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Machine Learning Framework for Predicting Cryptocurrency Return Trends: A Comparative Study

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ABSTRACT

Objective: Cryptocurrency markets are highly volatile, making return forecasting both valuable and difficult. This study develops a machine learning framework for predicting cryptocurrency return trends, formulated as a three-class problem (negative, near-zero, and positive next-day returns) rather than the conventional binary one.

Method: XGBoost, Random Forest, and Support Vector Machine (SVM) were evaluated on Bitcoin, Ethereum, and Solana using daily data from December 2024 to July 2025. The features combined technical indicators with macroeconomic variables, and hyperparameters were tuned via Bayesian Optimization using the Optuna framework. Performance was assessed by classification accuracy and per-class precision, recall, and F1-score.

Results: Average accuracies generally exceeded 60%. SVM achieved the highest average accuracy, while XGBoost was the most stable across assets and return classes. Positive returns were predicted more reliably than near-zero and negative returns, though strong positive-class recall was not always matched by precision.

Conclusions: The results suggest the potential of combining machine learning, technical indicators, and macroeconomic variables for return-trend prediction. As they derive from a single test window and three assets, they should be read as indicative rather than definitive.

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Introduction

Cryptocurrencies are increasingly regarded as a transformative technological innovation that simultaneously evokes optimism and concern among different groups of investors within the global economy. Divergent perspectives regarding the future of cryptocurrencies have contributed to substantial volatility in the market value of these assets. This volatility is one of several factors that has intensified researchers' interest in understanding the complex and often ambiguous nature of cryptocurrency markets (Guesmi et al., 2019).

A cryptocurrency, also referred to as digital currency, is a form of virtual digital asset that operates through cryptographic mechanisms and blockchain technology to validate transactions and maintain records. Due to their decentralized structure, highly volatile behavior, and considerable liquidity, cryptocurrencies have attracted significant attention in financial trading environments. In addition to enabling secure and anonymous transactions, cryptocurrency trading is associated with sharp price fluctuations that can create highly profitable opportunities while simultaneously exposing investors to substantial financial risk. As a rapidly evolving payment system in recent years, cryptocurrencies rely on blockchain as a digital ledger system that ensures transparency and immutability of data (Andrianto & Diputra, 2017; Yamin & Chaudhry, 2023).

Various types of cryptocurrencies have emerged to date, including Bitcoin, Solana, Ripple, Ethereum, and many others. Bitcoin remains the most widely used cryptocurrency and possesses the largest market capitalization among digital assets. Developed by Satoshi Nakamoto in 2009, Bitcoin is recognized as the pioneer of cryptocurrencies. One of Bitcoin's defining characteristics is decentralization, meaning that users retain direct control over their assets without the involvement of centralized regulatory authorities in transactions. The elimination of intermediaries significantly reduces transaction costs, which has been a major driver behind the growth of cryptocurrencies (Nakamoto, 2008; Brière et al., 2015).

Cryptocurrencies can generally be categorized into two primary groups: coins and tokens. Coins are native units of value within a blockchain and are mainly used for transactions such as payments and the exchange of goods and services. In contrast, tokens are secondary digital assets built on existing blockchains and may serve a variety of functions. Tokens are commonly classified into utility tokens, security tokens, and non-fungible tokens (NFTs). Well-known examples include stablecoins such as Tether, which is developed on the Ethereum blockchain. Stablecoins can function as safe-haven assets and portfolio diversifiers while contributing to market efficiency. At the same time, they also represent a fragile linkage to the U.S. dollar (Cavalli & Amoretti, 2021; Almeida & Gonçalves, 2023; Chernova et al., 2024).

With the rapid expansion of cryptocurrencies in 2017, the attention of both novice and experienced investors shifted toward this emerging market. The development of digital investment platforms has encouraged investors to reconsider traditional investment approaches. These platforms provide access to a broader range of assets, thereby supporting more informed investment decisions. Despite these promising developments, the cryptocurrency market remains highly complex and evolves rapidly. Consequently, investors must approach this market with caution (Ma et al., 2020; Youssefi et al., 2024; Zarezade et al., 2024).

The financial services sector has become increasingly dependent on advanced computational methods, where artificial intelligence together with machine learning technologies are transforming trading processes and investment strategies. Accurate forecasting of financial assets plays a critical role in supporting informed decision-making and achieving sustainable long-term growth. Although predicting the prices of financial assets is inherently difficult, previous studies have demonstrated that price movements and returns exhibit a certain degree of predictability (Jensen, 1978; Chen et al., 2021; Goodell et al., 2021). Beyond forecasting in isolation, accurate return-trend prediction is a building block for downstream portfolio decisions such as asset selection, position sizing, and risk control. This is particularly relevant for cryptocurrencies, which have been shown to offer diversification and, under certain conditions, hedging or safe-haven properties within broader portfolios, and which have motivated a growing body of work on portfolio optimization under uncertainty (Bouri et al., 2017; Shahzad et al., 2019; Peykani et al., 2020; 2022).

Accurate prediction of stock prices and other financial assets has consistently been one of the primary objectives of investors seeking to improve their market strategies. Time-series forecasting is considered one of the most widely studied regression problems within the machine learning community. A related but distinct problem is trend prediction in time series, which is typically formulated as a classification task. This challenge becomes particularly significant in the highly volatile cryptocurrency market (Baasher & Fakhr, 2017; Iqbal et al., 2024; Jabeur et al., 2024).

Although price forecasting studies have reported promising results, predicting directional changes as a classification problem has introduced several challenges that directly influence predictive accuracy. Among these challenges are the limited availability of extensive historical data, market volatility, and unknown external factors that may affect market evolution. Furthermore, cryptocurrencies exhibit relatively weak relationships with traditional financial markets, creating additional complications for predictive modeling (Iqbal et al., 2024; Viéitez et al., 2024).

Research Background

This section introduces the machine learning models employed in the present study, followed by the Bayesian Optimization approach used for hyperparameter tuning of the machine learning algorithms.

XGBoost

XGBoost is a gradient boosting model introduced in 2016. This method is characterized by low computational complexity, fast execution speed, and high predictive accuracy. The objective function in XGBoost combines a standard regularization term with a loss function to obtain an optimal solution while preventing overfitting. The model utilizes an ensemble of decision tree-based learners together with advanced optimization strategies. Among the most important hyperparameters of this model are the number and depth of trees, as well as the learning rate. (T. Chen & Guestrin, 2016; W. Chen et al., 2021).

Random Forest

Random Forest constructs multiple decision trees using different subsamples of the dataset. This model is based on an ensemble learning framework that combines the outputs of individual tree predictors. By averaging the predictions generated by each decision tree, Random Forest improves predictive accuracy while controlling overfitting. The main hyperparameters of this model include the number of trees and the maximum depth of each tree. (Breiman, 2001; Valencia et al., 2019).

Support Vector Machines (SVM)

SVM is a supervised learning algorithm that constructs a hyperplane or a set of hyperplanes in a high-dimensional or even infinite-dimensional feature space using a kernel function. SVM aims to maximize the distance between the hyperplane and the nearest training samples, known as support vectors, thereby improving classification performance. Optimization of the gamma hyperparameter and the regularization parameter (C) is of considerable importance in this model. (Cortes & Vapnik, 1995; Cherkassky & Ma, 2004; Thu & Xuan, 2018).

Bayesian Optimization

Bayesian Optimization is a global search approach designed to identify the minimum or maximum of complex and computationally expensive functions that are often non-differentiable. This method builds a probabilistic surrogate model of the objective function and uses it to select the most promising hyperparameter configurations to evaluate next, while accounting for uncertainty in the estimation process. In the present study, Bayesian Optimization was implemented using the Optuna framework, which by default employs the Tree-structured Parzen Estimator (TPE) as its surrogate model. Due to its high efficiency and sample effectiveness, Bayesian Optimization has become widely used in hyperparameter tuning problems for machine learning algorithms (Močkus, 1974; Snoek et al., 2012; Klein et al., 2017).

Literature Review

Numerous studies have investigated cryptocurrency market prediction, with most focusing on forecasting prices and returns of different digital currencies, while comparatively fewer studies have concentrated on trend prediction.

Among recent studies, Islam et al. (2025) employed XGBoost, Random Forest, and Logistic Regression models to predict the trends of cryptocurrencies such as Bitcoin and Ethereum. In their study, various indicators including the Relative Strength Index (RSI), together with factors such as investor sentiment, were utilized as input features for trend prediction. Their findings showed that Logistic Regression achieved the best performance with an average accuracy of 56%.

In another study Viéitez et al. (2024) focused on Ethereum trend prediction using Support Vector Machine (SVM). Their model achieved an average accuracy of 50%. The study primarily emphasized fundamental analysis and incorporated features such as Bitcoin prices, the S&P 500 index, and the NASDAQ index. In addition, the researchers employed LSTM and GRU models for Ethereum price forecasting.

Akyildirim et al. (2021) utilized SVM, Logistic Regression, Random Forests, and Artificial Neural Networks to predict the trends of cryptocurrencies including Bitcoin, Ethereum, and Ripple. The reported prediction accuracies of these models were generally between 55% and 60%.

Kwon et al. (2019) investigated the prediction of several cryptocurrencies, including Bitcoin and Ethereum, using LSTM and Gradient Boosting Tree models. The highest accuracy was achieved by the LSTM model for the DASH cryptocurrency, reaching approximately 68%. Moreover, the LSTM model improved performance by an average of 7% compared with the Gradient Boosting Tree approach. The weakest result was obtained for Bitcoin Cash, with an accuracy of nearly 58%.

In a study conducted by Jahanbin & Chahooki (2025), the influence of sentiment analysis derived from social media comments, particularly from X (formerly Twitter), on cryptocurrency market behavior was examined. The authors proposed a hybrid model consisting of DistilBERT, BiGRU, and an attention layer to perform aspect-based sentiment analysis and predict the price trends of eight cryptocurrencies. Using tweets from 70 influential cryptocurrency experts, the results demonstrated that the proposed model improved aspect-based sentiment analysis performance by 3% and achieved an average prediction accuracy of 68% regarding the impact of sentiment on cryptocurrency prices.

It should be noted that these accuracy figures are not directly comparable. The cited studies differ in the assets examined, the time periods covered, the sample sizes, and, most importantly, the classification setup, as most adopted a binary (up/down) formulation, whereas the present study addresses a more demanding three-class problem. Accordingly, the comparison is intended to situate our results within the broader literature rather than to claim a direct performance improvement.

Despite the growing body of literature in this field, previous studies have mainly concentrated on models such as SVM and Random Forest, while comparatively less attention has been given to gradient boosting approaches such as XGBoost. Furthermore, the use of newer high-market-cap cryptocurrencies such as Solana and Binance Coin (BNB), as well as advanced technical indicators including the Ichimoku Cloud, has remained limited. Another important limitation concerns the optimization of machine learning hyperparameters. Hyperparameters, which are manually configured by model developers, play a critical role in determining predictive accuracy and overall model performance. In the aforementioned studies, hyperparameters were generally optimized using conventional approaches such as Grid Search and Random Search. These methods are computationally expensive and only explore a limited range of parameter combinations. In addition, most existing studies have focused exclusively on binary classification of positive and negative returns, while comparatively little attention has been paid to neutral returns or varying levels of positive and negative returns as separate classes.

Accordingly, the present study employs three machine learning models, namely XGBoost, Random Forest, and SVM, to predict the trends of Bitcoin, Ethereum, and Solana across three distinct classes using a diverse set of technical indicators. In addition to incorporating both conventional and advanced indicators as input features, the hyperparameters of the proposed models are optimized through Bayesian Optimization.

Method

To predict return trends, historical data for three cryptocurrencies, namely Bitcoin, Ethereum, and Solana, were collected from December 29, 2024, to July 31, 2025. All datasets were extracted in Python using the Yahoo Finance library. After calculating daily returns relative to the previous day based on the closing price of each trading day, which represents the prediction target of this study, the returns were classified according to Table 1. All stages of the present research were implemented using the Python programming language.

Table 1. Return Classification

Class	Return Value
0	Less than -0.01
1	Between -0.01 and 0.01
2	Greater than 0.01

The ±0.01 threshold was selected on economic rather than purely statistical grounds. Daily returns falling between −1% and +1% are generally not actionable for short-term traders and investors once transaction costs, trading fees, and bid–ask spreads are taken into account; after these frictions are deducted, the net profit from acting on such small movements is often negligible or even negative. Days within this band effectively represent a ranging or directionless market in which initiating a position is typically unprofitable and the prudent action is to remain on the sidelines. Returns within this band are therefore grouped into a distinct "near-zero" class, allowing the models to separate genuinely directional moves that may justify a trade from economically negligible fluctuations that do not. This three-class design also reflects the practical decision faced by a trader, namely whether to take a short position, stay flat, or take a long position, more closely than a binary up/down formulation. Under this classification, the near-zero class remains well represented in all three datasets. In the training set, the negative/near-zero/positive split was 42/67/41 for Bitcoin, 55/49/46 for Ethereum, and 62/36/52 for Solana, indicating a reasonably balanced distribution in which no class is trivially sparse. This balance is important, as a severely underpopulated class would limit the models' ability to learn its characteristics and would render the corresponding performance metrics unreliable.

Input Features and Final Dataset

A diverse set of technical indicators was employed as input features for predicting return trends, selected to capture complementary aspects of market behavior, including momentum, trend direction, volatility, and support–resistance dynamics. These indicators include the 14-day Relative Strength Index (RSI), which measures momentum and potential overbought or oversold conditions; the 12- and 26-day Moving Average Convergence Divergence (MACD) together with its 9-day signal line and the resulting MACD trend, which capture shifts in trend and momentum; 20-day Bollinger Bands with two standard deviations, which reflect volatility and relative price levels; the 14-day Stochastic Oscillator together with its 3-day signal, which gauges momentum relative to the recent trading range; and trading volume and price. The Average Directional Index (ADX), along with its positive and negative directional components, was included to quantify trend strength, and the Ichimoku indicators, Senkou Span A, Senkou Span B, Kijun-sen, and Tenkan-sen, were incorporated to provide a multi-dimensional view of support, resistance, and trend direction. In addition, the daily price range, defined as the difference between the highest and lowest prices within a trading day, was used as a further measure of intraday volatility. Beyond technical indicators, the U.S. Dollar Index (DXY), short-term interest rates, and the S&P 500 Index were incorporated as fundamental and macroeconomic variables, capturing the broader financial environment in which cryptocurrencies trade. Table 2 presents the complete set of input features and the target variable.

Table 2. Input Features Summary and Prediction Target

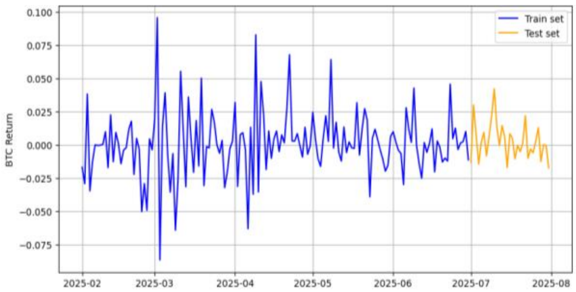
Attribute	Details	Attribute	Details
1	Short-Term Interest Rate	2	DXY
3	S&P 500 Index	4	RSI
5	MACD	6	MACD Signal
7	MACD Trend	8	Bollinger Bands
9	Upper Bollinger Band	10	Lower Bollinger Band
11	Stochastic Oscillator	12	Stochastic Signal
13	ADX	14	Positive ADX
15	Negative ADX	16	Ichimoku Senkou Span A
17	Ichimoku Senkou Span B	18	Ichimoku Kijun-sen
19	Ichimoku Tenkan-sen	20	Daily Price Range
	Prediction Target		**Next-Day Return Class**

After performing the required calculations and preprocessing procedures, a total of 181 daily observations remained in the final dataset. Among these observations, 150 days were allocated to the training set for model development, while the final 31 days were reserved as the testing set for prediction and evaluation. The final datasets for all three cryptocurrencies were organized according to Table 3.

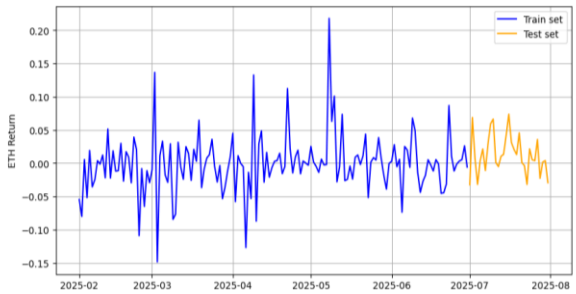
Table 3. Final Dataset Structure

Data Type	Date Range	Number of Days	Percentage
Training	01/02/2025 to 30/06/2025	150	82.87%
Testing	01/07/2025 to 31/07/2025	31	17.13%

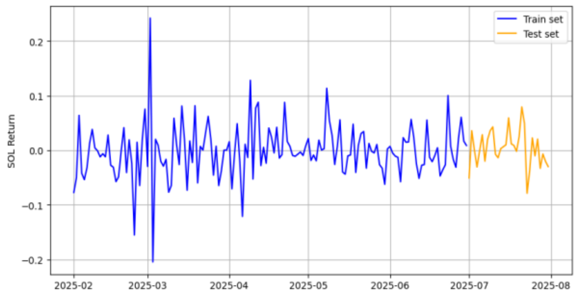
The return series of each cryptocurrency, separated into training and testing datasets, are illustrated in Figure 1. The blue color represents the training data, while the orange color represents the testing data.



A) Bitcoin



B) Ethereum



C) Solana

Figure 1. Cryptocurrency return series separated into training and testing datasets

After preparing the final dataset, the XGBoost, Random Forest, and SVM models were trained using the training data, and their hyperparameters were optimized through Bayesian Optimization. Bayesian Optimization and model training were performed exclusively on the training dataset in order to avoid information leakage from the testing period. All experiments were implemented in Python using the scikit-learn (v1.7.2), XGBoost (v3.5.0), Optuna (v4.5.0), and ta (v0.11.0) libraries. A fixed random seed (42) was set for all models to ensure the reproducibility of the reported results.

To preclude information leakage, the temporal structure of the data was preserved throughout. The technical indicators are causal, in that each value depends only on current and past observations; consequently, computing them on the full series prior to splitting does not transfer any future information into the test period. The train–test division was performed chronologically without shuffling, so that the test set consists strictly of the most recent observations. Feature scaling was fitted exclusively on the training data, and the resulting parameters were then applied to the test data, ensuring that no test-set statistics influenced model training.

Following the determination of the optimal hyperparameters and completion of the training process, predictions were generated for the testing dataset. Subsequently, the accuracy of each model was evaluated, and model performance across different cryptocurrencies was assessed using classification accuracy and confusion matrices. Tables 4 through 6 present the hyperparameters used for optimization together with their corresponding search ranges.

Table 4. XGBoost Hyperparameters

Hyperparameter	Details	Search Range
max_depth	Maximum Depth of a Tree	{3,4,…,10}
learning_rate	Step Size Shrinkage Used in Update	[0.01,0.3]
n_estimators	Total Number of Trees	{100,101,…,1000}
subsample	Ratio of Samples Used in Each Training Subsample	[0.6,1]
colsample_bytree	Ratio of Features Used in Each Subsample	[0.6,1]
reg_alpha	L1 Regularization Coefficient	[0.0,5.0]
reg_lambda	L2 Regularization Coefficient	[0.0,5.0]
min_child_weight	Minimum Sum of Instance Weight (Hessian) in Child Nodes	[1.0,10.0]

Table 5. Random Forest Hyperparameters

Hyperparameter	Details	Search Range
c	Regularization Parameter	[0.001, 100] (log scale)
kernel	Kernel Function Type	{"linear", "rbf", "poly", "sigmoid"}
gamma	Kernel Influence Parameter	{"scale", "auto"}
degree	Degree of Polynomial Kernel	{2, 3, ..., 5}
class_weight	Class Weighting Strategy	{"none", "balanced"}

Table 6. SVM Hyperparameters

Hyperparameter	Details	Search Range
max_depth	Maximum Depth of a Tree	{4, 5, ..., 30}
min_samples_split	Minimum Number of Samples Required to Split an Internal Node	{2, 3, 4…,10}
n_estimators	Total Number of Trees	{100,101,…,1000}
min_samples_leaf	Minimum Number of Samples Required in Each Leaf Node	{1, 2, ..., 10}
max_features	Maximum Number of Features Used in Each Split	{"sqrt", "log2", None}

The overall research framework and implementation procedure are illustrated in Figure 2.

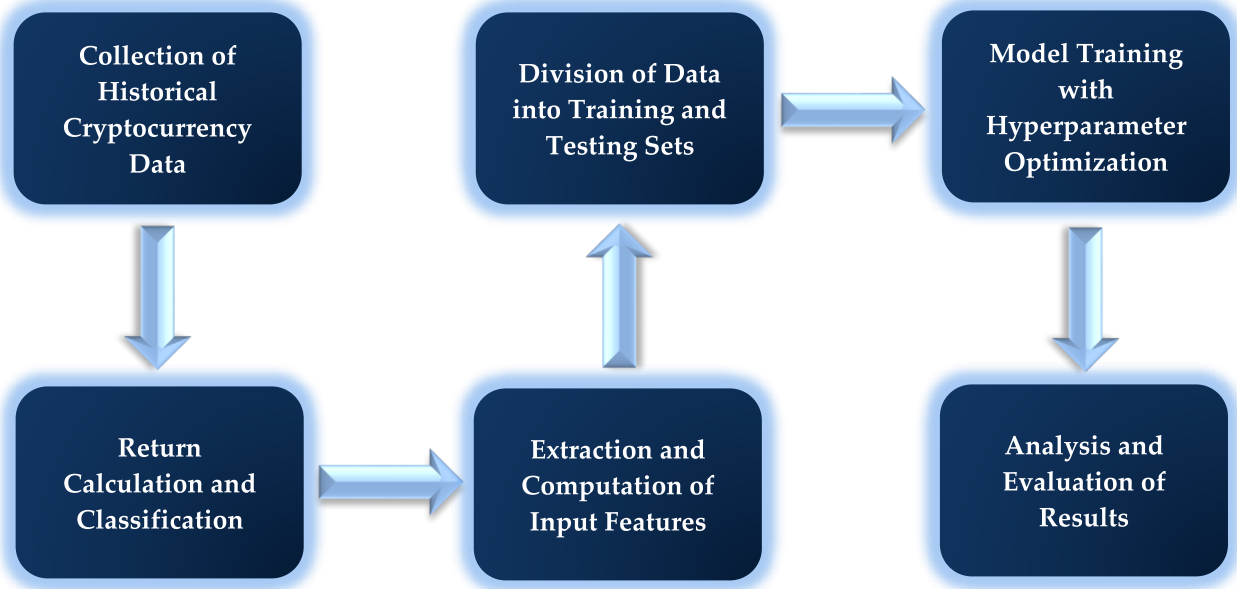


Figure 2. Research Methodology and Implementation Process

Results

After training the models and identifying the optimal hyperparameters, predictions were generated for the testing dataset. The Bayesian Optimization procedure was performed over 150 iterations. The search ranges of the most important hyperparameters for each model were determined based on empirical results, recommendations provided by the corresponding libraries, and expert knowledge prior to optimization. Following the training phase, predictions were conducted for the final 31 days of the dataset.

Comparison between the predicted values and the actual observations indicates that the SVM model achieved the best average performance among the evaluated models, while the models generally demonstrated stronger performance for Solana. The prediction accuracy of each model for each cryptocurrency is presented in Table 7.

Throughout, 'accuracy' (Tables 7–9) denotes overall classification accuracy, defined as the proportion of correctly classified observations across all classes. The per-class metrics in Tables 10–12 report precision, recall, and F1-score, and the class-wise averages in Tables 13–14 are based on per-class recall.

Table 7. Model Performance for Each Cryptocurrency (%)

Model	Bitcoin	Ethereum	Solana
XGBoost	64.52	67.74	70.97
Random Forest	58.06	64.52	70.97
SVM	77.42	58.06	70.97

In interpreting the results that follow, it is useful to distinguish two senses of "best": SVM attained the highest average accuracy across assets, whereas XGBoost was the most consistent performer across cryptocurrencies and across return classes. Both observations are reported below.

The results demonstrate that although all models achieved identical accuracy for Solana and SVM outperformed the other models for Bitcoin, XGBoost generally exhibited more stable performance across the three cryptocurrencies. In addition, XGBoost maintained acceptable predictive performance for all evaluated digital assets. Tables 8 and 9 respectively present the average accuracy of each model and the average model performance for each cryptocurrency.

Table 8. Average Accuracy of Each Model (%)

Model	XGBoost	Random Forest	SVM
Accuracy	67.74	64.52	68.81

Table 9. Average Accuracy of Each Cryptocurrency (%)

Cryptocurrency	Bitcoin	Ethereum	Solana
Accuracy	66.67	63.44	70.97

Based on the obtained results, the average prediction accuracy of the models exceeded 60%. Except for two cases, where the SVM and Random Forest models achieved accuracies of 58%, all remaining prediction accuracies were above 60%. In addition to the nature of the dataset itself, several factors contributed to these results, including the selection of appropriate technical indicators and input features, the integration of technical indicators with macroeconomic variables, and the optimization of model hyperparameters.

Bayesian Optimization was adopted because, as established in prior work, it is generally more sample-efficient than exhaustive strategies such as Grid Search: by using a probabilistic surrogate model to guide the search, it can explore wider continuous search spaces with fewer objective evaluations (Snoek et al., 2012; Klein et al., 2017). This motivated our use of the TPE-based Optuna framework for hyperparameter tuning, rather than a fixed grid.

The confusion matrices for each model and cryptocurrency are further examined to evaluate model behavior across different return classes. These matrices illustrate the classification performance of each model for individual classes. To evaluate model behavior at the class level in greater detail, Tables 10–12 report the per-class precision, recall, and F1-score for each model on Bitcoin, Ethereum, and Solana, respectively, together with the macro-averaged F1-score. Precision (P) is the proportion of observations predicted as a given class that truly belong to it, and thus reflects how reliable a positive prediction is for that class. Recall (R) is the proportion of observations actually belonging to a class that the model correctly identified. The F1-score (F1) is the harmonic mean of precision and recall, providing a single balanced measure when the two diverge. The macro-averaged F1 is the unweighted mean of the three class F1-scores and summarizes overall per-class performance without favoring more frequent classes. All values are expressed as percentages, and the three return classes are denoted 0 (negative), 1 (near-zero), and 2 (positive).

Table 10. Per-Class Precision, Recall, and F1-Score for Bitcoin (%)

Model	P_0	R_0	$F1_0$	P_1	R_1	$F1_1$	P_2	R_2	$F1_2$	Macro-F1
XGBoost	46.15	85.71	60.00	80.00	47.06	59.26	75.00	85.71	80.00	66.42
Random Forest	33.33	14.29	20.00	66.67	70.59	68.57	50.00	71.43	58.82	49.13
SVM	80.00	57.14	66.67	75.00	88.24	81.08	83.33	71.43	76.92	74.89

Table 11. Per-Class Precision, Recall, and F1-Score for Ethereum (%)

Model	P_0	R_0	$F1_0$	P_1	R_1	$F1_1$	P_2	R_2	$F1_2$	Macro-F1
XGBoost	75.00	50.00	60.00	71.43	50.00	58.82	65.00	86.67	74.29	64.37
Random Forest	44.44	66.67	53.33	66.67	40.00	50.00	75.00	80.00	77.42	60.25
SVM	40.00	66.67	50.00	53.33	80.00	64.00	100.00	40.00	57.14	57.05

Table 12. Per-Class Precision, Recall, and F1-Score for Solana (%)

Model	P_0	R_0	$F1_0$	P_1	R_1	$F1_1$	P_2	R_2	$F1_2$	Macro-F1
XGBoost	62.50	55.56	58.82	66.67	66.67	66.67	78.57	84.62	81.48	68.99
Random Forest	75.00	66.67	70.59	60.00	66.67	63.16	76.92	76.92	76.92	70.22
SVM	100.00	66.67	80.00	50.00	100.00	66.67	100.00	53.85	70.00	72.22

Examining precision and recall jointly provides a more complete picture than recall alone. Across all models and assets, the positive class (Class 2) remains the best predicted, with a mean F1-score of 72.55%, compared with 64.25% for the near-zero class and 57.71% for the negative class. However, the strong positive-class results are partly driven by recall that is not always matched by precision. For the tree-based models, recall on Class 2 tends to exceed precision, for example, Ethereum XGBoost attains 86.67% recall but only 65.00% precision, indicating a tendency to over-predict positive returns. SVM exhibits the opposite pattern, achieving very high precision on Class 2 at the cost of recall (100.00% precision but 40.00% recall for Ethereum, and 100.00% precision with 53.85% recall for Solana), meaning it predicts positive returns conservatively but accurately. SVM also performs strongly on the near-zero class, with recall of 88.24%, 80.00%, and 100.00% for Bitcoin, Ethereum, and Solana, respectively, whereas the negative class is the most difficult for all models, with Random Forest on Bitcoin the weakest case (F1 of 20.00%).

Considering the macro-averaged F1-score, which weighs all three classes equally, SVM attains the highest mean across assets (68.05%), closely followed by XGBoost (66.59%) and then Random Forest (59.87%); however, XGBoost is by far the most consistent, with its macro-F1 ranging only from 64.37% to 68.99% across the three cryptocurrencies, compared with much wider ranges for SVM and Random Forest. These observations reinforce, at the class level, the earlier finding that SVM achieves the best average performance while XGBoost offers the most stable performance. Tables 13 and 14 respectively present the average performance of each model and the average prediction results for each cryptocurrency.

Table 13. Average Accuracy of Each Model by Return Class (%)

Model	Class 0	Class 1	Class 2
XGBoost	63.75	54.57	85.66
Random Forest	49.21	59.08	76.12
SVM	63.49	89.41	55.09

Table 14. Average Accuracy for Each Cryptocurrency by Return Class (%)

Asset	Class 0	Class 1	Class 2
Bitcoin	52.38	68.63	76.29
Ethereum	61.11	56.67	68.89
Solana	61.11	77.78	71.79

Overall, the models demonstrated stronger performance in predicting positive returns, while their performance for negative returns was comparatively weaker. As observed in the previous tables, SVM achieved the best average predictive performance; however, as discussed earlier, XGBoost exhibited greater stability across different classes and cryptocurrencies. Furthermore, the accuracy of all models exceeded 50% across all classes, with the exception of Random Forest in the negative-return category.

Conclusions

The findings of the present study indicate that integration of machine learning algorithms with hyperparameter tuning can provide an effective framework for predicting cryptocurrency return trends. The evaluation of XGBoost, Random Forest, and SVM models across Bitcoin, Ethereum, and Solana revealed that although model performance depends on the characteristics of each asset and the structure of the underlying data, XGBoost generally exhibited more stable and balanced performance across different cryptocurrencies and return classes.

One of the primary contributions of this study is the prediction of return trends across three classes (negative, near-zero, and positive returns) rather than the conventional binary classification framework. This approach enables a more detailed analysis of market behavior. In addition, the simultaneous use of a rich set of advanced technical indicators together with macroeconomic variables improved the explanatory capability of the models compared with studies relying solely on price-based or technical indicators, consistent with broader evidence that integrating machine learning with diverse market and macro-financial features enhances financial prediction (Fischer & Krauss, 2018; Henrique et al., 2019).

The results further indicate that although the models achieved stronger performance in predicting positive returns, forecasting negative returns and especially near-zero returns remains challenging. This issue may be attributed to the highly volatile nature of cryptocurrency markets as well as the informational overlap among input features within these regions (Akyildirim et al., 2021; Sebastião & Godinho, 2021). In addition, Bayesian Optimization also offers a sample-efficient alternative to exhaustive Grid Search, allowing wider search spaces to be explored with fewer evaluations, as reported in prior work.

Despite the promising results, the present study is subject to several limitations. The first concerns the evaluation design: all reported results derive from a single contiguous out-of-sample window (July 2025). Because cryptocurrency markets are highly non-stationary, performance estimated on one fixed window may not generalize to other periods, and the relative ranking of the models could plausibly differ under a different test window. The results reported here should therefore be interpreted as indicative of performance within the studied period rather than as definitive evidence of one model's superiority. Further limitations include the relatively limited time horizon of the dataset and the focus on a specific group of cryptocurrencies. Future studies could address these issues by employing longer-term datasets or higher-frequency data such as hourly observations, and by adopting rolling-origin or walk-forward evaluation across multiple windows, which would provide a more robust assessment of model stability and generalizability.

Furthermore, the development of hybrid architectures incorporating deep learning approaches or advanced ensemble learning frameworks may further improve predictive accuracy, particularly for more challenging return classes. The integration of textual data and sentiment analysis extracted from social media platforms and financial news could also provide a more comprehensive understanding of investor behavior (Valencia et al., 2019).

Beyond model architecture, the hyperparameter optimization strategy itself offers another avenue for future work. While the present study employed Bayesian Optimization, metaheuristic algorithms such as genetic algorithms, particle swarm optimization, and differential evolution, offer an alternative family of global search methods that are well suited to the non-convex, mixed-type hyperparameter spaces typical of machine learning models, and have been shown to be effective for hyperparameter tuning (Yang & Shami, 2020; Bischl et al., 2023). Comparing Bayesian Optimization with such population-based metaheuristics, or hybridizing the two, could further improve tuning efficiency and predictive performance, particularly as the feature set and model complexity grow.

Finally, a promising direction is to connect the predicted return trends to portfolio construction. The class signals produced by the models could be translated into long, flat, or reduced-exposure positions across a basket of cryptocurrencies, and the resulting portfolios could be evaluated using risk-adjusted measures such as the Sharpe ratio, maximum drawdown, and cumulative return relative to buy-and-hold benchmarks, while accounting for transaction costs and rebalancing frequency. Such an extension would move beyond statistical accuracy toward measuring the practical, economic value of the predictions, connecting trend forecasting to the broader portfolio-optimization literature and to machine-learning-based approaches that translate predictive signals into investment decisions, including frameworks developed for uncertain and multi-period settings (Kolm et al., 2014; Fischer & Krauss, 2018; Peykani et al., 2021; 2023).

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Declaration of Generative AI and AI-assisted technologies in the writing process

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The authors declare no conflict of interest.

Ethical considerations

The authors avoided data fabrication, falsification, and plagiarism, and any form of misconduct.

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