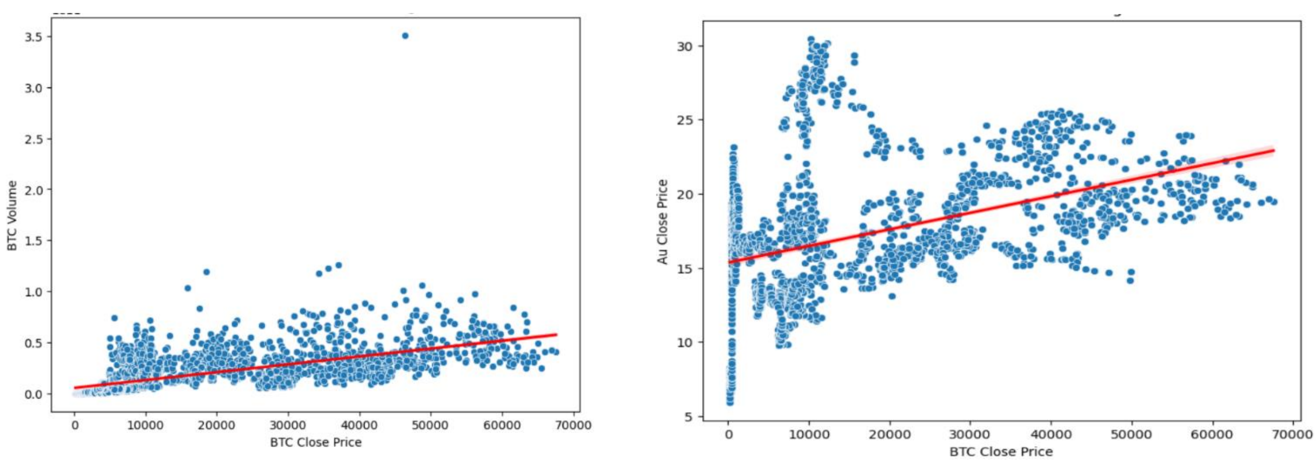


Fig 3: Scatter plot showing correlation between variables

10.0 REFERENCES

McNally S., Roche J., Caton S. 2018. Predicting the price of bitcoin using machine learning. 26th Euromicro International Conference on Parallel, Distributed and Network-based Processing, PDP, IEEE (2018)

Aggarwal, Apoorva, Isha Gupta, Novesh Garg, and Anurag Goel. 2019. Deep Learning Approach to Determine the Impact of Socio Economic Factors on Bitcoin Price Prediction. Paper presented at 2019 Twelfth International Conference on Contemporary Computing (IC3), Noida, India, August 8–10. [Google Scholar]

Owusu-Adjei, M., James Ben Hayfron-Acquah, Frimpong Twum and Gaddafi Abdul-Salaam (2023). A systematic review of prediction accuracy as an evaluation measure for determining machine learning model performance in healthcare systems. medRxiv (Cold Spring Harbor Laboratory). doi:https://doi.org/10.1101/2023.06.01.23290837.

Wang, P., Liu, X. and Wu, S. (2022). Dynamic Linkage between Bitcoin and Traditional Financial Assets: A Comparative Analysis of Different Time Frequencies. Entropy, [online] 24(11), p.1565. doi:https://doi.org/10.3390/e24111565.

CASE 4 REPORT

Introduction

This report is on the prediction of the price of bitcoin

In [182]:
```
# import neccesary libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestRegressor
#from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt
import numpy as np
from datetime import datetime
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from pandas.plotting import scatter_matrix
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score
from sklearn.metrics import accuracy_score
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
```

Data Exploration

In [183]:
```
# Load data
bitcoin_data = pd.read_csv('BTC-USD2.csv')
bitcoin_data.head()
```

Out[183]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	14/02/2024	49733.44531	51953.66016	49343.67969	51573.92969	51573.92969	3.989712e+10
1	13/02/2024	49941.35938	50358.39063	48406.49609	49742.44141	49742.44141	3.559305e+10
2	12/02/2024	48296.38672	50280.47656	47745.76172	49958.22266	49958.22266	3.451199e+10
3	11/02/2024	47768.96875	48535.93750	47617.40625	48293.91797	48293.91797	1.931587e+10
4	10/02/2024	47153.52734	48146.17188	46905.32031	47771.27734	47771.27734	1.639868e+10

In [184]:
```
# sort data by date from later to earlier
bitcoin_data['Date'] = pd.to_datetime(bitcoin_data['Date'], format='%d/%m/%Y')
bitcoin_data = bitcoin_data.sort_values(by = 'Date')
bitcoin_data.head()
```

Out[184]:

	Date	Open	High	Low	Close	Adj Close	Volume
3331	2015-01-01	320.434998	320.434998	314.002991	314.248993	314.248993	8036550.0
3330	2015-01-02	314.079010	315.838989	313.565002	315.032013	315.032013	7860650.0
3329	2015-01-03	314.846008	315.149994	281.082001	281.082001	281.082001	33054400.0
3328	2015-01-04	281.145996	287.230011	257.612000	264.195007	264.195007	55629100.0
3327	2015-01-05	265.084015	278.341003	265.084015	274.473999	274.473999	43962800.0

In [185]:
```
# Get more information about the data
bitcoin_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3697 entries, 3331 to 3696
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       3332 non-null   datetime64[ns]
 1   Open       3332 non-null   float64
 2   High       3332 non-null   float64
 3   Low        3332 non-null   float64
 4   Close      3332 non-null   float64
 5   Adj Close  3332 non-null   float64
 6   Volume     3332 non-null   float64
dtypes: datetime64[ns](1), float64(6)
memory usage: 231.1 KB
```

In [186]:
```
# Check for the number of null
bitcoin_data.isna().sum()
```

Out[186]:
```
Date         365
Open         365
High         365
Low          365
Close        365
Adj Close    365
Volume       365
dtype: int64
```

This shows that their are 365 null values in each of those columns listed

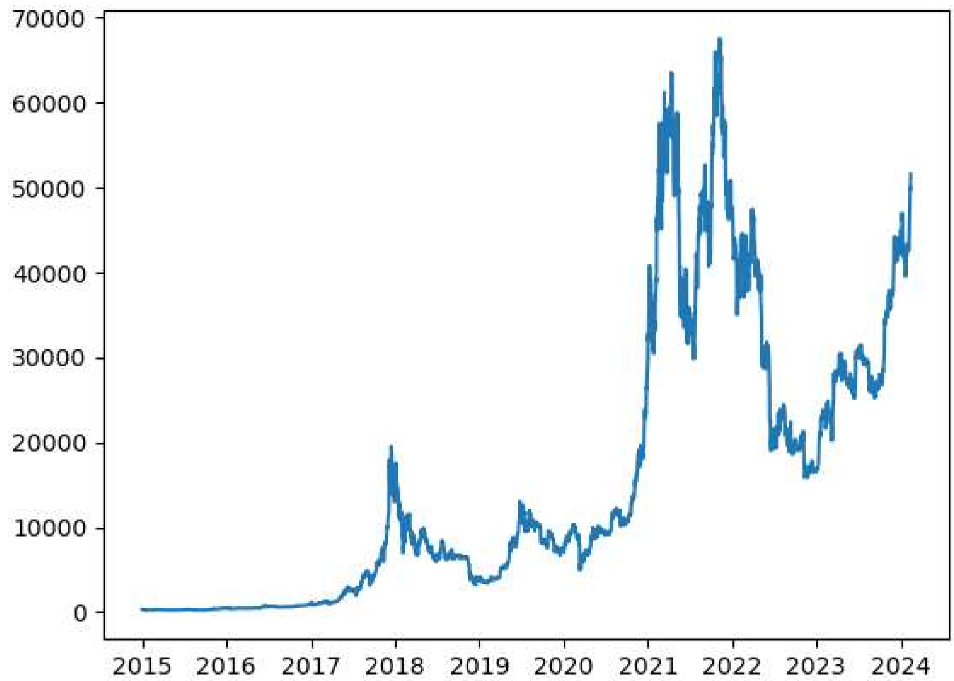
In [187]:
```
# Get the summary statistics for the data
bitcoin_data.describe()
```

Out[187]:

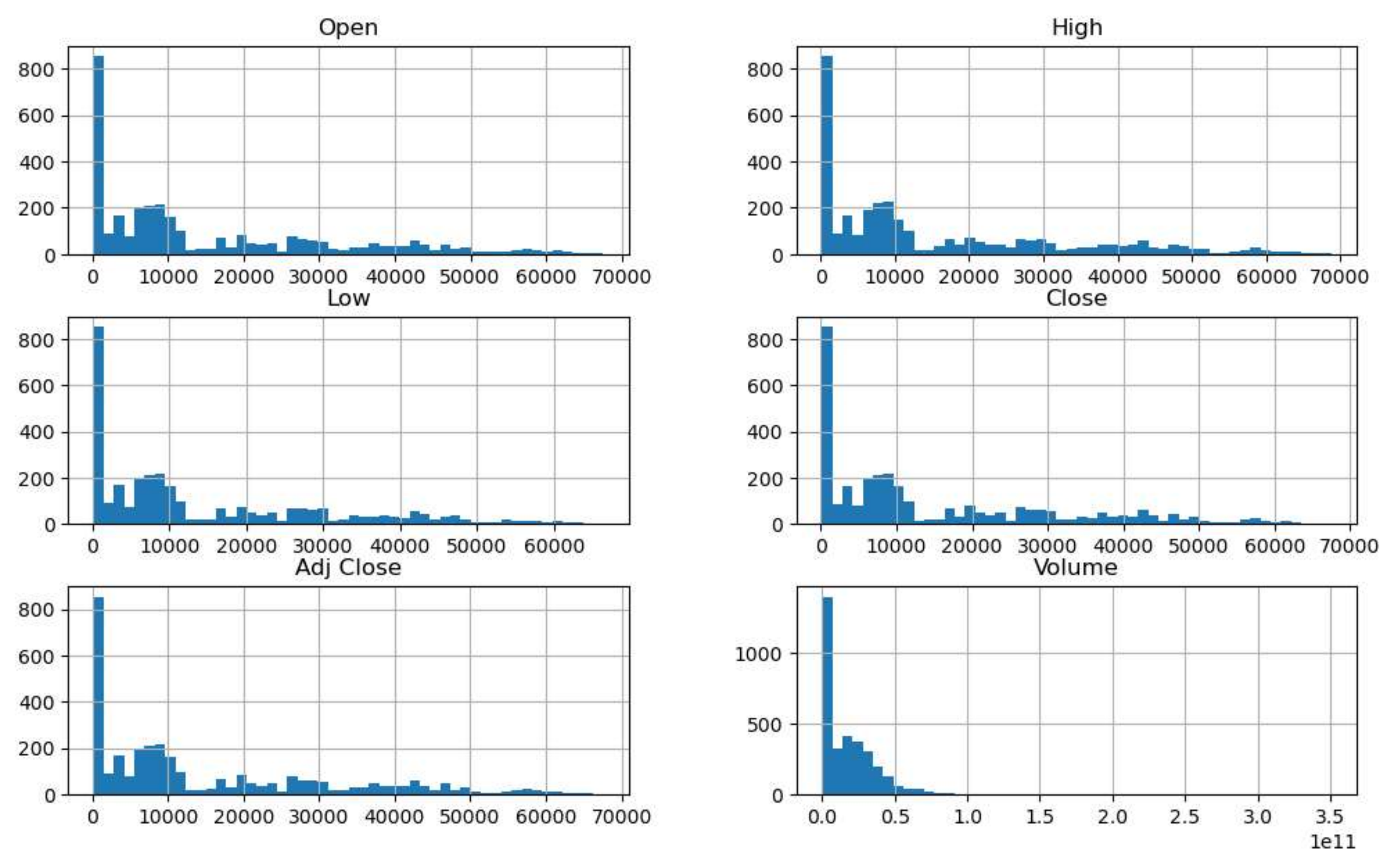
	Date	Open	High	Low	Close	Adj Close	Volume
count	3332	3332.000000	3332.000000	3332.000000	3332.000000	3332.000000	3.332000e+03
mean	2019-07-24 12:00:00	15416.339995	15775.534990	15032.748588	15430.377846	15430.377846	1.719896e+10
min	2015-01-01 00:00:00	176.897003	211.731003	171.509995	178.102997	178.102997	7.860650e+06
25%	2017-04-12 18:00:00	1223.099975	1239.935028	1207.577515	1223.280029	1223.280029	4.070770e+08
50%	2019-07-24 12:00:00	8788.635254	8957.514160	8573.421387	8790.644043	8790.644043	1.311849e+10
75%	2021-11-03 06:00:00	26303.238280	26720.072265	25913.203128	26329.301757	26329.301757	2.747484e+10
max	2024-02-14 00:00:00	67549.734380	68789.625000	66382.062500	67566.828130	67566.828130	3.510000e+11
std	NaN	16466.845922	16860.166998	16032.268512	16473.783274	16473.783274	1.908799e+10

Visualisation and KPIs

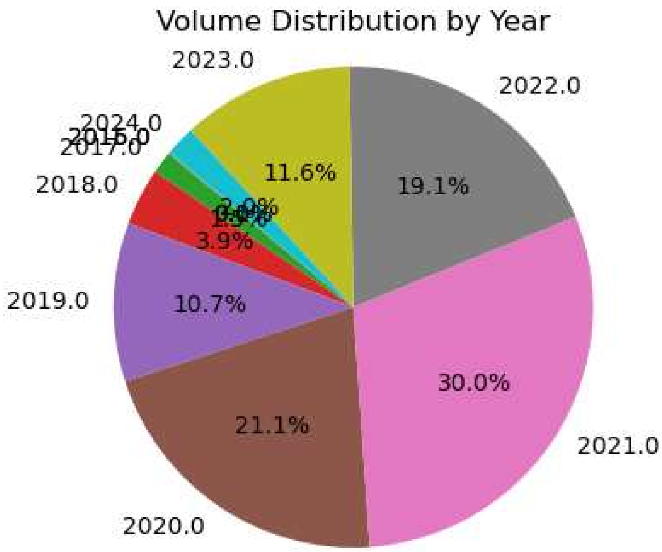
In [188]:
```
# plot chart to show price trend
plt.plot(bitcoin_data['Date'], bitcoin_data['Close'])
plt.show()
```



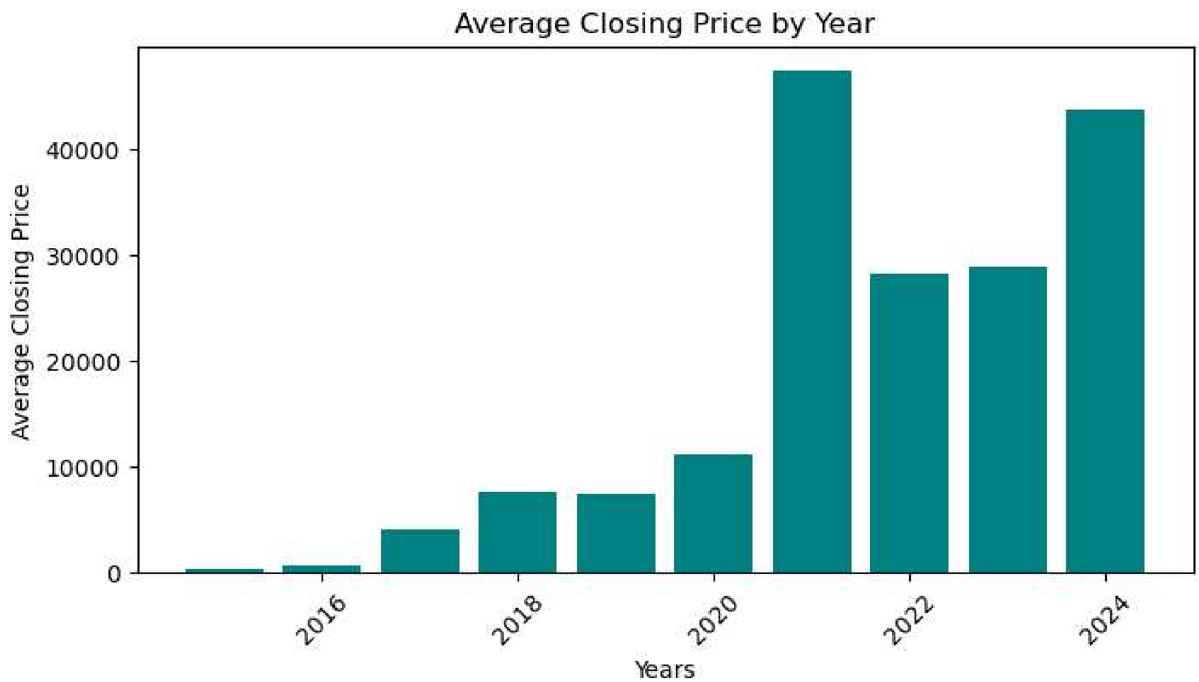
In [189]:
```
import matplotlib.pyplot as plt
%matplotlib inline
bitcoin_data_features = bitcoin_data.drop("Date", axis=1)
bitcoin_data_features.hist(bins=50, figsize=(12,7))
plt.show()
```



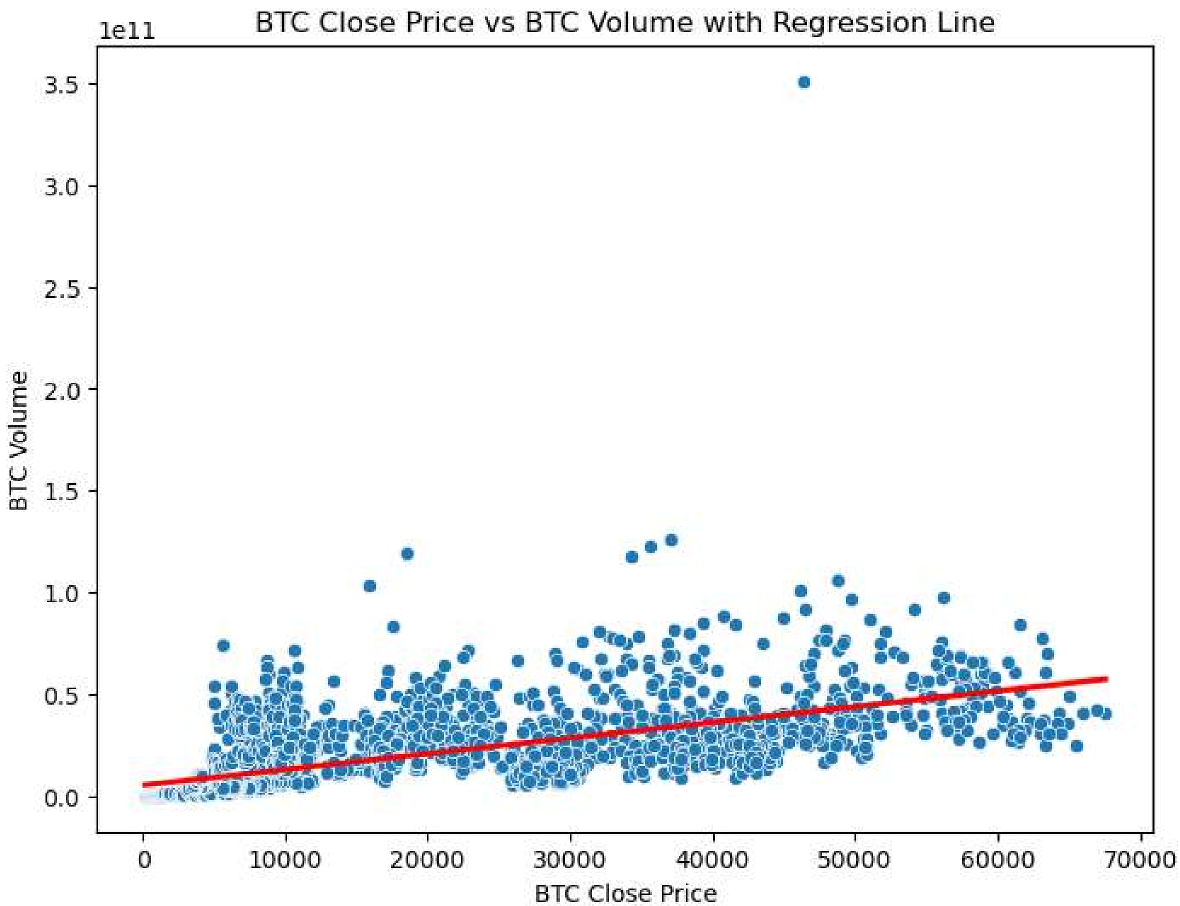
In [227]:
```
# Pie Chart showing the Volume distribution by year
bitcoin_data['Date'] = pd.to_datetime(bitcoin_data['Date'], dayfirst=True)
# Extract year from the 'Date' column
bitcoin_data['Year'] = bitcoin_data['Date'].dt.year
# Group by year and sum up the volume
volume_by_year = bitcoin_data.groupby('Year')['Volume'].sum()

plt.figure(figsize=(4, 4))
plt.pie(volume_by_year, labels=volume_by_year.index, autopct='%1.1f%%', startangle=140)
plt.title('Volume Distribution by Year')
plt.axis('equal')
plt.show()
```



In [191]:
```
# Plot a bar chart of the average closing Price of each year under consideration
average_close_by_year = bitcoin_data.groupby('Year')['Close'].mean()
# Extract labels (years) and values (average closing prices)
labels = average_close_by_year.index
values = average_close_by_year.values
plt.figure(figsize=(8, 4))
plt.bar(labels, values, color='teal')
plt.xlabel('Years')
plt.ylabel('Average Closing Price')
plt.title('Average Closing Price by Year')
plt.xticks(rotation=45)
#plt.tight_layout()
plt.show()
```



In [192]:
```
# Scatter plot of the closing price and the volume with a regression line
plt.figure(figsize=(8, 6))
sns.scatterplot(x=bitcoin_data['Close'], y=bitcoin_data['Volume'])
sns.regplot(x=bitcoin_data['Close'], y=bitcoin_data['Volume'], scatter=False, color='red')
plt.title('BTC Close Price vs BTC Volume with Regression Line')
plt.xlabel('BTC Close Price')
plt.ylabel('BTC Volume')
plt.show()
```



Preparing the Data

In [193]:
```
# Drop Null values
BitC_data = bitcoin_data.dropna()
BitC_data.isna().any()
```

Out[193]:
```
Date         False
Open         False
High         False
Low          False
Close        False
Adj Close    False
Volume       False
Year         False
dtype: bool
```

Feature Engineering

In [194]:
```
# Creating attribute for prediction - NextDay Close.  This is the closing price of the next day
BitC_data = BitC_data.copy()
BitC_data["NextDayClose"] = BitC_data['Close'].shift(-1)
BitC_data.head()
```

Out[194]:

	Date	Open	High	Low	Close	Adj Close	Volume	Year	NextDayClose
3331	2015-01-01	320.434998	320.434998	314.002991	314.248993	314.248993	8036550.0	2015.0	315.032013
3330	2015-01-02	314.079010	315.838989	313.565002	315.032013	315.032013	7860650.0	2015.0	281.082001
3329	2015-01-03	314.846008	315.149994	281.082001	281.082001	281.082001	33054400.0	2015.0	264.195007
3328	2015-01-04	281.145996	287.230011	257.612000	264.195007	264.195007	55629100.0	2015.0	274.473999
3327	2015-01-05	265.084015	278.341003	265.084015	274.473999	274.473999	43962800.0	2015.0	286.188995

In [195]:
```
# Create a new column that will store the target value
BitC_data.loc[:, "PriceTrend"] = (BitC_data["NextDayClose"] > BitC_data["Open"]).astype(int)
BitC_data["PriceTrend"].value_counts()
```

Out[195]:
```
PriceTrend
1    1824
0    1508
Name: count, dtype: int64
```

In [196]:
```
# Computing new features
# Price change
BitC_data.loc[:, "PriceChange"] = BitC_data["Close"] - BitC_data["Open"]

#Trend Indicators (e.g., 50-day and 200-day moving averages)
window_50days = 50
window_200days = 200
BitC_data.loc[:, "50days_MA"] = BitC_data["Close"].rolling(window=window_50days).mean()
BitC_data.loc[:, "200days_MA"] = BitC_data["Close"].rolling(window=window_200days).mean()

# Price Relative to Moving Averages
BitC_data.loc[:, "Price_vs_50days_MA"] = BitC_data["Close"] - BitC_data["50days_MA"]
BitC_data.loc[:, "Price_vs_200days_MA"] = BitC_data["Close"] - BitC_data["200days_MA"]

# Volatility Indicators (e.g., Bollinger Bands)
window_size = 20
BitC_data.loc[:, "RollingStd"] = BitC_data["Close"].rolling(window=window_size).std()
BitC_data.loc[:, "UpperBand"] = BitC_data["50days_MA"] + 2 * BitC_data["RollingStd"]
BitC_data.loc[:,"LowerBand"] = BitC_data["50days_MA"] - 2 * BitC_data["RollingStd"]

BitC_data = BitC_data.dropna()
BitC_data.head()
```

Out[196]:

	Date	Open	High	Low	Close	Adj Close	Volume	Year	NextDayClose	PriceTrend	PriceChang
3132	2015-07-19	274.766998	275.670013	272.513000	273.614014	273.614014	15332500.0	2015.0	278.980988	1	-1.15298
3131	2015-07-20	273.498993	278.980988	272.959991	278.980988	278.980988	22711400.0	2015.0	275.833008	1	5.48199
3130	2015-07-21	278.881989	280.546997	275.419006	275.833008	275.833008	22930700.0	2015.0	277.221985	0	-3.04898
3129	2015-07-22	275.657013	277.665985	274.381012	277.221985	277.221985	19389800.0	2015.0	276.049011	1	1.56497
3128	2015-07-23	277.341003	278.110992	275.716003	276.049011	276.049011	18531300.0	2015.0	288.278015	1	-1.29199

In [197]:
```
# Computing the correlation between the predictor features and the target features
corr_BitC_data = BitC_data.corr()

corr_BitC_data
corr_BitC_data["PriceTrend"].sort_values(ascending=False)
```

Out[197]:
```
PriceTrend             1.000000
PriceChange            0.361113
Price_vs_50days_MA     0.096641
Price_vs_200days_MA    0.051876
RollingStd            -0.022439
NextDayClose          -0.031573
Volume                -0.032087
Year                  -0.045828
Date                  -0.048995
Adj Close             -0.049463
Close                 -0.049463
Low                   -0.057872
High                  -0.058091
UpperBand             -0.066809
Open                  -0.067551
50days_MA             -0.071459
LowerBand             -0.076555
200days_MA            -0.077949
Name: PriceTrend, dtype: float64
```

In [198]:
```
# Performing feature scaling with StandardScaler
# Seperate the predictor and target features
ToDrop = ["Date", "PriceTrend"]
predictors = BitC_data.drop(ToDrop, axis=1)
BitC_targ = BitC_data["PriceTrend"]

# Create an instance of the scaler
scaler = StandardScaler()
BitC_pred = pd.DataFrame(scaler.fit_transform(predictors),  columns=predictors.columns)

BitC_pred.head()
```

Out[198]:

	Open	High	Low	Close	Adj Close	Volume	Year	NextDayClose	PriceChange	50days_MA	200days_MA
0	-0.975007	-0.974764	-0.976330	-0.975635	-0.975635	-0.953000	-1.732926	-0.975743	-0.018775	-0.974552	-0.973609
1	-0.975084	-0.974569	-0.976302	-0.975310	-0.975310	-0.952615	-1.732926	-0.975934	-0.010743	-0.974491	-0.973621
2	-0.974757	-0.974476	-0.976149	-0.975500	-0.975500	-0.952604	-1.732926	-0.975850	-0.021070	-0.974426	-0.973634
3	-0.974953	-0.974646	-0.976214	-0.975416	-0.975416	-0.952789	-1.732926	-0.975921	-0.015484	-0.974363	-0.973635
4	-0.974851	-0.974620	-0.976131	-0.975487	-0.975487	-0.952834	-1.732926	-0.975180	-0.018943	-0.974301	-0.973631

Feature Importance

In [199]:
```
# Splitting the dataset into train and test sets
BitC_pred_train, BitC_pred_test, BitC_targ_train, BitC_targ_test = train_test_split(BitC_pred, BitC_targ, t

rnd_clsf = RandomForestClassifier(n_estimators=100, min_samples_split=50, random_state=1)

#Training and testing the model
rnd_clsf.fit(BitC_pred_train, BitC_targ_train)
targ_predict = rnd_clsf.predict(BitC_pred_test)

rnd_clsf.feature_importances_
```

Out[199]:
```
array([0.03861424, 0.02323873, 0.02525366, 0.0201072 , 0.01755429,
       0.02990133, 0.00547404, 0.05417374, 0.56101119, 0.02664695,
       0.03456214, 0.04365235, 0.029524  , 0.03008009, 0.02685837,
       0.03334768])
```

In [228]:
```
# Streamlining the dataframe to include just a few features based on the feature importance
selected_features = [ "Open", "PriceChange","200days_MA", "Price_vs_50days_MA", "RollingStd"]
BitC_train = BitC_pred_train[selected_features]
BitC_test = BitC_pred_test[selected_features]
BitC_train.head()
```

Out[228]:

	Open	PriceChange	200days_MA	Price_vs_50days_MA	RollingStd
573	-0.931744	0.001448	-0.941934	-0.079102	-0.745202
3057	1.293318	1.157756	0.939792	1.071031	-0.152251
2848	0.797822	-0.785156	0.450285	0.003072	-0.139404
1213	-0.605562	-0.033963	-0.530766	-0.129868	-0.743195
2093	2.633853	0.416888	1.083109	1.408328	1.115931

Building Classification Models

Because our target feature has now been converted to binary, we have a classification problem of predicting the probability that the closing price of the next day is either higher than the openinf price on current day -class 1 or vice versa for class 0

Logistic Regression

In [201]:
```
# Instantiating the model
lg_reg = LogisticRegression()

# perform cross validation on the new train dataset
kf = KFold(n_splits=10, shuffle=True, random_state=1)
cv_scores = cross_val_score(lg_reg, BitC_train, BitC_targ_train, cv=kf, scoring="accuracy")

print("Cross-validation scores:", cv_scores)
print("Mean of CV accuracy:", cv_scores.mean())
print("Standard deviation of CV accuracy:", cv_scores.std())
```

```
Cross-validation scores: [0.70638298 0.67234043 0.69787234 0.71914894 0.66808511 0.71489362
 0.7106383  0.67659574 0.71489362 0.70940171]
Mean of CV accuracy: 0.6990252773231497
Standard deviation of CV accuracy: 0.018382130194198067
```

In [202]:
```
# Train and test the model
lg_reg.fit(BitC_train, BitC_targ_train)

lg_reg_pred = lg_reg.predict(BitC_test)

# Model Evaluation

# Get precision score
print("Precision Score: ", precision_score(BitC_targ_test, targ_predict))

# Get accuracy score
print("Accuracy Score: ", accuracy_score(BitC_targ_test, lg_reg_pred))

# Get confusion matrix
print("Confusion Matrix:")
confusion_matrix(BitC_targ_test, targ_predict)
```

```
Precision Score:  0.7666666666666667
Accuracy Score:  0.6896551724137931
Confusion Matrix:
```

Out[202]:
```
array([[246, 105],
       [ 87, 345]], dtype=int64)
```

Random Forest

In [203]:
```
# perform cross validation on the new train dataset
kf = KFold(n_splits=10, shuffle=True, random_state=42)
cv_scores = cross_val_score(rnd_clsf, BitC_train, BitC_targ_train, cv=kf, scoring="accuracy")

print("Cross-validation scores:", cv_scores)
print("Mean of CV accuracy:", cv_scores.mean())
print("Standard deviation of CV accuracy:", cv_scores.std())
```

```
Cross-validation scores: [0.73191489 0.76170213 0.76170213 0.72765957 0.73617021 0.76170213
 0.77446809 0.74893617 0.76595745 0.72649573]
Mean of CV accuracy: 0.7496708492453172
Standard deviation of CV accuracy: 0.016834709911545787
```

In [204]:
```
## Train and test the new dataframe with the already Instantiated Random Forest Classifier

rnd_clsf.fit(BitC_train, BitC_targ_train)
targ_predict = rnd_clsf.predict(BitC_test)

# Model Evaluation

# Get precision score
print("Precision Score: ", precision_score(BitC_targ_test, targ_predict))

# Get accuracy score
print("Accuracy Score: ", accuracy_score(BitC_targ_test, targ_predict))

# Get confusion matrix
print("Confusion Matrix:")
confusion_matrix(BitC_targ_test, targ_predict)
```

```
Precision Score:  0.7622222222222222
Accuracy Score:  0.7496807151979565
Confusion Matrix:
```

Out[204]:
```
array([[244, 107],
       [ 89, 343]], dtype=int64)
```

Bagging Classifier

In [205]:
```
# Instantiating the model
bag_clf = BaggingClassifier(
    RandomForestClassifier(n_estimators=100, min_samples_split=50, random_state=1)
)

# perform cross validation on the train dataset
kf = KFold(n_splits=10, shuffle=True, random_state=42)
cv_scores = cross_val_score(bag_clf, BitC_train, BitC_targ_train, cv=kf, scoring="accuracy")

print("Cross-validation scores:", cv_scores)
print("Mean of CV accuracy:", cv_scores.mean())
print("Standard deviation of CV accuracy:", cv_scores.std())
```

```
Cross-validation scores: [0.74893617 0.77021277 0.76595745 0.74893617 0.74893617 0.76170213
 0.7787234  0.74042553 0.75319149 0.73076923]
Mean of CV accuracy: 0.7547790507364975
Standard deviation of CV accuracy: 0.013681557772295364
```

In [206]:
```
#Train and test the Bagging Classifier
bag_clf.fit(BitC_train, BitC_targ_train)
targ_bag_pred = bag_clf.predict(BitC_test)
print(accuracy_score(BitC_targ_test, targ_bag_pred))

# Get precision score
print("Precision Score: ", precision_score(BitC_targ_test, targ_bag_pred))

# Get accuracy score
print("Accuracy Score: ", accuracy_score(BitC_targ_test, targ_bag_pred))

# Get confusion matrix
print("Confusion Matrix:")
confusion_matrix(BitC_targ_test, targ_bag_pred)
```

```
0.7458492975734355
Precision Score:  0.7527114967462039
Accuracy Score:  0.7458492975734355
Confusion Matrix:
```

Out[206]:
```
array([[237, 114],
       [ 85, 347]], dtype=int64)
```

GradientBoosting Classifier

In [207]:
```
# Instantiating the model
gb_clf = GradientBoostingClassifier(n_estimators=3, learning_rate=0.5, max_depth=1, random_state=0)

# perform cross validation on the train dataset
kf = KFold(n_splits=10, shuffle=True, random_state=42)
cv_scores = cross_val_score(gb_clf, BitC_train, BitC_targ_train, cv=kf, scoring="accuracy")

print("Cross-validation scores:", cv_scores)
print("Mean of CV accuracy:", cv_scores.mean())
print("Standard deviation of CV accuracy:", cv_scores.std())
```

```
Cross-validation scores: [0.73191489 0.7787234  0.75744681 0.76170213 0.73617021 0.74042553
 0.76595745 0.75744681 0.76170213 0.73931624]
Mean of CV accuracy: 0.7530805601018367
Standard deviation of CV accuracy: 0.01446966593271585
```

In [208]:
```
# Train and test the model
gb_clf.fit(BitC_pred_train, BitC_targ_train)
targ_ens_pred = gb_clf.predict(BitC_pred_test)

# Model Evaluation

# Get precision score
print("Precision Score: ", precision_score(BitC_targ_test, targ_ens_pred))

# Get accuracy score
print("Accuracy Score: ", accuracy_score(BitC_targ_test, targ_ens_pred))

# Get confusion matrix
print("Confusion Matrix:")
confusion_matrix(BitC_targ_test, targ_ens_pred)
```

```
Precision Score:  0.7707865168539326
Accuracy Score:  0.756066411238825
Confusion Matrix:
```

Out[208]:
```
array([[249, 102],
       [ 89, 343]], dtype=int64)
```

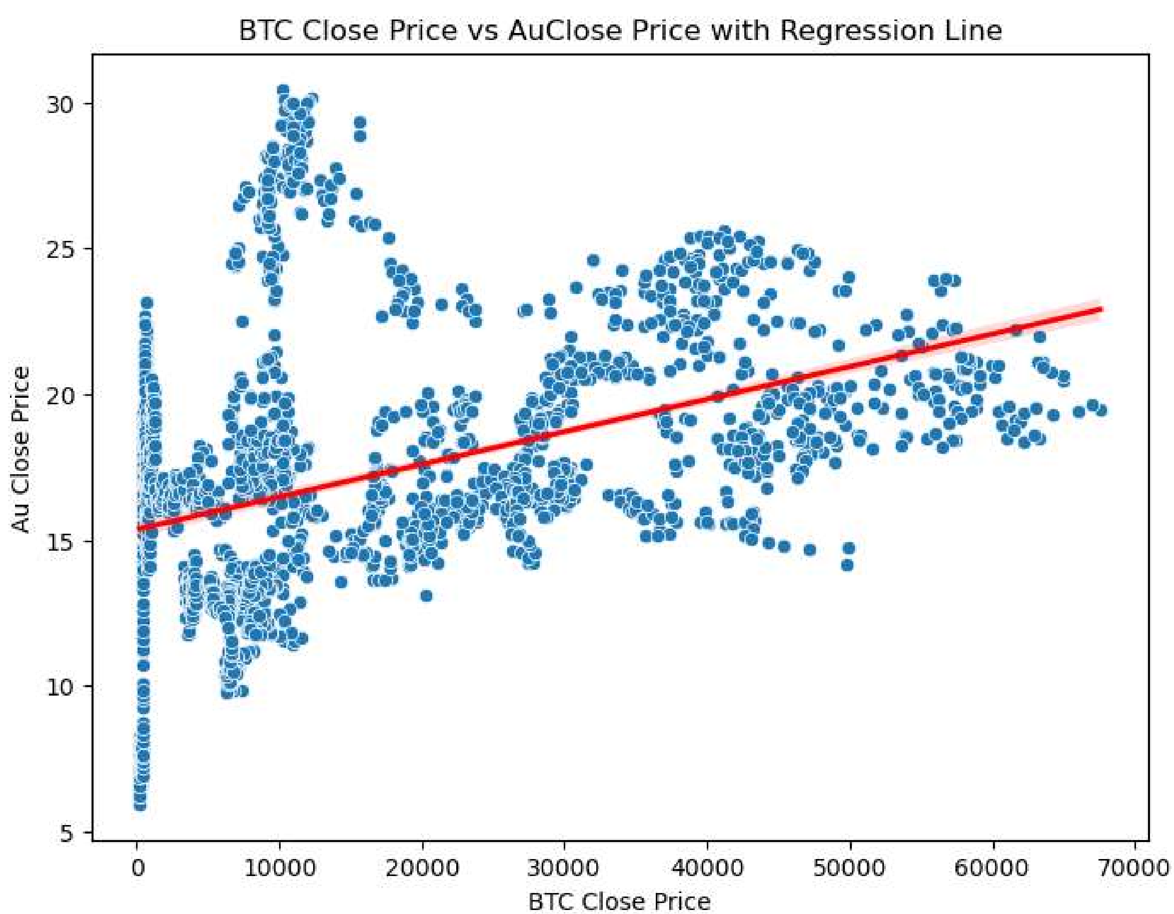
Correlation between the price of Gold and Bitcoin

In [223]:
```
# Load in the Gold dataframe
Au_data = pd.read_csv("Gold.csv")
```

In [224]:
```
# Computing the correlation between the predictor features and the target features
corr_Bitc_Au = Bitc_Au.corr()

corr_Bitc_Au
corr_Bitc_Au["PriceTrend"].sort_values(ascending=False)
```

Out[224]:
```
PriceTrend              1.000000
PriceChange             0.386541
Price_vs_50days_MA      0.129415
Price_vs_200days_MA     0.070365
Au_Close                0.000598
RollingStd             -0.019611
Volume                 -0.031999
NextDayClose           -0.033423
Adj Close              -0.050202
Close                  -0.050202
Date                   -0.053854
Low                    -0.060214
High                   -0.060313
Open                   -0.071692
UpperBand              -0.073335
50days_MA              -0.079228
LowerBand              -0.085834
200days_MA             -0.087359
Name: PriceTrend, dtype: float64
```

In [225]:
```
# Scatter plot of the closing price and the volume with a regression line
plt.figure(figsize=(8, 6))
sns.scatterplot(x=Bitc_Au['Close'], y=Bitc_Au['Au_Close'])
sns.regplot(x=Bitc_Au['Close'], y=Bitc_Au['Au_Close'], scatter=False, color='red')
plt.title('BTC Close Price vs AuClose Price with Regression Line')
plt.xlabel('BTC Close Price')
plt.ylabel('Au Close Price')
plt.show()
```



In [226]:
```
# Create a new dataframe consisting the earlier selected features and the close price of Gold  and seperati
updated_selected_features = [ "Open", "PriceChange","200days_MA", "Price_vs_50days_MA", "RollingStd", "Au_C
Bitc_Au_pred = Bitc_Au[updated_selected_features]
Bitc_Au_targ = Bitc_Au["PriceTrend"]

Bitc_Au_pred, Bitc_Au_targ
```

Out[226]:
```
(               Open  PriceChange    200days_MA  Price_vs_50days_MA  \
 0        273.498993     5.481995    246.832130           25.777970
 1        278.881989    -3.048981    246.636135           21.571849
 2        275.657013     1.564972    246.616835           21.932446
 3        277.341003    -1.291992    246.676105           19.755972
 4        276.005005    12.273010    246.745125           30.705896
 ...             ...          ...           ...                 ...
 2153  43090.019530  1228.203130  34442.675840         1330.068207
 2154  44332.125000   969.441410  34518.760977         2280.425628
 2155  45297.382810  1849.816410  34608.612393         4060.497501
 2156  48296.386720  1661.835940  34899.764219         6566.123831
 2157  49941.359380  -198.917970  35001.880196         6227.756566

        RollingStd  Au_Close
 0       13.918339      7.41
 1       13.313687      7.50
 2       12.331296      7.36
 3       11.263984      7.07
 4       10.615005      7.25
 ...           ...       ...
 2153  1319.386193     14.93
 2154  1501.297363     14.82
 2155  1852.414500     14.67
 2156  2651.406569     14.73
 2157  2820.461589     14.15

 [2158 rows x 6 columns],
 0       1
 1       0
 2       1
 3       1
 4       1
        ..
 2153    1
 2154    1
 2155    1
 2156    1
 2157    1
 Name: PriceTrend, Length: 2158, dtype: int32)
```

Build the Gradient Boosting Classifier for this Dataset

In [218]:
```
#splitting the dataset into testing and training set
Bitc_Au_pred_train, Bitc_Au_pred_test, Bitc_Au_targ_train, Bitc_Au_targ_test = train_test_split(Bitc_Au_pre

# Use the already instantiated Gradient Boosting Classifier

# perform cross validation on the train dataset
kf = KFold(n_splits=10, shuffle=True, random_state=42)
cv_scores = cross_val_score(gb_clf, Bitc_Au_pred_train, Bitc_Au_targ_train, cv=kf, scoring="accuracy")

print("Cross-validation scores:", cv_scores)
print("Mean of CV accuracy:", cv_scores.mean())
print("Standard deviation of CV accuracy:", cv_scores.std())
```

```
Cross-validation scores: [0.72839506 0.75308642 0.74074074 0.7962963  0.7962963  0.77160494
 0.82098765 0.7345679  0.77639752 0.7515528 ]
Mean of CV accuracy: 0.7669925619200981
Standard deviation of CV accuracy: 0.028990801673196783
```

In [219]:

```
# Train and test the model
gb_clf.fit(Bitc_Au_pred_train, Bitc_Au_targ_train)
new_targ_pred = gb_clf.predict(Bitc_Au_pred_test)

# Model Evaluation

# Get precision score
print("Precision Score: ", precision_score(Bitc_Au_targ_test, new_targ_pred))

# Get accuracy score
print("Accuracy Score: ", accuracy_score(Bitc_Au_targ_test, new_targ_pred))

# Get confusion matrix
print("Confusion Matrix:")
confusion_matrix(Bitc_Au_targ_test, new_targ_pred)
```

```
Precision Score:  0.7903225806451613
Accuracy Score:  0.7907407407407407
Confusion Matrix:
```

Out[219]:

```
array([[182,  65],
       [ 48, 245]], dtype=int64)
```