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Implementation of Bidirectional LSTM with Attention Mechanism for Predicting BTC Prices

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Abstract

Bitcoin price prediction remains a challenging task due to its high volatility and noisy market behavior, particularly in short-horizon forecasting. This study proposes the implementation of a Bidirectional Long Short-Term Memory (BiLSTM) model enhanced with an Attention mechanism to improve the predictive performance of Bitcoin (BTC) returns. The model was compared against a standard BiLSTM and a Gated Recurrent Unit (GRU) using hourly BTC/USD data from the Kraken exchange covering the period from 2021 onwards. Comprehensive feature engineering was performed, incorporating technical indicators such as Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands width, trading volume, and volatility, along with rolling cumulative returns (Ret_{10} and Ret_{50}). The prediction target was defined as the 6-hour ahead cumulative return. Model performance was rigorously evaluated using Walk-Forward Validation to simulate real-world out-of-sample testing.Experimental results showed that the BiLSTM with Attention mechanism achieved the best predictive performance among the tested models, with an average R^2 of -0.00627. However, all models produced negative R^2 values and directional accuracy close to 50%, indicating limited ability to outperform a simple mean return baseline. In the trading simulation with 0.1% transaction cost, all strategies yielded significant losses ranging from -48.23% to -91.88%. The Attention mechanism provided marginal improvements in R^2 but did not translate into superior trading performance.These findings highlight the inherent difficulty of short-horizon Bitcoin price prediction and suggest that integrating attention mechanisms alone may not be sufficient to capture meaningful patterns in highly noisy cryptocurrency markets. Future research should explore longer forecasting horizons, additional exogenous features such as market sentiment, and more advanced hybrid architectures.

Keywords: Bitcoin price prediction, Bidirectional LSTM, Attention mechanism, Walk-Forward Validation, cryptocurrency forecasting, Deep Learning

INTRODUCTION

Bitcoin (BTC), the world's largest cryptocurrency, is characterized by its exceptionally high volatility and complex price movements. Accurate short-term prediction of Bitcoin prices remains a significant challenge for researchers and market participants. Traditional statistical models often fail to capture the nonlinear and noisy nature of cryptocurrency time series, prompting the adoption of deep learning approaches. Among various architectures, Recurrent Neural Networks and their variants, such as Long Short-Term Memory (LSTM) and Gated

Recurrent Unit (GRU), have shown promising capabilities in modeling temporal dependencies in financial data.

Bidirectional LSTM (BiLSTM) has gained popularity due to its ability to process sequential information from both forward and backward directions, providing richer contextual representations compared to unidirectional LSTM. However, standard BiLSTM models may struggle to effectively focus on the most relevant time steps within noisy market data. To overcome this limitation, the integration of an Attention mechanism has emerged as an effective solution. The Attention mechanism allows the model to dynamically assign higher weights to the most informative parts of the input sequence, potentially improving prediction accuracy.

This study aims to evaluate the effectiveness of a Bidirectional LSTM model enhanced with an Attention mechanism for short-horizon Bitcoin price prediction. The proposed model is compared with a standard BiLSTM and a Gated Recurrent Unit (GRU) using hourly BTC/USD data from the Kraken exchange. Comprehensive feature engineering incorporating technical indicators, volume, volatility, and rolling cumulative returns was implemented. Model performance was assessed using Walk-Forward Validation with multiple evaluation metrics, including R^2, RMSE, MAE, MAPE, directional accuracy, Sharpe ratio, and maximum drawdown, while incorporating a realistic transaction cost in the trading simulation.

LITERATURE REVIEW

The application of deep learning techniques for financial time series forecasting has gained considerable attention in recent years. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been widely adopted due to their ability to capture long-term dependencies in sequential data. However, unidirectional LSTM only processes information in one direction, limiting its ability to fully utilize contextual information from future time steps. To address this limitation, Bidirectional LSTM (BiLSTM) was introduced, allowing the model to learn patterns from both past and future contexts within a sequence.

Althelaya et al. [1] evaluated the performance of Bidirectional LSTM for short- and long-term stock market prediction. Their study demonstrated that BiLSTM outperformed traditional unidirectional LSTM and other machine learning models, particularly in capturing temporal dependencies in financial data. Similarly, Yang and Wang [3] investigated the adaptability of BiLSTM for financial time series prediction and concluded that the bidirectional architecture significantly improved forecasting accuracy compared to conventional models.

In the context of cryptocurrency price prediction, several studies have compared different deep learning architectures. Öztürk Birim [4] conducted a comparative analysis of LSTM, GRU, and Bidirectional LSTM for cryptocurrency price prediction. The study highlighted the strengths of bidirectional models in handling volatile time series data. More recently, Chennupati et al. [5] performed a comparative study between LSTM, BiLSTM, ARIMA, and Transformer models for Bitcoin price prediction. Their findings indicated that BiLSTM generally provided competitive performance, although Transformer-based models showed potential advantages in certain scenarios.

The integration of Attention mechanisms with recurrent architectures has also shown promising results in enhancing model performance. Attention mechanisms enable the model to focus on the most relevant time steps, addressing the limitation of standard recurrent networks that treat all time steps equally. Several studies in stock market and financial forecasting have reported improved predictive performance when Attention layers are incorporated with BiLSTM [2].

Despite these advancements, most existing studies on cryptocurrency price prediction still face challenges in short-horizon forecasting due to extreme market noise and volatility. Many previous works primarily focus on daily or weekly predictions, while research on intra-day (hourly) Bitcoin price forecasting remains relatively limited. Furthermore, limited attention has been given to rigorous out-of-sample evaluation using Walk-Forward Validation and realistic trading simulations that incorporate transaction costs.

This study builds upon previous research by implementing a BiLSTM model enhanced with an Attention mechanism specifically for short-horizon (6-hour) Bitcoin return prediction. Unlike most prior studies that rely on simple train-test splits, this research employs Walk-Forward Validation to better simulate real-world trading conditions. Comprehensive feature engineering and multiple evaluation metrics, including trading performance with transaction costs, are also incorporated to provide a more practical assessment of model effectiveness.

RESEARCH METHOD

a. Dataset

The dataset used in this study consists of historical hourly Bitcoin (BTC/USD) trading data obtained from the Kraken cryptocurrency exchange. For computational efficiency and to focus on more recent market behavior, this study utilized data from the year 2021 onward.

The dataset contains the following columns:

Column Name	Notes
Date	Unix timestamp (in seconds)
Open	Opening price in the hourly interval
High	Highest price in the hourly interval
Low	Lowest price in the hourly interval
Close	Closing price in the hourly interval
Volume	Trading volume (in BTC)
Trades	Number of trades executed during the hourly interval

After preprocessing, the data was converted into a datetime format and filtered to include only records from 2021 onwards to ensure relevance to current market conditions.

Data shape: (15306, 6)

	date	close	volume	trades	Ret	year
52585	2021-01-01 00:00:00	29069.0	272.113148	2071	0.003792	2021
52586	2021-01-01 01:00:00	29452.8	718.037476	3675	0.013203	2021
52587	2021-01-01 02:00:00	29239.9	274.612863	1433	-0.007229	2021
52588	2021-01-01 03:00:00	29342.0	86.226981	750	0.003492	2021
52589	2021-01-01 04:00:00	29266.0	330.509906	1494	-0.002590	2021
...	...	...	...	...	...	...
67886	2022-09-30 19:00:00	19497.2	290.023381	1947	-0.008941	2022
67887	2022-09-30 20:00:00	19420.4	759.074836	1648	-0.003939	2022
67888	2022-09-30 21:00:00	19360.4	564.894247	1245	-0.003090	2022
67889	2022-09-30 22:00:00	19387.1	90.626135	1978	0.001379	2022
67890	2022-09-30 23:00:00	19425.2	57.986112	2466	0.001965	2022

15306 rows × 6 columns

b. Return Based Target Definition

The prediction target is defined as the cumulative return over a 6-hour horizon.

c. Research Objective

The primary objective of this study is to evaluate the effectiveness of a Bidirectional Long Short-Term Memory (BiLSTM) model integrated with an Attention mechanism for improving short-horizon Bitcoin (BTC) price prediction compared to a standard BiLSTM and Gated Recurrent Unit (GRU) model. The evaluation focuses on out-of-sample predictive performance using Walk-Forward Validation and practical trading interpretation based on the sign of predicted returns.

Specifically, this research aims to achieve the following objectives:

1. To implement and compare the predictive performance of three deep learning architectures standard BiLSTM, BiLSTM with Attention mechanism, and GRU for forecasting Bitcoin returns using hourly data.
2. To enhance the input representation through comprehensive feature engineering, incorporating technical indicators and rolling returns as follows:
   a. Base signal hourly return is defined as:

   $$r_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

   where *Pt* denotes the closing price of Bitcoin at time *t*.

   b. Engineered features:

   To capture momentum at different time scales, two rolling cumulative return features were constructed. The 10-hour cumulative return is defined as:

   $$\mathrm{Ret}_{10}(t) = R_t^{(10)} = \left(\prod_{i=0}^{9}(1 + r_{t-i})\right) - 1$$

   while the 50-hour cumulative return is given by:

   $$\mathrm{Ret}_{50}(t) = R_t^{(50)} = \left(\prod_{i=0}^{49}(1 + r_{t-i})\right) - 1$$

   where rt−i is the simple hourly return at i and the notation rt^n represents the n-period cumulative return ending at time *t*. These features allow the model to learn both short-term (10-hour) and medium-term (50-hour) price momentum from the historical return series.

   c. Additional technical indicators: Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands width, trading volume, and 20-period volatility.
3. To define the prediction target as the cumulative return over a 6-hour horizon :

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$$\mathrm{Ret}_6(t) = R^{(6)}_{t+6} = \left(\prod_{i=0}^{5}(1 + r_{t+i})\right) - 1$$

implemented by shifting the return series by -6 periods.

4. To assess model performance using Walk-Forward Validation with multiple evaluation metrics, including Campbell's R^2, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), directional accuracy, Sharpe ratio, and maximum drawdown, while incorporating a 0.1% transaction cost in the trading backtest.
5. To investigate whether the integration of the Attention mechanism can enhance the BiLSTM model's ability to focus on the most relevant temporal dependencies in the sequential Bitcoin price data.

METHODOLOGY

The methodology employed in this research is presented in this section. It includes the model architectures, training configuration, and evaluation framework.

a. Model Architectures

Three deep learning models were implemented and compared in this study:

1. Bidirectional LSTM (Baseline)
   The standard BiLSTM model consists of multiple stacked bidirectional LSTM layers with 64 units each, followed by dropout layers (rate = 0.25) to prevent overfitting. The bidirectional structure enables the model to learn temporal dependencies from both forward and backward directions.
2. Bidirectional LSTM with Attention Mechanism
   The proposed model enhances the standard BiLSTM by integrating a custom Attention mechanism. The architecture comprises four stacked Bidirectional LSTM layers. The final BiLSTM layer outputs sequences (return_sequences=True), which are then fed into the Attention layer. The Attention mechanism computes attention weights to emphasize the most relevant time steps in the sequence. A dense layer is then applied to produce the final prediction. This integration aims to improve the model's ability to focus on critical temporal information in volatile Bitcoin price movements.
3. Gated Recurrent Unit (GRU)
   A GRU model with two stacked layers (64 units each) was implemented as a competitive baseline. GRU was chosen due to its simpler architecture and faster training time compared to LSTM while maintaining strong performance in sequential modeling tasks.

b. Model Training

All models were trained using the Adam optimizer with a learning rate of 0.0001. A window size of 30 timesteps was used to create input sequences. The data was scaled using MinMaxScaler with a range of [-1, 1]. Training was conducted with a batch size of 64 and a maximum of 80 epochs. An Early Stopping callback with a patience of 6 was applied to prevent overfitting, restoring the best model weights based on validation loss. The Mean Absolute Error (MAE) was used as the loss function.

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c. Evaluation Framework

Model performance was evaluated using Walk-Forward Validation, which provides a more realistic assessment of out-of-sample predictive power by iteratively expanding the training window and testing on subsequent unseen periods. All experiments were implemented using Python with TensorFlow and Keras libraries.

The following metrics were used to evaluate model performance:

1. Predictive accuracy:
   R^2 (Campbell's), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy.
2. Trading performance:
   Strategy cumulative return, Sharpe Ratio, and Maximum Drawdown, with a realistic transaction cost of 0.1% per trade applied in the backtesting simulation.

RESULTS

This section presents the experimental results of the three deep learning models : BiLSTM, BiLSTM with Attention mechanism, GRU and also evaluated using Walk-Forward Validation of three deep learning models for 6-hour ahead Bitcoin return prediction on hourly BTC/USD data from the Kraken exchange.

Predictive Performance

WALK-FORWARD AVERAGE RESULTS

	R²	RMSE	MAE	MAPE (%)	Dir Acc (%)
BiLSTM	-0.01288	0.01839	0.01243	3311.21045	49.98316
BiLSTM+Attention	-0.00627	0.01833	0.01236	3374.73145	49.86527
GRU	-0.00834	0.01835	0.01242	6289.15674	50.89256

	Strategy Return (%)	Sharpe	Max DD (%)
BiLSTM	-87.23704	-2.38597	-144.09295
BiLSTM+Attention	-91.88251	-3.46584	-158.60435
GRU	-48.22984	-0.85054	-147.12829

Table 1. Walk-Forward Average Results

As shown in Table 1, the BiLSTM with Attention Mechanism, the proposed model in this study, achieved the best predictive performance with an average R^2 of -0.00627. This represents a noticeable improvement compared to the standard BiLSTM (-0.01288) and GRU (-0.00834). The integration of the Attention mechanism enabled the model to dynamically focus on the most relevant temporal dependencies within the input sequences, demonstrating its effectiveness as a novel enhancement to the BiLSTM architecture for Bitcoin price prediction.

Nevertheless, all models produced negative R^2 values, indicating that their predictions were still inferior to a naive mean return baseline. Directional accuracy remained close to 50% across all models, highlighting the difficulty of consistently predicting price direction in a 6-hour horizon.

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Trading Performance

In the trading simulation incorporating a realistic 0.1% transaction cost per trade, all strategies yielded significant losses. The BiLSTM+Attention strategy recorded a cumulative return of -91.88%, while the GRU strategy showed the smallest loss at -48.23%. Sharpe ratios were negative for all models, and maximum drawdowns exceeded -144%, underscoring the high risk involved in applying these models for actual trading.

Training Process

```
Retraing BiLSTM+Attention for plotting more accurate...
Epoch 1/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 41s 229ms/step - loss: 0.1157 - val_loss: 0.0706
Epoch 2/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 25s 217ms/step - loss: 0.1091 - val_loss: 0.0707
Epoch 3/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 25s 217ms/step - loss: 0.1070 - val_loss: 0.0695
Epoch 4/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 25s 218ms/step - loss: 0.1054 - val_loss: 0.0745
Epoch 5/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 25s 218ms/step - loss: 0.1050 - val_loss: 0.0694
Epoch 6/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 26s 228ms/step - loss: 0.1032 - val_loss: 0.0683
Epoch 7/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 25s 216ms/step - loss: 0.1035 - val_loss: 0.0687
Epoch 8/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 25s 217ms/step - loss: 0.1031 - val_loss: 0.0680
Epoch 9/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 26s 226ms/step - loss: 0.1018 - val_loss: 0.0682
Epoch 10/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 26s 227ms/step - loss: 0.1011 - val_loss: 0.0693
Epoch 11/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 26s 228ms/step - loss: 0.1015 - val_loss: 0.0696
Epoch 12/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 25s 218ms/step - loss: 0.1007 - val_loss: 0.0688
Epoch 13/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 25s 219ms/step - loss: 0.1004 - val_loss: 0.0706
Epoch 14/60
115/115 ━━━━━━━━━━━━━━━━━━━━ 41s 218ms/step - loss: 0.1005 - val_loss: 0.0682
Epoch 14: early stopping
Restoring model weights from the end of the best epoch: 8.
```

Figure 1. Training Log of BiLSTM+Attention Model

Figure 1 presents the training log of the BiLSTM with Attention mechanism model during the final retraining process for loss visualization. The model was trained for a maximum of 60 epochs but stopped early at epoch 14 due to the Early Stopping mechanism, with the best weights restored from epoch 8. Throughout the training, the training loss steadily decreased from 0.1157 to 0.1005, while the validation loss remained relatively stable in the range of 0.0682 to 0.0745. This behavior indicates good convergence and minimal overfitting. The training time per epoch was approximately 25–41 seconds, reflecting the computational complexity of the bidirectional architecture and attention layer. Overall, the log demonstrates that the model learned effectively, although the relatively high loss values confirm the inherent difficulty of predicting short-horizon Bitcoin returns.

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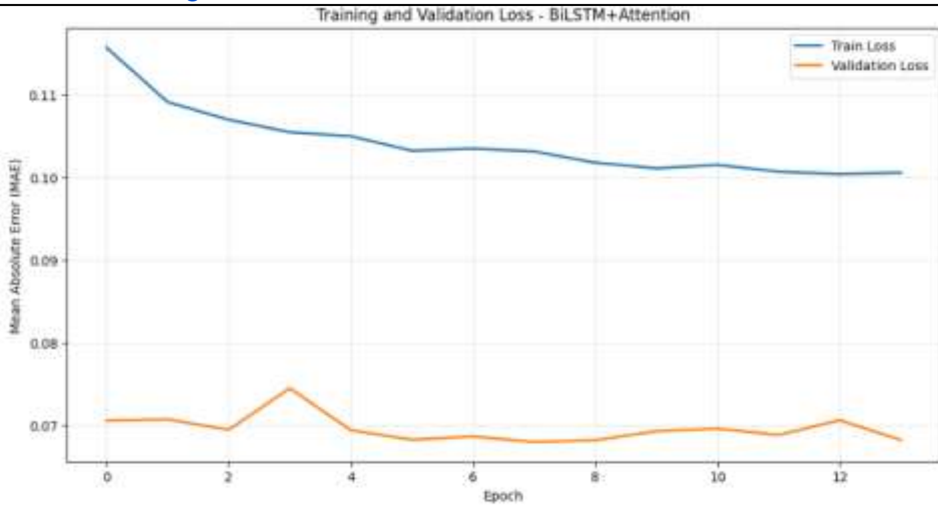

Figure 2. Training and Validation Loss of BiLSTM+Attention Model Curve

Figure 2 shows the training and validation loss curves of the proposed BiLSTM with Attention mechanism. The model converged stably and stopped at epoch 14 due to early stopping, with the best weights restored from epoch 8. The validation loss stabilized around 0.068–0.074, indicating no severe overfitting. The Attention layer contributed to more effective feature representation, as reflected in the relatively smoother loss reduction compared to standard recurrent models. Although the model demonstrated good convergence, the relatively high validation loss values indicate that predicting 6-hour ahead Bitcoin returns remains challenging, even with the integration of the Attention mechanism to capture important temporal dependencies.

Discussion of Results

The superior R^2 achieved by the BiLSTM with Attention mechanism validates the novelty and contribution of incorporating the Attention layer. By allowing the model to assign adaptive weights to important timesteps, the Attention mechanism successfully enhanced the BiLSTM's ability to extract meaningful patterns from noisy hourly Bitcoin data. Although the overall performance remains limited, primarily due to the extreme volatility and noise in short-horizon cryptocurrency markets, the proposed model demonstrates clear added value over both standard BiLSTM and GRU.

DISCUSSION

This study highlights the potential of integrating an Attention mechanism with Bidirectional LSTM as a novel approach to enhance short-horizon Bitcoin price prediction. The experimental results demonstrate that the proposed BiLSTM with Attention mechanism outperformed both the standard BiLSTM and GRU models, achieving the highest R^2 value of -0.00627. This marginal yet consistent improvement underscores the effectiveness of the Attention mechanism in enabling the model to dynamically focus on the most relevant temporal dependencies within noisy hourly Bitcoin data. Unlike conventional BiLSTM, which treats all timesteps equally, the Attention layer allows the model to assign adaptive weights to critical time periods, representing a meaningful architectural enhancement for cryptocurrency forecasting.

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Despite this advancement, all models still produced negative R^2 values and directional accuracy close to 50%. These findings indicate the persistent challenge of short-term (6-hour) Bitcoin return prediction, where market noise and volatility dominate. In trading simulations with a realistic 0.1% transaction cost, the BiLSTM+Attention model recorded a cumulative return of -91.88%. This substantial loss reveals that while the Attention mechanism improved statistical prediction accuracy, it has not yet translated into profitable trading strategies, primarily due to frequent incorrect signals and high transaction costs in volatile markets.

The results of this study contribute to the growing body of literature on deep learning for cryptocurrency prediction by empirically demonstrating the added value of Attention mechanisms in BiLSTM architectures. While previous studies have largely focused on standard LSTM or GRU models, this research provides evidence that incorporating Attention can enhance predictive capability, even if the overall performance remains limited in ultra-short horizons. The use of Walk-Forward Validation and comprehensive trading metrics further strengthens the reliability of these findings.

LIMITATION

Key limitations include the exclusive use of technical features and a short 6-hour prediction horizon. Future research should investigate longer horizons (12–24 hours), integrate sentiment analysis and on-chain metrics, and explore more advanced hybrid models such as Transformer or CNN-BiLSTM architectures to further capitalize on the potential of Attention mechanisms in cryptocurrency price forecasting.

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