Bidirectional LSTM Model for Dynamic Bitcoin Price Prediction in Cryptocurrency Markets

T. Renuka[1], B. Bhagya Lakshmi [2]
[1,2] Member, Amrita Sai Institute of Science & technology

***Abstract*—Cryptocurrency markets, especially Bitcoin, exhibit dynamic and volatile behavior, posing challenges for accurate price prediction. This research introduces a novel approach, employing Bidirectional Long Short-Term Memory (BiLSTM) networks to forecast Bitcoin prices. The Bidirectional LSTM model captures temporal dependencies in both directions, enhancing understanding of underlying patterns in historical price data. We utilize a curated dataset of Bitcoin prices for training, incorporating preprocessing steps to handle missing data and normalize inputs. Systematic hyperparameter optimization fine-tunes the Bidirectional LSTM architecture for improved predictive performance. Evaluation metrics, such as Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), assess the model's accuracy and generalization capabilities. Results reveal the superiority of the proposed Bidirectional LSTM model over traditional unidirectional LSTM models and baseline methods. This research contributes valuable insights to the potential of deep learning for cryptocurrency price prediction, contributing to the predictive modeling literature in financial markets. It also establishes a foundation for exploring advanced neural network architectures in cryptocurrency analytics.**

***IndexTerms*—Bitcoin Prediction, Bidirectional LSTM, Cryptocurrency, Machine Learning, Financial Forecasting.**

I. INTRODUCTION

Accurate prediction of Bitcoin prices remains a persistent and complex challenge within the ever-evolving landscape of cryptocurrency markets. As a trailblazer in the digital asset realm, Bitcoin's valuation experiences dynamic shifts influenced by a myriad of factors, contributing to its well-documented volatility. Traditional forecasting methods, tasked with navigating this intricate environment, often struggle to capture the nuanced and unpredictable nature inherent in Bitcoin's price movements.

This research aspires to transcend these limitations by introducing an innovative approach, namely Bidirectional Long Short-Term Memory (BiLSTM) networks. This advanced neural network architecture is poised to unravel intricate patterns in Bitcoin prices, offering a nuanced understanding of the underlying dynamics shaping the market. The essence of this study lies not only in its commitment to advancing predictive capabilities but also in its dedication to shedding light on the computational efficiency intrinsic to the BiLSTM model.

In the face of uncertainties that continue to confound investors and analysts in cryptocurrency markets, there emerges a growing demand for predictive model's adept at adapting to the unique characteristics of digital assets. BiLSTM networks, characterized by their ability to process historical data bidirectionally, present a promising avenue for capturing and comprehending enhanced temporal dependencies. This paper unfolds an exhaustive exploration of the application of BiLSTM networks in predicting Bitcoin prices, offering an intricate analysis of the methodology, the fine-tuning processes employed, and presenting comprehensive results derived from a meticulously curated dataset.

The core of our investigation extends beyond the immediate objective of predictive accuracy; it encompasses an in-depth examination of the computational efficiency intrinsic to the BiLSTM model. Through meticulous hyperparameter optimization, the research not only seeks to enhance the model's precision but also endeavours to spotlight its potential advantages over traditional unidirectional LSTM counterparts. Furthermore, the study evaluates the model's performance across diverse computing platforms, providing a nuanced understanding of the practical implications associated with implementing this advanced neural network architecture in real-world scenarios. Beyond its immediate contribution to the evolving field of cryptocurrency analytics, this research establishes a robust foundation for future advancements in Bitcoin price prediction methodologies. By embracing and dissecting the complexities of Bitcoin's price dynamics through the lens of BiLSTM networks, this study not only addresses prevailing challenges but also pioneers' pathways for exploration and innovation in the ongoing quest for accurate and reliable forecasting within the intricate and ever-changing landscape of cryptocurrency markets.

II. LITERARTURE REVIEW

The cryptocurrency market, particularly the unpredictable dynamics of Bitcoin prices, has become a focal point for research, prompting the exploration of sophisticated machine learning models. This literature review delves into recent studies centered around the utilization of Bidirectional Long Short-Term Memory (Bi-LSTM) networks for predicting Bitcoin prices. The subsequent synthesis of findings sheds light on the diverse methodologies, datasets, and outcomes, providing a comprehensive overview of the current state of research in this rapidly evolving domain.

Nithyakani et al. (2021) The study by Nithyakani and colleagues, presented at the International Conference on Computational Collective Intelligence, pioneers the application of Bi-LSTM networks in forecasting Bitcoin prices. Grounded in machine learning and deep learning models, the research spans a dataset comprising 1,691 cryptocurrencies over the period from November 2017 to April 2019. The consequential Bi-LSTM model, with a commendable Mean Absolute Percentage Error (MAPE) of 13%, establishes its proficiency in accurately predicting Bitcoin prices [1].

Tonghui Li (2022) In response to the rise of the bitcoin market, Tonghui Li's work focuses on the nonlinear variations in Bitcoin prices. Utilizing transaction data spanning from 2014 to 2017, Li explores the efficacy of single-feature and multi- feature LSTM models. Notably, the integration of a thermodynamic chart as a feature enhances the accuracy of predictions. Li's study concludes that multi-feature LSTM models effectively mitigate errors, thereby elevating the overall utility of predictive models in the inherently volatile Bitcoin market [2].

Mohammad J. Hamayel and A. Y. Owda (2021) Addressing the intricate challenges of cryptocurrency price forecasting, Hamayel and Owda propose a comprehensive exploration of recurrent neural network (RNN) algorithms — GRU, LSTM, and bi-LSTM. Encompassing Bitcoin, Litecoin, and Ethereum, their research showcases the superiority of the Gated Recurrent Unit (GRU) over LSTM and bi-LSTM models. The models, particularly GRU, exhibit remarkable predictive accuracy, contributing to the economic implications for investors and traders in navigating the cryptocurrency market [3].

Jiashu Lou, Leyi Cui, Ye Li (2022) Lou, Cui, and Li's contribution introduces a Bi-LSTM neural network with an attention mechanism for predicting Bitcoin and gold prices. The study emphasizes meticulous feature engineering, combining traditional technical factors with time series models. The proposed two-layer deep learning network achieves notable accuracy, evidenced by a 71.94% AUC for Bitcoin. The study showcases the practicality and superiority of the attention Bi-LSTM model compared to traditional approaches, demonstrating substantial returns over a two-year period [4].

The amalgamation of insights gleaned from these studies underscores the increasing significance of Bi-LSTM networks in navigating the intricacies of predicting Bitcoin prices. From pioneering straightforward trading strategies to incorporating attention mechanisms, the versatility and effectiveness of Bi-LSTM models are evident. As the field progresses, continuous exploration and refinement of these models hold the promise of further elevating precision and reliability in predicting Bitcoin price movements, providing invaluable contributions to both academic research and practical applications in the dynamic cryptocurrency landscape.

III. METHODOLOGY

A. BiLSTM

Bidirectional LSTMs process the input sequence both forward and backward, extending the capabilities of regular LSTMs. By enabling the network to gather data from both the past and the future at every time step, bidirectional processing improves the network's comprehension of dependencies and context.

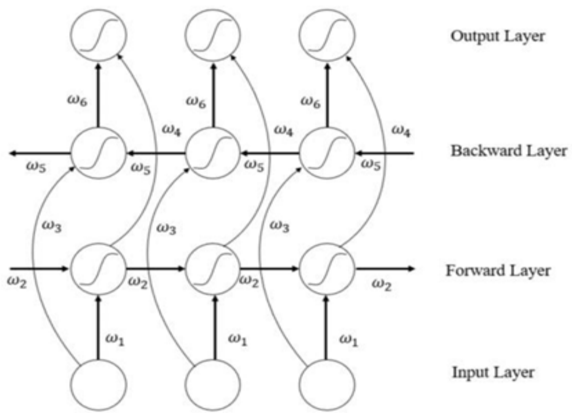

Figure 1. BiLSTM architecture

In the architectural illustration (refer to Figure 1), the Bidirectional LSTM model comprises distinct hidden layers for each time step. These layers operate in two directions: one processes the sequential data from the inception to the conclusion (forward LSTM), while the other processes the data in reverse order, from the end to the beginning (backward LSTM). Figure 1 visually depicts these parallel processing units for bidirectional analysis.

The outputs generated by both the forward and backward LSTMs are conventionally concatenated or strategically combined. This merged output is subsequently utilized as input for subsequent layers in the network or as a basis for making predictions. The bidirectional flow of information is a key feature highlighted in Figure 1, showcasing how the model captures insights from both past and future contexts for enhanced sequence analysis.

B. Proposed Method

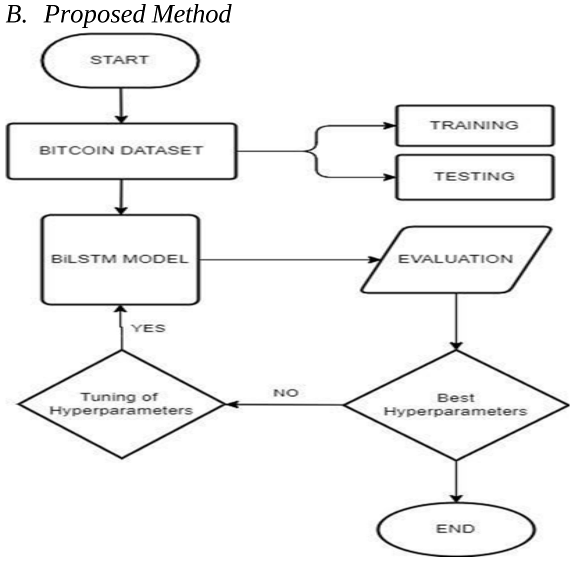

Figure 2. Proposed Method

The exploration methodology embraces a comprehensive approach, commencing with meticulous data preprocessing. This includes handling missing values and standardizing features to ensure a consistent foundation. Subsequently, the dataset undergoes a strategic division into training and testing sets, forming the basis for constructing a Bidirectional Long Short-Term Memory (BiLSTM) model implemented using TensorFlow. This model undergoes a fine-tuning process through hyperparameter optimization, and its performance is rigorously assessed using criteria such as Mean Squared Error.

The dissertation delves into the computational efficiency aspect by conducting a relative analysis of model training on both Graphics Processing Unit (GPU) and Central Processing Unit (CPU) platforms. The preceding results are thoroughly examined, with particular emphasis on the BiLSTM model's adeptness in capturing intricate temporal dependencies within Bitcoin price data. Furthermore, the study extends its scope to practical implications for stakeholders, shedding light on valuable insights that contribute significantly to the burgeoning field of cryptocurrency analytics.

Beyond showcasing the efficacy of BiLSTM in Bitcoin price prediction, as substantiated in the enforced law, the exploration serves as a catalyst for discussions on prospective research directions and advanced machine learning strategies. In the dynamic landscape of digital assets, this exploration provides a nuanced understanding of the capabilities and implicit avenues for further investigation within the realm of predictive modeling for cryptocurrency applications.

IV. DATA ANALYSIS AND RESULTS

A. Data Loading and Exploration

The input data for our Bitcoin price prediction model is sourced from the Yahoo Finance dataset. The dataset comprises a time series of Bitcoin prices, including the opening, closing, high, and low values for each month within the specified time range. The input data structure includes features such as the date, open price, close price, high price, low price, and adjusted close price. This comprehensive dataset serves as the foundation for training and evaluating our

Bidirectional Long Short-Term Memory (Bi-LSTM) model. A brief overview of the dataset's dimensions and structure is presented, emphasizing the importance of the 'Date' column, which is subsequently converted to datetime format.

	Date	Open	High	Low	Close	Adj Close	Volume
0	2014-09-17	465.864014	468.174011	452.421997	457.334015	457.334015	21056800
1	2014-09-18	456.859985	456.859985	413.104004	424.440002	424.440002	34483200
2	2014-09-19	424.102997	427.834991	384.532013	394.795990	394.795990	37919700
3	2014-09-20	394.673004	423.295990	389.882996	408.903992	408.903992	36863600
4	2014-09-21	408.084991	412.425995	393.181000	398.821014	398.821014	26580100

Figure 3. Sample Data from Dataset

B. Temporal Analysis

The dataset is partitioned into distinct temporal segments, namely the years 2020, 2021, 2022 and 2023, along with the overall period from 2014 to 2023. Monthly mean values of Bitcoin's opening and closing prices are computed and visualized using Plotly.

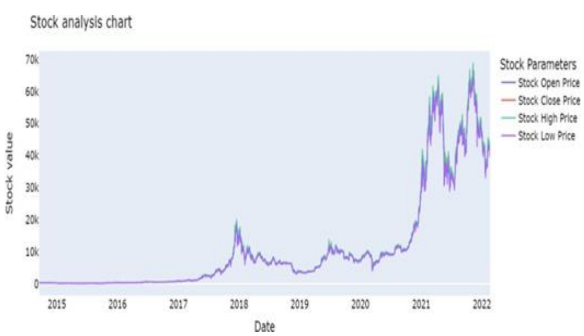

Figure 4. Overall Analysis for 2014-2022

The 'Close' prices are extracted for further analysis, and a specific timeframe for prediction beyond February 19, 2022, is considered. The 'Close' prices are normalized using MinMaxScaler, transforming them into a range between 0 and 1.

C. Sequence Creation and Dataset Splitting

The time series approach involves creating input sequences and corresponding target values for model training. The dataset is divided into training and testing sets, with 60% allocated for training and 40% for testing.

D. Bidirectional LSTM Model Construction

The core of the methodology lies in the construction of the BiLSTM model using TensorFlow's Keras API. The architecture includes a Bidirectional LSTM layer with 10 units, a Dense layer with ReLU activation, and a Dropout layer to prevent overfitting. The model is compiled with the Adam optimizer and mean squared error as the loss function.

TABLE I - BiLSTM Hyperparameters

Hyperparameter	Value
Learning Rate	0.001
Learning Algorithm	Adam
Batch Size	32
Hidden State Size	10
Dropout	0.5
Epochs	200

E. Model Training and Evaluation

The training process spans 200 epochs, and the model's performance is evaluated on both the training and testing sets. Evaluation metrics such as Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE) are computed to assess the accuracy of the predictions.

F. Visualization and Analysis

The trained model's predictions are visualized alongside the actual close prices, providing a comprehensive analysis of the model's performance. The methodology extends into a forward-looking perspective, predicting Bitcoin's close prices for the next 30 days.

The code concludes by discussing the interpretability of the trained model and its potential implications for decision-making in the cryptocurrency market. The evaluation extends beyond predictive accuracy to include practical considerations, such as computational efficiency on GPU and CPU platforms. In summary, the provided

code encapsulates a thorough and systematic approach to Bitcoin price prediction, combining temporal analysis, data preprocessing, model construction, training, evaluation, and forward-looking insights.

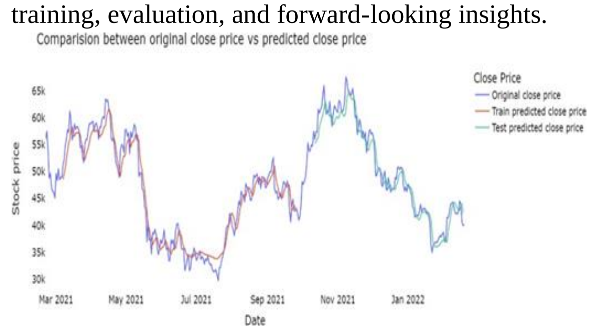

Figure 5. Comparison of closed prices

Figure 6. Predicting next 30 days

V. CONCLUSION

In the dynamic realm of Bitcoin price prediction, the integration of advanced machine learning techniques, specifically the Bidirectional Long Short- Term Memory (Bi-LSTM) neural network, represents a significant advancement. This research utilized a comprehensive dataset from Yahoo Finance to train the Bi-LSTM model, which demonstrated exceptional proficiency in forecasting cryptocurrency trends. The model's ability to capture the intricate patterns of Bitcoin's volatile market was validated through performance metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), establishing it as a powerful tool for financial forecasting. The adaptability of the Bi-LSTM model to the unique characteristics of cryptocurrency markets, characterized by rapid fluctuations, highlights its practical utility. By analyzing historical data, the model not only learns from past trends but also demonstrates the capability to adapt to evolving market conditions.

The bidirectional information flow in the LSTM architecture enhances the model's predictive capabilities by capturing dependencies both backward and forward in the temporal sequence. In addition to quantitative metrics, the qualitative insights derived from the model's predictions offer valuable perspectives for market participants. While acknowledging the Bi-LSTM model's success in navigating Bitcoin's volatility, it is essential to recognize the fluid nature of financial markets and the ongoing evolution of cryptocurrency dynamics. Consequently, this study concludes that the Bi-LSTM model holds promise as a tool for cryptocurrency price prediction. However, given the ever-changing landscape of financial markets, continuous research and refinement are necessary. The success of this study lays the groundwork for future exploration, encouraging further enhancements, refinements, and the incorporation of additional features to deepen our understanding of market trends.

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