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Comparative Study of Statistical and Machine Learning Models for Cryptocurrency Return Prediction

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ABSTRACT

This study compares the performance of traditional statistical models and modern machine learning methods in predicting Bitcoin (BTC) returns. Using data from January 2022 to December 2024, both daily and weekly datasets were constructed with a comprehensive set of features, including technical indicators, on-chain metrics, macroeconomic variables, and behavioral signals. Linear regression models, ensemble learning methods (Random Forest, XGBoost), deep learning (LSTM), and GARCH-based time-series models were evaluated for both numeric return prediction and directional classification. Results show that while all models struggle to forecast exact return values, classification models achieve better performance, particularly when using weekly data. Among all tested models, the XGBoost classifier achieved the highest directional accuracy of 67.8% on weekly data, outperforming both statistical and deep learning baselines. These findings highlight the value of frequency selection and nonlinear modeling in improving cryptocurrency return predictability.

KEYWORDS

Bitcoin; Return Prediction; Machine Learning; GARCH; Time Series; XGBoost; Cryptocurrency Forecasting

1. INTRODUCTION

Bitcoin (BTC) is the first decentralized digital currency that was officially launched in 2009 by Satoshi Nakamoto. Its key features include: decentralization, limited supply, immutabil-ity, transparency, and pseudonymity. In the last decade, BTC has attracted intense attention from investors, institutions and the media. at present its market capitalization is the highest. The price of Bitcoin has soared from about $10 in 2011 to $95,000 now, which fluctuates sharply. This growth comes with extreme volatility, posing both risks and opportunities for investors.

In recent years, a lot of studies focus on BTC price prediction. Roy, Nanjiba, and Chakrabarty (2018) [1] used time-series models (autoregressive integrated moving-average model, autoregressive model, and moving-average model) to forecast the bitcoin price. This study found that ARIMA model performed best. Greaves and Au (2015) [2] used various machine learning models (SVM, ANN linear regression, and logistic regression) to predict the price of bitcoin. An NN classifier with two hidden layers marked the highest price accuracy of 55%, followed by logistic regression and SVM. Phaladisailoed and Numnonda (2018) [3] compared the performance of traditional regression models (Theil–Sen regression, Huber regression) and deep learning models (LSTM, and GRU) in Bitcoin price prediction by using minute frequency data.

At present, there are relatively few studies comparing the performance of different fre-quency data. Chen et al. (2020) [4] emphasized that the importance of matching model com- plexity with data characteristics. They showed that for daily date with high-dimensional features, using traditional and simple statistical models is more effective, while for 5-minute data with low-dimensional features, machine learning methods perform better. Recent work also shows that ensemble methods such as XGBoost can outperform traditional econometric models in cryptocurrency return prediction, particularly on lower-frequency data (Li et al., 2024) [5].

Some studies directly predicted the exact numeric price of Bitcoin, and the model had as high as 98% R-square. So the authors thought the prediction results were good, but this was actually not reasonable. Acutally, when used a simple model, such as $\hat{y}_t = y_{t-1}$ can already obtain a very high R^2 value. It is more reasonable to predict the return of bitcoin. Additionally, there is a lack of comparison between the prediction results of daily frequency data and weekly frequency data. Hence, this study posed three key research questions:

Is it more effective to predict the precise return value or to focus on the directional movement?

Can the use of weekly data, improve the predictive performance compared to dail) data in BTC return forecasting?

Among a wide range of forecasting approaches—including traditional statistical models and modern machine learning techniques—which methods perform best?

2. DATA DESCRIPTION

2.1. Data Source

We collect data from Yahoo Finance, Coinmarketcap.com, Blockchain.com, Federal Reserve,

U.S. Treasury and Google Trends. The selected sample period for trading data spans from January 1, 2022, to December 31, 2024. The choice of starting on January 1, 2022 is because by then the direct impact of the COVID-19 pandemic had weakened and the prediction model was more stable.

2.2. Return Construction and Target Variable

To evaluate and compare the performance of Bitcoin price fluctuations across different time scales, both daily and weekly returns are constructed as target variables. Additionally, a binary directional indicator is derived to facilitate classification-based prediction tasks.

Daily Returns:

The daily return is computed as the percentage change in closing prices from one day to the next, and is formally defined as:

$$R_t^{daily} = \frac{P_t - P_{t-1}}{P_{t-1}} \quad (1)$$

Where P_t denotes the closing price of Bitcoin at time t. Figure 1 illustrates the daily return series from 2022 to 2024.

Weekly Returns:

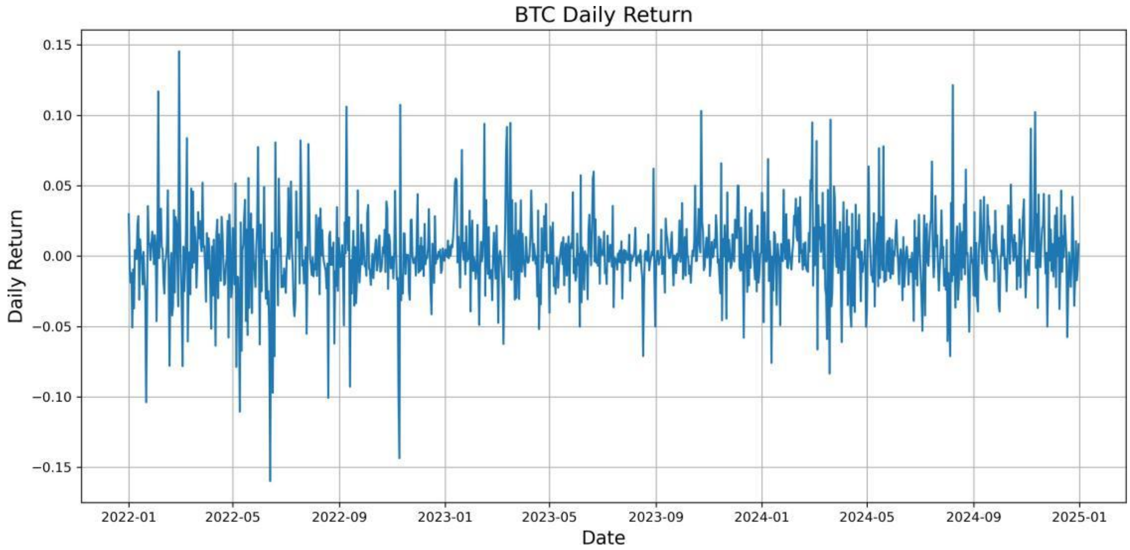


Figure 1. BTC Daily Return

We also construct a weekly return based on Monday closing prices. The weekly return is defined as:

$$R_t^{weekly} = \frac{P_t^{Mon} - P_{t-7}^{Mon}}{P_{t-7}^{MOn}} \tag{2}$$

Where P_t^{Mon} denotes the closing price on a given Monday. Figure 2 visualizes the resulting weekly return series.

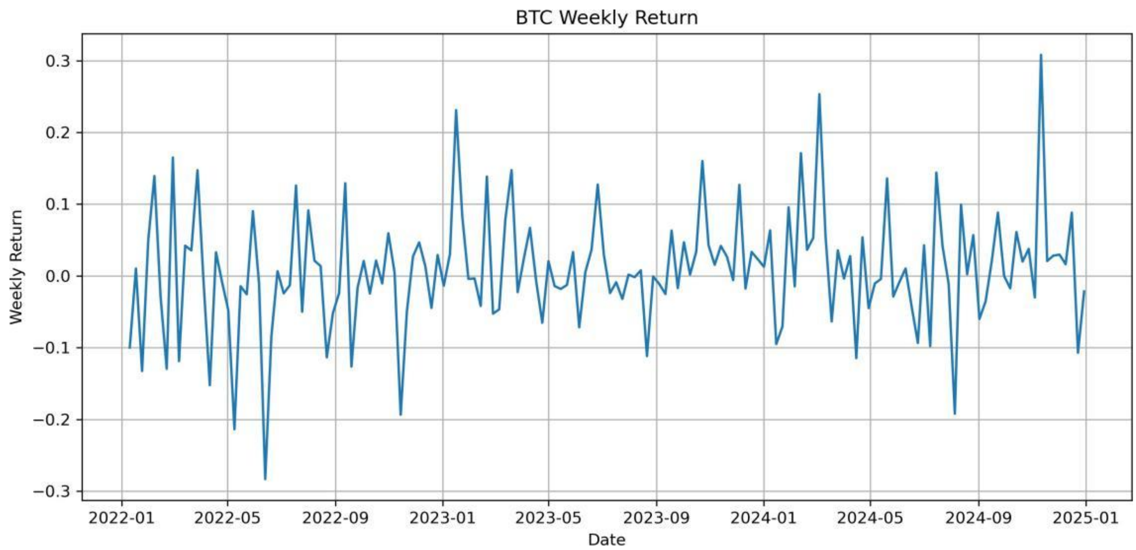


Figure 2. BTC Weekly Return

Directional Target:

For classification-based prediction tasks, we construct a binary target variable based on the sign of returns. The directional indicator is defined as:

$$Y_t = \begin{matrix} 1 & if\ R_t > 0 \\ 0 & otherwise \end{matrix} \tag{3}$$

This target allows the model to learn and predict whether the return is positive (indicating a price increase) or non-positive (indicating a decrease or no change), which is particularly relevant for directional trading strategies.

2.3. Predictive Features

The features used in this study are drawn from the following five categories:

Technical Indicators: Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Simple Moving Averages (SMA), etc.

Market-Based Indicators: S&P 500 daily and weekly returns, volatility indices (e.g., VIX), etc.

On-Chain Metrics: Active addresses, address ratios, network hash rates, etc.

Sentiment/Behavioral Factors: Crypto Fear & Greed Index, Google search volume, etc.

Macroeconomic Factors: Inflation data, 10-year U.S. Treasury yield, etc.

Table 1. List of Variables with Sources and Descriptions (1)

Variable	Source	Description
Date	Investing.com	The trading date
Price	Investing.com	The closing price of Bitcoin for the day
Open	Investing.com	The opening price of Bitcoin for the day
High	Investing.com	The highest trading price of Bitcoin for the day
Low	Investing.com	The lowest trading price of Bitcoin for the day
Vol.	Investing.com	The total trading volume of Bitcoin for the day
Change %	Investing.com	The percentage change in Bitcoin's price for the day
Daily return	Calculated	$\frac{P_t - P_{t-1}}{P_{t-1}}$, the Daily percentage return
Weekly return	Calculated	$\frac{P_t^{Mon} - P_{t-7}^{Mon}}{P_{t-7}^{Mon}}$, the weekly return based on Monday prices
COIN	Yahoo Finance	The daily closing stock price of Coinbase
HUT	Yahoo Finance	The daily closing stock price of Hut 8 Mining
MARA	Yahoo Finance	The daily closing stock price of Marathon Digi-tal Holdings
MSTR	Yahoo Finance	The daily closing stock price of MicroStrategy
RIOT	Yahoo Finance	The daily closing stock price of Riot Platforms
SQ	Yahoo Finance	The daily closing stock price of Block Inc.
TSLA	Yahoo Finance	The daily closing stock price of Tesla
Bitcoin CME Futures	Yahoo Finance	The daily closing price of Bitcoin futures
S&P 500	Yahoo Finance	The daily closing value of the S&P 500 Index
NASDAQ 100	Yahoo Finance	The daily closing value of the NASDAQ 100 In-dex
US Dollar Index	Yahoo Finance	The daily closing value of the U.S. Dollar Index
Transaction Count	Blockchain.com	The total number of transactions on the Bitcoin blockchain
Transaction Volume	Blockchain.com	The total transaction volume on the Bitcoin net-work
Block Size	Blockchain.com	The average size of mined blocks
Mining Difficulty	Blockchain.com	The adjusted mining difficulty
Hash Rate	Blockchain.com	The total computing power of the Bitcoin net-work
Mempool Transactions	Blockchain.com	The number of unconfirmed transactions
SMA 20	Calculated	The simple moving average over 20 days
RSI	Calculated	Relative Strength Index over 14 days
MACD	Calculated	The MACD indicator
MACDh	Calculated	The MACD histogram value
MACDs	Calculated	The MACD signal line
BBL	Calculated	Lower Bollinger Band
BBM	Calculated	Middle Bollinger Band (20-day SMA)
BBU	Calculated	Upper Bollinger Band
BBB	Calculated	Bollinger Band width
BBP	Calculated	Bollinger Band position
Monthly Inflation Rate	Federal Reserve	The monthly inflation rate
Unemployment Rate	Federal Reserve	The recorded unemployment rate
1 Mo	U.S. Treasury	Yield on a 1-month U.S. Treasury security
2 Mo	U.S. Treasury	Yield on a 2-month U.S. Treasury security
3 Mo	U.S. Treasury	Yield on a 3-month U.S. Treasury security

Table 1. List of Variables with Sources and Descriptions (2)

Variable	Source	Description
6 Mo	U.S. Treasury	Yield on a 6-month U.S. Treasury security
1 Yr	U.S. Treasury	Yield on a 1-year U.S. Treasury security
2 Yr	U.S. Treasury	Yield on a 2-year U.S. Treasury security
3 Yr	U.S. Treasury	Yield on a 3-year U.S. Treasury security
5 Yr	U.S. Treasury	Yield on a 5-year U.S. Treasury security
7 Yr	U.S. Treasury	Yield on a 7-year U.S. Treasury security
10 Yr	U.S. Treasury	Yield on a 10-year U.S. Treasury security
20 Yr	U.S. Treasury	Yield on a 20-year U.S. Treasury security
30 Yr	U.S. Treasury	Yield on a 30-year U.S. Treasury security
FEDFUNDS	Federal Reserve	Federal funds rate
M2SL	Federal Reserve	Seasonally adjusted M2 money stock
Bitcoin Views	Google Trends	Search interest index for Bitcoin
Wiki Views	Wikimedia API	Daily page views of the Bitcoin Wikipedia arti-cle
NA	Coinmarketcap.com	Daily number of newly created Bitcoin addresses observed on the network
AA	Coinmarketcap.com	Daily number of active Bitcoin addresses that either send or receive transactions
ZBA	Coinmarketcap.com	Total number of Bitcoin addresses with zero bal-ance at the end of the day
AAR	Coinmarketcap.com	Ratio of active addresses to total addresses, in-dicating user engagement and network activity
NT	Coinmarketcap.com	Total number of confirmed Bitcoin transactions on the blockchain for the given day
TV	Coinmarketcap.com	Total transaction volume (in USD) processed by the network
LHN	Coinmarketcap.com	Net difference between inflow and outflow of Bit-coin held by large holders (whales)
LHI	Coinmarketcap.com	Total amount of Bitcoin flowing into wallets identified as large holders
LHO	Coinmarketcap.com	Total amount of Bitcoin transferred out from wallets identified as large holders
NF	Coinmarketcap.com	Net Bitcoin flow across aggregated cryptocur-rency exchanges (inflow minus outflow)
TF	Coinmarketcap.com	Total volume of Bitcoin transferred in and out of aggregated cryptocurrency exchanges
MRR chg	Coinmarketcap.com	Change in the market-value-to-realized-value ra-tio

Note: Due to differences in data availability and update frequency across various factor categories, the set of predictors used in the weekly return model and the daily return model may differ slightly.

3. METHODOLOGY

3.1. Numeric Model

To evaluate the numerical prediction of Bitcoin returns, we implemented a wide range of models, spanning from traditional linear regression techniques to advanced ensemble and deep learning methods. The following models were compared:

Linear Models:

Ordinary Least Squares (OLS)

LASSO Regression

Ridge Regression

Elastic Net Regression

Machine Learning Models:

Random Forest Regressor

Support Vector Regression (SVR)

eXtreme Gradient Boosting (XGBoost)

Long Short-Term Memory Network (LSTM)

GARCH:

GARCH (1, 1)

AR (2) + GARCH (1, 1)

ARMA (1, 2) + GARCH (1, 1)

3.2. Classification Models

The task of predicting the directional movement of Bitcoin returns was formulated as a binary classification problem. The following models were implemented:

Statistical Model:

Logistic Regression

Machine Learning Models:

Support Vector Machine (SVM)

Random Forest Classifier

eXtreme Gradient Boosting (XGBoost)

Long Short-Term Memory Network (LSTM)

GARCH-Based Classification:

GARCH (1, 1) with sign-based directional signal

AR (2) + GARCH (1, 1)

ARMA (1, 2) + GARCH (1, 1)

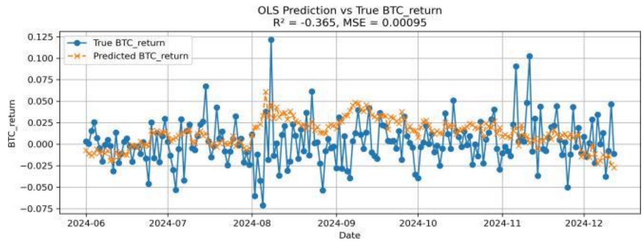
4. RESULTS AND ANALYSIS

4.1. Numerical Prediction Performance

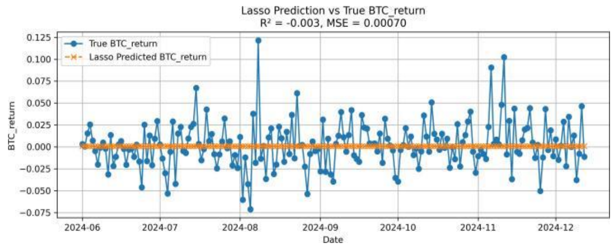
4.1.1. Linear and Machine Learning Method

To evaluate the models' ability to forecast the exact return values of Bitcoin, we trained a series of linear and machine learning models on both daily and weekly datasets. Figures 3 and 4 compare the predicted returns with the truth value.

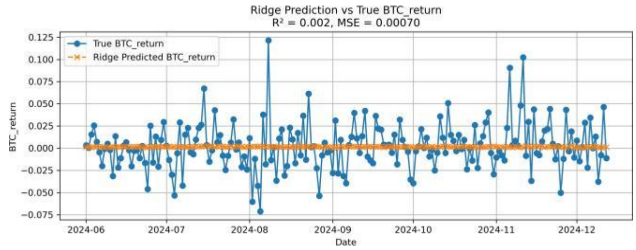
(1) Daily Frequency:



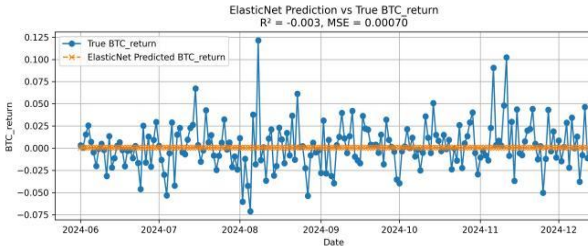
(a) OLS (Daily)



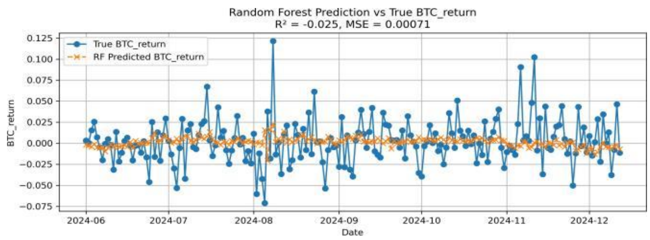
(b) Lasso (Daily)



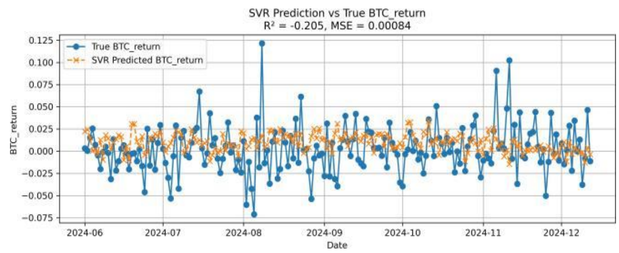
(c) Ridge (Daily)



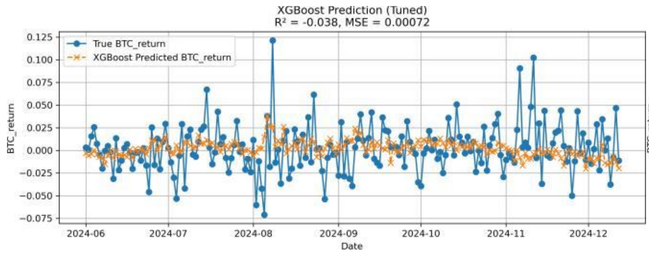
(d) ElasticNet (Daily)



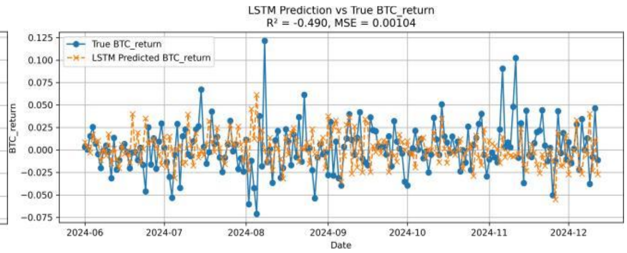
(e) Random Forest (Daily)



(f) SVR (Daily)



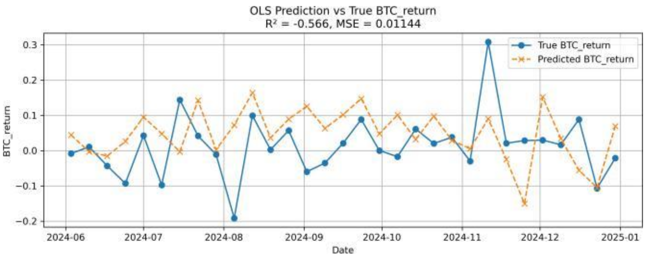
(g) XGBoost (Daily)



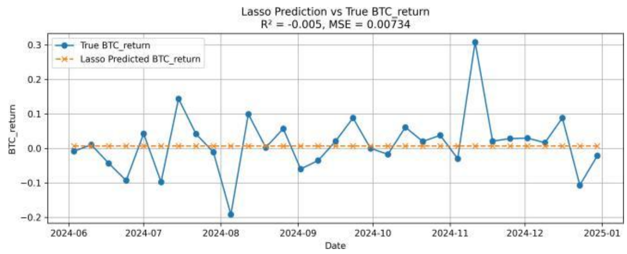
(h) LSTM (Daily)

Figure 3. True vs. Predicted Bitcoin returns using machine learning models on daily data

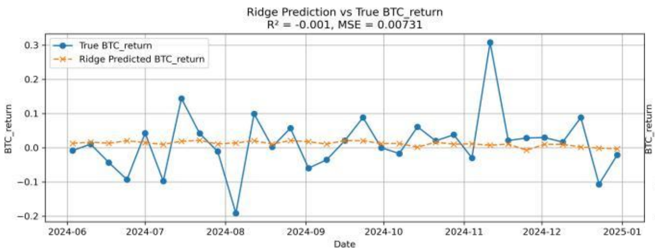
(2) Weekly Frequency:



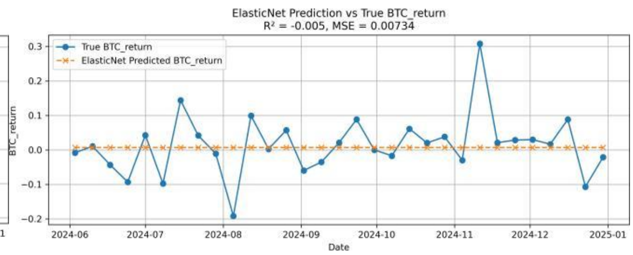
(a) OLS (Weekly)



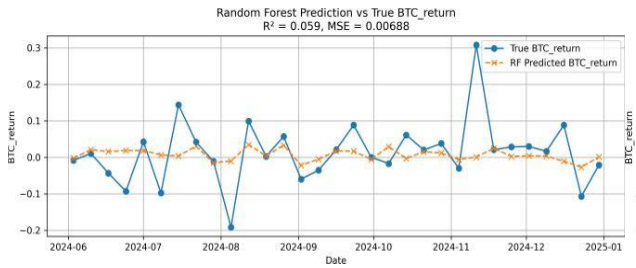
(b) Lasso (Weekly)



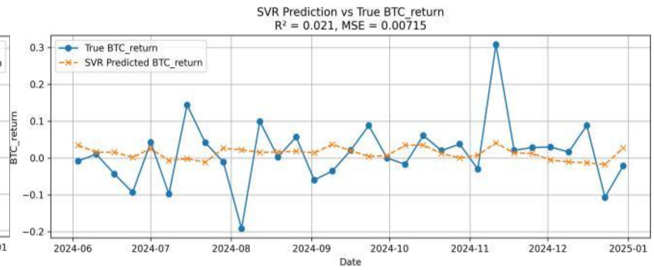
(c) Ridge (Weekly)



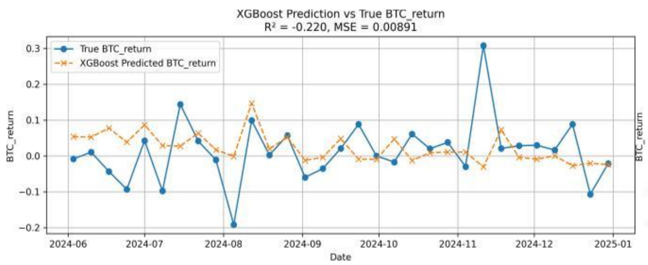
(d) ElasticNet (Weekly)



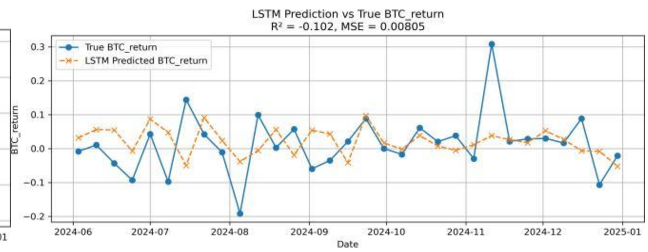
(e) Random Forest (Weekly)



(f) SVR (Weekly)



(g) XGBoost (Weekly)



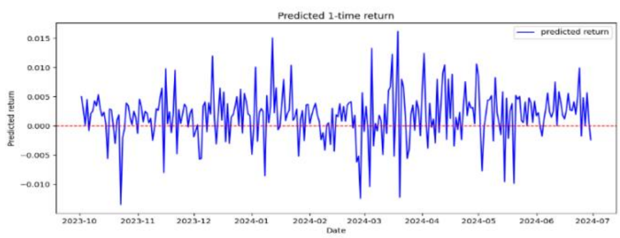
(h) LSTM (Weekly)

Figure 4. True vs. Predicted Bitcoin returns using machine learning models on weekly data

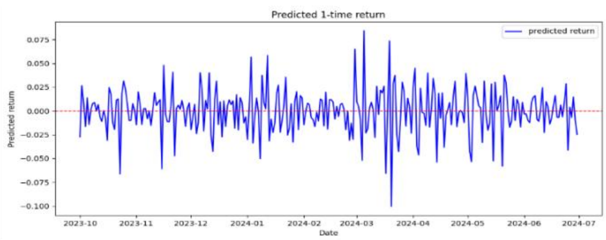
Summary: None of the linear or machine learning models achieve satisfactory perfor- mance in predicting daily Bitcoin returns. Most predictions were flat and failed to capture the fluctuations in true returns, with R^2 values close to or below zero. This showed that the difficulty of point forecasting.

4.1.2. ARCH/GARCH Method

(1) Daily Frequency:



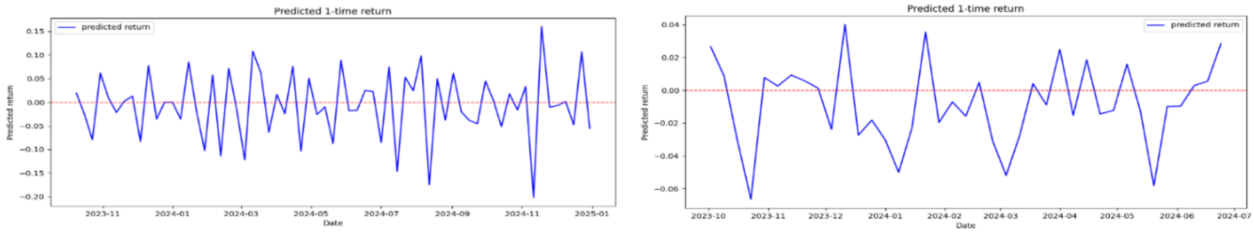
(a) AR (2)-GARCH (1, 1) (Daily)



(b) ARMA-GARCH (1, 1) (Daily)

Figure 5. Predicted 1-step returns using AR-GARCH models on daily data.

(2) Weekly Frequency:



(a) AR(2)-GARCH (1, 1) (Weekly) (b) ARMA-GARCH (1, 1) (Weekly)

Figure 6. Predicted 1-step returns using AR-GARCH models on weekly data.

Summary: GARCH-based models capture volatility clustering better than linear and machine learning. As shown in Figure 5, both AR(2)-GARCH (1, 1) and ARMA-GARCH (1, 1) generate return sequences with fluctuating variance, aligning with known stylized facts of financial time series. However, the predicted returns still exhibit substantial deviation from true values.

And for the subsequent comparison of classification medols, we will convert the numerical prediction results of garch-based models into directional indicators.

4.2. Direction Prediction Performance

4.2.1. Machine Learning Method

(1) Daily Frequency

Table 2. Performance metrics on daily classification task.

Model	Accuracy	$Precision_0$	$Recall_0$	$F1_0$	$Precision_1$	$Recall_1$
Logistic Regression	55.4%	0.57	0.30	0.39	0.55	0.79
SVM	55.9%	0.63	0.20	0.31	0.53	0.89
Random Forest	51.4%	0.49	0.46	0.48	0.53	0.56
XGBoost	51.3%	0.49	0.47	0.48	0.53	0.55
LSTM	52.5%	0.50	0.53	0.51	0.55	0.52

(2) Weekly Frequency

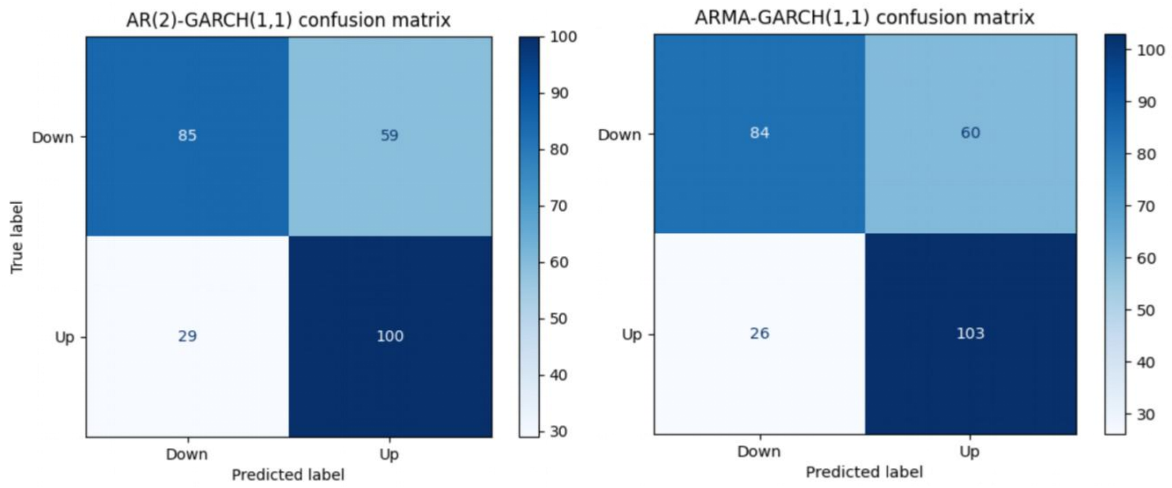
Table 3. Performance metrics on weekly classification task.

Model	Accuracy	$Precision_0$	$Recall_0$	$F1_0$	$Precision_1$	$Recall_1$
Logistic Regression	58.1%	0.50	0.69	0.58	0.69	0.50
SVM	58.0%	0.50	0.69	0.58	0.69	0.50
Random Forest	61.3%	0.52	0.85	0.65	0.80	0.44
XGBoost	67.8%	0.60	0.69	0.64	0.75	0.67
LSTM	58.1%	0.50	0.85	0.63	0.78	0.39

Summary: In daily frequency, the accuracy of all machine learning models are all between 51% - 56%, which are just a little higher than random(50%). This suggests that high-frequency noise significantly impairs the models' ability to make directional predictions. In contrast, the weekly classification results improved a lot, which are between 58% - 68%. And XGBoost outperformed all other models, achieving the highest accuracy (67.8%). These results indicate that using weekly data helps models better capture meaningful trends, leading to more stable and reliable directional forecasts.

4.2.2. ARCH/GARCH Method

(1) Daily Frequency:

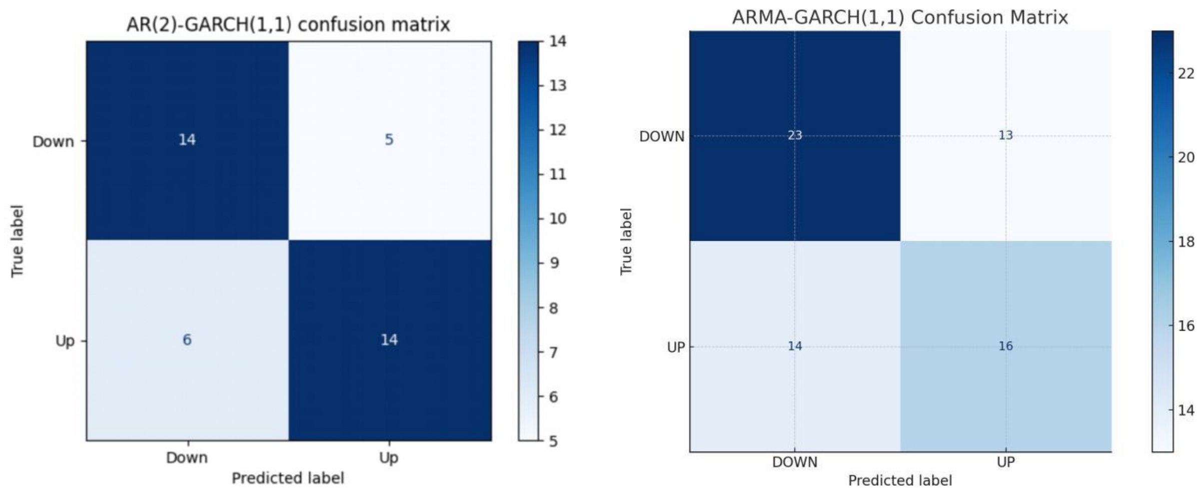


(a) AR(2)-GARCH (1, 1) (Daily) (b) ARMA (1, 1)-GARCH (1, 1) (Daily)

Figure 7. Confusion matrices of GARCH-based models on daily data.

The best model to predict daily directional return is ARMA (1, 2) + GACH (1, 1), with an accuracy of 53. 56%.

(2) Weekly Frequency:



(a) AR (2)-GARCH (1, 1) (Weekly) (b) ARMA (1, 1)-GARCH (1, 1) (Weekly)

Figure 8. Confusion matrices of GARCH-based models on weekly data.

The best model to predict weekly directional return is AR (2) + GARCH (1, 1), with 64.49% accuracy.

Summary: On the daily task, ARMA (1, 1)-GARCH (1, 1) achieved the best performance with an accuracy of 53.56%, showing slightly better balance between up and down clas-sifications. In contrast, performance improved significantly on weekly data. The AR (2)- GARCH (1, 1) model outperformed ARMA-GARCH with an accuracy of 64.49%. These results also indicate that using weekly data helps models better capture meaningful trends, leading to more stable and reliable directional forecasts.

5. CONCLUSION

First, this study used linear regression models(Ordinary Least Squares, LASSO Regression, Ridge Regression, Elastic Net Regression), machine learning methods (Random Forest, Sup- port Vector

Regression, eXtreme Gradient Boosting, Long Short-Term Memory Network) and GARCH-based models to predict the exact numerical bitcoin return values, but we found that while the GARCH-based models performed better than other models, all of them failed to forecast the return values. Then, we used Logistic Regression, machine learning methods (Random Forest, Support Vector Machine, eXtreme Gradient Boosting, Long Short-Term Memory Network) and GARCH-based models to do the classification prediction. We found that for daily data, all the models are all between 51% - 56%, which are just a little higher than random (50%). But for weekly data, most models have better performance, which are between 58% - 68%.

After this study, the answers to the three research questions are as follows:

First, Is it more effective to predict the direction of bitcoin return. It is difficult to predict the exact numerical return values. Among all the linear regression models, machine learning models and GARCH-based models, their R^2 are negative or positive but close to zero. In contrast, the performance of predicting direction of BTC return is better, no matter in daily data or weekly data.

Second, using weekly data can improve the accuracy of prediction compared to daily data. The weekly frequency significantly reduced noise from daily volatility, which resulted in better performance.

Finally, among all the models, GARCH-based models have better performance in cap- turing volatility clustering (predict exact value), but still limited. When forecasting direction of return, XGBoost has the best performance, which achieve 67.8%.

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