Performance Analysis of Forecasting Price Prediction of Crypto-Currency using Deep Learning algorithm

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Abstract –This paper makes an effort to accurately forecast the price of bitcoin while taking into account a number of factors that influence its value. The initial stage of study attempts to comprehend and identify daily patterns in the Bitcoin market while obtaining knowledge of the best aspects relating to the Bitcoin price. Our dataset comprises of several variables connected to the price of Bitcoin and payment networks throughout a five-year period that were daily recorded. In the second phase of the investigation, we make the most precise predictions of the daily price change indications using the information at our disposal. Twitter is being utilised more and more as a news source to inform users about the currency and its rising popularity in order to influence their purchase decisions. As a result, bitcoin users or traders may have a trading advantage if they have a rapid understanding of how tweets affect price direction. Instead of comments, which were generally supportive regardless of price direction, we discovered that tweet volume was a better predictor of price movement. Regarding the reasoning behind how the results are fetched, it makes use of a number of machine learning algorithms, including RNN with LSTM models.

Index Terms –Cryptocurrency, Machine Learning, LSTM, Bitcoin, Twitter sentiment.

1. INTRODUCTION

The number of linked news stories and social media posts, particularly tweets, has exploded along with the economic and social significance of cryptocurrencies [1-2]. Similar to conventional financial markets, a relationship between public opinion and cryptocurrency pricing seems to exist. Although there are many reasons why cryptocurrency prices fluctuate, we looked into whether online media sentiment research can forecast if a coin's price (or perceived value) will rise or decline. Text data from headlines and tweets that have been tagged and stored in chronological order to maintain their chronological character serve as the input to our system. The next step is to apply a conventional binary supervised learning classification algorithm to assign each news item and tweet a label of 0 or 1 in order to anticipate price changes for the next day to be presented [3]. The final daily forecast was based on the majority tag of each coin for each day.

We start by selecting a sample of 12 cryptocurrencies, as opposed to other studies that mostly focused on Bitcoin. This aids in our comprehension of the market's general pricing dynamics for all digital currencies. Second, previous research has often employed daily data, which includes samples with a frequency ranging from minutes to days. Given the current condition of the financial markets, where algorithmic (especially high frequency) trading is actively used and the typical holding period of an asset rarely exceeds a few minutes, this is particularly crucial [4]. It is crucial to examine cryptocurrency market price efficiency at the intraday level because many cryptocurrency exchanges provide algorithmic trading connections to their customers (Sensoy, 2018). Third, we refer to cutting-edge methodologies employed in decision science to present probable patterns of exploitation and patterns of outcomes rise rather than utilising the conventional statistical methods to verify pricing efficiency [5].

The bitcoin market is extremely unstable right now. It could be exceedingly risky to invest in. Before making an investment, investors should consider a number of factors, including the regulations of their country [6]. Prices are also impacted by news about the market, opinions, paperions from celebrities in space, and a variety of other factors. Prices could suddenly rise and decrease as a result of these unforeseeable events. In contrast to traditional markets where risk-averse investors can feel at ease, the bitcoin market is rife with risks.

The paper's main objective is to create a machine learning model that can forecast price changes more accurately than random sampling. The goal of this study is to determine how well machine learning algorithms can forecast the direction of the Bitcoin price. Essentially, this is a time series forecasting issue. While there is a number of studies on applying different machine learning approaches for time series forecasting, there is a dearth of research in this field specifically related to Bitcoin [7-8]. In addition, Bitcoin is still in its infancy as a currency, making it far more volatile than traditional ones like the US dollar.

2. RELATED WORK

Greaves et al. (2015) used Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) in one of their research articles to forecast the price of Bitcoin in the blockchain market. The likelihood of this happening, we found, is difficult. the range is constrained. Despite this, because neural networks can handle non-stationary and non-linear data, they have emerged as useful tools for forecasting time series issues. More research has turned attention away from the stock market and towards the cryptocurrency industry as the use of cryptocurrencies, particularly Bitcoin, grows annually. The methodologies and research questions of the article by Kaminski (2014) and Matta et al. (2015) are applied to earlier stock market research. The association between Bitcoin market indicators and emotional-laden Twitter tweets is examined in this study using Twitter data. In-depth relationships between emotional tweets and the closing price, trading volume, and price range of Bitcoin were discovered by the study. In order to determine the effect of search volume on cryptocurrency markets, we also look at the correlation between Google searches and Bitcoin transaction volume (Matta et al., 2015). Prior studies have mostly concentrated on categorising user comments in particular categories. Neologisms, slang, and emoticons are frequently used in online groups in addition to grammar.

In order to parse these expressions, CJ Hutto and Eric Gilbert developed an algorithm named VADER and suggested using rule-based models to examine social media texts. Lim Jaeho, Kim Taehyun, Shin Jinkang, Jang Hoon, Kim Youngbin, Kim Junki, Kim Wook, and Kim Taehyun Kim forecasts variations in cryptocurrency trading based on user feedback. Southern Methodist University's Jetin Abraham, Daniel Higdon, John Nelson, and Juan Ibarra used sentiment analysis and tweet volume to anticipate cryptocurrency prices.

It's interesting that four out of the last five years have seen the best performance from this currency. His prognosis therefore has a lot of promise, which spurs on this field's research. Our review of the literature demonstrates that machine learning algorithms perform significantly better when executed on GPUs as opposed to CPUs [10-11]. This is investigated by comparing the performance of RNN and LSTM network training on CPU and GPU. This provides the sub-researcher with the response to his inquiry. The random forest technique is then used to analyse the chosen dependent variables and determine the relative importance of each variable. Additionally, the capacity to forecast the course of an asset's price, such as the price of Bitcoin, presents the possibility of trading the asset for a profit. Only the precision of price direction prediction is discussed in this work. In essence, the model opens short bets when a price increase is expected and long ones when a price decrease is expected. To make this easier, some Bitcoin exchanges provide margin trading accounts [12]. The accuracy of the model and the amount of the positions taken are both important factors in this strategy's profitability. increase. Although this is outside the purview of the research, it might be covered in subsequent ones [13-15].

3. PORPOSED MODELLING

Understanding where and why the data was gathered, as well as how cryptocurrencies differ from conventional stock market standard currencies or corporate equities, is necessary for the research further in this whitepaper [16-18]. To contextualize the final analysis for the reader, this section gives further information about these data sources and explains why they were chosen.The suggested system architecture (Fig. 1) depicts the entire system's function, from building the model with the gathered datasets to showing the prediction outcomes and associated notifications in a web application.

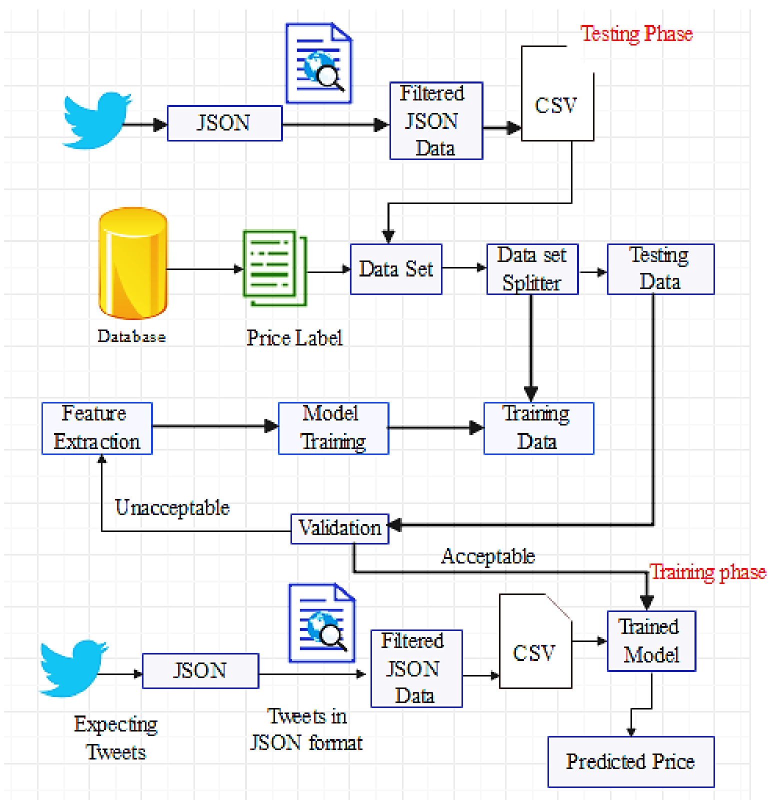

Figure 1 Proposed System Architecture

The training phase and the detection phase are the two stages of the proposed architecture (Figure - 1). The training stage is a single event. We gathered Twitter data and current Bitcoin and Litecoin prices to carry out the training phase. The pricing data we gather and the data from Twitter are not in the same format; the former is JSON and the latter is CSV. Data from Twitter is translated to CSV format to carry out the synchronization between the two.In Fig. 2 highlights the procedure for converting a JSON file to a CSV file. Polarity of sentiment is examined for tweets in the data. Positive tweets are those that have a polarity of greater than 0. Neutral tweets are those that have a polarity of 0. Negative tweets are those that have a polarity less than 0. The saved data is divided into chunks including tagged tweets published within the last two hours and contains all tagged tweets. It keeps track of the proportion of favourable, unfavourable, and disparaging tweets in each chunk. The average price that prevailed throughout the corresponding two-hour period is shown against these counted figures.

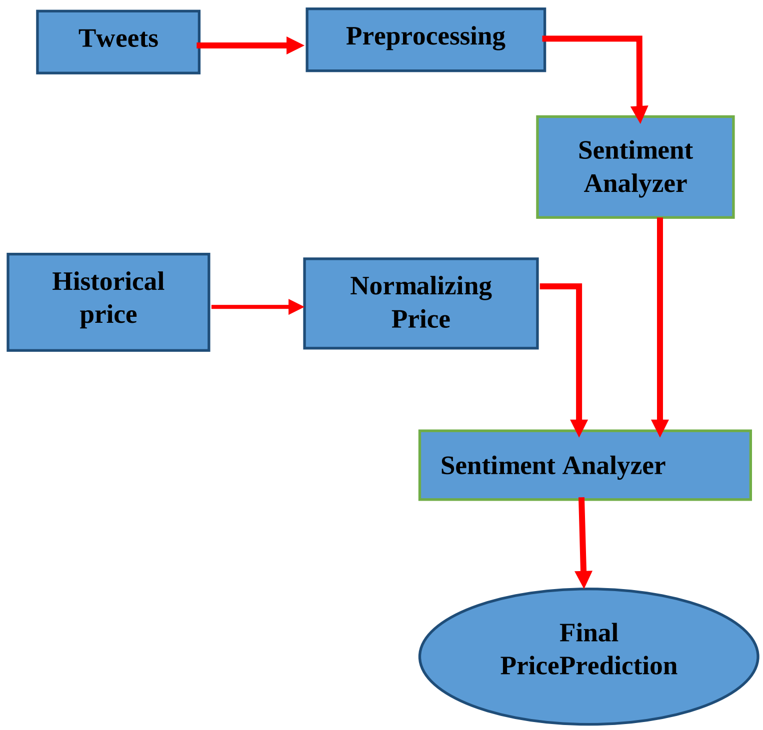

Figure 2 Flow Diagram

The dataset's properties include how many tweets were good, neutral, or negative, and its label is the average price of those tweets. The original labels from the provided data set are used to validate the model [19]. By examining real-time tweets, the model can be used to forecast future prices if the validation findings are satisfactory. You'll need to develop a new model if not. Iterative training and testing are used until a workable model is developed. The recognition phase starts once an acceptable model has been created [20]. During the detection phase, the model is given real-time tweets in order to anticipate his 2-hour average price.

The frontend and backend of the system's step-by-step execution are shown in the flowchart below.

3.1. Recurrent Neural Networks (RNN)

A generalization of feedforward neural networks with internal memory is Recurrent Neural Networks. RNNs are intrinsically recursive in that they carry out the same operation for each data input, but the result depends on the previous computation for the current input. Following production, the output is replicated and sent once more to the recurrent network [21]. We take into account the present input and the output that was discovered from earlier inputs while making a decision. RNNs can use internal states (memory), in contrast to feedforward neural networks, to process a set of inputs. As a result, it can be used for applications like speech recognition and unsegmented networked handwriting recognition. All inputs in other neural networks are unrelated to one another. However, in an RNN, every input is linked.Output h(0) after obtaining X(0) from the input sequence. Along with X(1), this serves as the input for the subsequent phase. Therefore, the next step's inputs are h(0) and X(1). In a similar vein, the input h(1) in next contains X(2) for the following step. This helps you remember the context during training.

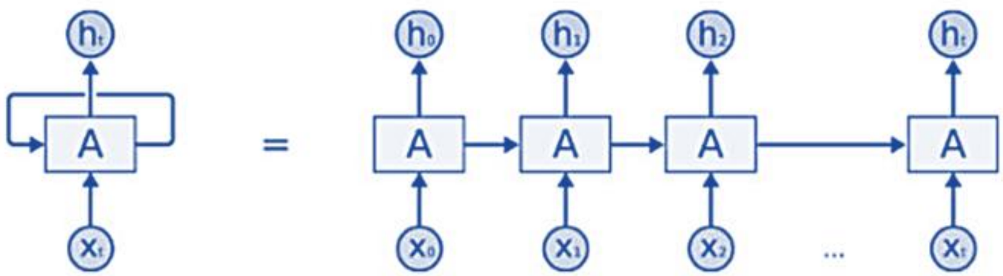

Figure 3. An RNN Architecture

The formula for the current state is

$$f_t = \sigma\left(W_f \left[h_{t-1,x_t}\right] + b_f\right) \qquad (1)$$

forget gate

Applying Activation Function:

$$h_t = \tanh(W_{hh} h_{t-1} + W_{xh} X_t \qquad (2)$$

W_{hh} is the weight of the previous hidden state, Whx is the weight of the current input state, and tanh is the activation function that carries out the nonlinearity that pushes the activation to range[-1.1] is output:

$$y_t = W_{hy} h_t \qquad (3)$$

The output state is Yt. The weight at the output state y.

3.2. LSTM

Recurrent neural networks are changed to create Long Short-Term Memory (LSTM) networks, which help the brain recall prior information. Here, the vanishing gradient problem for RNNs is resolved. Time series with uncertain time lags can be classified, processed, and predicted effectively using LSTMs. Make use of backpropagation to train the model. Three gateways make up the LSTM network.

1. Input Gate - Determine which input value is utilised to change the memory. The range of values that 0.1 goes over is determined by the sigmoid function. On a scale from -1 to 1, the tanh function weighs the provided values to determine their relevance.

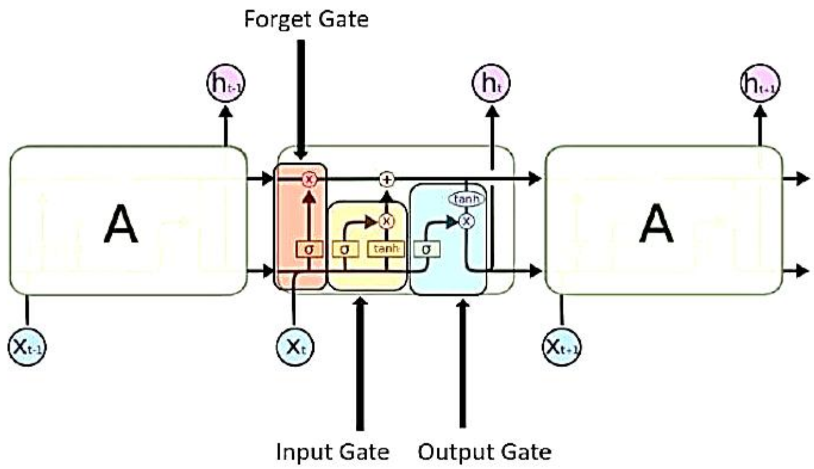

Figure 4 LSTM Gate

$$i_t = \sigma(W_t.[h_{t-1}, x_t] + b_i$$

$$C_t = \tanh(W_c.[h_{t-1}, x_t] + b_C \qquad (4)$$

2. Forgot Gates: Locate information to remove from blocks. The sigmoid function decides on this. Looks at the previous state (ht-1) and the content input (Xt) to return a number from 0 (omitted) to 1 (held) for each number in cell state Ct-1.

$$h_t = f(h_{t-1}.X_t) \qquad (5)$$

3. Output gates: Employ a block's input and memory to determine their output. When the output of the Sigmoid function is multiplied by the values that were supplied, the tanh function assigns weights to those values, determining their relevance on a scale from -1 to 1.

$$\sigma_t = \sigma(W_0.[h_{t-1}, x_t] + b_o$$

$$h_t = \sigma_t * \tanh(C_t) \qquad (6)$$

3.3. Data Representation

The dataset used is the history of Bitcoin prices per minute from March 1, 2020 to April 1, 2020. So there are 129316 data samples. Each of them has an associated timestamp and bitcoin price information. This work ignores some fields starting with the timestamp. This is because the intervals are constant and it is sufficient to know the order of the data as it is redundant. For simplicity, minimum and maximum values are not considered. It has a similar value to the weighted price that it predicts and is somewhat redundant. For the same reason as the previous field, the opening and closing prices are also ignored. In other words, the only value to consider is the weighted price, which can be conceptually thought of as the average Bitcoin price per minute (USD, USD).

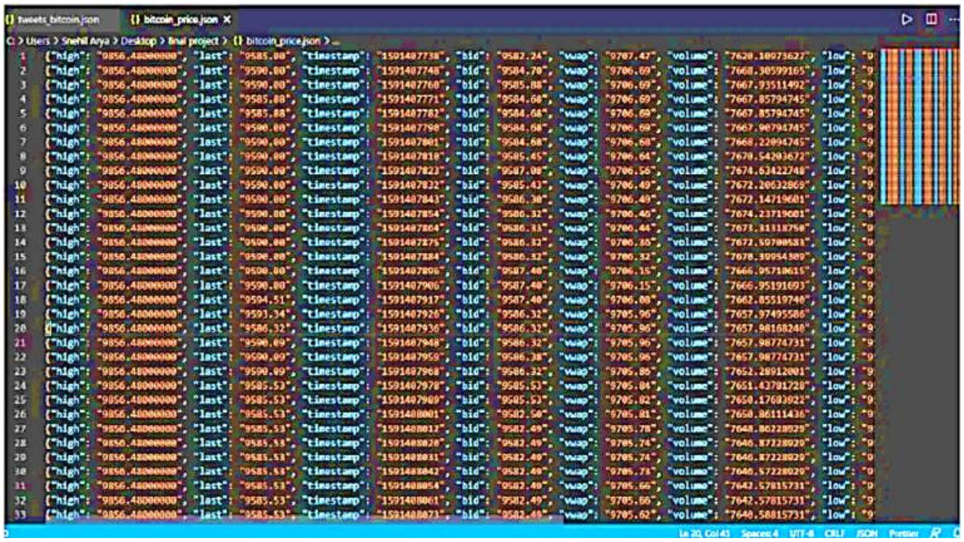

Figure 5 Live Bitcoin

3.4. Data Pre-Processing

Data were normalized with a min-max scaler. H. We transformed the entire set of price values into the 0-1 range by assigning 0 to the original lowest value, 1 to the highest value, and the rest to linear equivalent values between the extremes. Once the scaler has been fitted to the data, it can be used after building the model to reverse the transformation of the predictors and restore the original range of the predictors. The reason for normalizing the data is so that RNNs, especially backpropagation and gradient descent, learn faster by reducing the size of the value search space.

3.5. Data Split

As already mentioned, the data consists of 1293167 instances. The method of splitting the data was decided in order to learn a large portion of the data (the more data, the more the model can learn) and keep the heterogeneous sample for a fairly long time as the test sample. rice field. Therefore, the model was trained on the first 120000 instances (92.2% of the data) and the remaining 9316 (7.8%) were used as tests. These correspond to the period in the first half of 2020, when the value of Bitcoin changes significantly and rapidly, making the forecasting task very difficult.

3.6. Collection of Tweets

Data for this study was taken from Coindesk's contemporaneous pricing data and tweets titled "Cryptocurrencies - Bitcoin." Data collection for Bitcoin will begin utilising Twitter's REST API in March 2020 (30 days).5. Data is gathered by Litecoin from March 2020 to April. His Bitcoin price per minute is also noted at the same time. Prices are retrieved in.csv format, while collected tweets are retrieved in JSON format. Tweets are classified as favourable, Negative and neutral. This is accomplished by determining the sentiment of the tweet using the text blob's sentiment polarity. Textblob.sentiment.polarity returns values ranging from -1 to 1. Neutral tweets are those having a polarity value of 0. Negative tweets are those that have a polarity value between -1 and 0. Positive tweets are those that have a polarity rating between 0 and 1. We counted the number of tagged tweets in 2 hours after gathering tweets and prizes. The total number of tweets classified as favourable, negative, or neutral after two hours is included in the final dataset. We examined the quantity of tagged tweets for two hours because the model's efficacy rises up until that point, after which it falls.

3.7. Testing

System tests are actually a set of various tests whose main purpose is to thoroughly test a computer-based system. Although each test has a different purpose, all tests work to ensure that all system elements are properly integrated and performing their assigned functions. The testing process is hands-on to ensure that the product performs exactly what it's supposed to do. The testing phase attempts the following goals:

- Checkpaperquality.
- Findandeliminateresidualdefectsfrompreviousstages.
- To validatethesoftwareasasolution totheoriginalproblem.
- To ensure the operational reliability of the system.

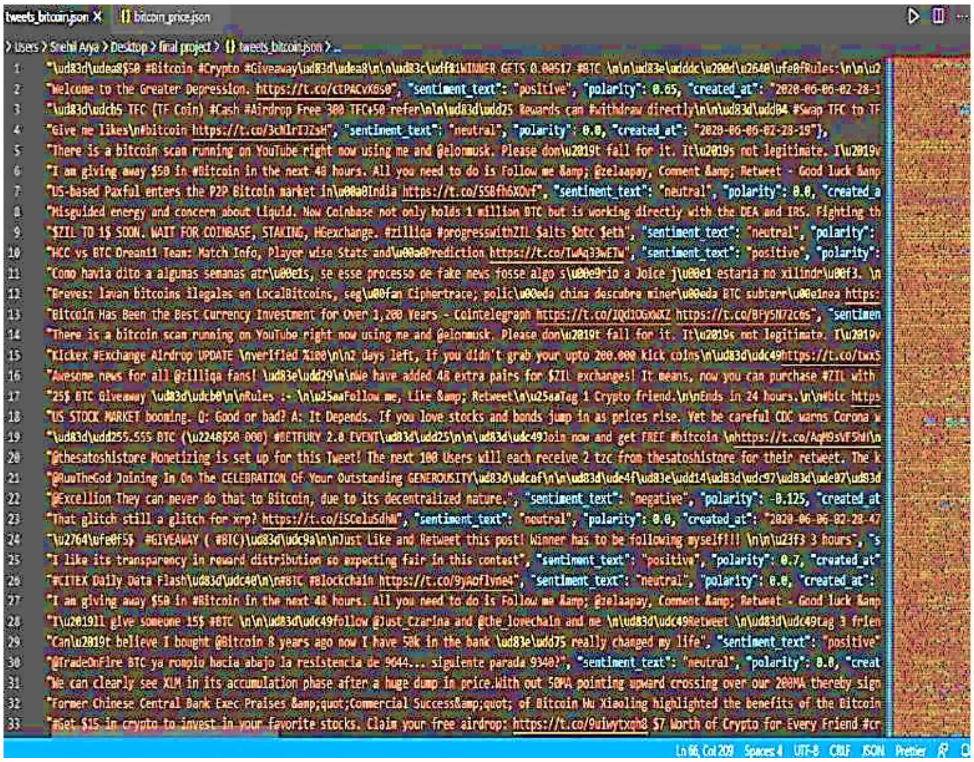

Figure 6 Bitcoin Tweets

While this model works relatively well in identifying general trends in coin prices, it has difficulty accurately predicting daily price movements that are inconsistent with general trends. Notably, Bitcoin's price generally increased during the test set period, and the model gets this right via the text input, most of the time predicting additional price increases. As a result, the final model failed to predict significant price increases during the test period

Configuration change	MSE	R²	Forecast bias	MAE	ME%
2 RNN layers	3.00632E-5	0.99930	60.07$	69.10$	0.46
1 RNN neuron	0.00180	0.95799	549.53$	549.73$	3.59
32 RNN neurons	3.755927E-6	0.99991	17.42$	23.22$	0.17
128 RNN neurons	2.70684E-6	0.99994	16.9$	21.39$	0.17
LSTM architecture	6.73593E-6	0.99984	18.5$	32.83$	0.25
500-neuron dense layer	1.66677E-5	0.99961	55.89$	57.66$	0.42
Dropout 0.25	5.76688E-6	0.99986	-35.52$	37.16$	0.30
Dropout 0.5	2.58831E-5	0.99940	-62.97$	68.50$	0.47
20 epochs	4.27518E-6	0.99990	22.01$	26.45$	0.20
30 epochs	2.68944E-6	0.99994	10.72$	18.91$	0.14
50 epochs	2.68130E-6	0.99994	8.79$	19.68$	0.15
Batch size 250	3.82469E-6	0.99991	20.41$	24.59$	0.18
Batch size 1000	4.35678E-6	0.99988	25.35$	29.71$	0.22
Nadam optimizer	2.11560E-5	0.99950	54.85$	58.52$	0.39
RMSprop optimizer	0.00037	0.99146	229.04$	243.55$	1.59
0.0001 learning rate	2.64888E-6	0.99994	13.12$	19.08$	0.14
0.01 learning rate	2.88746E-6	0.99993	16.22$	21.21$	0.16

Figure 7 Testing Values

4. RESULTS AND DISCUSSIONS

To put our findings into context, it's important to understand Bitcoin's general price behavior during the testing period. This graph (Fig. 8) shows how the price of Bitcoin relates to the total amount of Bitcoin tweets made during the day.

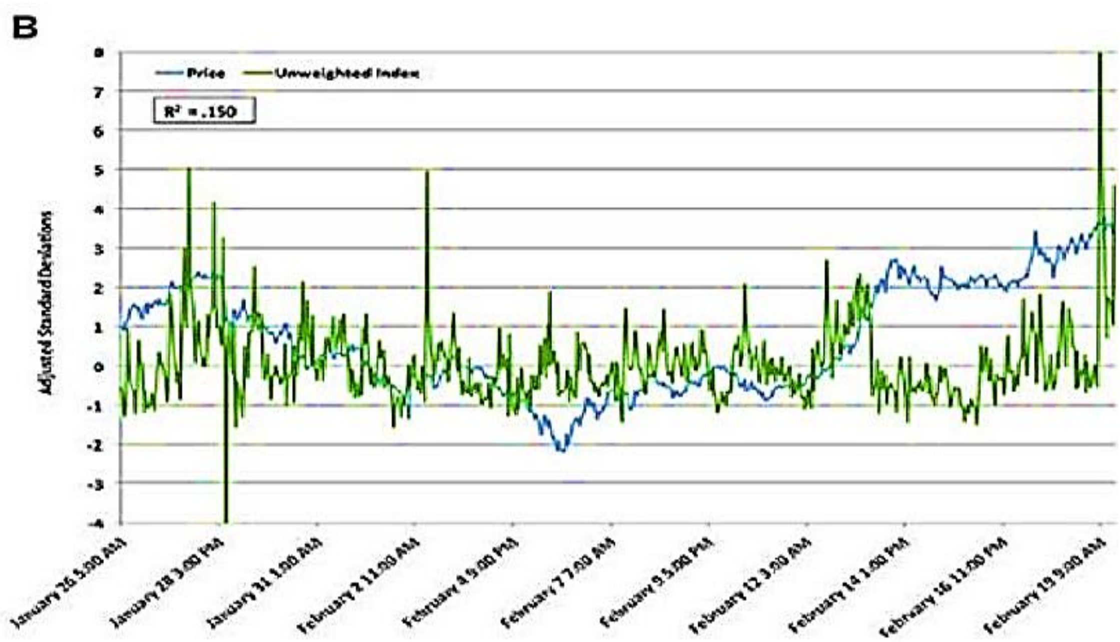

Figure 8 Price vs Volume

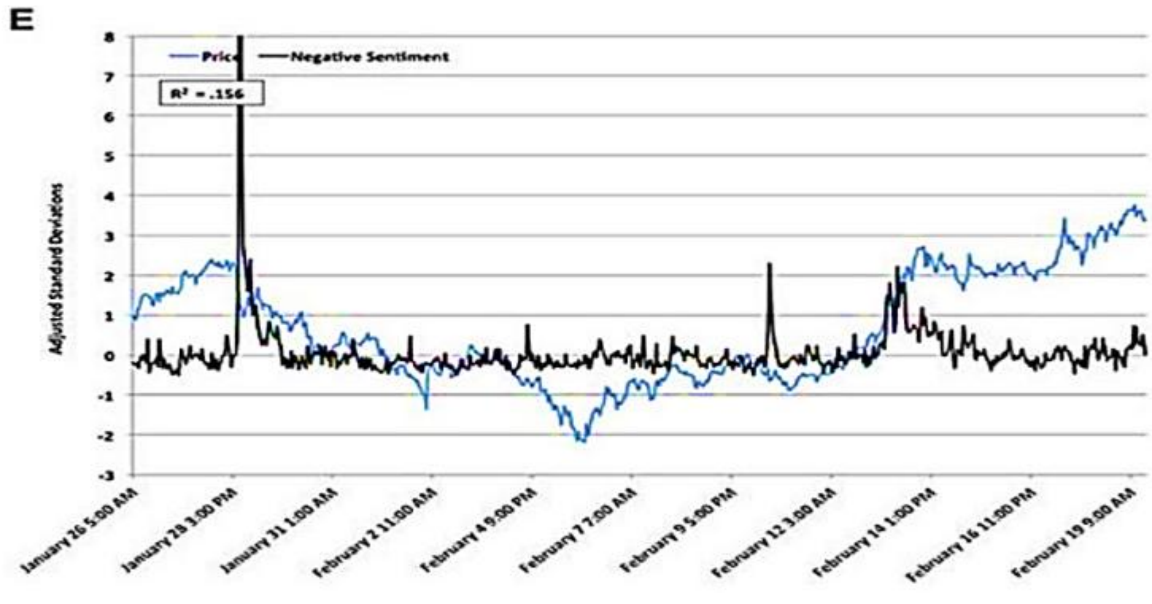

Figure 9 Price vs Unweighted Index

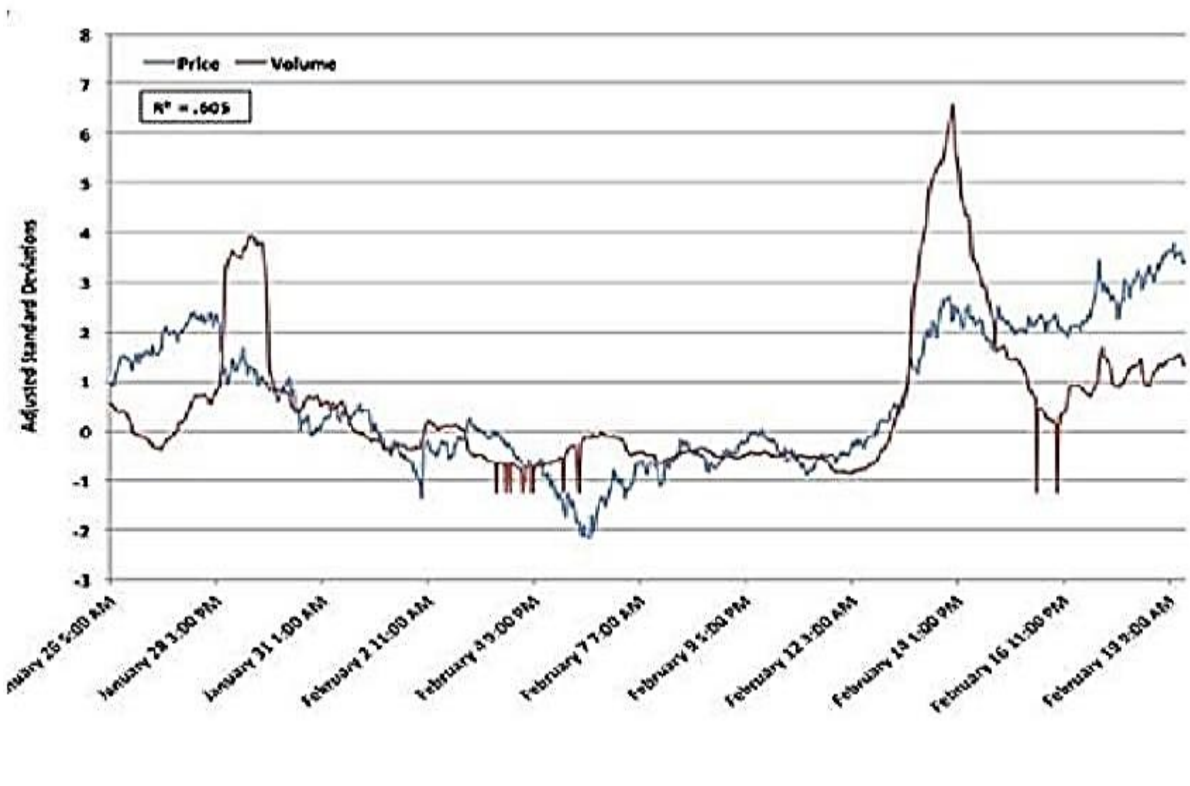

Figure 10. Price vs Weighted Index

This chart (Fig. 9) shows the relationship between Bitcoin price and tweets with no assigned polarity. All tweets have the same weight.This chart (Fig. 10) shows the relationship between Bitcoin price and tweets assigned a polarity. H. Different tweets have different weights and affect the Bitcoin price differently.

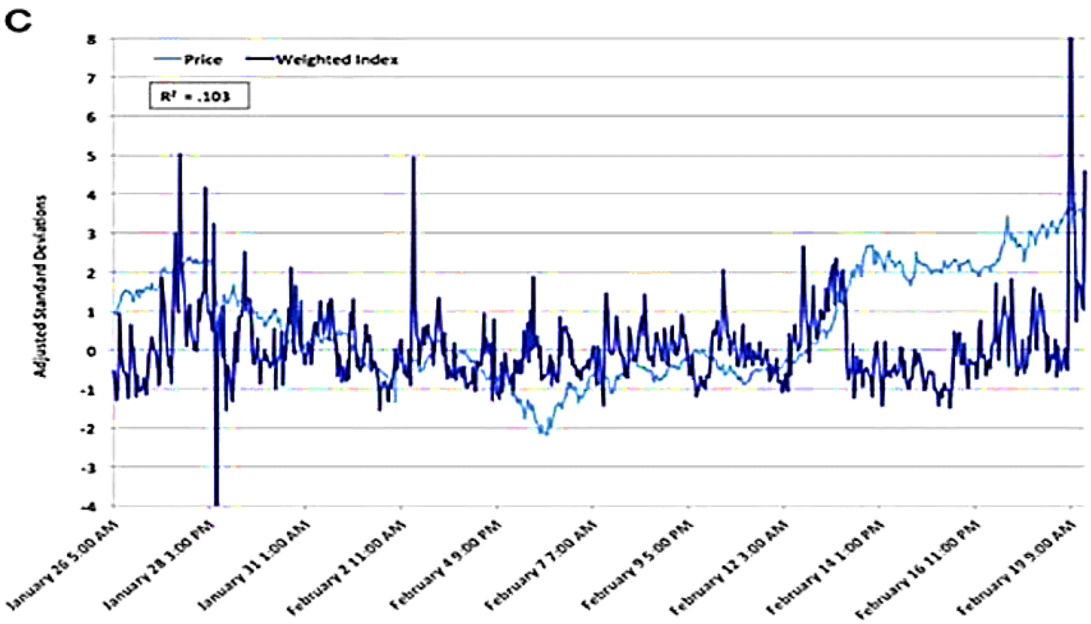

Figure 11 Price vs Positive Sentiment

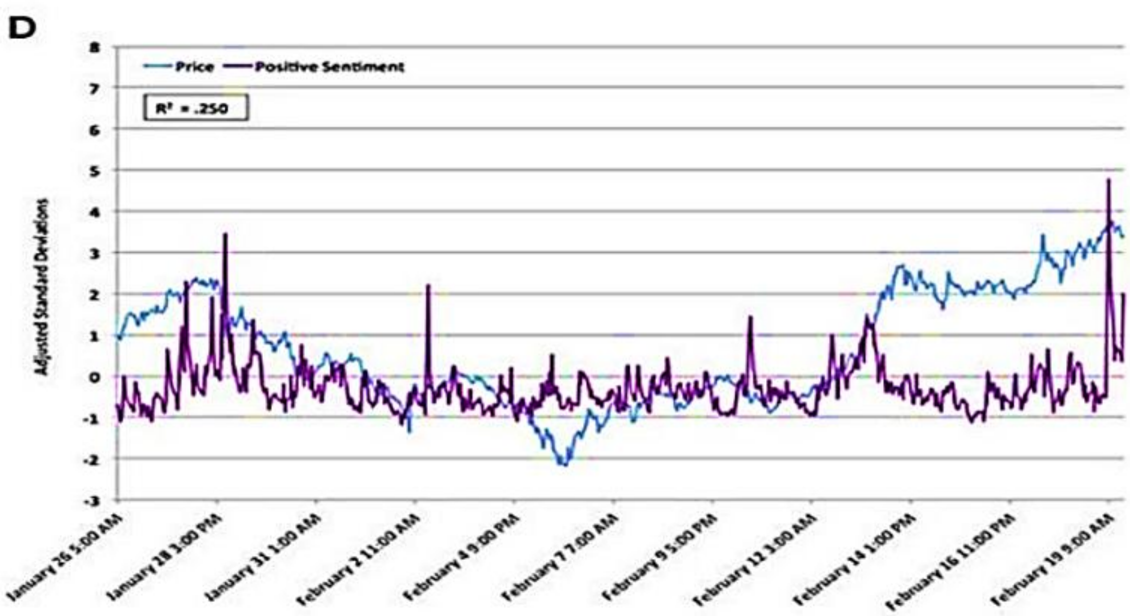

Figure 12 Price vs Negative Sentiment

This graph (Fig. 11) shows the relationship between Bitcoin price and positive polarity tweets. H. We know that Bitcoin price increases when there are positive tweets related to Bitcoin.This chart (Fig. 12) shows the relationship between Bitcoin price and negative tweets. From the H. chart, we can see that Bitcoin price goes down as the number of negative tweets increases.

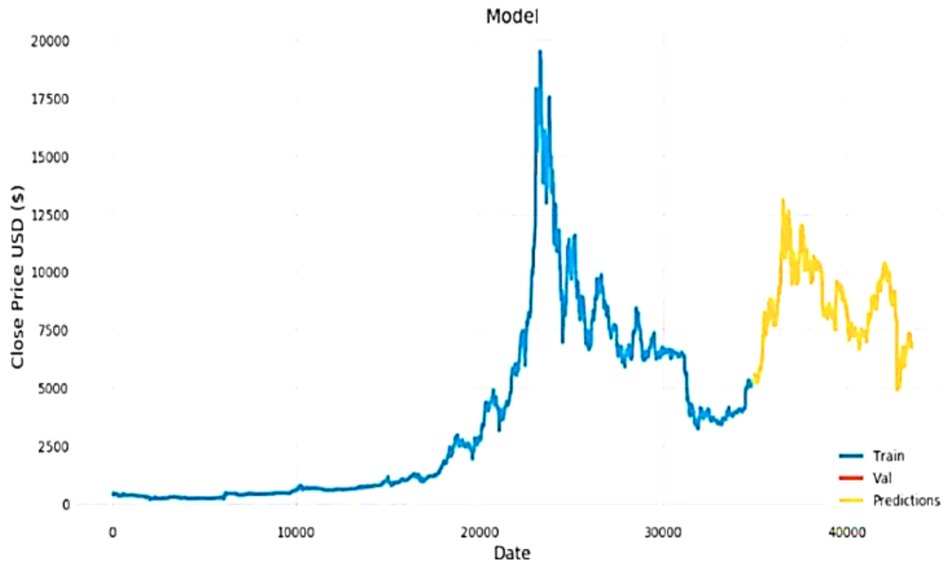

Figure 13 Train vs Test

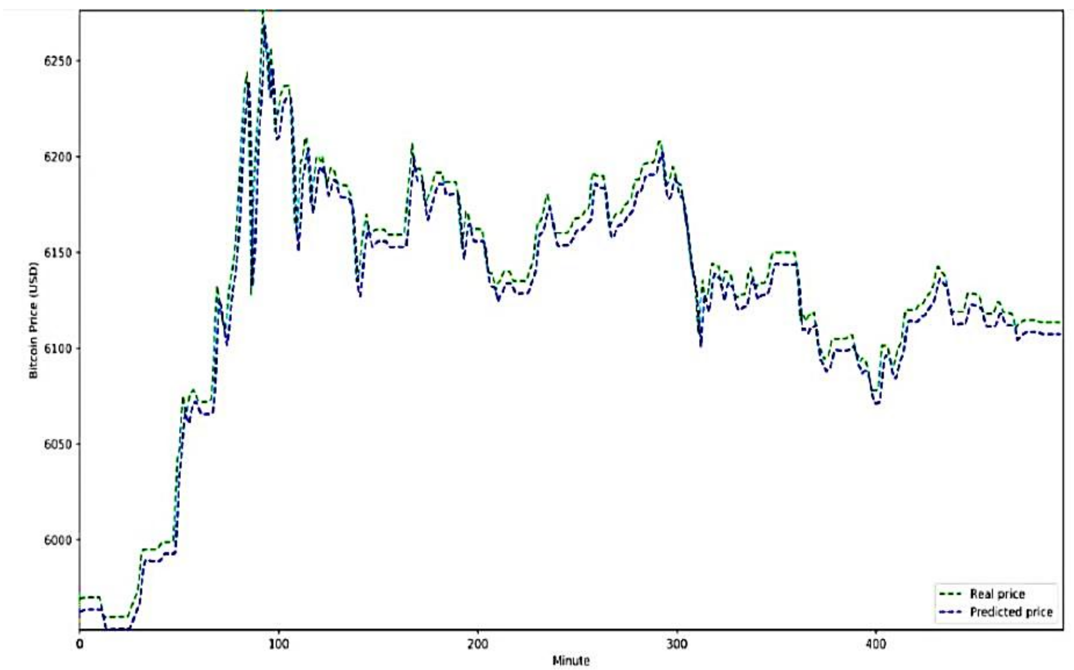

Figure 14 Actual vs Predicted Graph

This diagram (Fig13) shows the model training and testing phases. The blue curve is the period over which the model is trained using historical data. After this part of the curve, we can see the predictions made by the model. Accuracy to determine the model by comparing these predictions to the rest ofthe historical data.This chart (Fig. 14) shows the relationship between the actual price of Bitcoin and the price of Bitcoin predicted by the model. H. From the chart we can see that the predicted price error is small.

5. CONCLUSION

RNNs and LSTMs are examples of deep learning models that have shown to be proficient at learning from training data, and LSTMs are particularly good at recognising long-term dependencies. However, it is challenging to translate this into excellent validation results for a highly distributed work of this kind. It is nevertheless a difficult task as a result. The line between overfitting a model and obstructing its ability to learn is thin. A useful element to improve this is dropout. Good validation results were not assured, even optimising dropout selection via Bayesian optimisation. Although the measurements for sensitivity, specificity, and accuracy indicate good performance, the ARIMA error-based prediction's actual performance was noticeably inferior than the neural network models.RNN performed somewhat better than LSTM, but there was no discernible difference between the two outcomes. But it takes a long time to train an LSTM. His LSTM model performed 70.7% better when trained on GPUs as opposed to CPUs, demonstrating the performance benefit realised by parallelizing machine learning methods on GPUs. This supported the findings of the associated research.

Previous efforts to predict cryptocurrency volatility have relied on Twitter sentiment analysis to act as a proxy for future cryptocurrency demand leading to price increases or decreases. We indicated that these results were partially due to the fact that the survey was conducted when cryptocurrency prices were rising. tend to be positive regardless of People tweeting about cryptocurrencies, even when prices are falling, are interested in cryptocurrencies beyond investment opportunities, skewing their tweets positively. A more robust model would include a measure of global interest in volume. This white paper recommends using a proxy of general interest such as Google Trends or Tweet Volume. The search volume index showed that, like tweet volume, it was highly correlated with cryptocurrency prices for both rising and falling prices. The model accurately predicted future price movements. Future work should determine whether these results hold up in different pricing environments. Additionally, rather than just a linear model like the one we used, more complex models can be adjusted using Google Trends and Tweet volume as inputs to see if the results can be further improved.

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