Predictive Modeling of Bitcoin Transaction: Daily Analysis

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Abstract: With the fast development of the cryptocurrency market, the accurate price prediction of cryptocurrency has become a fault finding for traders. However, because of the difficult and unpredictable nature of price movements which do not have a simple pattern. This makes it complex to examine sequential data points covered over a long period of time. The prediction of cryptocurrency by researchers has explored various approaches which includes Machine Learning (ML) and Deep Learning (DL) to forecast price movements. Factors such as sudden market shifts, external events and investor sentiment contribute to unpredictability. To forecast the price of bitcoin cryptocurrency with Prophet, Long short term memory (LSTM), gated recurrent neural networks to segment the data which consists of daily and half-hourly data transactions were used. In terms of evaluation metrics Mean Absolute Error (MAE), R-Squared, Mean squared error (MSE) were used.

1 INTRODUCTION

Considering the high volatility of cryptocurrency and potential for rapid appreciation, cryptocurrencies have evolved into a prominent category of securities in the global financial system, grabbing the curiosity of both investors and researchers. The global trading of Bitcoin, Ethereum, and other digital currencies over a spectrum of platforms result in sophisticated price swings that are influenced by a multitude of factors, including sentiment among investors, transaction volumes, and external regulatory modifications. Although these markets are so unreliable and non-linear, estimating the pricing of bitcoin is still always pretty challenging promise.

Blockchain technology, which underpins cryptocurrencies, provides a wealth of publicly available transaction data. This data includes variables such as transaction volume, mining difficulty, and the total number of transactions, all of which can offer insights into market behavior and price trends. By leveraging this blockchain transaction data, researchers have turned to advanced time series forecasting models to predict market prices in real-time.

This literature review focuses on the application of three models—Prophet, Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) - to cryptocurrency price prediction. Each of these models has distinct strengths and weaknesses when dealing with time series data, particularly in the context of volatile markets. The review examines how these models have been employed in similar studies, compares their performance, and discusses the challenges and future directions in cryptocurrency price forecasting.

2 RELATED WORK

The research effort explores at how social media activity, including data from Twitter and Google Trends, might be used to forecast changes in the prices of Bitcoin and Ethereum. It emphasises that tweet volume, which is consistently overwhelmingly optimistic despite market trends, is a more accurate indicator of price fluctuations than sentiment analysis. Price changes are accurately predicted using a linear model that incorporates tweet volume and Google Trends data, providing traders with useful information for making decisions. The study comes to the conclusion that keeping an eye on tweet volume gives traders of cryptocurrencies a major advantage by improving their capacity to predict market

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moves(Abraham, Higdon, et al. , 2018). The survey article on change point identification in historical data is briefly represented in this paragraph. Change points, or sudden changes in data patterns, are usually employed to indicate state transitions and have a wide range of uses, such as human activity detection, healthcare inspection, climate analysis, and voice and depict processing. It also describes potential hurdles for the field's advancement and presents criteria for analysing these algorithms. Researchers as well as professionals interested in the analysis of time series and its various applications will find this thorough overview to be pertinent(Aminikhanghahi, and, Cook, 2016).

It examines the privacy restrictions of Bitcoin in an academic context by examining both simulated and actual transactions. Approximately 40% of the user database could be recreated even with the usage of suggested privacy precautions. This paper provides an in-depth assessment of Bitcoin's privacy concerns, highlighting its problems with transparency(Androulaki, Karame, et al. , 2013). The research used a vector Auto regression (VAR) model to examine what macroeconomic factors affected Ghana's exchange rates between 2000 and 2019. Real GDP granger causes exchange rate initiatives, whereas other variables have indirect effects, according to an analysis of the broad money supply (M2), lending rates, inflation, and real GDP. The analysis was supported by data from the Ghana Statistical Service, World Development Indicators, and the Bank of Ghana. In order to lower inflation, boost output, and eventually stabilise the exchange rate through higher GDP, the study suggests measures that lower lending rates and the money supply. (Antwi, Issah, et al. , 2020). A pair of methods for effectively detecting segment neighbourhoods—contiguous residue sets with common features—are presented in the current investigation. These methods, which support a variety of models and fit functions which includes maximum likelihood and least squares, estimate the model parameters essential define these communities and establish their boundaries. They provide versatility for a range of applications by iteratively detecting significant sequence properties. When one technique was used to the influenza virus's haemagglutinin protein, a break in the powerful heptad repeat structure suggested a possible mechanism for conformational shift. This demonstrates how useful the algorithms can be in researching structural biology (Auger, Lawrence, et al. , 1889). The increasing market value of digital currencies and their potential to consolidate power and lessen global dominance are examined in this article. It draws attention to the erratic nature of virtual currencies and the need for accurate techniques for predicting their prices. Incorporating characteristics like stock market the capitalisation, trade volume, distribution, and delivery indicators, a new forecasting model is presented. The method shows how effective the model is in predicting the values of digital currencies by using active LSTM networks to examine benchmark datasets and long-term trends. The results highlight how sophisticated machine learning methods might enhance cryptocurrency prediction(Biswas, Pawar, et al. , 2021).

Wild Binary Segmentation (WBS), a novel technique for estimating the quantity and positions of authority of many change-points in data, is introduced in this study. WBS uses a random globalisation mechanism, which allows it to detect small jump magnitudes and closely spaced change-points without the need for a window or span parameter, in contrast to normal binary segmentation. This method preserves implementation simplicity and computational efficiency. With suggested parameter defaults, the authors suggest two stopping criteria: thresholding and a reinforced Schwarz information criterion. The R function wbs on CRAN offers WBS's implementation, and comparative analyses demonstrate its superior performance (Fryzlewicz, , et al. , 2014). According to the paper's assessment of RNN models for cryptocurrency price prediction, GRU has the lowest MAPE scores and is the most precise for Bitcoin, Litecoin, and Ethereum. To increase predicting accuracy, future research suggests merging social media and trade volume (Hamayel, and, Owda, 2021). The paper evaluates deep learning models for predicting bitcoin prices, such as CNN, LSTM, and BiLSTM, and concludes that they are inadequate for capturing market complexity. To increase forecasting accuracy, it recommends investigating cutting-edge algorithms and feature engineering.

Using significant supply and demand-related aspects from blockchain data, this study investigates the use of Bayesian Neural Networks (BNNs) for modelling and forecasting Bitcoin price time series. When comparing BNNs to other benchmark models, empirical research shows how successfully they anticipate prices and account for the extreme volatility of Bitcoin. This demonstrates how BNNs can be used to increase the forecasting accuracy of price of bitcoin(Jang, Lee, et al. , 2017).

3 PROPOSED WORK

This section demonstrates the existing work relevant to blockchain technology. We have discussed the methods based on machine learning and deep learning.

3.1 Time Series

By investigating past developments while establishing an assumption that future trends will appear similar, it is one of the most effective approaches for anticipating circumstances with an appropriate degree of future unpredictability. With the goal to cope with forecasting obstacles with a time component, time series forecasting additionally incorporates data for efficient and effective preparation.

3.2 Approaches For Bitcoin Prediction

Recurrent Neural Network: Neural networks that are artificial were inspired by the information receiving processes that operate in the human brain. The computerized neurons that make up the neural network are defined by its architecture. RNNs differ from traditional neural networks in that they typically consist of feedback loops. Therefore, it matters whether the context of that data influences how well a prediction can be generated. The recurrent arrangement of an RNN's layers implies that each neuron's present configuration depends on its previous state, thereby giving the neural network a limited amount of memory. A neural network with recurrent operation can accept sequential data as input, and its result and input networks may both be sequences of different lengths that progressively visit each cell.

Prophet: Prophet is a strategy to anticipate time series data utilising an additive model. It combines non-linear trends with seasonality on a daily, weekly, and yearly schedule, alongside the effects from breaks. Strong seasonal consequences within time series and numerous seasons of historical information are ideal considering their efficacy. Prophet generally handles anomalies well and is impervious to insufficient figures and trend fluctuations.

Random Forest Regressor: Regarding regression-related responsibilities, an algorithm based on Deep Learning referred to as Random Forest Regressor is implemented. This collaborative technique of learning integrates numerous decision tree models in order to arrive at predictions. The Random Forest Regression Technique creates a forest of trees of decisions, whereas every one of them, after training on a randomly assigned portion of the training data including substitution (self-funded sample), generates a distinct prediction. Either the overwhelming percentage of the vote (for categorisation) or the computation of each tree's forecast (for regression) yields the final predicted value of the Random Forest Regressor (RF Regressor).

Long short-term memory: Recurrent neural network (RNN) layers with Long Short-Term Memory are specifically engineered to manage sequential data. By adding gating methods, they solve the vanishing gradient issue with conventional RNNs and improve their ability to capture long-term dependencies. The input gate (I), forget gate (F), and output gate (O) make up its three gates. Over time, the LSTM can recall or forget information thanks to these gates, which regulate the information flow across the cell state. Because of the extra gate (forget gate), LSTM usually has more parameters than GRU. This can increase the power of LSTM but also increase its susceptibility to overfitting, particularly on smaller datasets. LSTM has the capacity to discover more intricate patterns and relationships in the data because of its more intricate design. It works effectively for assignments where documenting long-term dependencies is essential.

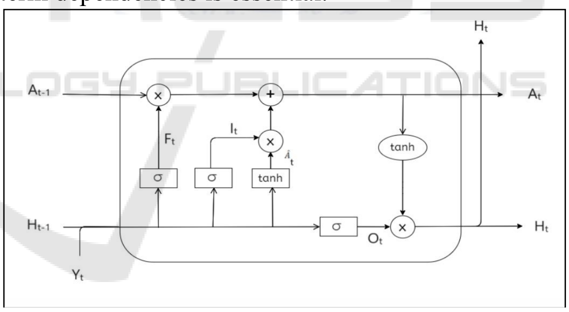

Figure 1: LSTM architecture.

Gated Recurrent Unit (GRU): The two gates that make up the simplified architecture of GRU are the reset gate (R) and the update gate (Z). The reset gate chooses what information should be erased from the past, while the update gate decides how much of the prior hidden state should be kept. Due to the forget gate's absence, GRU has fewer parameters. It can be less prone to overfitting and more computationally efficient as a result, which makes it an excellent option for smaller datasets. GRU is still capable of efficiently capturing long-term dependencies despite its simplicity. It is a common choice for a variety of sequence modeling applications and works well in many natural language processing jobs. GRU may be more effective for larger datasets because it can train more quickly with fewer parameters.

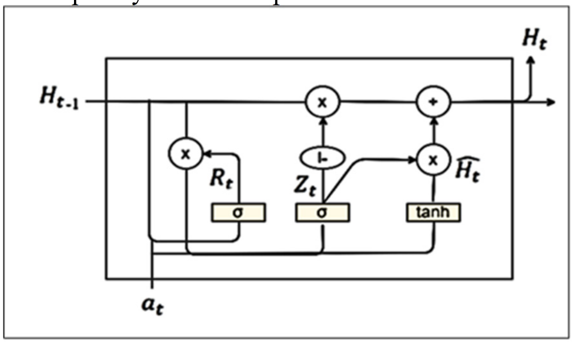

Figure 2: GRU architecture.

4 PROPOSED MODEL: PREDICTIVE ANALYSIS

This section on three basic elements. They are used to predict the price of cryptocurrency: 1) Collection of dataset over a time; 2) Pre-processing; 3) Model building based on the algorithm

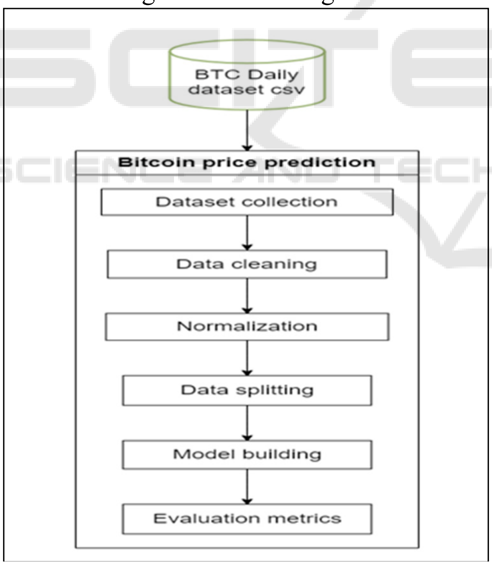

Figure 3 Proposed model for BTC transaction.

In our paper, we used similar methods which includes Prophet, LSTM, GRU with different datasets with huge amounts of data from Kaggle website. With all these algorithms we have evaluated. These all the methods helped to improve the accuracy.

5 TESTING THE PROPOSED MODEL

An experiment tested with the DL models (RNN, LSTM, GRU, Prophet) for forecasting BTC price.

5.1 Data Collection

The analysis used data that had been obtained from the Bitcoin digital currencies in CSV format, consult the Kaggle website. The dataset includes numerous rows, such as mempool size, transaction rate, market cap usd, average block size, market price usd, exchange volume usd, average confirmation time, hash rate, difficulty, miners revenue, total transaction fees as illustrated in Fig. 5, the time span 2015-01-01 to 2023-09-02.Sample information retrieved from the cryptocurrency records employed in the research, with the investigation serving to be the only primary variable and the present day market value for Bitcoin.

5.2 Data Preprocessing

Preprocessing steps are crucial for cleaning and preparing the data before analysis or modeling. Raw data often contains inconsistencies, formatting issues, or non-numerical elements that need to be addressed to ensure accurate results.

- Data Cleaning: The dataset contains more number of null values and they are preprocessed by calculating the mean value of the missing values and some formats are to preprocessed
- Feature Selection: Converting the values to a numerical format like float enables various mathematical calculations, statistical analyses, and machine learning algorithms that require numerical data. Before doing some numerical calculations we have to remove dollor signs, commas.
- Normalization or Standardization: The preprocessing of the dataset involves using the formulas for the standard scaler and minmax scaler functions. The data has been scaled with the aid of this function to provide values that lie between zero to one.
- Test-Train splitting: Use train_test_split to split the sequences and targets into training and testing sets (e.g., 80% training, 20% testing). The training set is used to train your model, while the test set is used to evaluate its performance on unseen data. This helps you avoid overfitting, which occurs when your model memorizes the

training data too well and doesn't generalize well to new data.

5.3 Bitcoin Price Movement Prediction using Deep learning models

The model processes historical data, including price, volume, and market trends, to forecast future price movements. The project helps traders and investors make informed decisions by providing accurate price predictions based on past patterns. The architecture of the DL models: (1) Prophet (2) LSTM (3) GRU is shown below:

Prophet : Facebook's Prophet model is a sophisticated forecasting engine that can handle time-series information effectively, especially during instances involving significant trends, seasonality, and anomalies. It is appropriate for datasets that can show abrupt shifts or cyclical patterns, such as transactions made on Bitcoin. The time sequence has been divided down by the model into the following three primary groups: trend, seasonality, and holidays/events. While the volatility component models recurrent patterns (such as weekly or annual cycles), the trend factor captures the broader long-term growth or decrease in the data. Furthermore, users can define additional occurrences (for instance, market announcements) that could influence the data; the seasonal component takes responsibility for everything.

A dataframe with two columns, y (the target variable) and ds (the timestamp), makes up Prophet's input. Regarding the forecasting of transactions made using Bitcoin, y could indicate for either the market price or the volume of transactions, while ds stands for the daily timestamps. In order to forecast the future, Prophet analyses this previous data and discovers the underlying trends. It is a useful option for cryptocurrency data since it can automatically identify the trend and seasonal patterns of the time-series and has the flexibility to take into account varying growth rates and irregular patterns.

Prophet can produce projections for a given number of future periods once the model has been trained. In order to present a range of possible outcomes, the output contains anticipated values (yhat) for each future time step together with uncertainty intervals (yhat_lower and yhat_upper). In your situation, this entails forecasting future transaction volumes or Bitcoin prices by utilising the seasonality and pattern identified from historical data. The output of the model is quite interpretable, which facilitates understanding of the elements influencing the forecasts and offers insightful information about potential future transaction behaviour.

Long Short Term Memory: A particular kind of recurrent neural network (RNN) called Long Short-Term Memory (LSTM) is made especially to process sequential data and identify long-term dependencies. When data points are temporally sensitive, such as in time-series forecasting jobs like predicting Bitcoin transactions, it works quite well. Because LSTM resolves the issue of vanishing and exploding gradients, it can learn patterns across lengthy sequences, in contrast to conventional RNNs. LSTMs control the information flow by combining input, forget, and output gates. This allows the network to gradually retain or forget different types of information based on how important they are to the prediction.

A three-dimensional tensor with the shape of (samples, time steps, features) is the input for an LSTM. Every time step in your model correlates to a point in the residual series that was derived from the predictions of the Prophet model. To anticipate the next point, the model uses sequences of ten points of information from the residual series as input, for example, if you set the time step to 10. The input units in each LSTM layer have 50 memory cells (or neurons), and the network is built in a way that sends an ordered set of variables to the subsequent LSTM layer or to the most dense layer, regardless of whether the output is returned for each time step or solely the last one as shown in Table I.

To improve the forecast, the Prophet model's predictions are coupled with the LSTM output, which is a projected future point. After that, MinMaxScaler is used to scale the residuals back to their original form, producing residual predictions that improve the accuracy of Bitcoin transaction forecasts.

Table 1: Long Short Term Memory (LSTM).

Layer(type)	Output shape	Param #
lstm (LSTM)	(None, 1, 50)	10,400
lstm_1 (LSTM)	(None, 50)	20,200
dense (Dense)	(None, 1)	51
Total params: 91,955 Trainable params: 30,651 Non-trainable params: 0 Optimizer params: 61,304		

Gated Recurrent Unit: The Gated Recurrent Unit (GRU) is a streamlined version of the LSTM model, intended to identify sequential patterns in time-series data while exhibiting reduced computational complexity. Similar to LSTM, GRU effectively manages long-term dependencies while streamlining its internal architecture by minimising the number of gates utilised. It uses just two gates—an update gate and a reset gate—to manage the flow of information. The update gate lets the model decide how much past knowledge needs to be carried forward, while the reset gate determines how much of the past information to forget. This reduced architecture makes GRU faster to train compared to LSTM, while still being powerful for jobs like forecasting Bitcoin transaction trends.

A Broader Regression (GRU) model handles a series of residuals gathered from the Prophet model using a three-dimension tensor input, comparable to an LSTM. Each layer of the GRU contains 50 neural networks that use the data to learn temporal correlations. The result is a series of anticipated residual values that demonstrate brief variations in Bitcoin transaction data. These values are merged with LSTM and Prophet forecasts to improve the forecast throughout its entirety, as shown in Table II.

Table 2: Gated Recurrent Unit (GRU).

Layer(type)	Output shape	Param #
gru _2 (GRU)	(None, 10, 50)	7,950
gru_3 (GRU)	(None, 50)	15,300
dense_6 (Dense)	(None, 1)	51
Total params: 69,905 Trainable params: 23,301 Non-trainable params: 0 Optimizer params: 46,604		

6 EXPERIMENTAL RESULTS AND DISCUSSION

6.1 Model Training

In the first step, we trained with DL models on the dataset, dividing it into two groups of eighty percent training and twenty per cent testing, in order to determine the optimal DL model. As will be discussed within Section 6, the DL models were evaluated and compared using four assessment measures: MSE, MAE, and R-squared error.

6.2 Epochs

An algorithm's complete traversal through a training dataset is called an epoch. When the information set completes both forward and backward passes, it has completed one pass. The aim of an epoch is used to modify the model's parameters in order eliminate error and enhance accuracy depending on the training set. The algorithm iterates through the training dataset based on the number of epochs; batch gradient descent iterates through a single batch. Until the error rate of the model is deemed acceptable, the process is repeated. Therefore, we used 100 epochs.

Table 3: Loss Vs Val_loss of LSTM.

Epoch	Loss	Val_loss
1/100	0.0611	0.0076
2/100	0.0030	0.0036
3/100	0.0018	0.0025
4/100	0.0017	0.0024
5/100	0.0016	0.0023

Table 4: Loss Vs Val_loss of GRU.

Epoch	Loss	Val_loss
1/100	0.0423	0.0052
2/100	0.0018	0.0019
3/100	0.0012	0.0013
4/100	0.0010	0.0013
5/100	0.0009	0.0012

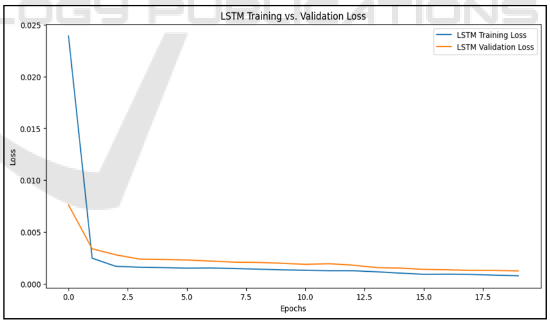

Figure 4: LSTM model loss for training and validation.

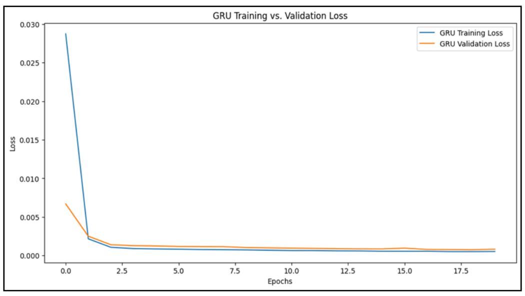

Figure 5: GRU model loss for training and validation.

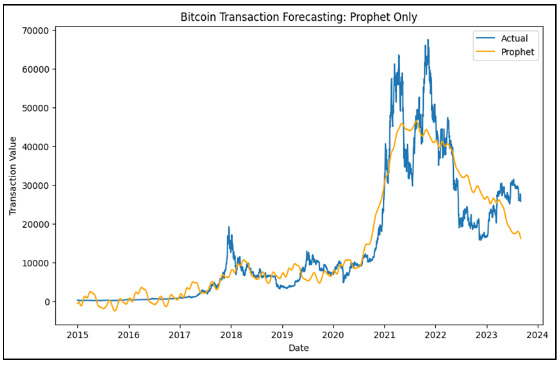

Figure 6: BTC transaction prediction based on Prophet model.

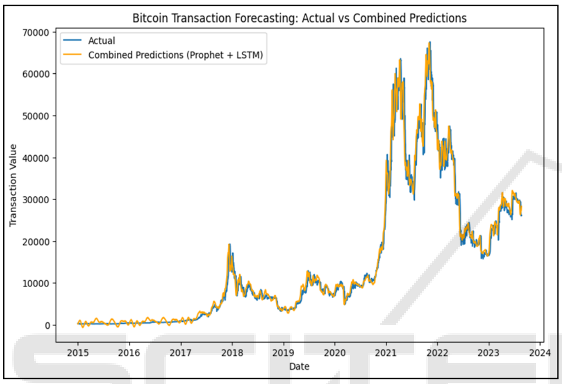

Figure 7: BTC transaction prediction based on Prophet+LSTM.

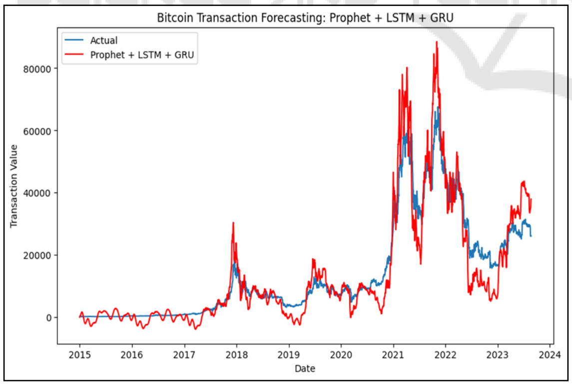

Figure 8. BTC transaction prediction based on Prophet+LSTM+GRU.

Tables III to IV shows the validation loss and loss of each epoch on LSTM and GRU. Fig 4 to 5, indicates the model performance which decrease for each epoch that performs optimally. The prediction model of actual and predicted pharse are shawn in Fig 6 to 8.

6.3 Evaluation Metrics

We measure the forecast mistakes using the Mean Absolute Error (MAE), Means Square Error (MSE) and Root Mean Squared Error (RMSE) in order to assess the effectiveness of model forecasting.

$$\text{MAE} = \frac{1}{x}\sum_{i=1}^{x}|z-\hat{z}|^2 \quad (1)$$

$$\text{MSE} = \frac{1}{x}\sum_{i=1}^{x}(z-\hat{z})^2 \quad (2)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{x}(z-\hat{z})^2}{x}} \quad (3)$$

Despite grabbing responsibility for their direction, the MAE evaluates the mean magnitude of the falls in a series of forecasting. Authenticity for variables that are continuous is tracked.

6.4 Prediction Model Outcomes

This section preforms predictive modeling of Bitcoin transaction dataset between 2015-01-01 and 2023-09-02. Table 5 shows the overall outcome of our error values. The comparison between actual and predicted values of BTC transaction of daily analysis is shown in Fig as well.

Table 5 shows that Prophet+LSTM has the lowest MAE, MSE values and the greatest R-squared values when compared to other. Prophet+LSTM is better than Prophet and combination of Prophet, LSTM and GRU.

Table 5: Summary Of Model Predictions.

Model	MAE	R2	MSE
Prophet	3752.754	0.8812	30643.45
Prophet+ LSTM	1274.5235	0.9818	46804.31
Prophet+ LSTM+GRU	4163.4421	0.8489	39044.20

7 CONCLUSION AND FUTURE WORK

In this research, the market capitalization price of transactional Bitcoin was used to predict the price using some DL algorithms. The method described here explains the suggested techniques to determine an accurate and profitable implementation of the digital currency bitcoin price prediction. The method renders use of methods involving deep learning to reach the established prediction goals. The project's primary objective is to forecast the incredibly volatile crypto price and provide profit for the investors. The dataset is assembled, trained, and then examined in order to carry out this. To do this, it will employ a variety of deep learning models to discover which methodology yields the greatest amount of accuracy. We have predicted the daily transaction of Bitcoin. The remaining process can be processed as the future work which will be continued

In the future, the researcher intends to use more hybrid DL models or deep learning algorithms to improve the accuracy of BTC predictions. To obtain a higher accuracy rate, the period size may also be raised. In addition, deep learning techniques will look into how tweets and emotion impact Bitcoin price.

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