

CryptoMamba: Leveraging State Space Models for Accurate Bitcoin Price Prediction

Mohammad Shahab Sepehri[†], Asal Mehradfar[†], Mahdi Soltanolkotabi, Salman Avestimehr

Department of Electrical and Computer Engineering

University of Southern California

{sepehri, mehradfa, soltanol, avestime}@usc.edu

Abstract—Predicting Bitcoin price remains a challenging problem due to the high volatility and complex non-linear dynamics of cryptocurrency markets. Traditional time-series models, such as ARIMA and GARCH, and recurrent neural networks, like LSTMs, have been widely applied to this task but struggle to capture the regime shifts and long-range dependencies inherent in the data. In this work, we propose CryptoMamba, a novel Mamba-based State Space Model (SSM) architecture designed to effectively capture long-range dependencies in financial time-series data. Our experiments show that CryptoMamba not only provides more accurate predictions but also offers enhanced generalizability across different market conditions, surpassing the limitations of previous models. Coupled with trading algorithms for real-world scenarios, CryptoMamba demonstrates its practical utility by translating accurate forecasts into financial outcomes. Our findings signal a huge advantage for SSMs in stock and cryptocurrency price forecasting tasks. The codebase is available in the following link: <https://github.com/MShahabSepehri/CryptoMamba>.

Index Terms—Bitcoin, Machine Learning, Cryptocurrency, State Space Models

I. INTRODUCTION

Predicting Bitcoin [1] prices is a critical problem due to the high volatility and unpredictability of the cryptocurrency market [2]. With the growing influence of cryptocurrencies, the demand for reliable prediction models continues to rise, especially for those seeking to capitalize on market opportunities or safeguard against losses. A successful solution to this problem would benefit traders, institutions, and regulators by offering deeper insights into market behavior, enhancing decision-making, and improving the overall stability of cryptocurrency markets.

The main challenge in Bitcoin price prediction lies in capturing the complexity, nonlinearity, and long-range dependencies within the data. Bitcoin's price movements are driven by a wide range of factors, including market sentiment [3], regulatory developments [4], and macroeconomic trends [5]. These factors interact in unpredictable ways, introducing non-stationarity into the data, making accurate forecasting particularly difficult.

Addressing these challenges requires models capable of effectively modeling temporal dependencies and adapting to dynamic market conditions. However, traditional statistical methods, such as ARIMA [6] and GARCH models [7], often

fall short in handling complex non-linearities and sudden regime changes. In contrast, deep learning models like LSTMs (Long Short-Term Memory) [8] and Transformers [9] have shown promise in learning complex nonlinear patterns but remain limited in scalability and generalizability.

State Space Models (SSMs) [10] offer a promising alternative by modeling time series data as a combination of latent states and observed variables. These models are particularly well-suited for handling the temporal and stochastic characteristics of financial data. Recently, advances in SSMs, such as [11], have demonstrated their capability to capture long-range dependencies in sequences more effectively than traditional recurrent models. Despite their success in natural language processing [12], [13] and computer vision [14], the application of SSMs to financial time series, particularly in cryptocurrency markets, remains unexplored.

In this work, we introduce **CryptoMamba**, which, to the best of our knowledge, is the first framework to leverage State Space Models (SSMs) to tackle the challenges of Bitcoin price prediction and among the first to apply Mamba-based models for time-series forecasting. Specifically, we:

- Propose CryptoMamba, a robust novel Mamba-based SSM architecture for capturing long-range dependencies in financial time-series data.
- Investigate the effects of volume as an input on the accuracy of the prediction.
- Define and evaluate two trading algorithms, Vanilla and Smart, to assess the real-world application of predictions.
- Compare CryptoMamba against multiple baselines, demonstrating its superior performance in forecasting accuracy, financial returns, and computational efficiency.

Our work bridges the gap between advancements in SSMs and their practical applications in financial prediction, paving the way for future research in adaptive and robust market forecasting techniques.

II. RELATED WORK

Early attempts at Bitcoin price forecasting predominantly employed classical time series models such as ARIMA (AutoRegressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity), which have been widely used for financial time series prediction due to their ability to model linear relationships and

[†]These authors contributed equally to this work.

volatility clustering, respectively. While ARIMA models, introduced by [6], are commonly used in financial forecasting [15]–[17], they assume constant variance for the data, limiting their ability to model time-varying volatility. To address this limitation, GARCH models [7] have been employed, as they excel at capturing volatility clustering, a key feature in financial markets. For instance, [18], [19] applied GARCH to model Bitcoin’s volatility, demonstrating its effectiveness for short-term forecasting. However, both ARIMA and GARCH struggle with the non-linearities and sudden regime changes that are typical of cryptocurrency markets.

To address these limitations, more recent studies have turned to machine learning techniques [20], [21] for time-series prediction tasks. Among these, LSTM (Long Short-Term Memory) networks and GRU (Gated Recurrent Units) have gained prominence due to their ability to model sequential dependencies. [22] uses LSTMs to forecast cryptocurrency prices and shows that deep learning models can outperform traditional methods in capturing complex temporal dependencies. [23] compares the effectiveness of three deep learning models, LSTM, GRU, and Bi-Directional LSTM (Bi-LSTM), for predicting cryptocurrency prices. Focusing on Bitcoin, Ethereum, and Litecoin, the study finds that Bi-LSTM provides the most accurate predictions, outperforming the other models. Nonetheless, these models are often prone to overfitting and require large amounts of data to generalize well, limiting their applicability in highly volatile markets with limited data, such as Bitcoin.

Additionally, [24] applies various machine learning algorithms, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), Naïve Bayes (NB), and Random Forest (RF), to the Bitcoin price prediction task. This study underscores the effectiveness of machine learning techniques in forecasting cryptocurrency prices and highlights the potential for improving prediction accuracy through modern modeling approaches. Similarly, [25] utilizes machine learning classification models to predict whether Bitcoin prices will increase or decrease, providing insights into their application for real-time trading decisions.

Despite the advancements in machine learning and time series models, existing approaches often struggle to effectively capture the long-range dependencies and regime shifts that characterize cryptocurrency markets. One promising approach to address the stochastic nature of Bitcoin prices is the use of State Space Models (SSMs) [10], [11]. SSMs offer a robust framework for time series analysis, particularly well-suited for capturing long-range dependencies [11], making them strong candidates for Bitcoin price prediction. Unlike traditional methods such as ARIMA and GARCH, which focus on linear relationships and short-term dependencies [15], [19], SSMs provide greater flexibility in modeling non-linearities and complex temporal interactions. Furthermore, compared to recurrent neural networks (e.g., LSTMs and GRUs), SSMs are computationally efficient, making them better suited for learning dependencies across longer time horizons. These advantages motivate the investigation of SSMs in the context

of Bitcoin price forecasting.

Recently, Mamba [12], a novel variant of SSM, has gained attention for its ability to address the challenges of sequence modeling by introducing a selectivity mechanism that adapts to input data. Building on this foundation, [26] proposed S-Mamba, a model specifically designed for time series forecasting. S-Mamba employs a bidirectional Mamba layer to encode inter-variate correlations and a feed-forward network to extract temporal dependencies. S-Mamba not only outperforms state-of-the-art models in accuracy but also significantly reduces computational overhead, making it particularly effective for high-dimensional time series forecasting tasks. These advancements suggest Mamba-based models as promising candidates for financial applications like Bitcoin price forecasting.

III. BACKGROUND

State Space Models (SSMs) [10], [11] are a recent class of sequence models with roots in control theory [27]. SSMs combine the advantages of Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), making them highly effective for capturing long-range dependencies in time series data. In particular, SSMs process 1-D input sequences, where each element of the array can interact with previously scanned elements through a low-dimensional hidden state. These models are discretizations of continuous-time systems described by:

$$\begin{aligned}\dot{x} &= Ax(t) + Bu(t) \\ y(t) &= Cx(t) + Du(t),\end{aligned}$$

where $u \in \mathbb{R}$ is the input, $x \in \mathbb{R}^N$ is the hidden state, $y \in \mathbb{R}$ is the output, and $A \in \mathbb{R}^{N \times N}$, $B \in \mathbb{R}^{N \times 1}$, $C \in \mathbb{R}^{1 \times N}$, and $D \in \mathbb{R}$ are model parameters. In discrete time, these equations become:

$$\begin{aligned}x_k &= \bar{A}x_{k-1} + \bar{B}u_k \\ y_k &= Cx_k + Du_k,\end{aligned}$$

where \bar{A} , \bar{B} , and \bar{C} are derived through discretization methods like zero-order hold for a given time step Δ , and D is often omitted.

Traditional SSMs are linear time-invariant (LTI) systems where model dynamics do not depend on the inputs. Mamba [12] added context awareness to SSMs by making B , C , and Δ input-dependent, creating a time-varying system. Moreover, Mamba leverages a hardware-aware algorithm to maintain computational efficiency, and as a result, its computational cost scales linearly with sequence length (similar to traditional SSMs). Empirical results demonstrate that Mamba achieves state-of-the-art performance in language, audio, and genomic tasks, outperforming both standard SSMs and Transformers. Inspired by Mamba’s advancements, our approach is designing a custom Mamba-based architecture tailored for time-series forecasting.

IV. METHODOLOGY

CryptoMamba leverages Mamba-based SSMs to tackle the challenges of Bitcoin price prediction, offering a robust approach to capturing long-range dependencies in highly volatile financial data. This section provides an overview of the dataset utilized, the components of CryptoMamba, and the metrics employed to evaluate its performance against baseline models.

A. Dataset

A critical gap in Bitcoin price prediction literature is the inconsistent datasets, with studies often focusing on either early adoption periods [18] or more recent years with higher trading volumes [23]. These inconsistencies hinder the accurate assessment of the models' generalization capabilities. To address this, we use the most recent publicly available dataset, reflecting current market trends, and evaluate CryptoMamba against baseline models to assess its effectiveness under real-world conditions.

We use historical daily Bitcoin price data from Yahoo Finance covering the period from September 17, 2018, to September 17, 2024, for our experiments. The data was partitioned into distinct intervals as shown in Table I. For our experiments, we isolate the test and the validation sets to evaluate model performance on genuinely unseen data, enabling a more robust assessment of the model's generalization capacity.

TABLE I
DATASET SPLITS

Split	Time Interval
Train	September 17, 2018 - September 17, 2022
Validation	September 17, 2022 - September 17, 2023
Test	September 17, 2023 - September 17, 2024

The data includes five main features: open, close, high, low, and volume. Since the intervals in our dataset are daily, the open and close prices represent the value of Bitcoin at the start and end of each day, which in Yahoo Finance data corresponds to the UTC time zone. The high and low prices are the maximum and minimum values recorded during each day, highlighting price volatility. Volume represents the number of Bitcoin units traded over the day, providing potential insights into market activity and sentiment that may affect price trends. Table II summarizes different features and their descriptions.

We conducted separate analyses with and without the volume data to evaluate its impact on forecast accuracy. Volume is hypothesized to be a valuable feature as it reflects trading activity, which can signal demand and market sentiment, potentially affecting price movements. However, its effectiveness in prediction remains unknown, as most previous works do not incorporate it as an input. We test both scenarios to investigate the effect of using volume data in prediction.

B. CryptoMamba Architecture

CryptoMamba is a Mamba-based architecture specifically designed for financial time-series prediction, leveraging

TABLE II
DATASET SPECIFICATIONS

Parameter	Description
Open	Daily opening price of BTC-USD
High	Daily highest price of BTC-USD
Low	Daily lowest price of BTC-USD
Close	Daily close price of BTC-USD
Volume	Daily number of Bitcoin units traded
Timestamp	Date of the observation

Mamba blocks to handle long-range dependencies in sequential data. The model consists of several stacked computational blocks, referred to as C-Blocks, followed by a final Merge block that generates the prediction output. The input to CryptoMamba is the features of a fixed number of past days, and the output is the predicted closing value for the next day. The overall architecture is depicted in Figure 1.

Each C-Block is composed of multiple CMBlocks and a Multi-Layer Perceptron (MLP). A CMBlock includes a normalization layer followed by a Mamba block. The output of each CMBlock feeds into subsequent CMBlocks within the same C-Block, allowing hierarchical feature extraction. The MLP at the end of each C-Block is a linear layer that adjusts the sequence length to prepare the output for the next C-Block. The outputs of all C-Blocks are aggregated by the Merge block, which is a simple linear layer to integrate the extracted features and produce the final prediction.

The hierarchical structure of CryptoMamba enables it to progressively refine features across multiple C-Blocks, capturing both short-term and long-term temporal dependencies. Additionally, the Mamba block's input-dependent dynamics ensure adaptability to the variability and stochastic nature of financial data.

C. Metric

For evaluating the forecasting accuracy of our models, we use three standard metrics: Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). The formulas for these metrics are presented in Table III, where y_i represents the actual value, \hat{y}_i is the predicted value, and n is the total number of predictions.

TABLE III
DEFINITIONS OF THE EVALUATION METRICS

Metric	Formula
RMSE	$\sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$
MAPE	$\frac{100}{n} \sum_{i=1}^n \left \frac{y_i - \hat{y}_i}{y_i} \right $
MAE	$\frac{1}{n} \sum_{i=1}^n y_i - \hat{y}_i $

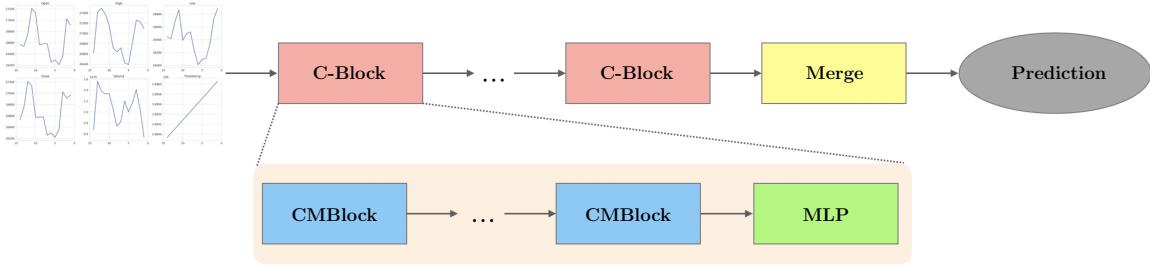


Fig. 1. CryptoMamba model consists of several C-Blocks followed by a Merge block. In each C-Block, we have several CMBlock and an MLP at the end.

RMSE penalizes larger errors more heavily due to the squaring of deviations, making it particularly useful in scenarios where large forecasting errors are costly. MAPE expresses error as a percentage, offering scale-independence and making it particularly valuable when comparing across different ranges, as Bitcoin prices can vary widely over time due to high volatility, and different time intervals may exhibit vastly different price ranges. However, it can inflate errors when actual values are small. MAE measures the average absolute error, treating all deviations equally, providing a robust and balanced measure of accuracy without overemphasizing outliers.

Lower values across all three metrics indicate better performance, with RMSE and MAE measuring absolute error and MAPE capturing relative error. Together, these metrics provide a well-rounded evaluation of forecasting accuracy from multiple perspectives.

V. EXPERIMENTS

To evaluate the effectiveness of CryptoMamba in Bitcoin price prediction, we conduct comprehensive experiments comparing its performance with several baseline models: LSTM, Bi-LSTM, GRU, and S-Mamba. The evaluation focuses on two aspects: prediction accuracy, measured using RMSE, MAPE, and MAE, and model efficiency, quantified by the number of parameters. Additionally, we assess the impact of incorporating trading volume as a feature by conducting experiments under two setups: with and without volume. This section presents the experimental setup, results, and analysis, providing insights into the advantages of CryptoMamba over traditional and state-of-the-art baselines.

A. Setup

To evaluate the performance of CryptoMamba, we compare it with four widely used baseline models: LSTM, Bi-LSTM, GRU, and S-Mamba. These models represent a diverse set of approaches for time-series forecasting, ranging from traditional recurrent architectures to advanced state space models.

- **LSTM (Long Short-Term Memory) [23], [22]:** Configured with 3 layers and a hidden size of 100. LSTM is a popular recurrent neural network architecture and is chosen for its ability at capturing long-term dependencies in sequential data. It is widely used in financial forecasting tasks.

- **Bi-LSTM (Bidirectional LSTM) [23]:** Configured with 3 layers and a hidden size of 100. The bidirectional setup allows the model to learn both forward and backward temporal dependencies, potentially capturing richer patterns and contextual dependencies in the data.
- **GRU (Gated Recurrent Unit) [23]:** Uses 3 layers and a hidden size of 100. The GRU model is a variant of LSTM that achieves comparable performance with fewer parameters. It is included as a lightweight alternative for evaluating the trade-off between accuracy and model complexity.
- **S-Mamba [26]:** Configured with `d_model` 128, `d_state` 32, `d_ff` 128, 0.1 dropout, and `e_layers` 2. S-Mamba has not been previously applied to Bitcoin price prediction or other cryptocurrency datasets. We include S-Mamba to assess CryptoMamba's performance against a state-of-the-art model with similar underlying principles.
- **CryptoMamba:** Configured with 3 C-Blocks, each containing 4 CMBlocks. The sequence lengths for the C-Blocks are 14, 16, and 32, respectively, with a state dimension (`d_state`) of 64 for the Mamba blocks.

In the experiments, each model receives data from the previous 14 days as input to predict the *close* value for the following day. To ensure consistency across models, we use the Adam optimizer [28] with RMSE loss as the loss function. All models are trained with a batch size of 32. Additionally, we employ a learning rate scheduler and weight decay to mitigate overfitting and tune these hyperparameters for each model. Early stopping is applied, and the model checkpoint with the best validation loss is selected to avoid overfitting.

All models use the same train-validation-test split to enable fair comparisons. To avoid data contamination, our predictions in each data split period start from 14 days after the start of that period. This means that, for example, for validation samples, our prediction starts with a 14-day delay to avoid using training samples in the input. This gap ensures that each set remains completely isolated, preventing any overlap and enabling a more accurate assessment of each model's performance on unseen data. Additionally, we conduct experiments under two different setups: with and without trading volume as a feature. This allows us to analyze the impact of volume on prediction accuracy and assess the robustness of the models.

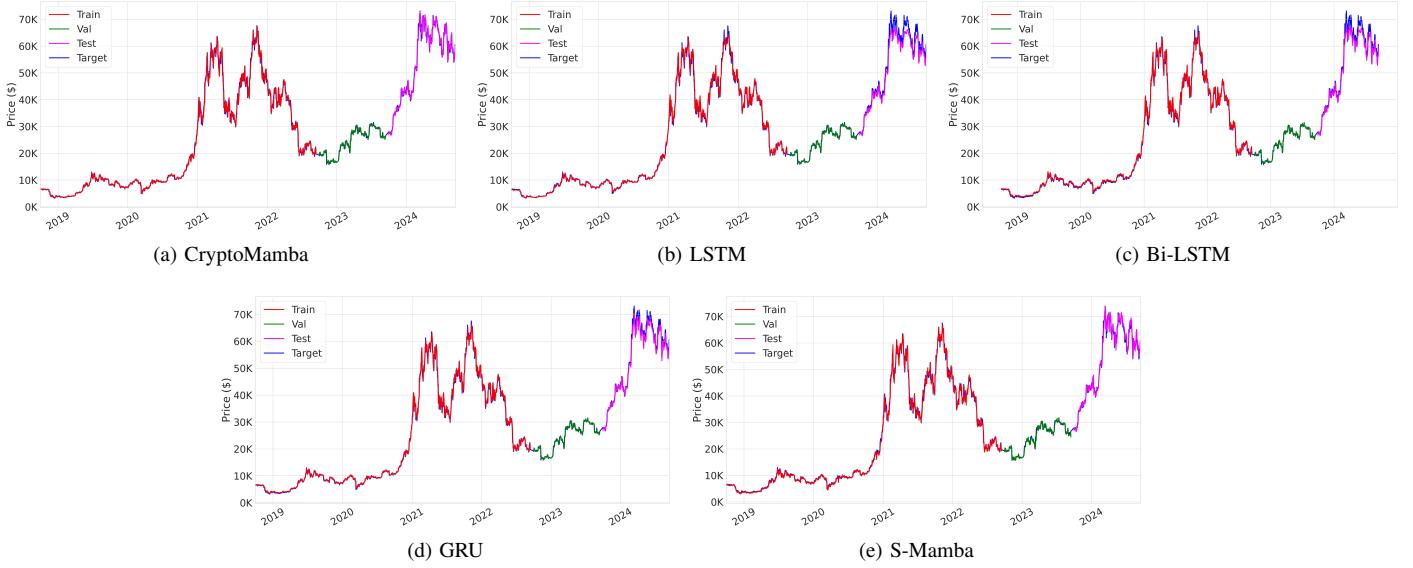


Fig. 2. Forecasting results for all models (a) CryptoMamba, (b) LSTM, (c) Bi-LSTM, (d) GRU, and (e) S-Mamba on the training, validation, and test sets without using volume data. Non-Mamba models struggle to capture large price fluctuations, often underperforming during periods of high volatility.

under varying input configurations.

For all baselines, we use hyperparameters that align with their respective best practices, ensuring a fair comparison. Additionally, to maintain reproducibility, we set a fixed random seed for all experiments.

B. Evaluation

The results of our experiments, conducted with and without trading volume on the test data, are summarized in Table IV. These results show that CryptoMamba consistently outperforms all baseline models, including LSTM, Bi-LSTM, GRU, and S-Mamba, across all evaluation metrics. This demonstrates CryptoMamba’s superior ability to capture the complex dynamics of Bitcoin price movements with high generalization. Notably, CryptoMamba-v, the volume-inclusive variant, achieves the best performance with an RMSE of 1598.1, a MAPE of 0.02034, and an MAE of 1120.7. Even without volume, CryptoMamba surpasses the volume-inclusive versions of all baseline models, highlighting its robustness.

Among the baselines, S-Mamba performs competitively, particularly in the volume-inclusive setup, with an RMSE of 1651.6. This highlights the strength of advanced state space models in capturing long-range dependencies. However, CryptoMamba’s tailored architecture further improves upon these results, demonstrating the benefits of its design for financial time-series forecasting. Similarly, Bi-LSTM and LSTM show significant improvements when volume data is included, whereas GRU sees minimal gains, indicating that the impact of volume depends on the model architecture.

Overall, the results confirm CryptoMamba’s effectiveness in both setups, with the inclusion of volume data consistently enhancing prediction accuracy across most models. This highlights the importance of trading volume as a feature

in capturing market dynamics, particularly in highly volatile settings like Bitcoin price forecasting.

TABLE IV
RESULTS ON TEST DATA, -v SHOWS INCLUDING VOLUME IN THE DATA

Method	RMSE	MAPE	MAE
LSTM [23], [22]	2672.7	3.609	2094.3
Bi-LSTM [23]	2325.6	3.072	1778.8
GRU [23]	1892.4	2.385	1371.2
S-Mamba [26]	1717.4	2.248	1239.9
CryptoMamba	1713.0	2.171	1200.9
LSTM-v	2202.1	2.896	1668.9
Bi-LSTM-v	2080.2	2.738	1562.5
GRU-v	1978.0	2.526	1454.3
S-Mamba-v	1651.6	2.215	1209.7
CryptoMamba-v	1598.1	2.034	1120.7

Figures 2 and 3 illustrate the forecasting results of all models on the training, validation, and test sets, without and with volume data, respectively. While all models perform well on the training set, the non-Mamba baselines, struggle to maintain accuracy on the test set during volatile periods, showing significant divergence from actual values. S-Mamba performs better than the recurrent models but still falls short in capturing large price fluctuations. In contrast, CryptoMamba consistently tracks actual price trends, demonstrating superior generalization and robustness across both setups. The inclusion of volume data further improves the performance of most models, with CryptoMamba leveraging this additional information to achieve the most accurate predictions, particularly during



Fig. 3. Forecasting results for all models (a) CryptoMamba, (b) LSTM, (c) Bi-LSTM, (d) GRU, and (e) S-Mamba on the training, validation, and test sets with volume data included as an additional feature. While volume data helps non-Mamba models slightly, they still face challenges in accurately predicting large price changes, especially during volatile periods.

periods of high volatility.

C. Efficiency

Table V compares the number of parameters across all models, highlighting the efficiency of CryptoMamba in terms of model complexity. With only 136k parameters, CryptoMamba has the lowest parameter count among all models, significantly outperforming the much larger Bi-LSTM (569k parameters) and S-Mamba (330k parameters). Notably, LSTM and GRU, with 204k and 153k parameters, respectively, also have higher complexity than CryptoMamba. This compact architecture demonstrates CryptoMamba’s ability to effectively capture the essential patterns in the data without relying on a large number of parameters.

TABLE V
NUMBER OF PARAMETERS

Method	Parameters
LSTM [23], [22]	204k
Bi-LSTM [23]	569k
GRU [23]	153k
S-Mamba [26]	330k
CryptoMamba	136k

Despite its smaller parameter size, CryptoMamba achieves state-of-the-art performance as shown in Table IV, indicating an optimal balance between efficiency and accuracy. The reduced parameter count not only lowers computational requirements, making CryptoMamba more suitable for deployment in resource-constrained environments, but also minimizes the

risk of overfitting, ensuring better generalization on unseen data. Compared to S-Mamba, which has a moderately high parameter count of 330k, CryptoMamba achieves superior accuracy with less than half the complexity, further validating the benefits of its architecture for financial time-series forecasting.

VI. APPLICATION IN REAL-WORLD TRADING

In this section, we evaluate the practical utility of CryptoMamba by applying its predictions in a real-world trading scenario. Using two trading algorithms, we simulate trading with an initial balance of 100 dollars at the beginning of the validation and test period. The goal is to compute the net worth at the end of each period and compare the profits of different models.

To evaluate model predictions, we use two trading algorithms: Vanilla and Smart. Algorithm 1 describes the **Vanilla Trading Algorithm**, which makes simple buy or sell decisions based on the predicted and actual prices. At its core, the algorithm computes the ratio of the absolute difference between the predicted price and today’s price to today’s price. This ratio, referred to as the change ratio d , determines whether any trading action is required. If the change ratio is below a predefined threshold (0.01 in our case), the algorithm refrains from making any trades. This safeguard is introduced to account for transaction fees, which can render small trades unprofitable, especially when the predicted price change is minor. However, if the change ratio meets or exceeds the threshold, the algorithm takes decisive action.

Algorithm 2, the **Smart Trading Algorithm**, introduces a risk-aware approach by considering an interval around the predicted price, determined by a risk percentage (set to 2% based on the validation MAPE of the models). This interval, defined by an upper bound (y_{\max}) and a lower bound (y_{\min}),

Algorithm 1 Vanilla Trading Algorithm

Require: Prediction, Today's Price, threshold

- 1: $x \leftarrow$ Today's price
- 2: $y \leftarrow$ Prediction
- 3: $d \leftarrow \left| \frac{x-y}{x} \right|$
- 4: **if** $d \geq$ threshold **then**
- 5: **if** $x > y$ **then**
- 6: Sell all of your shares
- 7: **else**
- 8: Buy with all of your money
- 9: **end if**
- 10: **else**
- 11: Do not buy or sell
- 12: **end if**

accounts for prediction uncertainty and provides a range within which tomorrow's price is likely to fall:

$$y_{\max} = \left(1 + \frac{\text{risk}}{100}\right)y, \quad y_{\min} = \left(1 - \frac{\text{risk}}{100}\right)y,$$

where y is the predicted price.

The algorithm makes decisions based on the position of today's price (x) relative to this interval:

- If $x > y_{\max}$: Sell all shares, as tomorrow's price is expected to drop significantly.
- If $y < x \leq y_{\max}$: Sell a fraction of shares, proportional to the difference between x and y .
- If $x < y_{\min}$: Buy with all available money, as tomorrow's price is expected to rise significantly.
- If $y_{\min} \leq x < y$: Buy a fraction of available funds, proportional to the difference between y and x .

By dynamically adjusting trading actions based on this interval, the Smart Trading Algorithm balances risk and returns, offering a more adaptive and realistic trading strategy compared to the threshold-based Vanilla algorithm.

Algorithm 2 Smart Trading Algorithm

Require: Prediction, Today's Price, risk

- 1: $x \leftarrow$ Today's price
- 2: $y \leftarrow$ Prediction
- 3: $y_{\max} \leftarrow \left(1 + \frac{\text{risk}}{100}\right)y$
- 4: $y_{\min} \leftarrow \left(1 - \frac{\text{risk}}{100}\right)y$
- 5: **if** $x \geq y$ **then**
- 6: **if** $x \geq y_{\max}$ **then**
- 7: Sell all of your shares
- 8: **else**
- 9: Sell $\frac{x-y}{y_{\max}-y}$ of your shares
- 10: **end if**
- 11: **else**
- 12: **if** $x \leq y_{\min}$ **then**
- 13: Buy with all of your money
- 14: **else**
- 15: Buy with $\frac{y-x}{y-y_{\min}}$ of your money
- 16: **end if**
- 17: **end if**

TABLE VI
THE FINAL BALANCE AFTER ONE YEAR OF TRADING WITH \$100 IN THE VALIDATION AND TEST PERIOD. FINAL BALANCES THAT ARE LOWER THAN THE INITIAL INVESTMENT ARE IN *Italic* FONT.

Model	Final Balance (\$)			
	Validation		Test	
	Vanilla	Smart	Vanilla	Smart
LSTM	133.10	128.93	111.23	103.66
LSTM-v	136.93	149.95	102.09	102.06
Bi-LSTM	134.78	141.36	100.00	100.00
Bi-LSTM-v	156.98	134.41	122.40	109.96
GRU	115.12	109.06	118.46	112.64
GRU-v	153.57	125.04	104.82	106.96
S-Mamba	<i>75.94</i>	86.77	146.08	173.00
S-Mamba-v	77.25	<i>91.05</i>	182.63	203.17
CryptoMamba	113.24	106.8	175.05	184.56
CryptoMamba-v	124.09	127.12	246.58	213.20

The trading results during the test period are presented in Figures 4 and 5 for the Vanilla and Smart Trading Algorithms, respectively, with the validation and test period final net worth summarized in Table VI. In the test period, CryptoMamba consistently achieves the highest returns in both Vanilla and Smart trading setups, with CryptoMamba-v ending with \$246.58 in the Vanilla setup and \$213.20 in the Smart setup, outperforming all baselines. In the validation period, CryptoMamba-v again demonstrates strong performance, achieving \$124.09 and \$127.12 in Vanilla and Smart setups, respectively. These results underscore CryptoMamba's ability to generalize effectively across different market conditions and adapt to varying levels of volatility.

The difference between the validation and test periods lies in the price movement dynamics: the validation period features slight, steady changes, whereas the test period exhibits large price fluctuations and volatility. Traditional baselines, such as Bi-LSTM, perform well during the validation period. However, they consistently underperform, particularly in the test period with higher volatility. This can be attributed to their lack of generalization and tendency to predict lower prices in the test period (Figures 2 and 3). In contrast, S-Mamba demonstrates strong performance in the test period, particularly under the Smart setup with \$203.17, underscoring its generalization ability and strength in capturing long-range dependencies. However, it struggles in the validation period, with final balances lower than the initial investment, suggesting it is less effective in stable market conditions.

CryptoMamba exhibits superior generalization across both scenarios. Unlike the baselines, CryptoMamba performs consistently well in both steady and volatile intervals, translating accurate predictions into tangible financial gains. Its robust design allows it to adapt dynamically to market trends, achieving consistent profitability in all setups and outperforming state-

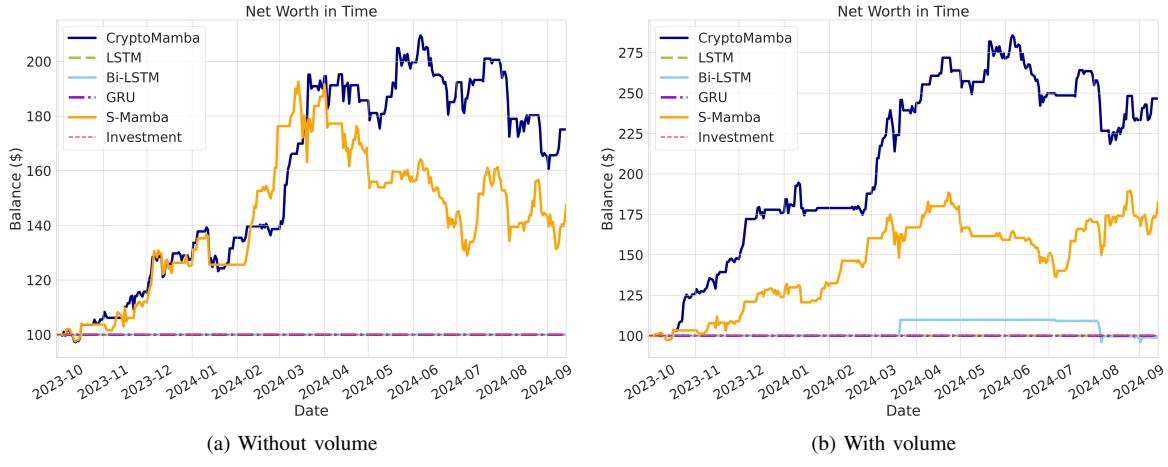


Fig. 4. Net worth during trading in the test period with the vanilla trading algorithm

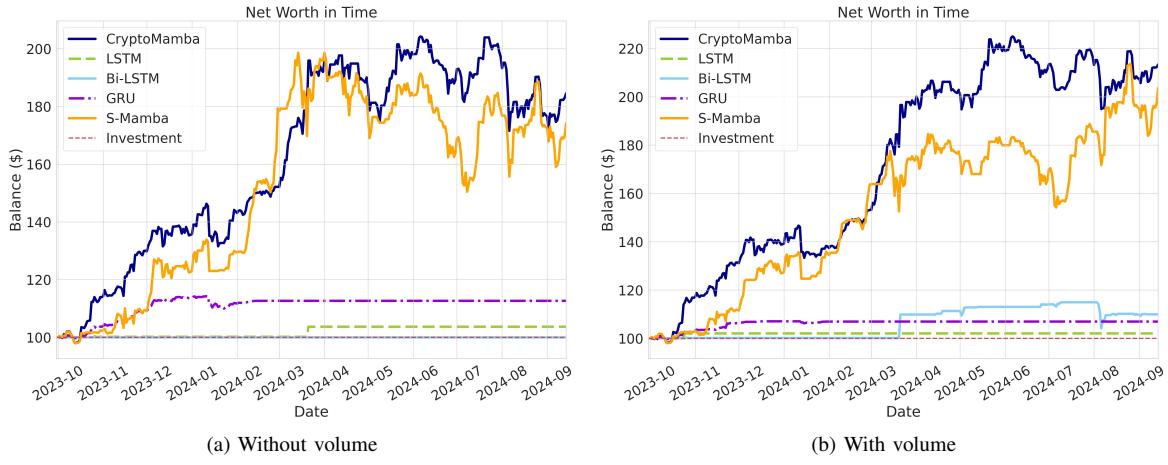


Fig. 5. Net worth during trading in the test period with the smart trading algorithm

of-the-art baselines in both the validation and test periods.

These results emphasize the practical utility of CryptoMamba for real-world financial applications. By combining accurate predictions with trading strategies, CryptoMamba demonstrates its ability to excel under diverse market conditions, making it a reliable solution for adaptive financial forecasting.

VII. CONCLUSION AND FUTURE WORK

In this work, we introduced CryptoMamba, a novel Mamba-based architecture tailored for financial time-series forecasting, and demonstrated its effectiveness in predicting Bitcoin prices. Leveraging state space models (SSMs) with Mamba enhancements, CryptoMamba efficiently captures long-range dependencies and outperforms traditional models such as LSTM, Bi-LSTM, GRU, and S-Mamba in both predictive accuracy and financial performance. Our results show that CryptoMamba, especially in its volume-inclusive variant, achieves the highest returns in real-world trading scenarios, highlighting the importance of incorporating volume data for enhanced market insights.

The trading simulations using Vanilla and Smart algorithms emphasize the practical utility of CryptoMamba in real-world trading. By employing trading algorithms as evaluation tools, we were able to effectively compare prediction models in terms of their financial impact, moving beyond regression metrics alone. CryptoMamba design not only proves its capability in modeling cryptocurrency markets but also showcases its potential for forecasting other time series data, such as stocks or commodities, where long-range dependencies are critical.

Future work could explore extending CryptoMamba to other financial assets and testing its adaptability to multi-asset portfolios. Additionally, refining trading algorithms to better leverage prediction intervals and incorporating external factors, such as sentiment analysis or macroeconomic indicators, may further improve performance. While CryptoMamba demonstrates strong generalization and profitability, further research into integrating risk management strategies within the architecture itself could provide even greater robustness in highly volatile markets.

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