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Bitcoin Price Prediction Using LSTM and FB PROPHET-Based Hybrid Approach

R. Amutha[1], Mareeswari V[2], G G Sivasankari[3], P Sravani[4]

[1]Associate Professor, Department of CSE, AMCEC, Bengaluru
[2]Professor, Department of CSE, AMCEC, Bengaluru
[3]Executive Director at Wells Fargo, United States of America
[4]PG Student, Department of Data Science, AMCEC, Bengaluru

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Abstract: Cryptocurrencies are popular and trending in different countries due to their security and way of processing. Less control or restriction by the government makes it more popular for investors to invest huge amounts in their businesses. The main technology behind cryptocurrency is blockchain. Blockchain mining is one of the important tasks performed for doing analytics and getting useful insights on the blocks. Many deep learning and machine learning approaches such as RNN, LSTM, GRU, SVM, ARIMA, FB PROPHET, Bi-directional LSTM, Ridge Regression, k-Nearest Neighbors, Random Forest, and Ada Boost are used for the Bitcoin price prediction. The key idea in all algorithms is to consider all possible parameters that can affect the Bitcoin prediction price and use them in the model to predict the price accurately. LSTM machine learning technique has been considered due to its better prediction capability in long-term prediction. We have tested our proposed LSTM and FB PROPHET-based model for the dataset obtained from Kaggle. The model with the least RMSE of 0.125 with an accuracy of 90%. can accurately predict the stock price. The proposed hybrid approach has shown significantly improved performance in terms of reduced errors and better prediction by considering important external factors such as seasonal factors etc.

Keywords: ARIMA. Bitcoin, Cryptocurrencies, FB PROPHET, LSTM, RNN, SVM, Stock price prediction

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INTRODUCTION

The digital era has replaced currency notes with digital cryptocurrencies called bitcoins. The transaction of these cryptocurrencies is made over the Internet in a decentralized manner between any two people across the globe. Bitcoin is a decentralized digital currency that is enabled with various encryption and digital signature verifications for ensuring security [4]. As there is no involvement of any global bodies like the government, banks, or any other institutions, it is very much essential to keep track of every bitcoin transaction. To maintain a record of these transactions, Blockchain technology is utilized that resembles a bank's ledgers. Since the time Nakamoto introduced the bitcoin technology, it has attracted the attention of various investors and researchers. It is observed that recently more than 2200 various bitcoins have been introduced through various mining techniques [6]. Thus, predicting the price of these bitcoin has become a challenge to researchers.

Bitcoin is the most popular currency adopted worldwide. Many big companies have joined with bitcoin such as Amazon, Dell, Overstock, and others [26]. Formerly, the blockchain network was smaller in size and was more vulnerable to hackers. Currently, these bitcoins are more secure due to the Ethereum architecture in the cryptocurrency network. During the mining process, the transactions are verified and assigned the hash to the blocks. Many research works are carried out in bitcoin price predictions based on deep neural networks and time-series prediction models such as ARIMA and Facebook PROPHET. Although Bitcoin is one of the widely used cryptocurrencies, in the market several other cryptocurrencies are also used. According to *time.com* (*last updated – using the CoinDesk 20 – on Nov. 30, 2021,* the top 10 cryptocurrencies are- Bitcoin, Ethereum, XRP, Tether, Cardano, Polka dot, Stellar, USD Coin, Dogecoin, Chain-link [27]. In the year 2015, the Linux group created a hyperedge project to get collaboration from cross-industry for the development of blockchain and distributed ledgers [28]

With the involvement of artificial neural networks, the ease of the prediction model has improved in predicting the price variation among bitcoins. The architecture of a recurrent neural network (RNN) is used to train the prediction model with previous states of transaction[19,29].

A. Motivation

Most of the techniques proposed in earlier research have addressed the issue of high fluctuation of Bitcoin prices

***Corresponding Author:** P Sravani

due to external factors that are not modeled properly. The motivation behind the research is to find an efficient technique that can do Bitcoin price prediction with minimum error in prediction considering seasonal factors on the time series data. Therefore, we have proposed a technique that considers some external factors such as seasonal factors into consideration so it can predict the Bitcoin price accurately.

B. Contribution

A hybrid approach is proposed that can predict the Bitcoin price accurately. It will be able to achieve 90% prediction accuracy through our approach. The proposed model uses the LSTM model inherently which is good for prediction for the long term and also it has managed seasonal factors which have influenced Bitcoin price prediction.

C. Organization

In the next section, we are reviewing various techniques used for Bitcoin price prediction. The main challenge of Bitcoin price prediction is the fluctuation of the cryptocurrency price due to external factors such as government policies, market conditions, and social and economic factors. We have reviewed the related technologies that deal with the time series and transitional datasets. The neural network and deep neural network have been state-of-the-art techniques in many research problems. For Bitcoin price prediction, different techniques related to neural networks such as LSTM, RNN, and Bi-LSTM are used. External factors that influence the price of Bitcoin ARIMA and Facebook PROPHET techniques are reviewed. Our proposed system is based on a Hybrid LSTM that has shown better performance in terms of accuracy while predicting the Bitcoin price.

The further article is organized as follows: Section 2 contains a brief study of various RNN and LSTM-based works. Followed by Section 3 describes the basics of LSTM, RNN. Section 4 describes the overall system model description of FB Prophet followed by section 5 which explains the methodology. Section 6 discusses the results and finally, this work is concluded in section 7.

LITERATURE REVIEW

In this section, a study of various blockchain and bitcoin algorithms and architecture is presented. Primarily, cryptocurrency is a network-based medium for exchanging digital currency. Blockchain technology has made the transactions secured, transparent, and immutable using secure hash algorithm-2 (SHA-2) and message-digest-5 (MD5) [9] Due to the involvement of cloud technologies in predicting the prices of bitcoins, many cloud service providers have established their infrastructure to help in predicting the price of bitcoin [16-18]. Though stock price prediction is one of the challenging tasks, many machine learning approaches have been adopted to ease the prediction. Some of the machine learning models are ANN, Random Forest (RF), LSTM, ARIMA-LSTM hybrid model, and Facebook Prophet (FB) [This is general] [Generally, to evaluate the performance of the prediction model, various features are used. Vijh *et al.,* [1] have generated new features from the existing features and evaluated their ANN model work with RMSE, MAPE, and MBE and found ANN performed better than other models with root mean square error (RMSE) and mean absolute percentage error (MAPE).

Further, Ferdiansyah *et al.* [2] described LSTM-based techniques for the Bitcoin price prediction for the Yahoo Finance stock market. Their work is based on a machine learning approach that can predict Bitcoin prices over a few days. They have also studied the impacts of political, economical, and other uncertainties that lead to variations in RMSE below 100 or near 50. S. Tandon *et al.* [3] have proposed an RNN and LSTM-based approach along with 10-fold cross-validation. Their work analyses the trend in Bitcoin price by comparing the performance of LSTM with RNN, Random Forest, and Linear Regression on Livestream datasets. Yang Li *et al.* [4] described Bitcoin price fluctuation by considering features related to basic features, technical trading indicators, and features related to denoising autoencoders. To overcome the problem related to fluctuation due to external factors and features an LSTM and a novel embedding network (ALEN) model have been proposed. Through the performance evaluation, it is found that the LSTM network possessed a good record for sequenced tasks and time-series data.

Many time-series financial data are hidden and to solve that, denoising autoencoders (DAEs) are used. Patrick Jaquart *et al.,*.[5] have analyzed various machine learning algorithms such as random classifier, RNN, and gradient boosting (xgboost[7]) and used different feature sets- technical, blockchain-based, sentiment, or interest-based.

The dataset is collected from Bloomberg, Twitter, and *blockchain.com* from the months of March to December 2019. Mohammad Hamayel *et. al.,* [8] have proposed a recurrent neural network (RNN) based approach to predict the price of Ethereum, Litecoin, and Bitcoin. The gated recurrent unit (GRU) provides better predictions in terms of mean absolute percentage error (MAPE). It is evident from the research that the GRU provides improved results in long short-term memory (LSTM) and bidirectional LSTM (bi-LSTM) which makes this model better[20-22]. Their model has shown the prediction almost equal to the actual. Still, the work has the scope for improvements in terms of considering external factors (social media, government policy, etc.). Mohil Mahesh Kumar Patel *et al.,* [9] have proposed a hybrid approach based on GRU, and LSTM to analyze the factors affecting cryptocurrency prices for Litecoin and Monero cryptocurrencies.

Nithyakani P *et al.,*[10] have also proposed a technique based on bi-directional LSTM for the Bitcoin price prediction where the mean absolute percentage error (MAPE) is 13%. The time-series prediction plays an important role in Bitcoin price prediction; therefore, we need a machine learning algorithm that suits well to handle time-related data. Ensemble-enabled LSTM has shown better accuracy in prediction and risk time. Linear regression-based Bitcoin prediction is also described in many research works, one such approach is described by Azim Muhammad Fahmi *et al.,* [11] in that different linear regression variants such as Linear regression, Bayesian linear regression, boosted decision tree regression, and neural network regression have been analyzed for the Bitcoin price prediction.

Temesgen Awoke Muniye *et al.,* [12] have described a deep learning-based approach based on LSTM and GRU. The compilation time for both LSTM and GRU-based approaches is evaluated for a given number of iterations. To evaluate the performance of these two approaches MAPE and RMSE are calculated and compared. The study concluded that GRU based approach is better as compared to LSTM in terms of prediction accuracy. However, the research gap is found in terms of external factors such as the political system, public relations, marketing strategies, or other seasonal factors.

As the Bitcoin price prediction depends on many external and seasonal factors, therefore, ARIMA and Facebook Prophet (FB) based approaches can be suggested to get better accuracy considering seasonal and external factors. In their approach, the Bitcoin dataset is collected for a period from 2012 to 2018 from the Kaggle website. The parameters collected for the analysis are-Timestamp, Open, High, Low, Close, Volume, and weighted price value. Dataset is further pre-processed and split into training and test dataset. PROPHET is open-source software that supports Python and R languages to develop a forecasting model. It supports the option to examine the prediction on a daily, weekly, monthly, and yearly basis considering a shift in trends and external or seasonal factors. The results obtained conclude that the PROPHET and ARIMA fit well on the training and test dataset. A similar approach is proposed by Aykut Cayir *et. al.,* [13] where PROPHET and ARIMA models are compared for the Bitcoin prediction. The studies show that the PROPHET outperforms ARIA in terms of *R2* values.

Ruchi Mittal *et.al.*, [15] focus on market price prediction of the number of cryptocurrencies based on their historical pattern. The daily trends in the cryptocurrency market are to be identified by considering the features which are more related to the cryptocurrency price. In this, the Multivariate linear regression model is used to predict the price. But they have found that there is not much data for long-term analysis. Leonardo Felizardo *et.al.,* [23] have compared LSTM, ARIMA, Random Forest (RF), SVM, and Wave Nets to predict the Bitcoin price. They have found that the essence of time series data on price prediction included different external factors. The ARIMA and Support Vector Regression (SVR) performed equally well in all the prediction gaps. They have found that working with time-series data is relatively complex and we need to address the cross-validation issues. Mohammed Mudassir *et. Al.,* [24] have considered the high dimensional features for Bitcoin price prediction. The authors have proposed an SVM, LSTM, ANN, SANN based approach for the prediction of Bitcoin price prediction. The LSTM showed better overall performance as compared to other machine learning approaches.

Temesgen Awoke *et. al.* [25] have used Long short-term memory (LSTM) and gated recurrent unit (GRU) to handle the Bitcoin price considering their volatile nature. The GRU is similar to LSTM but it is based on the principle of never generating recurrent neural networks (RNN). The GRU is based on two important gates known as Reset Gate and Update Gate. The Reset gate decides how much past information to forget whereas the Update Gate decides how much information to leave and how much new information to be added. The proposed research work compares the performance of the two models- LSTM and GRU. The dataset is collected from 1st January 2014 to 20th February 2018 considering prices related to opening, closing, high, and low. The dataset is collected from Kaggle and after collection, they are combined, organized, and structured for further processing. The experiment is conducted for the collected dataset and they found that GRU is giving better performance in terms of compilation time. They have also compared the model loss for both techniques for 7 days ahead prediction. Further, the performance of both models is compared in terms of different measurement parameters such as RMSE and MAPE. The result indicates that GRU performs better as compared to LSTM for less number of days ahead prediction as both MAPE and RMSE are lower for the GRU but 15 number of days ahead prediction it has been found that RMSE is same whereas MAPE in LSTM is lower than GRU. The authors described GRU as better for immediate or next-day prediction however the result indicates further that if the prediction has to be done for long-duration we can consider LSTM as well.

BACKGROUND STUDY

In this section, we will discuss the architecture of RNN and LSTM.

A) Recurrent Neural Networks (RNN)

The LSTM is a type of RNN that unlike RNN keeps the previous states in memory that helps in the prediction of an event. Both are a type of neural network that have intermediate layers to process the tasks with greater accuracy.

***Corresponding Author:** P Sravani

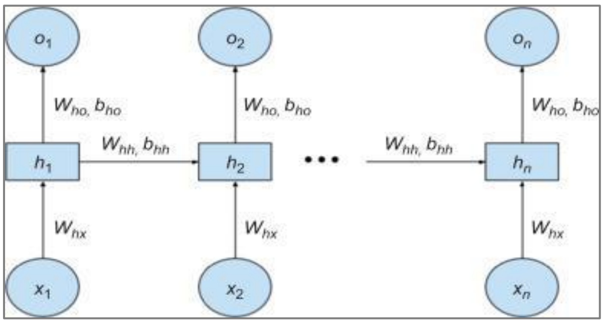

Fig 1. RNN Network Architecture (Hiriyannaiah et al. [29])

An overall RNN architecture can be seen in Fig.1 where W_{hx} is the parameter that governs the connection from the x to other hidden layers. W_{hh} is the parameter that governs the horizontal connection. W_{ho} is the parameter that governs the output predictions model. The value of W_{hx}, W_{hh}, and W_{ho} is the same every time step. During forward propagation, we move forward in every step whereas we move backward in backward propagation through time. The current state is represented as ht that can take the input from the previous state ht-1. For a longer sequence of equations, multiple states are taken into consideration. During the single-time step Xt is supplied as input to the network then we calculate the current state using the previous state value and the new input Xt. The Oi represents the output obtained at every step whereas the final output is obtained as On. The weight Wi is combined with the input every time to tune the result.

B) Long Short-term Memory (LSTM)

Long short-term memory (LSTM) is a type of recurrent neural network (RNN) used for learning ordered and sequence prediction problems. It is used in the complex areas of machine learning problems such as speech recognition, translation, etc [32] Fig.2 shows the LSTM architecture.

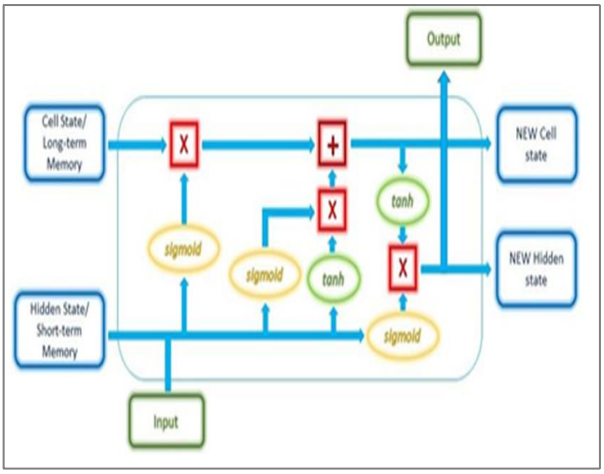

Fig 2. LSTM Architecture (Gabriel Loye [30]

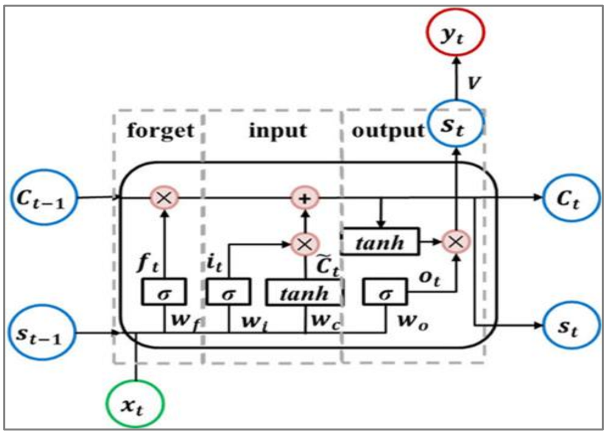

Fig.3. LSTM States (Zhao et al. [31])

Fig.3 shows the detailed overview of LSTM states-forget, input, and output. These gates learn to keep some input sequences while rejecting others by doing this the network will have a long chain of sequences that is relevant for the prediction. The RNN cell takes input from the previous cell state *Ct-1* and current input *xt*. The Softmax function *st* is used to compute predicted value-*St*. RNN keeps track of long-term dependencies of input sequences. The forget gate *ft* represents to what extent to forget previous data, the output gate *ot* represents the output or next hidden state from the current state, *Ct* represents the current internal cell obtained from vector multiplication of input gate and input modulation gate. Then calculate element-wise vector multiplication, forget gate, and previous internal cell state.

A supervised learning approach is used to train the model that uses gradient descent along with backpropagation. Traditional artificial neural networks can't think of a previous sequence of input which makes it difficult for them to learn new things from the sequence. The RNN has come up with an improvement where it loopbacks to them to preserve the persistent information. All RNNs have a chain of repeating neural network modules, this repeating module has a single *tanh* layer. The LSTM has also a similar chain but the repeating module has a different structure.

The activation function is computed as follows:

$$tanh\,(m) \;=\frac{e^{m}-e^{-m}}{e^{m}+e^{-m}} \qquad (1)$$

The vector state values are computed as follows:

$$Ct^{\cdot} = tanh(w_c[St-1, xt] + \delta_r) \qquad (2)$$

The gates' output values are calculated by activation function as follows:

$$f_t = \sigma(w_f[St-1, xt] + \delta_f) \qquad (3)$$
$$i_t = \sigma(wi[St-1, xt] + \delta_i) \qquad (4)$$
$$O_t = \sigma(w_o[St-1, xt] + \delta_o) \qquad (5)$$
$$\sigma(m) = \frac{1}{1+e^{-m}} \qquad (6)$$

Where w_f, w_i, and w_o represent the weight matrices. δ_f, δ_i, and δ_o represent the bias positions.

To get output terms yt, the element-wise product is taken among previous cell states and gate outputs.

Though cryptocurrencies have many advantages there are a few problems also about them. False decentralization is an issue where a large group of people verifying blockchain transactions does form a quasi-centralized entity. Those people are the miners who validate the blocks and hashes. They are also inefficient compared to fiat currencies. The real-time transfer of money takes seconds whereas a few cryptocurrency projects take hours to compute and consume more energy and time. Also, cryptocurrency is volatile and its value depends on several factors including social, political, and seasonal. Cryptocurrencies are the revolutionizing technique that can transform many industries but they have high risks of loss as well. They rely on several complex security protocols therefore these protocols need to be ensured before buying cryptocurrencies.

FB PROPHET

PROPHET is based on an additive model used for forecasting time series data implemented in python and R language.

Overall System Model Description

A high-level conceptual model is given in Fig.4 In that, a hybrid model is proposed by combining LSTM and FB Prophet. The LSTM model is used to get the longest accurate sequence of values that can be used in the prediction. FB Prophet model does the exclusion and inclusion of seasonal factors while modeling to make sure that we get an accurate prediction.

The proposed model is then trained on the Bitcoin dataset obtained from kaggle.com. The dataset is divided into train and test datasets and then the model is tested. The model performance is further evaluated in terms of reduced error while predicting price and for that, we have considered RMSE and MAPE.

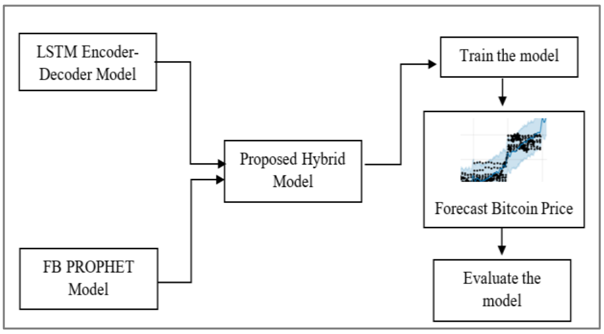

Fig.4. Proposed Hybrid Bitcoin Forecast Model

METHODOLOGY

To build an LSTM model for the Bitcoin price prediction, we need to prepare data for training and testing. Building a model requires different methodologies such as data collection, dividing them into training-test-validate groups for better model accuracy, detecting patterns or anomalies, and representing them in graphical form to visualize them using exploratory data analysis (EDA).

A) Dataset Collection

Data collection from a reliable source is one of the important tasks that need to be done to ensure the accuracy of prediction. The data can be collected from data sources in several ways, a few of them are through web-scraping, and Restful APIs to collect them in JASON form from reliable government sites or the database or repository. We have collected Bitcoin stock data from September 17, 2014- August 24 2021 from Kaggle.com. The dataset contains Bitcoin price at the opening, closing, high, low, and adjusted closing whereas volume represents the number of shares traded in stock. As the price prediction depends on time-series data and is also influenced by different factors, therefore, we need to do factor adjustment while doing prediction (typically using FB PROPHET and ARIMA)

B) Preparing Data for Training and Testing

The basic idea behind splitting data into training, testing, and validation set is to ensure that the model will not overfit and thus accurately evaluate the model. After collecting the dataset, they prepare for further analysis. They classify into train and test datasets before processing. They are also checked for missing or unwanted data and importantly consider external factors that can influence the prediction results. Especially for Bitcoin stock market prediction, it is evident that socio-economic and political factors can influence forecasts. The time series dataset has seasonal impacts. Bitcoin datasets are time-series in nature.

C) LSTM Model

The collected dataset is classified into the train-test-validate dataset to ensure the quality of the prediction obtained through the model. **Algorithm 1** shows the workflow carried out in LSTM modeling for Bitcoin prediction.

D)Preparing Data for Training and Testing

The basic idea behind splitting data into training, testing, and validation set is to ensure that the model is not going to overfit and thus accurately evaluate the model. After collecting the dataset, they are prepared for further analysis. They are classified into train and test datasets before processing. They are also checked for missing data or unwanted data and most importantly considering external factors that can influence the prediction results. Especially for Bitcoin stock market prediction, it is evident that socio-economic and political factors can influence the prediction. The time series dataset normally has seasonal impacts and here also Bitcoin datasets are time-series in nature

Table 1: Sample Training Dataset

Date	Open	High	Low	Close	Adj Close	Volume
17-09-2014	465.864	468.174	452.422	457.334	457.334	21056800
18-09-2014	456.86	456.86	413.104	424.44	424.44	34483200
19-09-2014	424.103	427.835	384.532	394.796	394.796	37919700
20-09-2014	394.673	423.296	389.883	408.904	408.904	36863600
…	…	…	…	…	…	…
12-10-2021	57526.83	57627.88	54477.97	56041.06	56041.06	41083758949
13-10-2021	56038.26	57688.66	54370.97	57401.1	57401.1	41684252783
14-10-2021	57372.83	58478.73	56957.07	57321.52	57321.52	36615791366
15-10-2021	57345.9	62757.13	56868.14	61593.95	61593.95	51780081801
16-10-2021	61609.53	62274.48	60206.12	60892.18	60892.18	34250964237
17-10-2021	60887.65	61645.52	59164.47	61553.62	61553.62	29032367511
18-10-2021	61653.52	62519.73	61260.5	61260.5	61260.5	33256517632

E) Exploratory Data Analysis (EDA)

Exploratory data analysis (EDA) is a critical way to analyze data, perform analytics, identify patterns and detect anomalies. In this section, we have analyzed the stock data to identify the pattern useful for the Bitcoin stock price prediction. The collected dataset is analyzed for the trends in the stock market every year for the stock-open price, close price, high price, and low price. Fig.4 shows the month-wise high and low stock prices during the year 2015 whereas Fig.5 shows the comparison of month-wise open and close prices of stock.

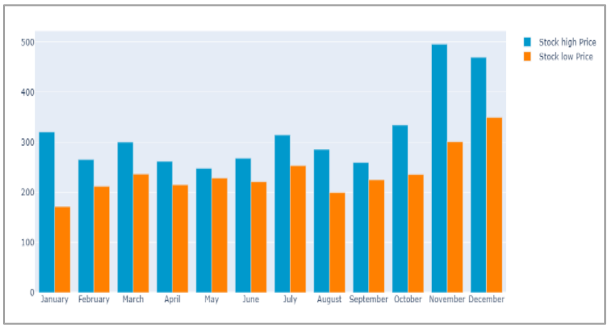

Fig. 4. Month-Wise High and Low Stock Price (in the year 2015)

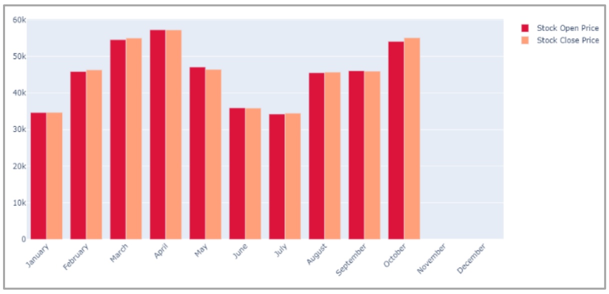

Fig.5. Month-Wise Comparison of Stock Open and Close Price (For the Year 2021)

Algorithm 1: ITSFM Workflow

1. **Begin**
2. **Initialization Stage**
3. {

Train LSTM model *(Epochs, Batch Size, Input, Learning Rate)*

$y(t) = g(t) + s(t) + h(t) + e(t)$

where,

$g(t)$ = trend

$s(t)$ = periodic (monthly, weekly, and yearly) changes

$h(t)$ = represents holiday component

$e(t)$ = error term

Improved Time-Series Forecasting Model (ITSFM) ← LSTM model + $y(t)$

}

4. **Prediction and Classification Phase**
5. {

Perform LSTM

For execution time ≤ *t*

Gate outputs equation

Weight updating equation

Predicted output (LSTM outputs)

}

6. **Evaluation Stage**
7. {

Compute **MSE**

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$$

where,

MSE = Mean Squared Error

n = Total number of data points

Y_i= True values

$\hat{Y}_i$= Predicted values

Compute **MAE**

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - x_i|$$

where,

y = Prediction

x = True value

n = Total number of data points

}

8. **End**

Facebook PROPHET

It is an open-source forecasting method implemented in Python and R. It gives the automated forecast for the bitcoin price prediction. It does the efficient prediction considering seasonal components in the time series data.

The prediction model is defined as-

$$y(t) = g(t) + s(t) + h(t) + e(t) \quad (7)$$

Where, g (t) represents trend s (t)periodic (monthly, weekly, and yearly) changes h(t)represents the holiday component and the error term.

RESULTS AND DISCUSSION

Fig 6. shows the stock analysis from the year 2015 to 2021 for the different stock prices. The stock value ranges from 0-60000. The stock values are significantly higher during the year 2021. The stock parameters used for Stock are- open price, closed price, high price, and low price. This shows the variable Bitcoin stock values between the years 2015 to 2021.

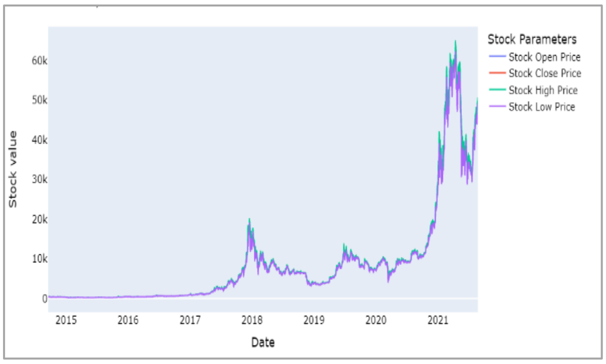

Fig. 6. Stock Price Fromthe Year 2015-2021

Fig. 7 shows the comparison of close vs predicted close price. It shows the original, train, and test prices in that the test predicted close price is very close to the original close price. This shows the prediction model's accuracy.

Fig. 7. Comparison Between Original Close Price Vs Predicted Close Price (For the Year 2020-21)

Fig. 8 represents the predicted next 30 days' close price. Fluctuation can be seen due to external socio-economic and political factors in the time series dataset. Many fluctuations are observed during the first 15 days. However little flattened curve is sheen during the next 15 days, which indicates the predicted value.

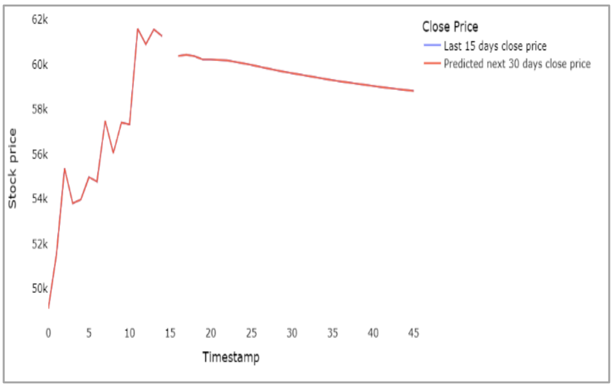

Fig.8. Last 15 Days' Stock Price and Predicted Next 30 Days' Price

Fig. 9 shows the whole closing price with prediction. The graph has multiple peaks and falls due to fluctuating Bitcoin stock prices. It shows the closing price for the timestamp taken in the range from (0-400 s) range.

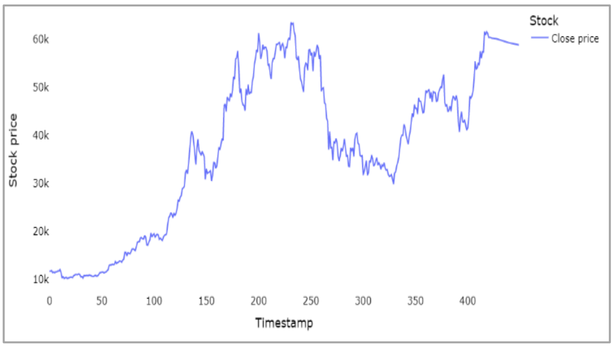

Fig.9. Whole Closing Price with Prediction

Table 2 represents the performance matrix of the proposed LSTM technique. We have evaluated the performance of the proposed algorithms in terms of Root Mean Squared Error (RMSE), Mean Square Error (MSE), and Mean Absolute Error (MAE). We have also evaluated the performance of LSTM in terms of R^2 score, Mean Gamma deviance regression loss (MGD), and Mean Poisson deviance regression loss (MPD).

The *MAE* is calculated using equation (8)-

$$MAE = \frac{\sum_{i=1}^{n} abs(y_i - \lambda(x_i))}{n} \quad (8)$$

where *MAE* is the mean of all *n* absolute errors considered. This represents the model quality. The basic performance evaluation parameters are used as per the LSTM modeling algorithm described in the section Model and Methodology. The coefficient of determination also called R^2 that is used to evaluate the performance of the linear regression model. The R^2 is computed as in equation (9) which indicates the sum of the square of residual error and SS_{tot} represents the total sum of the errors.

$$R^2 = 1 - SS_{res} / SS_{tot} \quad (9)$$

***Corresponding Author:** P Sravani

Mean Gamma deviance regression loss (MGD) is used for scaling the target variable and measuring the relative errors. The goodness of fit is also evaluated using Mean Poisson deviance regression loss (MPD). Table 2 shows that most of the evaluation parameters give lower results for the training dataset and higher for the test dataset.

Table 2: Performance Matrix LSTM

Types of data	RMSE	MSE	MAE	Variance	R^2	MGD	MPD
Train dataset	2018.44	4074108.09	1421.64	0.99	0.99	0.0028	97.628
Test dataset	2545.87	6481439.85	2060.15	0.89	0.88	0.0039	157.425

***MGD- Mean Gamma deviance regression loss**
***MPD- Mean Poisson deviance regression loss**

The Bitcoin price prediction relies on time series data and it is also observed that the external factors influenced the price prediction therefore we have also analyzed the price prediction using the Facebook PROPHET tool to get greater insights on the trend and predictions

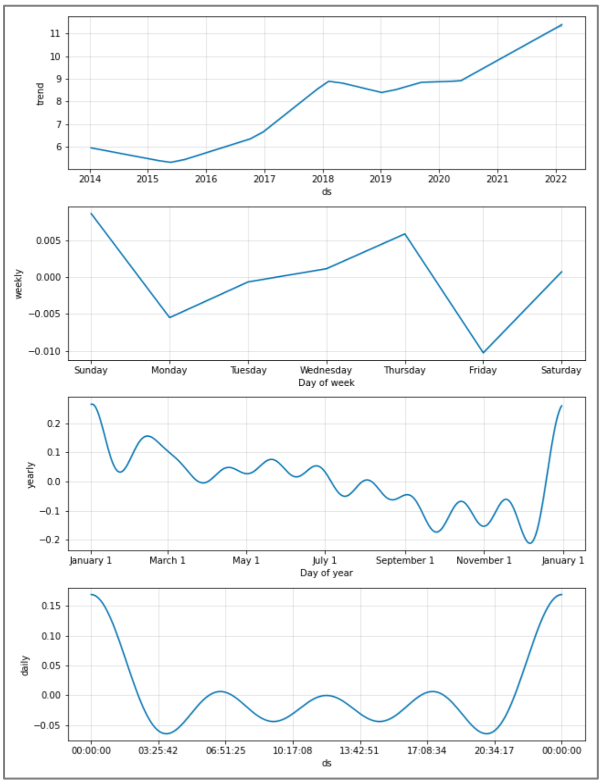

Fig.10. Bitcoin Price Forecasting in Terms of Trends, Weekly, Yearly, and Daily Seasonality Components

The *plot_components* function of FB PROPHET shows the forecast into trends, and weekly and yearly seasonality components.
The predict method maps each row in the *future* to the predicted value *yhat*. In the Python API, the data frame with *ds* and *y* represents the date or timestamp and numeric value respectively. Fig. 11 shows the Bitcoin price forecast data frames and future trends.

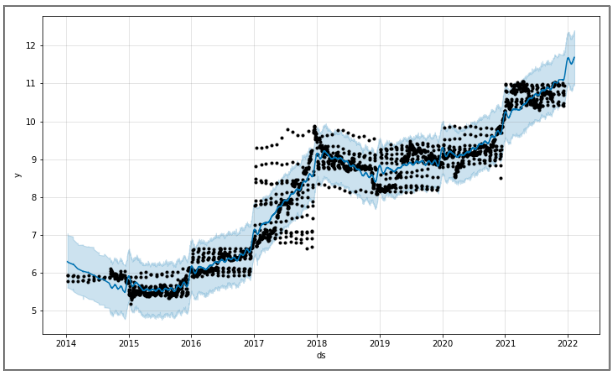

Fig. 11. Bitcoin Price Forecast

Table 3 shows the performance comparison of FB PROPHET with LSTM, ARIMA, and LSTM. It is observed that FB-PROPHET has shown a significantly improved result compared with ARIMA and LSTM.

Table 3: Performance Comparison of Bitcoin Prediction Between FB Prophet With LSTM, LSTM, And ARIMA

Techniques	RMSE	MSE	MAE	MAPE	Variance regression score	R^2
Improve Improved Time-Series Forecasting Model (FB PROPHET+ LSTM)	0.125071	0.870	0.737	0.106828	0.26	0.255
LSTM	2018.44	4074108.09	1421.64	21.87	0.99	0.99
ARIMA	694.748	482674.78	565.1911	8.703098	0.29	0.28

Table 4 shows the performance matrix of FB PROPHET for Bitcoin price prediction

***Corresponding Author:** P Sravani

Table 4: Performance Matrix FBPROPHET

	HORIZON (Days)	HORIZON	MSE	RMSE	MAE	MAPE	MDAPE	SMAPE
0	36	0.315792	0.561954	0.437063	0.050569	0.041655	0.051084	0.801120
1	37	0.322600	0.567979	0.441585	0.051066	0.041880	0.051628	0.792997
2	38	0.323917	0.569137	0.441380	0.050956	0.041655	0.051601	0.790476
3	39	0.326659	0.571541	0.441660	0.050917	0.041151	0.051636	0.790476
4	40	0.333967	0.577898	0.443180	0.050991	0.040733	0.051810	0.790756
325	361	1.736563	1.317787	1.126874	0.125007	0.110515	0.125200	0.549331
326	362	1.746565	1.321577	1.125956	0.124832	0.108656	0.124929	0.552754
327	363	1.758418	1.326053	1.125769	0.124794	0.108015	0.124787	0.553377
328	364	1.773299	1.331653	1.127419	0.125020	0.106828	0.124888	0.554622
329	365	1.787067	1.336812	1.128031	0.125071	0.106828	0.124831	0.557423

CONCLUSION

In the research work, we reviewed different machine learning approaches for Bitcoin price prediction. We have proposed an LSTM and FB PROPHET-based hybrid approach to predict the Bitcoin price and found that the prediction accuracy is more with low errors in terms of MAE, RMSE, R2, MGD, and MPD. LSTM technique is good for a greater number of days prediction as compared to other machine learning approaches such as GRU. The selection of LSTM is due to its capability to remember the past sequences that improve the prediction based on that, which means this task has not been done from scratch every time it can remember the previous sequences that help in prediction. We have also taken FB PROPHET along with LSTM to predict the Bitcoin price. We have also examined the factors that can influence bitcoin prices and the algorithm used to perform time-series data evaluation. The result is also compared with ARIMA.

We further conclude that the PySpark and the R-based tool can be also used to do Bitcoin prediction and analytics when the data size grows big.

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