Bitcoin trading indicator: a machine learning driven real time bitcoin trading indicator for the crypto market

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ABSTRACT

As opposed to other fiat currencies, bitcoin has no relationship with banks. Its price fluctuation is largely influenced by fresh blocks, news, mining information, support or resistance levels, and public opinion. Therefore, a machine-learning model will be fantastic if it learns from data and tells or indicates if we need to purchase or sell for a little period. In this study, we attempted to create a tool or indicator that can gather tweets in real-time using tweepy and the Twitter application programming interface (API) and report the sentiment at the time. Using the renowned Python module "FBProphet," we developed a model in the second phase that can gather historical price data for the bitcoin to US dollar (BTCUSD) pair and project the price of bitcoin. In order to provide guidance for an intelligent forex trader, we finally merged all of the models into one form. We traded with various models for a very little number of days to validate our bitcoin trading indicator (BTI), and we discovered that the combined version of this tool is more profitable. With the combined version of the instrument, we quickly and with little error root mean square error (RMSE: 1,480.58) generated a profit of $1,000.71 USD.

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1. INTRODUCTION

A person [1] going by the name of Satoshi Nakamoto originally published one of the finest cryptocurrencies, bitcoin, on January 9, 2009. Each bitcoin was only worth $2.26 when the bitcoin to US dollar (BTCUSD) pair first entered the currency market. The most volatile cryptocurrency now that demands more general attention is bitcoin. Everyone, from researchers to traders, is searching for a pricing pattern to invest in and make the biggest return they can. Bitcoin: a peer-to-peer (P2P) electronic cash system that was introduced as a forward-thinking electronic cash alternative on just nine pages.

On the surface, cryptocurrencies like bitcoin [2] and others resemble fiat money a lot. As with regular money, a bitcoin can be broken into smaller pieces known as Satoshi's and used to make purchases from businesses that take bitcoin. To store bitcoins, a user must first build a wallet. On a computer or a mobile device, this wallet can be downloaded and installed. Some websites also offer access to online wallets, and some hardware vendors sell USB sticks that are actual wallet devices. These wallets come with a bitcoin address that may be used to send or receive money. In technical terms, a bitcoin address is a hashed representation of a public key. The corresponding private key is retained in the wallet and is encrypted and secret [3]. The foundation of the entire bitcoin network is the blockchain, a decentralised public ledger. It records all previous exchanges between various bitcoin addresses, including the amounts sent. This makes it possible to determine how much money is available in each wallet. It also enables the ownership of the spent bitcoins to be confirmed. The integrity and chronological order of the blockchain are guaranteed by cryptography [3].

All transactions are published to the P2P network through mining [4]. Miners put a lot of time and effort into creating hashes that meet certain criteria. The process of adding new bitcoins to circulation is known as bitcoin mining. By resolving incredibly difficult math puzzles, new bitcoins are created through the process of mining, which also verifies bitcoin transactions. When a bitcoin is successfully mined, the miner is given a certain number of bitcoins.

A decentralised or over-the-counter (OTC) market for trading foreign currencies is known as the foreign exchange market (forex, FX, or currency market) [5]. The foreign exchange rate for each currency is set by this market. It includes all transactions involving the buying, selling, and exchanging of currencies at set or prevailing rates. "Percentage in point" or "price interest point" is abbreviated as pip [6]. In the foreign exchange market, it is a tiny unit of measurement that denotes a change in a currency pair. Either the stated currency or the underlying currency may be used to represent it as a percentage. The smallest alteration in a currency quote is represented by a standardised unit called a pip. A lot [7] is a predetermined sum of money used along with pips to execute a trade in forex. Fortunately, a range of lot sizes are available to traders. Typically, in order to take a deal, traders must choose the lot size. On a normal trading account for excess, lots start at 0.0001 and can reach a maximum of 5. By putting more money into various accounts, you can raise the size of your lots.

Natural language processing (NLP) is used in sentiment analysis [8], [9] to determine if data is favourable, negative, or neutral. Organizations typically employ sentiment analysis on textual data to analyse brand and product sentiment in consumer feedback and gain a better understanding of client wants. To evaluate and derive objective quantitative findings from unprocessed text, sentiment analysis uses NLP machine learning and other data analysis approaches. Sentiment analysis is a branch of text mining.

In 1998, one of the earliest books on stock market forecasting [10] was published. Information was acquired by Wüthrich and associates from the Wall Street Journal, Financial Times, Reuters, and Bloomberg. According to Borges [11] any positive or negative news is immediately absorbed by the market, and stock prices change in accordance. Therefore, it is impossible to outperform the stock market because there are never any undervalued stocks to buy or overvalued stocks to sell. Over extended periods, many investors, including Warren Buffet, have been able to outperform the market. A single-layered convolutional neural network (CNN) model was created by Cavalli and Amoretti [12] to increase earnings when the trend is bullish and decrease losses when the market is bearish. Their creations were based on text from several social media profiles. A trading strategy test revealed that it had superior accuracy and return compared to a single source system [13]. An recurrent neural network (RNN)-based model was employed in a depth literature analysis [14] to forecast the price of bitcoin based on Twitter sentiment. By using analysis, we can predict the price of bitcoin based on the emotion of tweets that come from specific sources. I particularly like how they use gradient descent, another machine-learning method, to extract a significant price from Twitter sentiment analysis by using daily high and low prices from historical data. A number of machine learning techniques are detailed in the reference paper by Colianni *et al.* [15] that predict the price of bitcoin. Before using their model, they even conducted extensive literature research. They used two datasets to distribute their model. One was for hourly data followed by time series, and the other was for daily time series data. Additionally, they used supervised learning to classify Twitter sentiment using data from Twitter. The accuracy and maximum result they were able to achieve using Bayesian Naive Bayes was 95% for day-basis data and 76.59% for hour-basis data. Research by Garcia and Schweitzer [16] published a companion piece. The researchers used a trading simulation engine and two daily Twitter sentiment time series. The latter was based on a collection of positive and negative terms from the linguistic inquiry and word count (LIWC) lexicon, as well as the daily ratio between them.

To trade in forex, we must do a market analysis, determine the present stance of the market pair, and make a prognosis or projection. It is difficult for one person to consider every angle because humans make mistakes, and doing so has so far taken a lot of time. Additionally, because of how quickly time passes, traders must act more quickly while making decisions. Therefore, our goal is to create a real-time "bitcoin" trading indicator for the currency market that is powered by machine learning. To be more precise, we want to predict whether we should "buy" or "sell" on the following day. We'll employ current market support and resistance in real-time to work toward this objective. We won't purchase actual bitcoin. But we'll deal in bitcoin on the foreign exchange market. The tone of the tweet from the day before is the main focus. In order to see the market trend and do a seasonal study, we also create a time series forecasting model.

2. RESEARCH METHOD

In this segment, data collection, web scraping, data handling/pre-processing, time series generation, data analysis with forecasting, and developing BTI trading indicator has complied, which represent in Figure 1; the details explanation is given orderly.

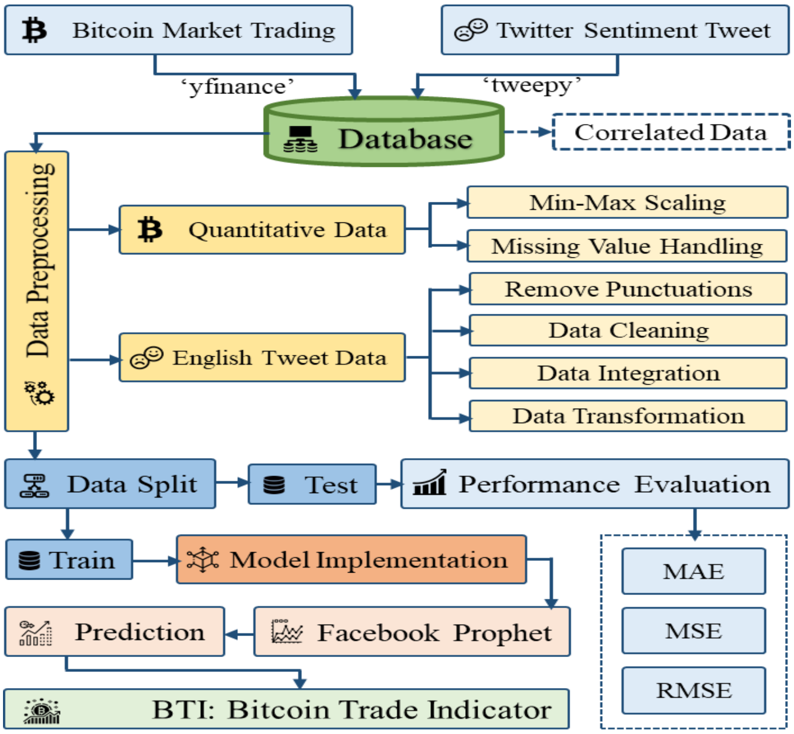

Figure 1. Workflow diagram of proposed study

2.1. Data collection

It is impossible to emphasise the significance of datasets in machine learning research [17]. This study uses two different forms of data: tweets from Twitter and quantitative bitcoin price data obtained using the Python module "tweepy" [18]. We construct the exact symbols of currency prices, such BTCUSD, using ticker parameters. This cost is expressed as a percentage of the US dollar per bitcoin.

The current datetime for the last range of data pulling was generated using a Python datetime object. We run the programme using the Python package "yfinance" and extract the bitcoin data in USD as our bitcoin data for time series analysis from Figure 2. We first requested a "Twitter developer" [19] account based on Figure 3. Using a Python module named "tweepy," we later produced consumer key, consumerSecret, accessToken, and accessSecret to authenticate on Twitter. In this instance, the search phrase included the hashtags #bitcoin and #bitcoin. However, in order to balance my dataset and maintain data uniqueness, we filtered retweets. We still entered dates manually into our application. Users must enter the year, month, and day. Due to the bitcoin market's extreme volatility and frequent movements, we typically create 2,000 rows of pertinent tweets for the previous day. Tweets that are saved as string data with indexes ranging from 0 to 1,999. Tables 1 and 2 provide a sample dataset.

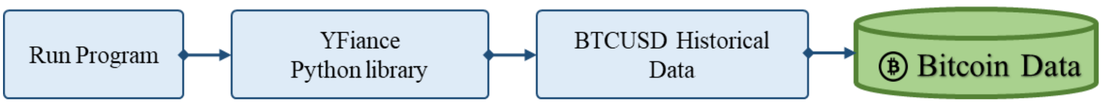

Figure 2. Bitcoin data extraction procedure diagram

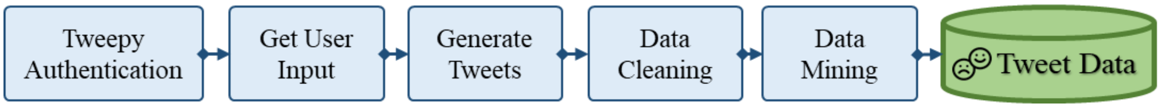

Figure 3. Tweet data extraction procedure diagram

Table 1. Sample data for bitcoin data

Date	Close	Volume
9/17/2014	457.3340149	21056800
9/18/2014	424.4400024	34483200
9/19/2014	394.79599	37919700

Table 2. Sample data for tweet data

Index	Tweets
1	RT @xZ3R0x_: $CPHX is pumping! ðŸ “ˆ#ETH gas fees are low! The 1st January another airdrop of Phoenix Coin for all @Phoenix_Crypto_ holdersâ€¦
2	RT @BTC_Archive: The government just prints money...and doesnâ€™t seem to have any consequences. They canâ€™t make more #Bitcoin - Billionaireâ€¦

2.2. Data pre-processing

Before the arrangement takes place, data pre-handling is an essential task. For bitcoin, "yfinance" [20] is a very rich library that provides those data in a suitable style, so we do not need to fill in any kind of rows with a simple imputer. Since the bitcoin market is open around-the-clock, there is no risk of seasonal statistics being broken. To normalise the data, it was standardised to convert from 0 to 1. Next, the tweet data that we are collecting through the Twitter application programming interface (API) is distorted by several superfluous symbols, capitalization, or even new lines and hyperlinks [21]. It will be horrible if we manually clean up by capturing each row of tweets. We developed a technique to extract a pandas data frame and apply a function to eliminate new lines, hashtags (#), letter formatting, and hyperlinks that contain the http symbol because of this. We must save every tweet in a new data column after the tweets have been cleansed. For that reason, we can create a new column to hold all cleaned-up tweets. Table 3 now includes the sample data with clean tweets following the preprocessing of the twitter data.

Table 3. Tweet data after preprocess

Index	Raw tweets	Clean tweets
1	RT @xZ3R0x_: $CPHX is pumping ! ðŸ“ˆ#ETH gas fees are low !The 1st January another airdrop of Phoenix Coin for all @Phoenix_Crypto_holdersâ€¦	RT @xZ3R0x_: $CPHX is pumping ! ðŸ“ˆTH gas fees are low ! The 1st January another airdrop of Phoenix Coin for all @Phoenix_Crypto_holdersâ€¦
2	RT @BTC_Archive: the government just prints money and doesnâ€™t seem to have any consequences. They canâ€™t make more #bitcoin-Billionaireâ€¦	RT @BTC_Archive: the government just prints money and doesnâ€™t seem to have any consequences. They canâ€™t make more bitcoin-Billionaireâ€¦

2.3. Data feature generating

We cleaned up the tweets, and as a result, several data columns about cleaned tweets have been generated. We first retrieve each row's subjectivity. The subjective scale ranges from (-1) to (+1). Higher subjectivity is indicated by a value near +1. A value nearer to -1 denoted less subjectivity. In order to shed insight on the subjectivity of tweets relating to bitcoin, this subjectivity column was pulled from the cleaned tweets column. More subjectivity means a bigger impact. The majority of tweets have subjectivity levels above 0.50 and significantly affect the market. Polarity is a different column that displays the strength of the subjectivity. Let's discuss the first tweet from our collection. As you can see, it has 0.1 subjectivity but 0.00 polarity. The tweet has less subjectivity and no market linkage, which is why polarity there displays as 0. We chose tweets that would be more polarising and subject to do an excellent sentiment analysis.

2.4. Sentiment generating using TextBlob

A Python package for text processing is called TextBlob [22]. It provides a fundamental API for doing common NLP tasks, such as part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, and translation, among others [23]. It is easier to understand and more enticing. We use sentiment analysis to extract subjectivity, followed by polarity to determine the range of each subjective tweet. This is because, when performing our operation that will produce more realistic outcomes when it comes to conducting Forex or stock market trading, we require the total number of tweets. The movement of a currency like Bitcoin on the FX market is correlated with public opinion. Therefore, if a trader can in some way comprehend the current mood, they can in some way comprehend market tendencies to execute their transaction.

The sentiment polarity of the element, which decides whether the text conveys the user's positive, negative, or neutral feeling about the subject, defines the orientation of the stated emotion, which is between [-1,1]. Subjectivity [24] exists between [0, 1]. Subjectivity is a metric used to determine how much of a text is made up of fact and personal opinion. The text is more subjective than usual; therefore, it offers personal opinions rather than objective information. We can begin writing the function to create a Sentiment class once we have determined the subjectivity and polarity of a data collection. I utilised the sentiment classes positive, negative, and neutral in this instance. Polarity is defined as "positive" if it is greater than 0 and "negative" if it is less than 0. Sometimes it might be 0, in which case the sentiment class will be displayed as "neutral". For our tool, this sentiment class is crucial. since judgements made by the computer will be based on this class. The entire algorithm could deliver incorrect information if our sentiment analysis is flawed. If that occurs, we might suffer a large financial loss.

We can filter tweets about subjectivity to get some more ordinal results. The outcome might be more appealing if we filter away tweets with more subjectivity. Table 4 details the Sentiment class and the filtered tweets dataset.

Table 4. Subjectivity and polarity results for tweet dataset

Index	Tweets	Cleaned tweets	Subjectivity	Polarity	Sentiment
1	RT @intocryptoverse: #bitcoin great accumulation: lessons from the stock market *https://t.co/XH4ao5KgZv*	RT @intocryptoverse: bitcoin great accumulation: lessons from the stock market	0.75	0.8	Positive
2	RT @xZ3R0x_: $CPHX is pumping ! ðŸ“ˆ #ETH gas fees are low ! The 1st January another airdrop of Phoenix Coin for all @Phoenix_Crypto_holdersâ€¦	RT @xZ3R0x_: $CPHX is pumping ! ðŸ“ˆTH gas fees are low ! The 1st January another airdrop of Phoenix Coin for all @Phoenix_Crypto_holdersâ€¦	0.3	0	Neutral
3	RT @RepTedBudd: given @BrianBrooksUS's previous experience as head of the OCC, I asked him if the U.S. government is "behind the curve" wheâ€¦	RT @RepTedBudd: Given @BrianBrooksUS's previous experience as head of the OCC, I asked him if the U.S. government is "behind the curve" wheâ€¦	0.433333	-0.28333	Negative

2.5. Facebook prophet

A piecewise linear or logistic growth curve trend is one of the four fundamental parts of the Prophet process, an additive regression model. Prophet chooses change points from the data to automatically detect changes in trends. an annual seasonal element that is modelled using fourier series. The decomposable time series model used by FBProphet [25] has three main parts: seasonal, trends, holidays or events influence, and error, as shown in "(1)".

$$f(x) = g(x) + s(x) + h(x) + e(t) \tag{1}$$

FBProphet utilises a linear model to match the data, but by adjusting its parameters, it can convert to a nonlinear model (logistics growth). By default, FBProphet fits our model into a linear model. Some things will be fully realised as prediction technology advances. Carrying capacity is what it is known as, and the anticipated increase should reach it. Time-series forecasting is the process of building a model to forecast future values based on recent and historical time-series data.

Therefore, the first thing we must do is to get the data. The Prophet demands that we change the name of the "date" column to "ds" and that we call our y-column just "y." Although Prophet does most of its work in the background, there are a few hyperparameters that let us easily adjust our models. To work with FB-Prophet in this instance, i used the "date" column as "ds" and the "close" column as "y". The intended data set's head portion is depicted in Figure 4(a).

Once the data has been generated, we can now use Prophet's forecast method to obtain other forecasted variables. Figure 4(b) shows "yhat," which is the anticipated closing price, "yhat lower," which stands for the day's support, and "yhat upper," which stands for the day's resistance. The "ds" column, specifically, represents the future date.

	ds	y
0	2014-09-17	457.334015
1	2014-09-18	424.440002
2	2014-09-19	394.795990
3	2014-09-20	408.903992
4	2014-09-21	398.821014

(a)

	ds	yhat	yhat_lower	yhat_upper
2965	2022-11-03	92830.467995	84875.578735	101347.796385
2966	2022-11-04	92944.180143	84876.459496	101226.715683
2967	2022-11-05	92953.269616	84878.922380	101081.949794
2968	2022-11-06	92956.648545	85058.349411	100964.350994
2969	2022-11-07	93005.926598	85216.972599	101335.413645

(b)

Figure 4. Data (a) preparation for FBProphet and (b) forecast data using FBProphet

2.6. Performance measure (error/accuracy)

The method of mean absolute error (MAE), mean squared error (MSE), root mean square error (RMSE), and model correctness are used to assess the performance of the models [26]. The MAE in a measurement is the sum of the errors. The same event is expressed by the measurement of errors between the paired observations. Additionally, it highlights the discrepancies between measured and real values. It is the arithmetic average of the total absolute error. Include variations between predicted and observed values in the Y versus X example. "(2)" is the formula for MAE.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - x| \quad (2)$$

Here, n denotes the number of errors, $|xi - x|$ the absolute errors, and the summation sign (it means to add all). The MSE of the estimator determines the average squared error in statistics. The true value and the estimated value are contrasted using the average squared. It demonstrates how close a regression line must be to a group of points. The distance from the regression line point demonstrates this, followed by a square. All of the negative value is turned positive by this square. We determine the square of error using MSE. "(3)" is the formula for MSE.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}|Actual - forcast|^2 \quad (3)$$

Here, n is the number of elements, is the sum, actual is the original y-value, and forecast is the regression y-value. The RMSE stands for the standard deviation of prediction error. We can determine the locations of the data points on the regression line using residuals or prediction error. The RMSE method determines how large these prediction mistakes are. It demonstrates how closely the data are related to the best fitting line. RMSE is typically used in climatology, regression analysis, and forecasting to validate experimental results. "(4)" is the formula for RMSE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|s_i - o_i|^2} \quad (4)$$

Here, o_i =observations, s_i =variables predicted values, n=Observations number for analysis which is available.

3. RESULTS AND DISCUSSION

3.1. Time series analysis

The breakdown of the daily bitcoin price following "2014-09-17" is depicted in Figure 5. The first graph displays the recent increase in the price of bitcoin after 2018. The year is indicated on the x-axis, and the y-axis displays the daily "close" price of bitcoin. The tendency for a time series to generally increase, decrease, or get worse across the entire dataset. It is also known as the time series' gradual evolution.

The "ds" chart displays the daily basis seasonal variation of the price of bitcoin. As we can see, when the market opened at 0:00 Greenwich mean time (GMT), or 6:00 AM Bangladesh time, the price was at its lowest point. It takes 4 hours for something to move up from one position, and the final 4 hours are when it moves down to the lowest position of the day. The yearly and weekly fluctuations in the price of bitcoin in relation to the dataset are displayed on two more random charts that are also random. If we examine the "day of the week" chart, we can see that its price increases most on friday.

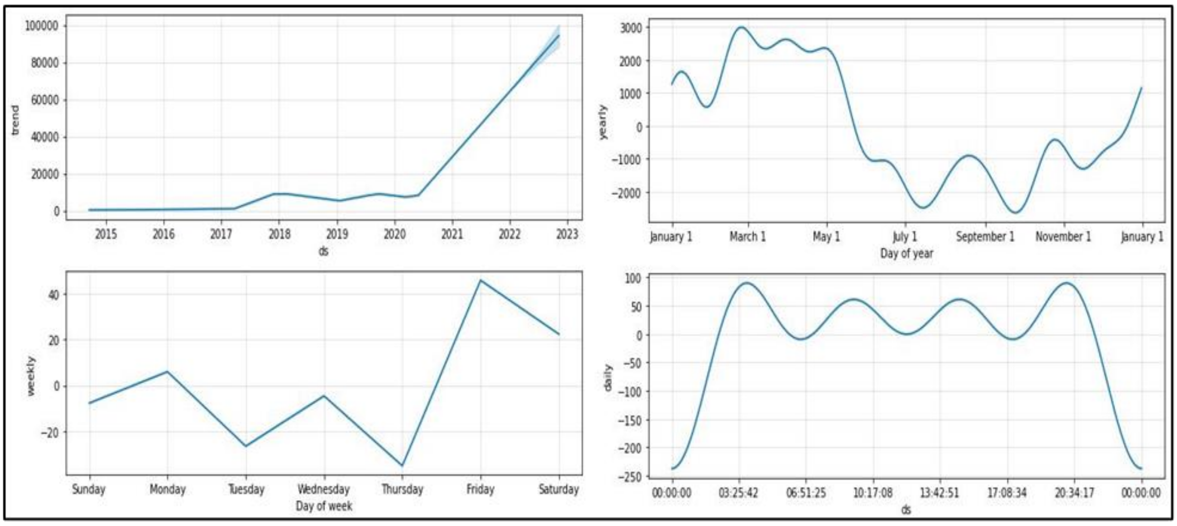

Figure 5. Decomposition of daily additive bitcoin price

3.2. Prediction target as close price

The daily close price of bitcoin in USD is thought to be the main focus of this effort. The bitcoin trade marketplaces, which were considered to be the end of lengthy financial exchanges, are open every day of the week, 24/7, throughout the entire year. Temporary closures for support and updates are the main exception. As a result, the price of bitcoin fluctuates quickly between trade markets. The website *coinmarketcap.com* reported 16,123 distinct digital currency transaction markets as of January 2019. The significance of a local pricing could be incorrect due to the continually open business hours. On this record, the current price is equal to the maximum distance of the projected 23:59 coordinated universal time (UTC) last trading moment for every day.

3.2. Bitcoin trading indicator

Our BTI was created by combining several techniques such as site scraping, sentiment analysis on Twitter, and cryptocurrency prediction values. The act of retrieving a website and gathering data from it is known as web scraping. When a user visits a website, a browser downloads the page, a process known as fetching. Web crawling is therefore a crucial component of web scraping because it enables us to gather pages for further processing.

We utilised the well-known Python module "BeautifulSoup" version 4 to extract helpful data from numerous websites. Without using any machine learning models, we traded by using the ecrowdwisdom.live URL. This website is useful for making predictions about bitcoin and other cryptocurrencies. In the end, its forecasted outcome is favourable and is well received by many traders. Figure 6 illustrates the fundamental workings of Python-based web scraping. We combine our model with data from our sentiment analysis of tweets from earlier days, anticipated data visualisation, and web scraping technologies to create a useful tool that can provide a signal for short-term trading. Figure 7 shows an illustration of our whole model.

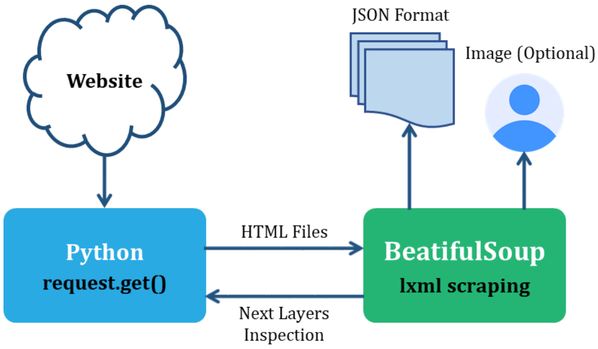

Figure 6. Web page data scraping basic mechanism

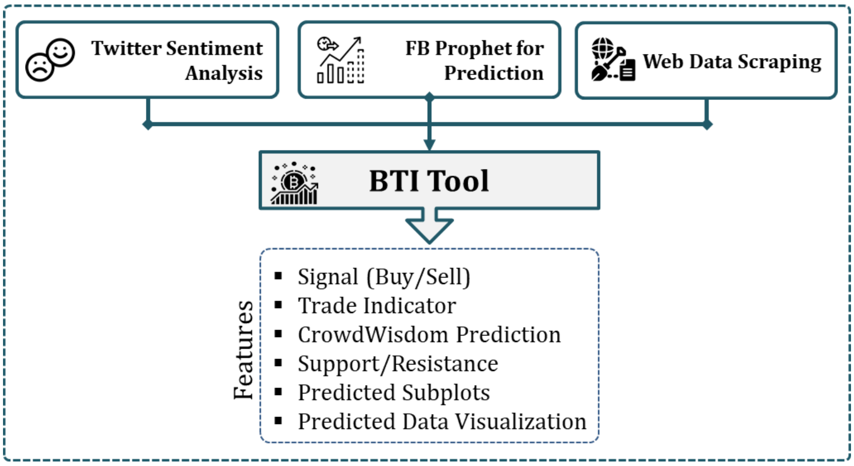

Figure 7. The BTI

3.3. Performance measurement

Now, our constructed model can perform well with a low error rate in terms of model correctness. Table 5 shows the MAE, MSE, and RMSE. We created three different systems that geared up the final model after compiling the BTI into data. The results of a $1,000 USD cryptocurrency market deposit. Table 6 shows the deposit value, profit, and remaining balance for the four developed models.

Table 5. Model performance metrics

Model Name	MAE	MSE	RMSE
Bitcoin's sentiment analysis using TextBlob	13140.41	220262701.56	14841.25
Time series forecasting using FBProphet	2084.47	12745971.02	3570.15
Web scrapping (by following internet)	2167.96	12661285.40	3758.27
The final model (combined version)	914.74	2192117.14	1480.58

Table 6. Findings of all implemented models

Model Name	Deposit ($)	Profit ($)	Remain Balance ($)
Bitcoin's sentiment analysis using TextBlob	1,000	439.65	1,439.65
Time series forecasting using FBProphet	1,000	-1000	000
Web scrapping (by following internet)	1,000	128	1128
The final model (combined version)	1,000	1,000.71	2,000.71

Table 6 demonstrates that the combined model's profitability is the highest. That implies that bitcoin's price movement is not only dependent on a single element; rather, there are a number of additional factors that might influence the market's direction. The first model only generates tweets and examines sentiment analysis of tweets using #bitcoin to see if it produces output in three categories. which are polar opposites, positive, and neutral. Although we can make some money there, it is insufficient for professional trading. Time series forecasting with FBProphet can provide market trends and other time series forecasting details, however employing this method exclusively would not be a suitable strategy because there are very few shortcomings in it.

3.4. Prediction and indicator

Figure 8 depicts the outcome after combining all trading logic into an if/else condition. A non-technical person may easily utilise it, and as i already indicated, we employed an online learning system to collect real-time qualitative and quantitative data sets. Even the support and resistance pip counts coming from a stable web platform.

We attempted to signal trading using our bitcoin data from our BTI indicator. The trades in Table 7 are shown together with their open time, types, size, price, T/P value, and close time. We demonstrate the profit and highlight the buy or sell types using the BTI indicator.

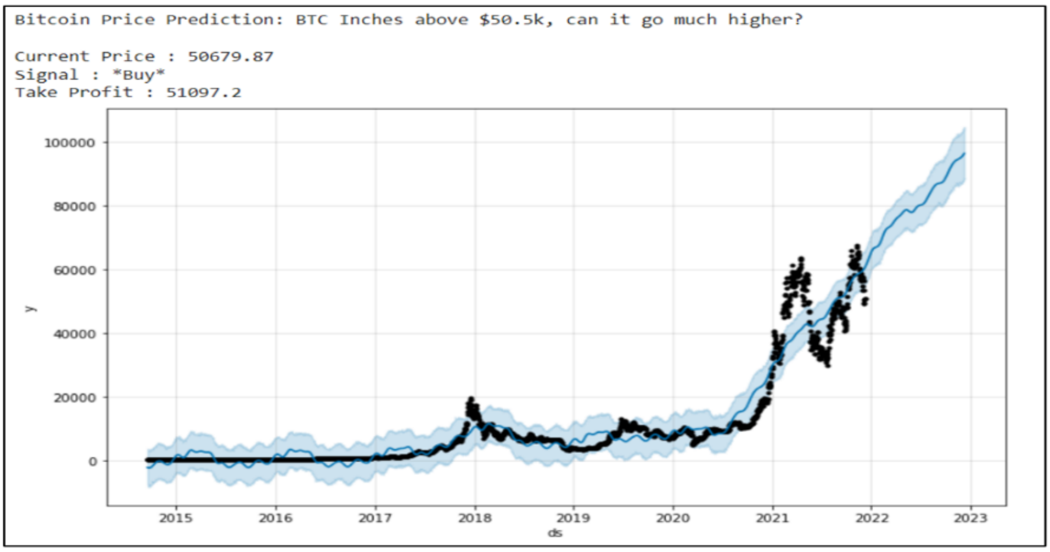

Figure 8. Bitcoin prediction and visualization from final model

Table 7. Trading statement summary using BTI indicator

No	Trade	Open time	Type	Size	Price	T/P	Close time	Profit	BTI indicator
1	2183156	2021.11.06 11:16:22	buy	0.05	60437.95	61399.82	2021.11.06 21:22:20	46.48	Buy
2	1505512	2021.10.30 19:18:14	sell	0.2	61567.89	61450.19	2021.10.30 22:16:56	23.54	Sell

4. CONCLUSION

We demonstrated that price movement can be predicted by the overall mood analysis. To accomplish our main objective, we added up all subjective polarity and divided it by the size of the data frame to maintain a polarity between -1 and +1. The final step of this analysis is a function that determines our options. In order to achieve our goal, we evaluated our model by combining it with other variables. In order to provide more details about the BTCUSD market, we generally gathered certain site material and extracted historical pricing data. Additionally, when needed, our model is able to detect and retrieve the current date. The study's most important finding was that we were able to profit by $1,000.71 USD in just 10 days with little error (RMSE: 1480.58) using the combined version of the programme. At a glance, we can state that Twitter sentiment analysis can provide sentiment towards the state of the market, and other data can provide entry and exit points for a certain trade.

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