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An Ensemble Machine Learning Technique for Bitcoin Price Prediction

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Abstract

This research proposes an ensemble approach for Bitcoin price prediction, leveraging historical price data and sentiment analysis. The proposed ensemble approach combines the model with Gated Recurrent Unit (GRU) and Bidirectional Long Short-Term Memory (BiLSTM) to further improve the accuracy in prediction by considering dynamics in the market. The model also addresses the problem of generalization and overfitting, adaption to the changing, dynamic nature of the market. Historical price data and sentiment scores from the preprocessing of the text are combined to the ensemble framework. These data are then fed into GRU and BiLSTM models for training, as the data contain not only complex temporal patterns but also sentiment-driven trends. The ensemble strategy could be beneficial for the strengths of the models and for improving the performances of the predictors. Most importantly, features are engineered in terms of technical indicators, lagged variables, and external factors impacting the price of Bitcoin. Sentiment analysis with the news and on social media complements insight into market sentiment, which adds value to the prediction power of the model.

Keywords: Bitcoin, Sentiment, Ensemble, Prediction.

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1. Introduction

Due to the fact that Bitcoin is by far the most volatile and exhibits the most potential strength in returns, it receives a great deal of attention within financial markets. Correct prediction of Bitcoin prices is a hard but very important task for the investors, traders, and researchers. Traditional financial models find it very hard to model such highly dynamic and complex markets of cryptocurrencies, which most of the time results in very limited predictive accuracy and generalization [7-10].

Using deep learning models such as Gated Recurrent Unit (GRU) and Bidirectional Long Short-Term Memory (BiLSTM) has shown great promise in improving the performance of cryptocurrency price predictions. By capturing temporal dependencies and patterns, these models can handle sequential data like historical price movements. Additionally, tools such as sentiment analysis of news articles, social media posts, and other textual data have become valuable in understanding market sentiment and its influence on asset prices [11-14].

2. Related Works

This section offers a brief summary of the literature on bitcoin price prediction that is currently available, looking at the many approaches used in these fields.

In this respect, the study has proposed a new methodology, called SDAE-B, by combining Bootstrap Aggregation with Stacking Denoising Autoencoders, which is used for forecasting Bitcoin prices in the presence of market volatility. In this research, data characteristics were represented by a model on deep learning. Some of the variables analyzed were size of blocks and hash rate, besides market events. As a result, these achieved much better accuracy (MAPE = 0.016; RMSE = 131.643; DA = 0.817) over all other techniques, which gave quite an apparent intuition that it was relatively successful to grasp the nonlinear aspects of Bitcoin pricing. This would suggest that using SDAE-B can be extremely useful for investors traversing a vague Bitcoin market. [1]

This paper's [2] approach investigated the use of two deep learning-based models, LSTM and GRU, to predict the daily price of bitcoin. These models evaluated and recognized important factors on their own, making it possible to objectively assess how accurate they were at predicting future prices. The purpose of the article was to compare the two models' performances in order to identify which strategy was more successful and to adjust the parameters for better outcomes. Because of the natural volatility of Bitcoin values, it makes sense to apply cutting-edge methods like LSTM and GRU, which provide effective answers to short-term forecasting problems inside the framework of the wildly popular cryptocurrency.

The research [3] presented a brand-new ensemble deep learning model for predicting the future price of bitcoin at a 30-minute horizon. It utilized basic statistical techniques and an approach to combine LSTM and GRU neural networks using stacking ensemble while—apart from time-lapse data—capturing real-time comments and sentiment from social media. Financial forecasting also benefited from technical indicators. Near real-time results, delivered through the model in action upon data from September 2017 to January 2021, showed that the mean absolute error decreased by 88.74%. This study proves that the ensemble method is a very rewarding one.

The paper [4] proposed a new model: the Fractional Grey Model (FGM (1,1)) to predict the price of blockchain cryptocurrencies, i.e. Bitcoin, Ethereum, Litecoin. The proposed methodology develops an FGM (1, 1) by closing prices further optimized it with a Particle Swarm Optimization (PSO) algorithm. It gave criteria for the evaluation in the form of MAPE, MAE and RMSE between FGM (1, 1) and GM (1, 1). The results show "high predictive accuracy" for FGM (1, 1), which is higher compared to GM (1,1). Such a paper signals out FGM (1,1) as being quite promising in predicting the prices of cryptocurrencies. At the theoretical level, it serves not only practitioners in government but also scholars and investors.

The paper [5] was centered on developing an algorithm of high accuracy that forecasts Bitcoin prices, utilizing both Random Forest Regression and LSTM. However, it did not reveal any clear superiority of one method over the other, although random forest regression had slightly better prediction errors (RMSE and MAPE) in comparison to LSTM. This research managed to find key variables affecting Bitcoin prices, and over time, it saw the switch in trend from an effect by U.S. stock market indexes and oil prices to that of ETH price and the Japanese stock market index. It has further been given to understand that a model with only a lag of the explanatory variables gives the most accurate prediction in terms of Bitcoin prices to the next day. A general paper brought an insight into the prediction models and their influential factors in the dynamic landscape of Bitcoin prices.

The paper [6] entails a machine-learning framework in predicting Bitcoin movements based on a dataset of 24 finance-related variables tested from December 2014 through July 2019. Out of all tested models, it seems that traditional logistic regression is doing best compared to the linear support vector machine and random forest algorithms since it produces an accuracy rate at 66%. The results reflect rejection of the weak form efficiency hypothesis in the Bitcoin market, therefore pointing out that maybe past prices do not reflect available information. These results signal insight into cryptocurrency dynamics and, more interestingly, offer a test case for predictive modelling in this market.

3. Techniques used for Bitcoin Price Prediction

Machine learning is a subfield of artificial intelligence that focuses on developing algorithms and statistical models allowing a computer to perform and improve some tasks on its own, based on experience rather than explicit instructions. For this study, it is proposed to implement advanced ML approaches, notably deep learning algorithms. GRU and BiLSTM networks are two specialized types of recurrent neural networks, which allow capturing complex temporal structures of Bitcoin price data. GRU can capture short-term dependencies, e.g., price fluctuations within a day or an hour. BiLSTM, on the contrary, captures long-term trends and cycles. The combination of GRU and BiLSTM results in an ensemble model that capitalizes on the strengths of both models, compensating for the weaknesses of each model by integrating their strengths.

3.1 BiLSTM

Bidirectional Long Short-Term Memory is a more powerful variant of Long Short-Term Memory, which is a type of recurrent neural network RNN . The primary innovation of BiLSTM lies in its capability to process input sequences going forward and backward at once. In other words, while LSTM processes the sequence from one end to the other, BiLSTM does it from both directions. By doing so, the model acquires the capability not only to understand the past context from past to future but also the future context from future to past. As a result, the model can learn and model long-range dependencies more effectively. It is beneficial for predicting Bitcoin price changes because the model can comprehend past and future trends in historical price data over a long period.

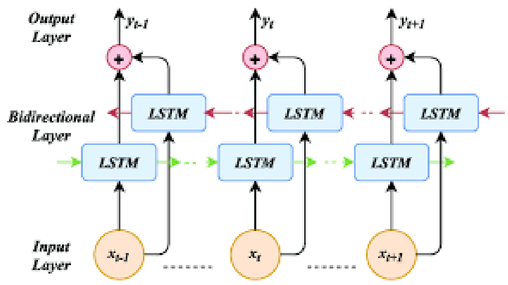

Figure 1. Model Architecture for Bidirectional LSTM

3.2 GRU

The other type of Recurrent Neural Network (RNN) architecture that performs well in modeling data such as Bitcoin price movements is the Gated Recurrent Unit (GRU). The GRU addresses weaknesses of the classical RNN, such as the vanishing gradient problem, by using gating mechanisms to control information flow within the network. This allows the GRU to selectively update and reset its internal state, effectively capturing long-term dependencies in sequential data. For Bitcoin price prediction, the GRU captures short-term dependencies and patterns, like daily or hourly price fluctuations, while retaining important past information. This capability makes the GRU particularly effective in analyzing time-series data with complex temporal dynamics, thereby enhancing the accuracy and robustness of predictive models in cryptocurrency markets.

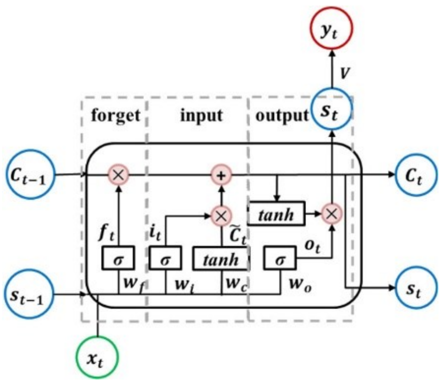

Figure 2. Model Architecture for Gated Recurrent Unit

3.3 Ensemble Approach

The averaging ensemble averages individual model predictions of, say, the Gated Recurrent Unit (GRU) or the Bidirectional Long Short-Term Memory (BiLSTM). This ensemble technique combines the predictions of the GRU and BiLSTM models. This helps in stabilizing the effect of outliers and model biases, thus giving a stable and reliable prediction. Helps in stabilizing the average ensembling of prediction by growing the accuracy and robustness in using collective intelligence of the different models. This makes the technique very useful when applied in volatile and uncertain markets like cryptocurrencies.

4. Proposed Work

The proposed work involves a multi-step process to develop and implement the ensemble model. Firstly, historical Bitcoin price data is preprocessed, and relevant features such as technical indicators and lagged variables are extracted. Simultaneously, sentiment analysis is conducted on news and social media data to obtain sentiment scores. Next, the GRU and BiLSTM models are trained on the preprocessed data to capture temporal patterns and sentiment-driven trends. The ensemble strategy combines the strengths of both models to improve predictive performance and generalization capabilities.

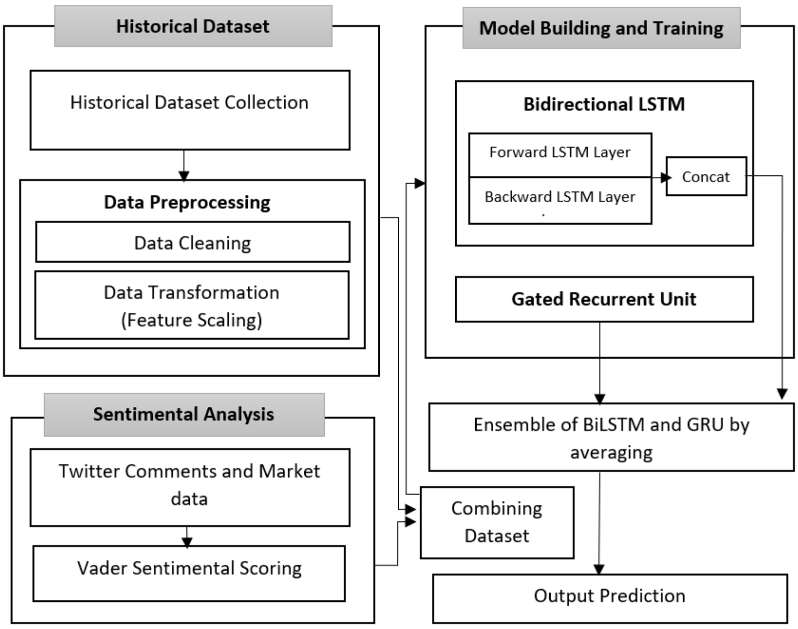

Figure 3. Model Employed in this Study

4.1 Data Collection

The sample data consist of daily records from January 2, 2018, to May 5, 2023, collected from Kaggle.com. The target variable is the price of Bitcoin in USD. Ten explanatory variables, divided into eight categories, are used to predict future Bitcoin prices: (a) Bitcoin price variables, (b) specific technical features of Bitcoin, and (c) New York stock market data.

Table 1. Input Parameters used for Price Prediction

Input Parameters	Definition	Number of Samples
Date	Timestamp indicating when Bitcoin price data was recorded	1974 (2nd January 2018 to 5th May 2023)
Open	The price of Bitcoin at the beginning of a trading period.	
High	The highest price reached by Bitcoin during a trading period.	
Low	The lowest price reached by Bitcoin during a trading period.	
Close	The price of Bitcoin at the end of a trading period.	
Adjacent Close	The adjusted closing price of Bitcoin, accounting for factors such as dividends and stock splits.	
Volume	The total number of Bitcoin units traded during a specific timeframe.	
Market Capitalization	The total value of all Bitcoins in circulation, calculated by multiplying the current price by the total supply.	
NYSE	New York Stock Exchange, a major stock exchange where Bitcoin-related assets may be traded.	
NYSE Volume	The trading volume of Bitcoin-related assets on the New York Stock Exchange.	
Tweets	Twitter comments related to bitcoin	1048576 (2nd January 2018 to 5th May 2023)

4.2 Data Preprocessing

The data cleaning process involved several key steps to ensure the quality and integrity of the dataset. Missing values were handled using a backward fill (bfill) method, ensuring that each data point had appropriate values for analysis. Date-time information was converted to a standardized format and set as the index for time series analysis.

After data cleaning, feature scaling was applied using the MinMaxScaler, which transformed the data into a common range (0 to 1) to mitigate the impact of varying scales across features. This scaling process preserved the relationships and patterns within the data while preparing it for training deep learning models.

The text preprocessing and sentiment analysis were conducted using NLTK. Initially, the text was cleaned by removing special characters and numerical, retaining only alphabets. Subsequently, NLTK's punkt tokenizer was employed to tokenize the cleaned text. Stopwords were then eliminated from the tokenized text, followed by stemming using NLTK's PorterStemmer.

4.3 Sentimental Analysis

The VADER lexicon was downloaded to enable sentiment analysis. Subsequently, the SentimentIntensityAnalyzer from NLTK was initialized for this purpose. For each review in the text, the sentiment scores were computed using VADER. This involved calculating the compound score, which represents the overall sentiment of the text and takes into account both positive and negative sentiments. The compound score ranges from -1 (extremely negative) to 1 (extremely positive), with scores around 0 indicating a neutral sentiment. These sentiment scores were then stored in a new column for further analysis and interpretation.

4.4 Technical Indicator

Technical indicators like moving averages is crucial in financial analysis for several reasons. First, they aid in trend identification by reducing short-term noise and highlighting the underlying direction of price movements. Traders and analysts rely on these trends to make informed decisions about market entry and exit points. The moving averages for various financial indicators like NYSE, NYSE_Volume, Market Capitalization and sentimental score is calculated in a DataFrame, using a window size of 7 days. This approach helps smooth out short-term fluctuations and reveals underlying trends in the data.

4.5 Model Building and Training

The Bidirectional Long Short-Term Memory (BiLSTM) model for Bitcoin price prediction used Hyperparameters like timesteps and features define the input data shape, while 64 units per LSTM layer and return_sequences=True ensure each layer returns a sequence of outputs. Dropout regularization with a rate of 0.2 is applied after each BiLSTM layer to prevent overfitting. The model uses the Adam optimizer with a learning rate of 0.001 and mean squared error as the loss function.

Similarly, A Gated Recurrent Unit (GRU) model with hyperparameters such as timesteps, features, and 64 units per GRU layer is used. The return_sequences=True setting ensures each layer returns a sequence of outputs, while dropout regularization with a rate of 0.2 is applied after each GRU layer to prevent overfitting. The model also uses the Adam optimizer with a learning rate of 0.001 and mean squared error as the loss function.

4.6 Ensemble

In addition to the individual models, an ensemble approach is implemented by averaging the predictions of both BiLSTM and GRU models. This ensemble technique involves training both models for 30 epochs with a batch size of 32. After obtaining predictions from each model, NumPy's mean function is used along the 0 axis to average the predictions, enhancing overall prediction accuracy and stability in Bitcoin price forecasting.

Table 2. Libraries used in Implementing and Evaluating the Performance of the Model

Library	Purpose
numpy	Supports large, multi-dimensional arrays and matrices, and provides a collection of mathematical functions.
pandas	Facilitates data manipulation and analysis, offering data structures like DataFrames.
matplotlib.pyplot	Creates static, interactive, and animated visualizations in Python.
sklearn	Provides simple and efficient tools for data mining and data analysis.
MinMaxScaler	Scales features to a specified range, usually between 0 and 1.
LabelEncoder	Encodes target labels with values between 0 and n_classes-1.
mean_squared_error	Calculates the mean squared error regression loss.
keras.models.Sequential	Constructs a linear stack of layers to build neural network models.
keras.callbacks.EarlyStopping	Stops training when a monitored metric has stopped improving.

keras.layers	Provides various neural network layers, such as Dense, LSTM, GRU, Dropout, and Flatten.
tensorflow.keras.models.Sequential	Offers a high-level neural networks API for building models on top of TensorFlow.
tensorflow.keras.layers	Supplies a collection of different types of layers for constructing neural networks.
tensorflow.keras.optimizers.Adam	Implements the Adam algorithm, optimizing the loss function during training.
sklearn.metrics	Offers functions like mean_squared_error (MSE) and r2_score to assess how well the model's predictions match the actual values (ground truth).
math	Built-in library provides the sqrt function to calculate Root Mean Squared Error (RMSE) from MSE, giving the error in the same units as the data.

5. Results

The analysis yielded promising results regarding the accuracy and reliability of Bitcoin price predictions. Integrating sentiment scores from tweets using VADER notably enhanced the models' predictive capabilities, leading to more precise forecasts. Aligning sentiment scores with Bitcoin price data and merging them with other pertinent features such as market metrics and blockchain indicators contributed to a more comprehensive insight into market dynamics. Additionally, considering market data from prominent indices like NYSE and NASDAQ, alongside commodity prices and calculating moving averages, provided valuable insights into price trends.

The trained Bidirectional Long Short-Term Memory (BiLSTM) and Gated Recurrent Unit (GRU) models exhibited strong performance in capturing temporal patterns in the data, resulting in accurate predictions. The ensemble of BiLSTM and GRU models further improved prediction accuracy, showcasing the effectiveness of combining diverse models for enhanced forecasting in volatile cryptocurrency markets. Overall, these results underscore the significance of integrating sentiment analysis, market data, and advanced deep learning techniques for robust and precise Bitcoin price prediction.

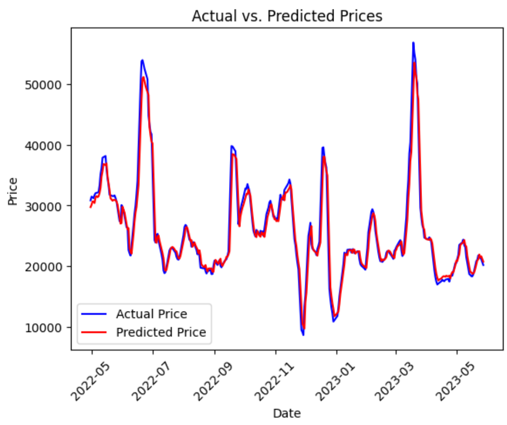

Figure 4. Predicted vs Actual Price Comparison with Respect to Date

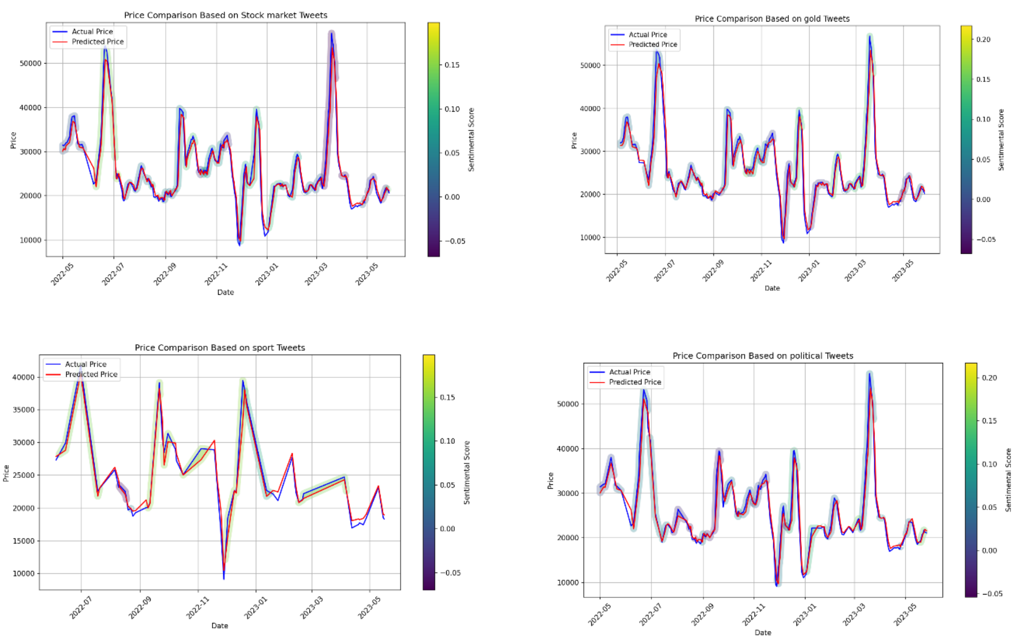

Figure 5. Response of Price According to Stock Market, Politics, Sports, Gold Rate.

From the analysis of Figure 4, it appears that Bitcoin prices are notably impacted by trends in the stock market, movements in gold prices, and political discourse on social media. Conversely, the data suggests that sports-related tweets have a less significant influence on Bitcoin price fluctuations.

5.1 Errors and Evaluation Criteria

The results presented indicate the performance of various models in a predictive task, as evaluated by two common metrics: Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Root Mean Square Error is calculated as the square root of the average of the squared differences between the forecasted values and the actual values. In general, this metric reflects the scale of the model's prediction errors.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} |y(i) - \hat{y}(i)|^2}{N}} \tag{1}$$

Mean Absolute Percentage Error measures the average's absolute percentage difference between predicted values and actual values. It gives an idea of the accuracy of the model in terms of percentage errors.

$$MAPE = \left(\frac{1}{n}\right) * \sum \frac{|actual - forecast|}{|actual|} * 100 \tag{2}$$

The R2 score, also known as the coefficient of determination, is a statistical measure of how well a regression line matches actual data.

$$R^2 = \frac{1 - RSS}{TSS} \tag{3}$$

From the Table 3, the evaluation metrics indicate that the predictive model performs well in forecasting Bitcoin prices. The low MSE, RMSE, and MAE values suggest that the model's predictions are close to the actual prices, indicating high accuracy. Additionally, the high R2 Score reflects a strong correlation between the predicted and actual prices, demonstrating the model's effectiveness in explaining the variability in Bitcoin price movements. Overall, the analysis suggests that the model is reliable and capable of making accurate predictions for Bitcoin prices.

Table 3. Performance Metrics of the Different Methodologies.

Model	MSE	RMSE	MAE	R2 Score
Bidirectional LSTM	0.0005	0.023	0.13	0.43
GRU	0.0004	0.021	0.12	0.55
Ensemble of BiLSTM and GRU without market data	0.00059	0.024	0.13	0.59
Ensemble of GRU and BiLSTM with market and sentimental analysis	0.0001	0.014	0.089	0.88

6. Conclusion

Integrating ensemble techniques like Bidirectional LSTM and GRU models, coupled with sentiment analysis from social media like Twitter and insights from major stock markets such as the New York Stock Exchange (NYSE), forms a multifaceted approach to refining Bitcoin price predictions. This strategy leverages the strengths of advanced deep learning architectures, like Transformers, to capture intricate data relationships and long-term dependencies effectively. Additionally, developing quantitative risk assessment models tailored to Bitcoin enables a thorough analysis of potential risks, enhancing decision-making processes and risk management strategies in cryptocurrency investments. This holistic approach not only enhances prediction accuracy but also provides a comprehensive understanding of market sentiment, external influences, and risk factors affecting Bitcoin's volatility and value.

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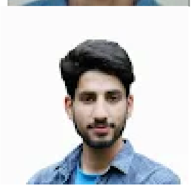

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