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Monitoring the Sequence Recovery in Bitcoin Using Convolutional Neural Network and Long Short-Term Model to Hybrid Model

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Abstract: This study attempts to evaluate the prediction performance of a hybrid short-term memory network (LSTM) and convolutional neural network (CNN) model in terms of the US dollar relative to Bitcoin. Since bitcoin is a pseudonymous currency, the money is associated with bitcoin addresses as opposed to actual individuals or companies. Although the proprietors of the bitcoin address are kept anonymous, every transaction on the block chain are accessible to the general world. Bit-fine provides Pycurl with up-to-date pricing information. LSTM model is implemented using Keras and Tensor Flow. As a Money Service Business (MSB), or registration, the US Financial Crimes Enforcement Network (FinCEN) classifies US bitcoin miners who have violated the regulatory guidelines for decentralized virtual currencies.

Keywords: *BITCOIN, Convolutional Neural Network, Hybrid Model. Knowledge Discovery, Long Short-term Model, Sequence Recovery*

1. Introduction

Through the peer-to-peer bitcoin network, users can send and receive Bitcoin, a decentralized digital money, without the need for middlemen. A block chain is a distributed public ledger in which transactions are recorded and cryptographically validated by nodes inside the network. As payment for taking part in the mining process, bitcoins are created. They are convertible into other currencies, products, and services. Bit coin's use in illegal operations, price swings, exchanging fraud, and the substantial electrical and carbon footprint required for mining have all been criticized. Economists and investors have called it a speculative bubble on several occasions. Others have invested in it in spite of several regulators' warnings.

Since Bitcoin uses pseudonyms, money is associated with Bitcoin addresses rather than actual businesses. Every single transaction on the block chain is visible to the public, even though the owners of the Bitcoin addresses are not made publicly known. The authors Velankar et al., (2018), Wu et al., (2018), Jang and Lee, (2018) and Karasu et al., (2018) explain how "use idioms" can be used to link transactions to individuals and companies. For instance, actions that spend coins from several inputs suggest that the inputs might be owned. Together, confirm the transaction in public. Information that is known regarding the owners of particular addresses. Additionally, law to gather personally identifying data can mandate exchanges that deal in bitcoins and convert them into fiat money. For instance, Gox blocked account holders in 2012 who were depositing newly pilfered bitcoins. To increase financial privacy, each transaction can generate a new Bitcoin address. Technically, wallets and similar software treat all bitcoins as equal, establishing the fundamental level of fungibility. The authors Anupriya and Garg, (2018), Li et al., (2019) and Singh et al., (2019) stated that the history of each bitcoin is recorded on the blockchain ledger and is publicly available, and that a smaller amount of bitcoins may be available for funding if certain users decide not to take bitcoins from contentious operations..

In 2014, the annual price dropped from $770 to $314. On July 30, 2014, the Wikimedia Foundation began accepting Bitcoin donations. Prices in 2015 increased from $314 to $434 over the course of the year. Prices increased in 2016, reaching a high of $998 on January 1, 2017. Bitcoin Core was decommissioned in October of 2016.The "Segwit" soft fork, which was first released in version 13.1, included a scaling enhancement intended to maximize the size of Bitcoin blocks. Thirty-five developers have agreed to implement the fix, which was completed in April. According to the authors Aggarwal et al., (2019) and Demir et al., (2019), this version includes a separate token called SegWit, whose purpose was to reduce transaction fees. No need for a main source. The release of version 0.13.1 has been postponed due to rigorous testing and investigation. Different types of transaction malleability are prevented by SegWit. Prices began at $998 in 2017 and reached an all-time high of $19,783.06 on December 17, 2017, before rising to $13,412.44 on January 1,

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2018. The price of bitcoin improvements from 2014 to the present are shown in Figure 1.

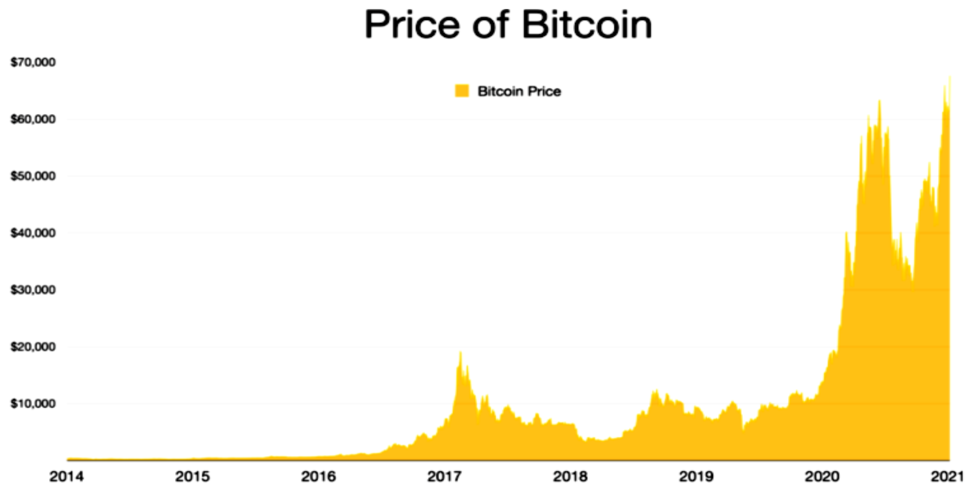


Fig. 1. price of bitcoin

After trading above $10,000 in February 2020, During the market sell-off on March 13, 2020, the price of bitcoin dropped below $4,000. On March 11, 2020, 281,000 bitcoins were sold after being held by owners for only thirty days. The authors Ali and Shatabda., (2020) and Serafini et al.,(2020) focused their research on Bitcoin worth $250 million US dollars as a treasury reserve asset. Elon Musk posted the bitcoin handle () on his Twitter profile on January 19, 2021, and tweeted, "In retrospect, it was inevitable," causing the price to briefly drop by around $5,000 from within an hour to US Dollars. 37,299. On January 25, 2021, Micro-strategy announced that it continues to buy bitcoins while holding ฿70,784 worth of $2 in shares at the same time.38 billion. On February 8, 2021, Tesla's announcement of a $1.5 billion bitcoin purchase and plan to accept bitcoin as payment sent the bitcoin price skyrocketing to $44,141. On February 18, 2021, Elon Musk said, "Owning bitcoin is only slightly better than owning traditional cash, but the slight difference makes it a better asset." In June 2021, the Salvadoran Legislative Assembly will vote on a bill that would establish Bitcoin as legal money in El Salvador. The law became operative on September 7th. The law's implementation was met with protests and calls for the currency to be made optional rather than required. In addition, the authors Moore and Christin, (2013), Stokes,2012 and Teigland et al., (2013) assessed the level of trust that people have in Bitcoin, finding that 14.1% have a great deal of trust, 13.2% have some trust, and 35.3% have very little.36.3% of respondents use bitcoin at least once a month, whilst 56.6% of those surveyed have downloaded the official wallet. Of those surveyed, 62.9% have never used bitcoin or have only done so once.

2. Related Literature

Many local and foreign experts are now conducting extensive research on the pricing of digital cryptocurrencies, particularly Bitcoin. Numerous recent research has sought to develop effective mechanical trading systems using machine learning algorithms for estimating crypto currency prices. Because of the huge variations in Bitcoin's price, several researchers have investigated the elements influencing Bitcoin's pricing, which are summarised here. Li and Dai (2020) proposed a hybrid neural network model based on long short-term memory (LSTM) and convolutional neural networks (CNN) to estimate the price of bitcoin. The outcomes show that in terms of value and direction prediction, the CNN-LSTM hybrid neural network performs better than the single structure neural network. A hybrid deep learning model was developed by Kang et al. (2022) which includes a 1-multifaceted convolutional neural network (1DCNN-GRU) with a stacking gated recurrent unit (1DCNN-GRU). The suggested 1DCNN-GRU model beat the previous approaches in terms of RMSE, with results on the Ethereum dataset being 3.511, the Bitcoin dataset being 43.933, and the Ripple dataset being 0.00128. Li and colleagues (2022) proposed a novel hybrid bidirectional Deep learning model for forecasting daily variations in the price of Bitcoin, based on data decomposition. The study's findings demonstrate that the suggested model works better than cutting-edge approaches, such as econometric, neural network, and models for machine learning. Moreover, the proposed model outperformed the buy-and-hold strategy and all benchmark models as far as of return on investment in a trading simulator.

Luo et al., (2022) used machine learning and multiscale analysis to match different machine learning methods to matching multiscale components and build ensemble prediction models. The empirical results reveal that 95.12% of the predictions made by the ensemble algorithms are accurate outperforming the benchmark models, and are resilient in both rising and negative market circumstances. Guo et al., (2021) used a Multi-scale In their study, they used a Long Short-Term Memory (LSTM) and a Residual Convolutional Neural Network (MRC) to predict Bitcoin closing values. The findings showed that by combining these two strategies, the model can produce highly expressive features while also learning patterns and interactions in multivariate time series.

As a result of the research, the price of Bitcoin is influenced by a number of factors with significant volatility, which is impossible to anticipate using standard approaches. Machine learning, on the other hand, can train and learn complicated non-linear data, making it perfect for Bitcoin estimate of price. In addition, because the price of Bitcoin changes a lot, this study focuses on the short-term price of Bitcoin.

3. Interrelated Bitcoin Prediction

Data mining or knowledge discovery in databases (KDD) is the process of examining hidden information patterns from different perspectives to categorize them into knowledge that is helpful. These days, statisticians, data analysts, and information systems specialists utilise data mining and KDD interchangeably. A range of services, such as web mining, graphical data mining, text analysis, video and audio mining, and social network mining, are included in this process. The authors Torraco, (2005), Trautman, (2014), Alstyne, (2014), Hooff, (2014) and Möser et al., (2014) found that real-world databases are highly prone to lost, unpredictable, and noisy data due to their typically enormous size and likely origin from multiple, heterogeneous sources. Different algorithms are used in data mining to accomplish a range of objectives. These algorithms look at sample data for a problem and generate a model that roughly represents the problem's solution. Figure 2 divides the model that finds a solution to a problem into predictive and descriptive versions.

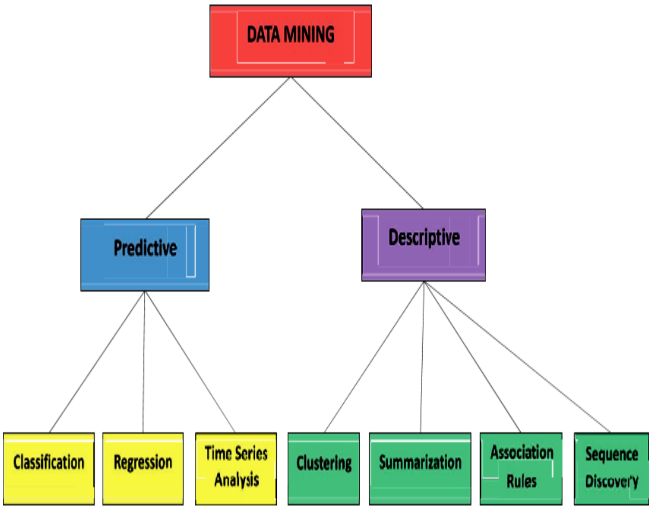


Fig. 2. Data Mining Tasks

It is possible to analyse a wide variety of computer programmes. Figure 3 displays a few of the statistical data mining programmes that are frequently employed. For large-scale data analysis, data miners frequently utilise R, an open-source that supports the statistics programming tongue. In addition to data mining, the authors Vasek et al., (2014), Tromp, (2021) Taylor, (2021) and SirbuandTygar, (2021) have developed most of the graphical and statistical tools. An R integrated development environment (IDE) called R Studio enables users to create and modify R software programmes. STTCRAFT: STTCRAFT is a web server-based platform that dispenses with the requirement for users to write sophisticated R code by enabling them to conduct data analysis in R through a browser-based GUI. It is easier for analysts to concentrate on analysis rather than coding when they use STTCRAFT. Similar to stocks, but in a different way, the value of bitcoin fluctuates.

Many algorithms are available for predicting prices using data from the stock market. Nonetheless, there are variations in the characteristics that impact Bitcoin. Therefore, in order to make wise investment decisions, it is essential to know the future value of bitcoin. Bitcoin's price is independent of both business events and government intervention, in contrast to the stock market. Therefore, we think that using artificial intelligence to forecast the cost of Bitcoin is essential in order to determine the value.

4. Convolutional Neural Network (CNN)

Predicting Bitcoin, a popular topic around the world, using this structured data and machine learning models. This chapter offered a hybrid model suggestion of a CNN+LSTM models based on the process of attention in order to address the issue of the low precision of the long-term and short-term recall model (LSTM) in Bitcoin forecasting Yuvaraj et al., (2021). The proposed model is shown in Figure 3 and can learn the importance of each past value for the current value from the extensive historical cost data stream, enabling the extraction of additional useful features. He used the Bitcoin data from Wuhan's central region to construct a dataset for his tests, and he contrasts the modified model's performance with that of the original LSTM network.

Successful results for the handwritten digit classification problem have been obtained with the gradient learning algorithm applied to CNNs. Later, scientists continued to improve CNNs and reported recent results on many detection tasks. CNNs have numerous advantages over DNNs. Above all, it should have a structure highly optimized for processing 2D and 3D images, match the human visual processing system more closely, and be effective in creating and retrieving 2D feature representations.

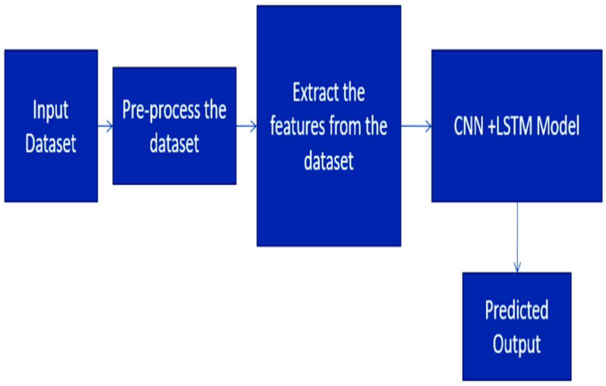


Fig. 3. Hybrid Model for Prediction

The max pooling layer absorbs shape fluctuations very effectively. Likewise, it consists of tenuous links with attached weights. CNNs feature far fewer parameters than a fully linked network of a comparable size. The gradient-based learning process is a strength of almost all CNNs, and they rarely experience the gradient-decreasing issue. When the network is trained to reduce an error criterion directly using a gradient-based approach, CNN can produce highly optimised weights.

Each network layer accepts the output of the neighboring previous layer as input for the feature extraction layers. Likewise, it passes its output as input to the layer below. The CNN architecture includes a combination of three types of layers: convolution, maximum pooling, and classification. The bottom and middle layers of the network include two types of layers. They are convolution layers and maximum pooling layers. The even layers are for convolutions and the odd layers for maximum pooling operations.

A feature map is a 2D plane that contains the output nodes from the convolution and max-pooling layers clustered together. Each level in the hierarchy is often derived from a layer by combining one or more preceding layers. The nodes of a level are attached to a portion of each connected level of the level before it. Convolution operations on the input nodes extract the features of the input images from each node of the convolution layer. Figure 4 illustrates the general architecture of the convolutional neural network, which consists of an input layer, many alternating layers for maximal pooling and convolution, a fully connected layer, and a classification layer.

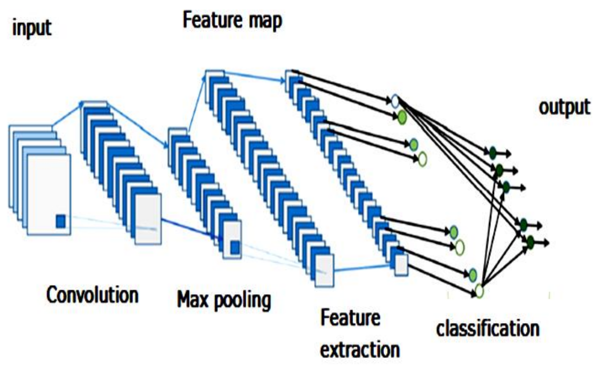


Fig. 4. The Overall Architecture of the CNN

Features propagating from lower-level levels derive higher-level features. When propagation features to the top tier or tier, feature dimensions for convolutional or max pool operations are lowered, according to the kernel size. However, more feature maps are typically used in order to guarantee classification accuracy and more accurately capture the distinctive characteristics of the input images. The categorization layer is another name for the fully linked network. This fully linked network receives its input from the CNN layer that came before it. Feed-forward neural networks were employed as the layer for classification due to their outstanding accuracy. Regarding the dimension of the weight matrix of the final neural network, the extracted features are taken as inputs to the classification layer. On the other hand, fully connected layers are expensive in terms of network or learning parameters. Mean pooling and global mean pooling are some of the new techniques that have emerged in recent years. Networks with complete connectivity can be substituted using these methods. In the top categorization layer, a soft max layer is utilized to determine each class score. Based on the highest score, the classifier gives results for the relevant classifications. The mathematical specifics of the various CNN layers are covered in the next section.

5. Convolutional Layer

This tier involves convolving learning cores with feature maps from earlier tiers. After the output kernel is passed through a quadratic or non-linear activating function—such as the B. sigmoid, parabolic tangent, SoftMax, rectified linear operations, and identity functions—the output feature maps are formed. There is a possibility to connect several feature map inputs to each of the resultant feature maps. In general, it can be expressed as in equation (1).

$$X_j^1 = f\left(\sum X_j^{1-j} * K_{ij}^1\right) + K_{ij}^1) + B_j^1) \qquad (1)$$

where kijl denotes the current level's kernel, bjl denotes its preloads, xjl indicates the output of the present level, and xil-1 denotes the output of the preceding level. The choice of input cards is denoted by mj. An additive bias b is specified for each output map. To create the matching output maps, Different kernels are used to convolve the input maps. The output maps are eventually subjected to a linear or complex activation function (such as a sigmoid, hyperbolic tangent, soft max, corrected linear, or identity function). The subsampling layer, also known as the pooling layer, does the down sampling of the input cards. The number of input and output feature maps in this layer will remain constant. For example, if N input cards are present, there will always be exactly N output cards. By using a down sampling mask size, the down sampling procedure shrinks each and every dimension of the final maps. For example, if a 2×2 down sampling kernel is used, each output dimension is half the size of the corresponding input dimension for all images. This process can be expressed as given in equation (2).

$$X_j^1 = down\left(X_j^{1-l}\right) \qquad (2)$$

where down () means a down sampling function. In general, two types of operations are performed in this layer: either average pooling or maximum pooling. The function usually sums more than N × N patches from the previous level feature maps and chooses the average value in case of average pooling approach. Instead, the greatest value from the N×N patches of the feature maps is found in the case of maximum clustering. This results in an N-fold reduction in the output card's size. Each output cards gets multiplied by a scalar in certain unique circumstances. Convolutional subsampling and the fraction maximum pooling layer are two additional subsampling layers that have been suggested.

6. Network Parameters and Required Memory for CNN

One key indicator of a machine learning model's complexity is the quantity of computational parameters. Equation (3) can be used to calculate the output map's feature sizes. In this case, N stands for the input feature map dimensions, F for the filters or reception field dimensions, M for the output feature map dimensions, and m for the stride length. In order to safeguard the identically sized input and output map features, convolution techniques usually utilize padding. The size of the kernel determines how much padding is used. The following formula is used to determine the Ith layer's parameter count (Parml) (4).

$$M = \frac{(N-F)}{S} + 1 \qquad (3)$$

$$Parm_j = \left(F * F * FM_{i-j}\right)$$

The following is an expression for the above equation when bias and weights are applied:

$$Parm_j = \left(F * F * FM_{i-j}\right) \qquad (4)$$

where the total number of parameters of l_{th} lathe year can be denoted with $Parm_l$, F denotes the total number of output feature maps, and FM^{l-1}denotes the total number of input feature maps or channels.

7. Construction of Attention-LSTM Perfect

The LSTM model's basic idea is introduced in brief in this article. As seen in Figure 5, LSTM is a type of repeating neural network. As Figure 6 illustrates, the construction of this LSTM repeat module A is more intricate than that of the conventional RNN.

The forgotten gate, the entrance gate, and the exit door are the three components that make up this module. σ represents the sigmoid function. It produces a value, ranging from 0 to 1, indicating the maximum amount of each component that can occur. ft decides how much information we want to reject, among other factors decides how much fresh data we should include. It chooses the amount of data we wish to produce. The input at time is xt. The output of the preceding gate is represented by t.ht−1, the weights are Wf, Wi, Wc, and Wo, the bias is bf, bi, bc, and bo, and the cell state is represented by Ct, the current state, and Ct−1 represents the cell state at the previous instant.

The attention approach is used to verify the performance of the LSTM model for large prediction lag times and extended time series. The identical set of data is used to build each prediction engine. The LSTM model has 64 and 64 concealed neurons, two hidden layers, and a learning rate of 0.05 set up. Moreover, RMSprop serves as the network planner. Algorithm shows how to train an Attention-LSTM network.

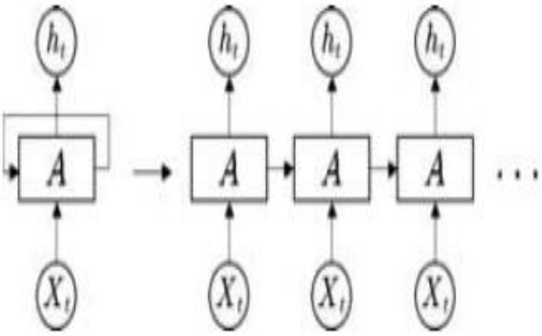


Fig. 5. Recurrent Neural Networks

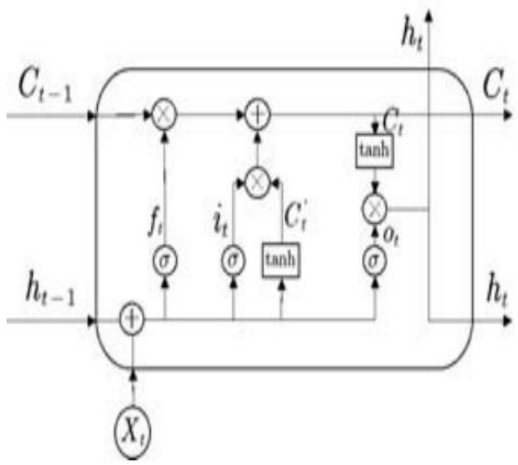


Fig. 6. Structure of LSTM

Production: A trained Attention-LSTM model.

1: Create a dataset that has a sliding time window that includes Xt and Zt.

2: Standardization Xt and Zt.

3: Present illness vector Zt and the feature input matrix Xt are fed into the A-LSTM networks.

4: If the training epoch fails to attain the predetermined value, do

5: Put (Xt, Zt) into the Attention-LSTM network for forward propagation.

6: Compute the attention weight corresponding to each element

7: Make Yt

8: Calculate mean square error.

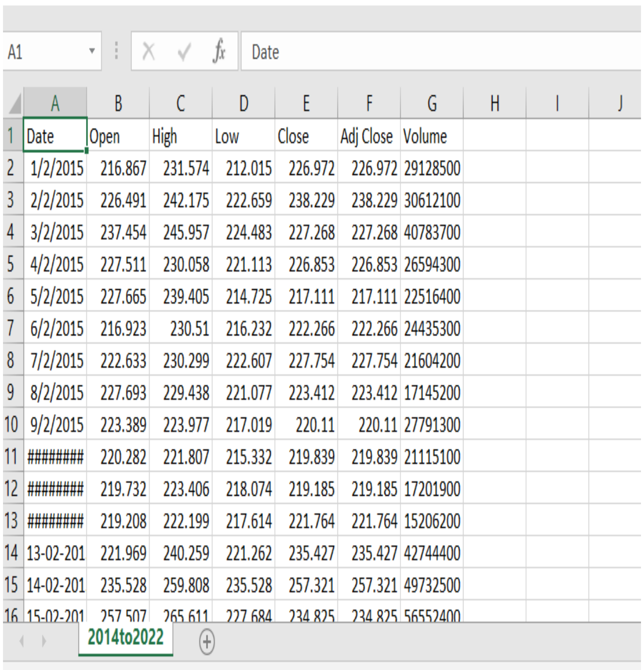
9: Use RMSProp update weights for A-LSTM network.

10: end while

11: come back a model of trained Attention-LSTM.

8. Simulation Result

This article describes the implementation of all approaches based on the data extracted from the Bitcoin Historical Data Kaggle. The data is then randomly split into the training, validation, and test subsets in the ratio 0.7:0.1:0.2, namely the size of the training, validation, and testing subsets. For each prediction model, the suggested method facilitates training using mini batches that have 100 iterations and 1,024 sequences every epoch. In order to enhance the models' generalization performance, the data was divided into separate sets and each model underwent 10 training and testing cycles. Lastly, the report of the average evaluation metrics in the 10 test outcomes is shown in Figures 7 and 8 below.



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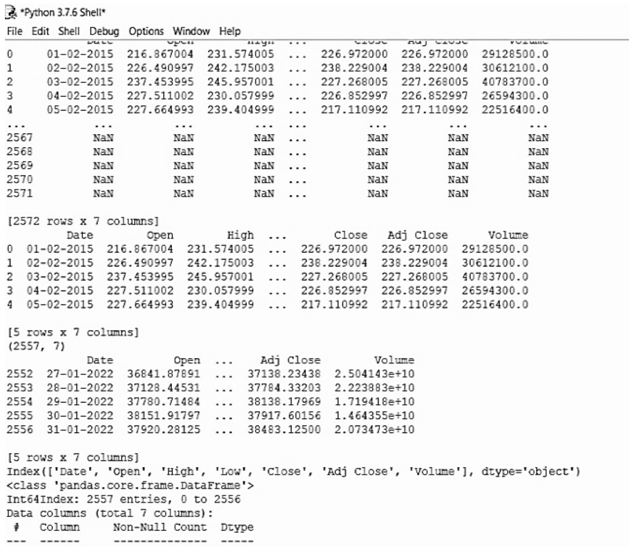
3	2/2/2015	226.491	242.175	222.659	238.229	238.229	30612100
4	3/2/2015	237.454	245.957	224.483	227.268	227.268	40783700
5	4/2/2015	227.511	230.058	221.113	226.853	226.853	26594300
6	5/2/2015	227.665	239.405	214.725	217.111	217.111	22516400
7	6/2/2015	216.923	230.51	216.232	222.266	222.266	24435300
8	7/2/2015	222.633	230.299	222.607	227.754	227.754	21604200
9	8/2/2015	227.693	229.438	221.077	223.412	223.412	17145200
10	9/2/2015	223.389	223.977	217.019	220.11	220.11	27791300
11	########	220.282	221.807	215.332	219.839	219.839	21115100
12	########	219.732	223.406	218.074	219.185	219.185	17201900
13	########	219.208	222.199	217.614	221.764	221.764	15206200
14	13-02-201	221.969	240.259	221.262	235.427	235.427	42744400
15	14-02-201	235.528	259.808	235.528	257.321	257.321	49732500
16	15-02-201	257.507	265.611	227.684	234.825	234.825	56552400

2014to2022

Fig.7. Data Set Description



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File  Edit  Shell  Debug  Options  Window  Help
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1      02-02-2015  226.490997  242.175003  ...  238.229004  238.229004  30612100.0
2      03-02-2015  237.453995  245.957001  ...  227.268005  227.268005  40783700.0
3      04-02-2015  227.511002  230.057999  ...  226.852997  226.852997  26594300.0
4      05-02-2015  227.664993  239.404999  ...  217.110992  217.110992  22516400.0
...           ...         ...         ...  ...         ...         ...         ...
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[2572 rows x 7 columns]
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1  02-02-2015  226.490997  242.175003  ...  238.229004  238.229004  30612100.0
2  03-02-2015  237.453995  245.957001  ...  227.268005  227.268005  40783700.0
3  04-02-2015  227.511002  230.057999  ...  226.852997  226.852997  26594300.0
4  05-02-2015  227.664993  239.404999  ...  217.110992  217.110992  22516400.0

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Fig. 8. LSTM Training

Table 1 displays the LSTM model's results based on the focus process for the Random Forest, Gradeint Boost, and Proposed CNN neural networks. The results should explain the F-Score, Recall, Precision and Accuracy using the common term method, with the performance analysis result also shown in Figure 9 to Figure 13.

Method	F-Score	Recall	Precision	Accuracy
NN	0.0-1.0	0.0-1.0	0.0-1.0	0-100
RF	0.0-1.0	0.0-1.0	0.0-1.0	0-100
GB	0.0-1.0	0.0-1.0	0.0-1.0	0-100
CNN	0.0-1.0	0.0-1.0	0.0-1.0	0-100

Table 1. Values for LSTM Model

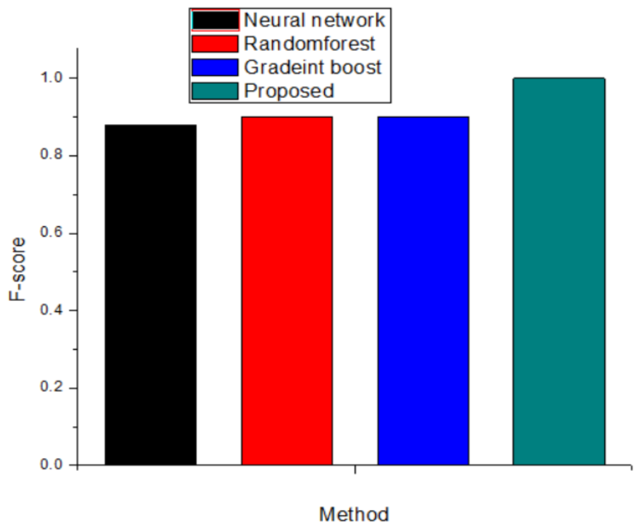

Fig. 9. Testing Result with F-Score

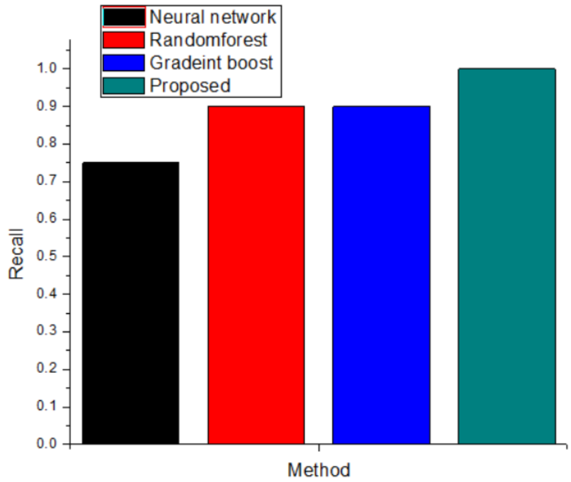

Fig.10. Testing result with Recall

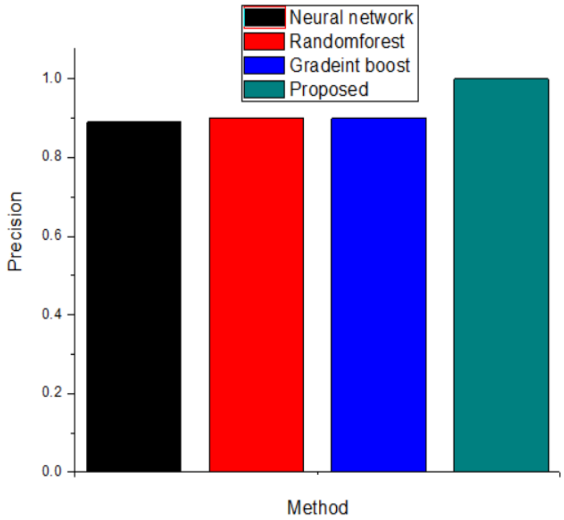

Fig. 11. Testing result with Precision

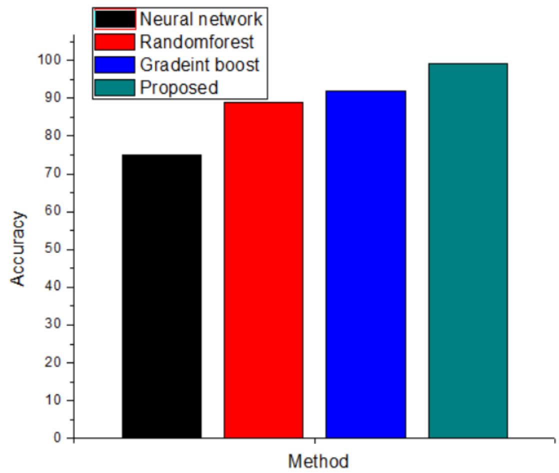

Fig. 12. Testing result with Accuracy

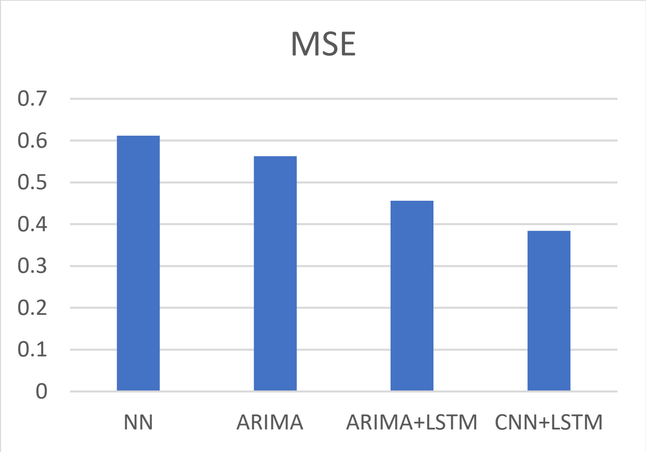

Fig.13. Performance Analysis

The proposed system helps and compares the performance of other machine learning algorithm and the comparison of result is CNN and LSTM having high accuracy is defined in the Table 2.

Performance	**NN**	**ARIMA**	**ARIMA+ LSTM**	**CNN+L STM**
Accuracy	89	92	96	97.8
MSE	0.612	0.563	0.456	0.384
RMSE	0.586	0.504	0.411	0.339

Table 2. Comparison of Results

9. Conclusion

With the advent of information technology, the digital economy is growing tremendously and boasting a large market capitalization. Bitcoin is one of the most important crypto currencies with the highest market capitalization among all other crypto currencies. Accurate price predictions and price projects help investors and traders, with the aim of this proposed bitcoin price prediction work using CNN + LSTM models. The project price per month is provided on site by hybrid models. Experimental results suggest that the hybrid outperforms the others in price prediction. Make a seven-day bitcoin price prediction with a linear regression model. The evaluation of the LSTM-based forecasting framework at various historical window dimensions and network settings. The experimental findings demonstrate that the suggested LSTM-based multi-input forecasting framework offers the risk-informed price for Bitcoin's option calls and decreases our blockchain data to the root-Mean Square Error (RMSE) by up to 46.2%. Lastly, this article contrasts its performance to the standard model without blockchain technology statistics supplies. The proposal helps train the linear regression model by identifying a suitable block of data and applying the percent error method for the error calculation, which gives an accuracy of 96%.97 %.

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