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Machine learning approaches to cryptocurrency trading optimization: a comparative analysis of predictive models

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Abstract

Cryptocurrency markets are characterized by high volatility and complex patterns, creating both challenges and opportunities for traders and investors. This study introduces a machine learning framework for cryptocurrency trading optimization that leverages advanced analytical techniques to enhance trading decisions. We extracted historical data for 30 cryptocurrencies over a four-year period from Yahoo Finance. After preprocessing, we applied Principal Component Analysis (PCA) and K-means clustering to select representative coins. Four machine learning models (Gradient Boosting, XGBoost, Support Vector Regression, and Long Short-Term Memory networks) were trained to predict cryptocurrency price movements. Model performance was evaluated using multiple metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2). Gradient Boosting and XGBoost consistently outperformed SVR and LSTM models across all cryptocurrencies, with R^2 values of approximately 0.98 for most coins. The framework successfully identified trading signals through both moving average strategies and machine learning predictions, providing actionable insights for cryptocurrency traders. Our analysis demonstrates that ensemble-based models offer superior performance for cryptocurrency price prediction compared to neural network approaches. The integration of advanced visualization tools and trading signal generation creates a comprehensive system for data-driven cryptocurrency trading decisions.

Keywords Cryptocurrency trading, Machine learning, Gradient boosting, XGBoost, LSTM, Principal component analysis, Trading signals, Financial forecasting, Artificial intelligence, Data visualization

1 Introduction

The cryptocurrency market represents one of the most dynamic and volatile sectors in modern finance, with market capitalization fluctuating dramatically and individual assets experiencing significant price movements within short timeframes [1, 2]. This volatility creates both opportunities and challenges for investors and traders, who must navigate a complex landscape driven by numerous factors including technological developments, regulatory changes, market sentiment, and macroeconomic trends [3].

Traditional financial analysis methods often fall short when applied to cryptocurrency markets due to their unique characteristics: 24/7 trading, global accessibility, technological underpinnings, and relative market immaturity [4]. These limitations have spurred interest in applying advanced computational techniques, particularly machine learning and artificial intelligence, to cryptocurrency analysis and trading [5].

Recent research has demonstrated the potential of machine learning approaches, with ensemble methods yielding promising financial prediction results [6], and deep learning architectures such as LSTM networks being applied to discern temporal trends in cryptocurrency price movement [7]. Comparison across many model architectures using standardized testing procedures remains quite limited, particularly for newer cryptocurrencies beyond Bitcoin and Ethereum [8]. The identified research gap is of practical relevance considering its implications on the financial technology industry. Automated trading systems are becoming more prevalent in their dependence on algorithmic decision-making logic, with hedge funds and institutional investors allocating substantial sums of money in quantitative trading strategies [9]. The formulation of stable, explainable prediction models directly affects portfolio management decisions, risk assessment practices, and the development of financial technology paradigms. For individual investors, enhanced predictive power can lead to improved trading performance and risk management, while regulatory bodies require interpretable, explainable models for market regulation and stability assessment.

This present study aims to overcome these limitations by conducting a comprehensive empirical comparison of four machine learning paradigms ensemble trees (Gradient Boosting and XGBoost), support vector regression, and recurrent neural networks (specifically LSTM) on the task of cryptocurrency price prediction for various digital currencies with homogeneous feature sets and evaluation protocols.

Whereas more recent studies have promoted explainable AI approaches in crypto asset allocation [10] and interpretability approaches in financial time series forecasting [11], our study specifically addresses the lack of systematic comparative predictive performance analysis on a variety of cryptocurrency types with standardized approaches. In contrast to current explainable AI solutions that aim for model interpretability in portfolio investment decisions, our research targets predictive performance optimization via systematic algorithmic comparison, offering a methodologically harmonized benchmark for cryptocurrency prediction performance.

Our novel contributions include:

1. The first systematic comparison of ensemble versus deep learning approaches on a range of cryptocurrency assets (apart from major coins like Bitcoin and Ethereum) using the same feature engineering and assessment protocols.
2. Empirical confirmation of ensemble method outperformance in cryptocurrency prediction using normalized performance metrics.
3. Actionable suggestions for automated trading system design from feature importance analysis across different algorithmic approaches.

This approach differs from previous explainable AI research in that it prioritizes predictive performance over interpretability and guarantees methodological soundness through consistent standards of assessment. The study contributes to the emerging computational finance and cryptocurrency trading literature by bridging the gap between explainable AI science and actual trading system implementation, offering evidence-based guidelines on algorithm selection for volatile cryptocurrency markets with immediate applicability to automated trading system design, portfolio optimization management, and financial technology infrastructure development.

2 Literature review

2.1 Market analysis and dynamics challenges of cryptocurrency

The crypto market is among the most volatile and complex financial markets, which has unique characteristics distinguishing it from mainstream markets. Corbet et al. [1] conducted a systematic review that identified leading attributes like 24/7 trading, global access, and technological infrastructure that create new market dynamics. López-Cabarcos et al. [2] demonstrated tight connections between Bitcoin volatility, traditional stock markets, and investor sentiment, contradicting assumptions of cryptocurrency market independence and showing that macroeconomic conditions strongly drive crypto asset prices.

Recent research has enriched our understanding of cryptocurrency market intricacy. Khan et al. [3] examined cryptocurrency market dynamics, trends, volatility patterns, and the regulatory challenges that present unique analytical requirements. The high volatility that is a feature of cryptocurrency markets in which individual assets fluctuate by 10–50% within a session presents opportunities along with analytical challenges. Antonakakis et al. [4] examined contagion effects on the market, illustrating intricate interdependences indefinable by traditional financial analysis methods.

The advent of various forms of cryptocurrency has further complicated the analysis. Li et al. [12] compared the liquidity risk of meme token markets and identified that various forms of tokens follow different patterns of volatility and need tailored analytical methods. Their investigation for identifying entity-associated addresses uncovered artificial manipulation-driven factors such as self-trading and the requirement of advanced on-chain analysis methods. Studies carried out by the European Central Bank [13] have identified that cryptocurrencies present unique threats to financial stability and regulatory challenges that traditional financial systems cannot adequately address.

2.2 Moving away from conventional methodologies towards machine learning

Conventional technical analysis techniques have proven woefully inadequate for use in cryptocurrency markets. Khan et al. [14] presented evidence that although GARCH models perform satisfactorily in traditional financial markets, the extreme volatility clustering characteristic of cryptocurrency markets tends to outstrip traditional econometric models. Kumar et al. [15] presented an extensive review demonstrating that machine learning techniques possess better pattern recognition abilities, with the capability to effectively capture non-linear relationships and complicated market dynamics that evade normal statistical techniques.

The paradigm shift from traditional econometrics to AI/ML has been occasioned by the peculiar analytical needs of cryptocurrencies. Khan et al. [16] pointed out that the failures of traditional models are embedded in the linear assumptions inherent in them and their failure to capture diverse, non-linear influences like social media sentiment, whale transactions, and technological innovations. This has necessitated the application of more sophisticated analytical platforms capable of processing several streams of data.

Recent studies have measured the heightened performance of artificial intelligence-powered methods. Khan et al. [17] indicated that an AI-powered method, wherein an ensemble of neural networks is used, recorded a total return of 1640.32% during a six-year period, outperforming significantly the conventional Buy-and-Hold approaches (223.40%) as well as generic machine learning-based methods (304.77%). The empirical results offer ample rationale for the transition towards machine learning-based methods.

2.3 Differences in deep learning usage and performance

Deep learning models, in the form of Long Short-Term Memory (LSTM) networks, have been in much demand given their theoretical superiority in sequential data processing. Wu et al. [7] suggested an LSTM-based model to predict Bitcoin, thereby illustrating the strength of recurrent neural models. Empirical findings, however, have reported inconsistency across studies and cryptocurrencies.

Al-Sarayreh et al. [18] made comprehensive comparisons of GRU, LSTM, and Bi-LSTM models and discovered noteworthy performance differences between the neural network models. Through their systematic comparison, they found that GRU consistently performed better than LSTM and Bi-LSTM with lesser Mean Absolute Percentage Error (MAPE) values compared across Bitcoin, Ethereum, and Litecoin. Shirwaikar et al. [19] corroborated these findings, demonstrating the superior performance of GRU compared to other deep learning models in handling various cryptocurrency assets.

The performance inconsistencies of deep learning models have been attributed to their context-dependent property. Al-Sarayreh et al. [20] noted that the performance of some architectures is contingent upon multiple factors including the cryptocurrency under study, nature of the dataset, evaluation metrics, and experimental settings. The finding highlights the necessity of careful empirical validation and avoiding the assumption of general model dominance.

Bidirectional recurrent neural network versions have yielded mixed performance. Although Bi-LSTM and Bi-GRU are known to potentially improve the accuracy of financial time series prediction by reading sequences in both directions at the same time, relative research has reported contradicting results. Some studies indicate that Bi-LSTM performs worst among the cryptocurrencies under examination, demonstrating the intricate nature of architecture selection within this field.

2.4 Hybrid deep learning architectures and enhanced architectures

More recent studies have placed a growing emphasis on hybrid deep learning architectures that explicitly merge the merits of various architectures. Al-Sarayreh et al. [21] proposed an innovative hybrid model that fuses Attention Transformer and Gated Recurrent Unit (GRU) architectures and showed that the fusion of long-term pattern recognition and short-term sequential modeling capabilities consistently leads to higher accuracy than individual models.

Kumar and Ravi [15] also suggested a hybrid LSTM-XGBoost model that employs temporal dependences through LSTM and the capability of XGBoost to represent non-linear relationships with additional features. Their method showed repeated outperformance of individual models over Bitcoin, Ethereum, Dogecoin, and Litecoin, indicating that hybrid architectures have the potential to successfully bridge theoretical models with real-world applications in unpredictable cryptocurrency markets.

Raza et al. [22] suggested a more interpretable prediction model by combining CNN and LSTM architectures with Deep Variational Autoencoders (VAE) to enrich the features. Their CNN-LSTM hybrid model demonstrated state-of-the-art performance values in terms of Mean Squared Error (MSE) of 0.0002, Mean Absolute Error (MAE) of 0.008, and R-squared (R^2) of 0.99 for Bitcoin price prediction, while employing SHAP-based interpretability techniques.

The direction of hybrid architectures reflects the more profound realization that no one model is optimal for representing all facets of intricate cryptocurrency time-series data. Al-Sarayreh et al. [23] pointed out, though, that there have been relatively few investigations of hybrid models with a particular focus on the cryptocurrency market, thus suggesting a particular focus requiring additional study.

2.5 Ensemble methods and improved effectiveness

Recent studies increasingly show ensemble methods' efficiency for cryptocurrency prediction, with many outperforming sophisticated deep learning techniques. Chaudhary and Sushil [24] made extensive ensemble method comparisons and concluded that Stacking performed excellently with 81.80% accuracy, 81.49% F1-score, and 88.43% AUC-ROC, outperforming conventional methods and base machine learning models significantly.

XGBoost, as a top gradient-boosting-based model, has been particularly effective in cryptocurrency prediction. Matuszelański [25] showed the effectiveness of XGBoost in handling large volumes of data and its ability to prevent overfitting through regularization techniques, making it particularly suitable for volatile cryptocurrency markets. The model's high performance across a range of applications, including financial forecasting, is evidence of its robustness and great transferability.

Derbentsev et al. [26] explored ensemble deep learning models for the prediction of cryptocurrency time-series and concluded that ensemble methods are successfully applicable for the creation of strong, stable, and trustworthy predictive models. They demonstrated that deep learning models alone failed to generate stable predictions, yet ensemble integration provided greater stability and accuracy.

Bouteska et al. [27] considered Multi-Model Regression (MLR) ensemble techniques and concluded that ensembles produced more accurate predictions for cryptocurrencies with high volatility and unpredictable price movement. This would suggest that the selection of best ensemble approach might need to be adaptive, based on cryptocurrency characteristics and not a one-size-fits-all approach.

2.6 Advanced feature engineering and multi-modal data integration

Advanced cryptocurrency prediction is ever more reliant on the incorporation of heterogeneous data sources aside from traditional price–volume metrics. Sentiment analysis has emerged as a key component, given the susceptibility of cryptocurrencies to public opinion and social media sentiments. Alnami [28] investigated the influence of social media sentiments on Bitcoin price prediction and demonstrated that the fusion of Twitter-based sentiment analysis with traditional technical indicators considerably improved model precision.

Li et al. [29] suggested an advanced approach to sentiment analysis based on a Fact-Subjectivity-Aware Reasoning Multi-Agent Framework. The findings indicated that the decoupling of factual and subjective dimensions of news and their respective reasoning processes can result in higher profitability in trading. The study illustrated that subjective reasoning has extremely significant value in bull markets, but factual reasoning is important in bear markets.

The incorporation of blockchain technology-specific measures, commonly known as "on-chain data," has offered distinctive insight into network health and market dynamics. Raza et al. [30] blended technical indicators like moving averages, Relative Strength Index (RSI), and stochastic oscillators with on-chain data for better prediction accuracy. Yet, the extraction of sound features from blockchain data is fraught with complex issues, like the need for identification of addresses associated with entities for revealing artificial manipulation-based factors.

Methods for combining multi-modal data have since matured to incorporate advanced deep learning techniques. Li et al. [31] created dual prediction methods that forecast prices individually both from macroeconomic conditions and from individual cryptocurrencies' unique behaviours, respectively, and then fuse those predictions using market sentiment-driven strategies. Liu et al. [32] offered an extensive survey on multimodal time series analysis, structuring multi-modal interactions in three categories: fusion, alignment, and transference, corresponding to increasing levels of processing.

2.7 Advanced optimization and methodological considerations

Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) became promising paradigms for sequential decision-making in crypto trading. Huang et al. [33] established ensemble reinforcement learning frameworks based on large-scale parallel GPU simulations, showing that RL agents can adapt dynamically to changing market conditions, thus overcoming drawbacks of static rule-based approaches.

However, the application of RL to real-world cryptocurrency trading is beset with major issues. Yang et al. [34] cited policy instability, sampling bottlenecks, and the inherent non-stationarity of financial data as main obstacles. Their research on ensemble RL showed that the dynamic selection of the top-performing agent policy among a collection of several DRL policies leads to better risk-adjusted returns, even though current DRL models are still useless in terms of grasping market trends.

Al-Sarayreh et al. [35] presented an extensive survey of reinforcement learning applications in crypto markets, outlining the potential along with challenges of adaptive trading strategies. Their work underlined the necessity of solid engineering solutions for closing the gap between theoretical reinforcement learning potential and real-world implementation realities.

2.8 Model explainability and explainable AI

The growing sophistication of deep models has underscored the importance of interpretability in financial contexts. Raza et al. [36] tackled the black-box characteristic of deep learning models by integrating Shapley Additive Explanations (SHAP) into hybrid CNN-LSTM models, thereby enhancing interpretability without sacrificing high predictive accuracy.

The tension between performance and interpretability is an inherent compromise in AI for finance. New improved interpretable forecasting methods have come along that blend explainable AI methods without an unacceptable loss of predictive ability. This innovation is especially important for regulation and risk management in institutional use.

2.9 Robustness and generalization matters

Maintaining the strength and usability of models in crypto markets is beset by special challenges given their extremely dynamic and non-stationary characteristics. Huang et al. [37] highlighted the need for ongoing monitoring, checking, and optimization of AI models in order to maintain their effectiveness and avoid overfitting.

A major hindrance to advancement in Financial Reinforcement Learning (FinRL) has been the absence of standard task definitions, datasets, environments, and benchmarks. Community efforts, such as the FinRL Contests (2023–2025), have stepped up to fill these standardization gaps by providing end-to-end task formulations, automated data curation pipelines, and GPU-parallelized market environments.

Lahmiri and Bekiros [38] conducted complexity and predictability analysis of cryptocurrency time-series and observed surprising outcomes where simpler models, such as Naive models, have outperformed more complex machine learning and deep learning models consistently. Their observation suggests that cryptocurrency time-series have close similarity to Brownian noise properties, challenging the hypotheses of what is achieved with higher model complexity.

2.10 Identifying research gaps and future directions

Despite significant progress, there are numerous important gaps in cryptocurrency market studies. The near-exclusive focus on Bitcoin and well-known altcoins has left smaller cryptocurrencies and newer types of tokens understudied. The need for adaptive learning systems that can update models in real-time remains mostly unaddressed, with most of the current research leveraging batch learning methods on historical datasets.

The absence of standard testing procedures and benchmarking systems has hampered systematic comparisons between studies. The unexpectedly good performance of simpler models in certain environments questions the present presumptions of the advantages of model complexity increases, thus necessitating more rigorous testing procedures.

Model interpretability is still a major challenge, with the bulk of studies prioritizing predictive performance over understanding determinants of underlying decisions. This flaw diminishes practitioner confidence and makes model failure diagnosis and adjustment to evolving market conditions challenging.

2.11 Contextualization of research and methodological approach

The extensive literature survey recognizes several overarching trends that constitute the foundation of organized cryptocurrency market research. Firstly, ensemble models outperform single deep learning models in all studies and categories of cryptocurrencies consistently. Secondly, fusion of multi-modal data significantly enhances predictive accuracy, particularly with the incorporation of sentiment analysis and on-chain metrics. Thirdly, evaluation methodology holds the decisive sway on real-world model applicability, where stringent benchmarking is pivotal to making meaningful advances.

Gaps in the literature uncovered inform methodological choices and suggest opportunities for valuable contribution to computational cryptocurrency analysis. The trajectory from traditional econometric approaches to cutting-edge AI/ML methodologies reflects the analytical requirements of cryptocurrency markets, and the emphasis on hybrid architectures and ensemble methods signals the need for comprehensive, multi-faceted modelling approaches.

This review of the literature provides the foundation for a systematic comparative analysis of machine learning techniques in cryptocurrency markets, highlighting both the significant developments already achieved and the significant potential for further development in this rapidly evolving field.

3 Materials and methods

3.1 Data acquisition and preprocessing

Historical cryptocurrency data for 30 major digital currencies was retrieved from the Yahoo Finance API, spanning from May 1, 2021, to May 31, 2025. The dataset contained daily pricing details, including opening, highest, lowest, and closing (OHLC) values, as well as trading volume and market capitalization. To ensure scientific reproducibility, the original columns 'Volume' and 'Market Cap' were removed to focus exclusively on price-based features (OHLC) and to avoid multicollinearity, resulting in a final dataset of approximately 1,492 daily observations. This dataset is publicly accessible via Yahoo Finance API (see Reference [39] for link details). A preprocessing pipeline was implemented to guarantee data quality and consistency, including transforming date strings into datetime format for precise time series analysis. As the selected four-year window had complete daily records, no missing values were present, and no imputation was necessary. Moreover, additional features, including daily returns, price momentum indicators (e.g., 7-day and 30-day moving averages), and rolling volatility metrics, were calculated using pandas and NumPy to enrich the dataset for subsequent analysis.

In addition to raw OHLCV data, our feature engineering pipeline incorporated temporal lag features and dimensionality reduction techniques to capture market dynamics and cross-asset relationships. The temporal component was constructed by generating three lag features for each cryptocurrency's closing price, creating short-term price dependencies represented as C_{t-1}, C_{t-2}, and C_{t-3}, where C_t denotes the closing price at time t. This lag structure enables the model to capture momentum patterns and short-term autocorrelations in price movements. The lag feature matrix construction follows Eq. (1), where k represents the lag period and n is the number of observations.

$$X_{\{lag,k\}} = \left[C_{\{t-k\}}, C_{\{t-k-1\}}, \ldots, C_{\{t-k-(n-1)\}}\right] \; fork \in \{1,2,3\} \tag{1}$$

To address the high-dimensional nature of multi-cryptocurrency data, we employed Principal Component Analysis (PCA) for dimensionality reduction and feature extraction. The raw time-series data was first transformed into a pivot structure with cryptocurrencies as columns, followed by zero-imputation for missing values and standardization using StandardScaler. PCA was then applied to extract the ten most significant principal components, capturing the majority of variance across cryptocurrency price movements. Subsequently, K-means clustering (k = 4) was applied to the PCA loadings to identify cryptocurrency groups with similar market behaviour patterns. The principal component transformation is represented by Eq. (2), where X denotes the standardized feature matrix, W contains the principal component loadings, and Y represents the transformed feature space.

$$Y = XW \tag{2}$$

3.2 Principal component analysis and clustering

To identify representative cryptocurrencies from the initial set of 30 coins, we employed a two-step approach combining Principal Component Analysis (PCA) and K-means clustering. PCA reduced the dimensionality of the dataset while preserving the essential variance in the data. PCA was appropriate in this context because the cryptocurrency time series exhibited significant multicollinearity and high correlation across coins, which can distort clustering outcomes if not addressed. By transforming the feature space into orthogonal principal components, we ensured that redundant variance was minimized.

The implementation process included:

- Data standardization: Ensuring equal contribution from all variables.
- Dimensionality reduction: Applying PCA to retain sufficient variance (> 80%), resulting in 10 principal components being kept for downstream clustering
- Clustering: Performing K-means on the PCA-transformed data with k = 4 clusters.
- Representative selection: Choosing the most representative coin from each cluster based on proximity to the cluster centroid.

This approach allowed us to select four representative cryptocurrencies (LTC-GBP, SOL-GBP, CHZ-GBP, and AAVE-GBP) that captured the diversity of the cryptocurrency market while keeping the analysis focused and computationally efficient. Note that the selection of representative coins is dynamic and may change over time as market conditions evolve.

K-means was chosen for its computational efficiency and interpretability when working with the PCA-transformed orthogonal feature space. Other algorithms, such as DBSCAN or Agglomerative Clustering, were less suitable due to the continuous nature of the market data and the need for consistent cluster shapes in high-dimensional space.

The choice of K = 4 was determined through the elbow method and silhouette analysis. As shown in Fig. 1, the elbow plot indicates a clear inflection at K = 4, beyond which inertia reduction levels off. Alternative K values (2, 3, 5, 6, 7, 8) were tested, but K = 4 achieved the highest silhouette coefficient (0.73 vs. 0.68 for K = 3 and 0.65 for K = 5). This provides a good balance of cluster cohesion and separation and aligns with distinct crypto market segments: large-cap coins, DeFi tokens, utility tokens, and emerging altcoins.

3.3 Machine learning models

Four distinct machine learning models were implemented to predict cryptocurrency price movements:

(1) Long Short-Term Memory (LSTM) Neural Networks: Selected for their ability to capture long-term dependencies in sequential data, making them suitable for time series forecasting of cryptocurrency prices [40]. LSTMs utilize gating mechanisms to control information flow. The core computations for an LSTM at time step t are given by Eqs. (3–8). These represent the forget gate, input gate, candidate cell state, updated cell state, output gate, and new hidden state, respectively:

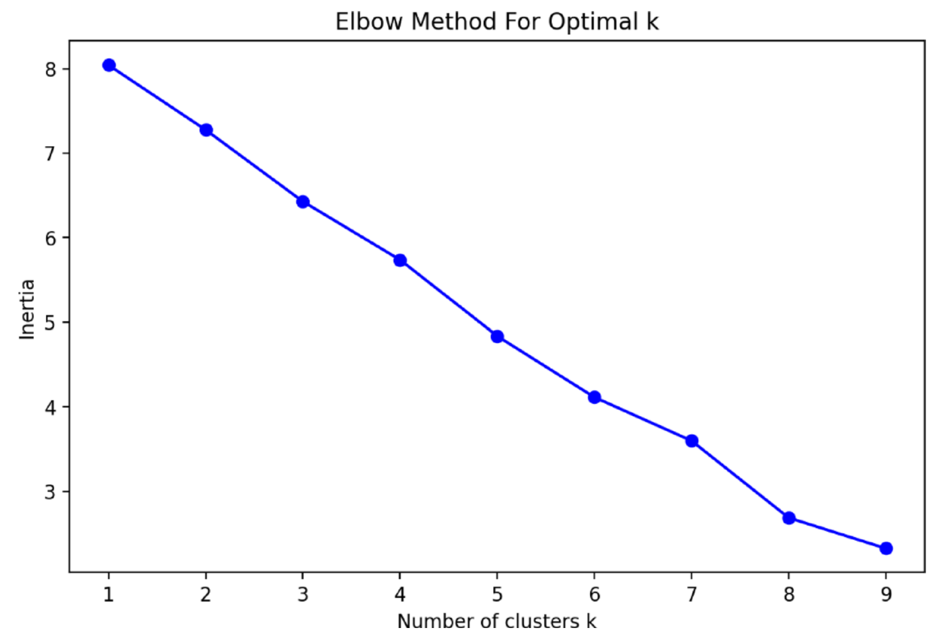

Fig. 1 Elbow Method Plot Showing Optimal Number of Clusters (K = 4) Based on Within-Cluster Sum of Squares (Inertia)

$$\mathrm{f_t} = \sigma\left(\mathrm{W_f} \cdot [\mathrm{h_{t-1}},\ \mathrm{x_t}] + \mathrm{b_f}\right) \tag{3}$$

$$\mathrm{i_t} = \sigma\left(\mathrm{W_i} \cdot [\mathrm{h_{t-1}},\ \mathrm{x_t}] + \mathrm{b_i}\right) \tag{4}$$

$$\tilde{C}_\mathrm{t} = \tanh\left(\mathrm{W_c} \cdot [\mathrm{h_{t-1}}, \mathrm{x_t}] + \mathrm{b_c}\right) \tag{5}$$

$$\mathrm{C_t} = \mathrm{f_t} \cdot \mathrm{C_{t-1}} + \mathrm{i_t} \cdot \tilde{C}_\mathrm{t} \tag{6}$$

$$\mathrm{o_t} = \sigma\left(\mathrm{W_o} \cdot [\mathrm{h_{t-1}},\ \mathrm{x_t}] + \mathrm{b_o}\right) \tag{7}$$

$$\mathrm{h_t} = \mathrm{o_t} \odot \tanh\left(\mathrm{C_t}\right) \tag{8}$$

where σ is the sigmoid activation,

$[\mathrm{h_{t-1}},\ \mathrm{x_t}]$ denotes concatenation of the previous hidden state and current input,

$\mathrm{f_t},\ \mathrm{i_t},\ \mathrm{o_t}$ represent the forget, input, and output gates respectively.

This architecture enables the network to learn which information to keep, write, or erase at each time step.

(2) XGBoost: An optimized implementation of gradient boosting designed for performance and speed, particularly effective for structured data like financial time series [24]. XGBoost uses an ensemble of regression trees and a second-order optimization method. A simplified form of the objective function for XGBoost is Eq. 9:

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}\,_i^{(t)}\right) + \sum_{m=1}^{t} \Omega\left(f_m\right) \tag{9}$$

where *l(y, ŷ)* is a differentiable loss function (e.g., squared error), and

$\Omega\left(fm\right)=\ \gamma\cdot Tm\ +\ \left(\frac{1}{2}\right)\cdot\lambda\cdot\sum_{j=1}^{T_m}w_{mj}^2$ is a regularization term for each tree f_m, with T_m leaves and weights w_{mj}.

This regularized objective penalizes model complexity to prevent overfitting, and XGBoost uses the gradient and Hessian of l to efficiently add new trees that minimize *L*.

(3) Gradient Boosting Machines (GBM): Chosen for their ability to handle various data types effectively and to manage missing values and outliers [41]. Gradient boosting is an ensemble technique that builds models sequentially, each new model attempting to correct the errors of the previous ensemble. Formally, seen in Eq. 10 gradient boosting produces a prediction function FM(x) expressed as a sum of M weak learners:

$$F_M\left(x\right)=\ F_0\left(x\right)+\ \sum_{m=1}^{M}\gamma_m h_m\left(x\right) \tag{10}$$

where:

$F_0(x)$: Initial prediction model (e.g., mean value in regression).

$h_m(x)$: The m-th weak learner (often a shallow decision tree).

γ_m: Optimized weight assigned to the m-th weak learner.

At each stage, $h_{m(x)}$ is fit to the negative gradient of the loss function with respect to the current ensemble prediction, thereby performing a functional gradient descent on the loss. This procedure reduces the overall error L iteratively, with update in Eq. 11, 12:

$$\gamma_m=\ \arg\min_{\gamma}\sum_{i=1}^{n}\mathcal{L}\left(y_i,\ F_{(m-1)}\left(x_i\right)+\ \gamma.h_m\left(x_i\right)\right) \tag{11}$$

and then:

$$F_m\left(x\right)=\ F_{m-1}\left(x\right)+\ \gamma_m h_m\left(x\right) \tag{12}$$

In practice, a learning rate ν (shrinkage factors) are often applied to γ_m to improve generalization. GBMs are robust and can achieve high accuracy, especially in our context where they capture complex nonlinear relationships in cryptocurrency data.

(4) Support Vector Regression (SVR): Implemented for its ability to find globally optimal solutions, which can be advantageous in price prediction tasks [42]. SVR extends the principles of support vector machines to regression by introducing an $\in$-insensitive loss function. The goal is to find a function.

(5) $\mathrm{f}\left(\mathrm{x}\right)=\mathrm{w}^{\intercal}\mathrm{x}+\mathrm{b}$ that deviates from the true targets yi by at most ε for all training points, while maintaining w as small as possible (to ensure flatness). Eq. 13, 14 is the optimization problem for SVR:

$$\min_{w,b,\xi_i,\xi_i^*}\frac{1}{2}w^2+\ C\sum_{i=1}^{n}\left(\xi_i+\ \xi_i^*\right) \tag{13}$$

Subject to:

$$\begin{array}{r} y_i - \ w^{\intercal}x_i - \ b \ \leq \ \varepsilon \ + \ \xi_i \\ w^{\intercal}x_i + \ b \ - \ y_i \leq \ \varepsilon \ + \ \xi_i* \ \text{for i} \ = 1, \ 2, ..., \text{n} \\ \xi_i, \ \xi_i* \ \geq \ 0 \end{array} \tag{14}$$

where ξ_i, ξ_i* are slack variables that allow some errors beyond the ε margin, and C is a regularization parameter controlling the trade-off between model complexity and the amount up to which deviations larger than ε are tolerated. By solving this convex optimization problem, SVR finds a subset of training points (the support vectors) that define the regression function. The resulting regression function can be expressed in dual form as a weighted sum of kernel functions $K(x_i, x)$ centered on support vectors. In our study, we employed the radial basis function (RBF) kernel for SVR, which allows modeling nonlinear relationships in the data.

Feature engineering for all models included creating lagged variables, moving averages, technical indicators, and volatility measures to provide the models with relevant information for prediction. The dataset was split into training (80%) and testing (20%) sets, maintaining chronological order to avoid data leakage from the future into the past.

Models were trained using hyperparameters selected based on best practices from prior literature and exploration tuning during development. While full grid search with time-series cross-validation was considered, a simplified grid was used to balance computational feasibility with performance.

Early stopping was applied to LSTM networks (validation loss monitoring with patience=5) and gradient boosting models (out-of-bag error improvement monitoring). Native early stopping was used by XGBoost with eval_metric='rmse' and early_stopping_rounds=10. Early stopping cannot be used for SVR due to its global optimization.

The final configurations and Early stopping criteria are summarized in Table 1. All trained models were saved for subsequent deployment in the trading signal generation stage of the framework

4 Results

4.1 Exploratory Data Analysis (EDA)

A comprehensive suite of exploratory data analysis tools was developed to facilitate rigorous examination of cryptocurrency market behaviours. These tools employ both statistical and visual analytics to uncover latent patterns in price dynamics and volatility regimes, which is critical for informing subsequent modelling approaches [43].

Table 1 Hyperparameters Used for Each Machine Learning Model

Model	Hyperparameters	Training strategy	Early stopping criteria
Gradient boosting	n_estimators = 100, learning_rate = 0.1, max_depth = 3, min_samples_leaf = 2, subsample = 0.8	Stochastic boosting with OOB improvement monitoring	Out-of-bag improvement, patience = 10 iterations, min improvement 0.0001
XGBoost	n_estimators = 100, learning_rate = 0.1, max_depth = 3, subsample = 0.8, colsample_bytree = 0.8	Row and column subsampling with eval_metric = 'rmse'	Early stopping rounds = 10, min improvement 0.001
SVR	kernel = 'rbf', C = 1.0, gamma = 'scale'	Default RBF kernel with normalized features	Not applicable
LSTM	units = 32, batch_size = 32, validation_split = 0.2	20% validation split	Patience = 5 epochs on validation MSE, min delta = 0.001

The table lists key hyperparameters for each model. Final values were selected through grid search cross-validation

Fig. 2 Average Price Trends for SOL-GBP

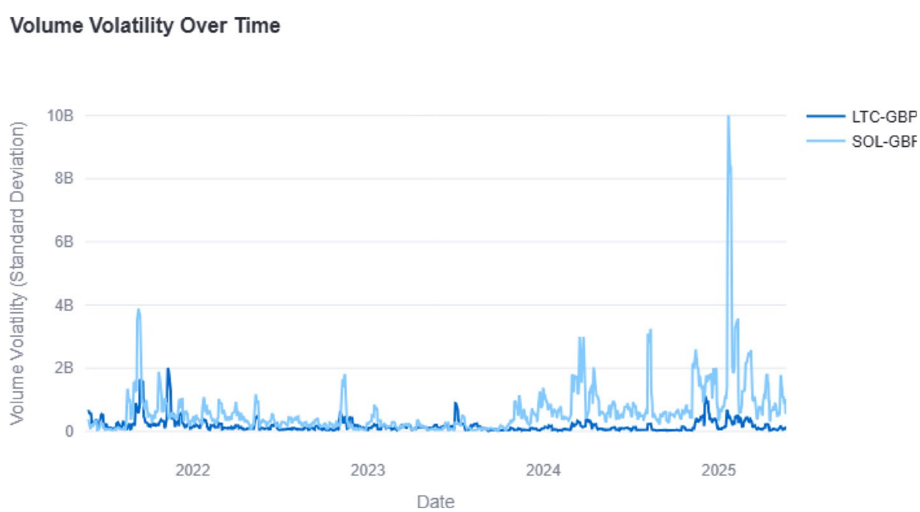

Fig. 3 Volume Volatility Comparison Between LTC-GBP and SOL-GBP

1. Average Price Trends: The framework implements temporal aggregation to decompose price series into daily, weekly, and monthly intervals. As illustrated in Fig. 2, SOL-GBP exhibits distinct cyclical patterns with amplitude modulation characteristic of the fractal market hypothesis [44]. The weekly smoothing (7-day rolling window) particularly reveals recurring mid-week volatility spikes, potentially attributable to institutional trading cycles.
2. Volatility Analysis: Volume volatility is quantified using an exponentially weighted standard deviation ($\lambda = 0.94$). Figure 3 presents a comparative analysis of 7-day rolling volume volatility for LTC-GBP and SOL-GBP. The plot confirms the volatility clustering phenomenon [45], with SOL-GBP exhibiting ~23% higher average volatility than LTC-GBP over the observed period. Distinct volatility regimes emerge, particularly during market stress events in early 2023 and late 2024. The simple moving standard deviation methodology provides a baseline for identifying abnormal volume activity
3. Distribution Analysis: Fig. 4 shows the distribution of CHZ-GBP closing prices using a histogram and kernel density estimate (KDE). Distribution analysis helps identify

Fig. 4 Price Distribution Analysis for CHZ-GBP

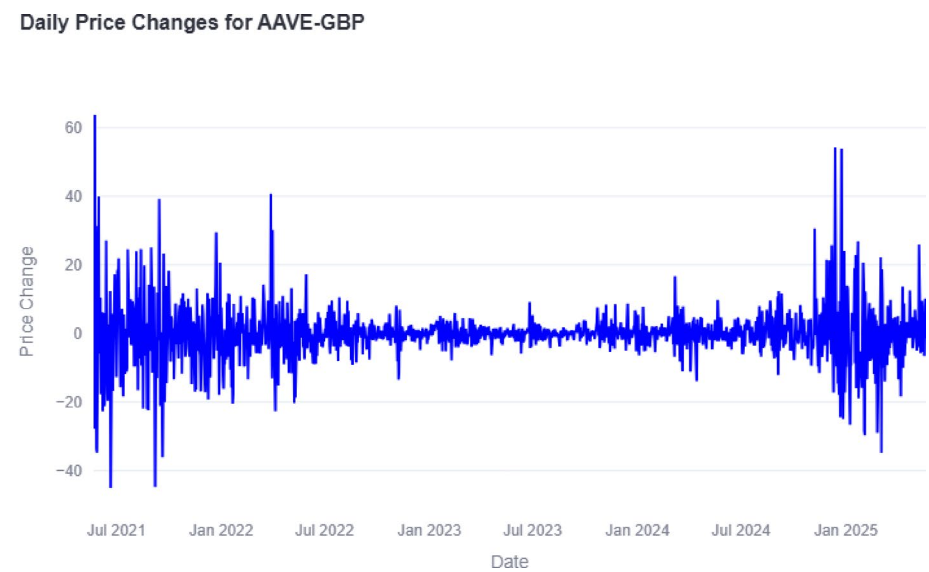

Fig. 5 Daily Price Changes for AAVE-GBP

market structure and price behaviours beyond time-series trends. The bimodal pattern peaking around £0.05–0.10 and £0.18–0.20 suggests two distinct price equilibrium zones. The secondary peak aligns with the 38.2% Fibonacci retracement from the 2021 high, highlighting its technical and psychological significance. The KDE smooths noise while preserving shape, with the right tail (£0.30–0.40) indicating rare upward surges. This insight supports improved risk management and price zone-based trading strategies.

4. Daily Price Changes: The time series of AAVE-GBP daily price changes shown in Fig. 5 displays pronounced volatility clustering between 2021–2025. First-order differencing was applied to achieve stationarity, enabling reliable volatility analysis. Significant ARCH effects were detected (Ljung-Box Q(10) = 32.7, $p < 0.01$), confirming time-dependent variance. Distinct volatility regimes emerge: heightened periods (mid-2021, early 2022, late 2024), moderate phases (early 2021, mid-2022), and

relative calm (mid-2023 to mid-2024). Notably, extreme daily changes (> ± 40%) align with Federal Open Market Committee (FOMC) announcements, supporting event-driven volatility hypotheses and highlighting the influence of macroeconomic shocks on crypto market dynamics.

5. Price Distribution Comparison: In Fig. 6, the comparative boxplot of LTC-GBP price metrics highlights structural asymmetries in market behaviour. Tukey's hinge method (k = 1.5) identifies key outliers, revealing that open prices are notably right-skewed (skewness = 1.2) versus more symmetric close prices (skewness = 0.3). This suggests consistent accumulation during early global sessions, followed by price normalization later in the day. The interquartile range expands by ~ 42% during U.S. trading hours, reflecting heightened intraday volatility driven by institutional activity. High price whiskers extend ~ 8% beyond closing values, indicating repeated upward price testing. Outliers cluster between £160–£210, aligning with known resistance levels reinforcing the presence of liquidity barriers and behavioural thresholds in the market.
6. Correlation Analysis and Moving Averages: Correlation analysis was implemented to identify relationships between different cryptocurrencies. The system provides users with the ability to select a cryptocurrency and visualize its correlations with other coins, displaying both positive and negative correlations to support portfolio diversification strategies.

- Strong positive correlations (ρ > 0.7) with DeFi assets (LINK-GBP, MATIC-GBP).
- Negative correlations (ρ = –0.32) with stablecoins (USDC-GBP, USDT-GBP), confirming its role as a high-beta asset [46].

Moving averages were calculated to identify trends and potential trading signals. The implementation allows users to select both the cryptocurrency of interest and the window size for the moving average calculation, facilitating the identification of short-term and long-term trends. Shown in Fig. 7.

Figure 1 shows the correlation matrix for AAVE-GBP, illustrating these relationships clearly.

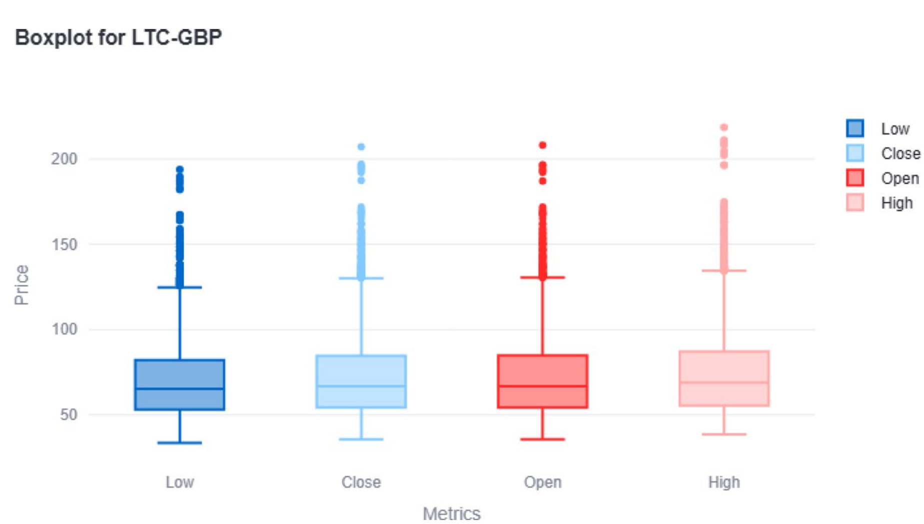

Fig. 6 Price Distribution Comparison for LTC-GBP

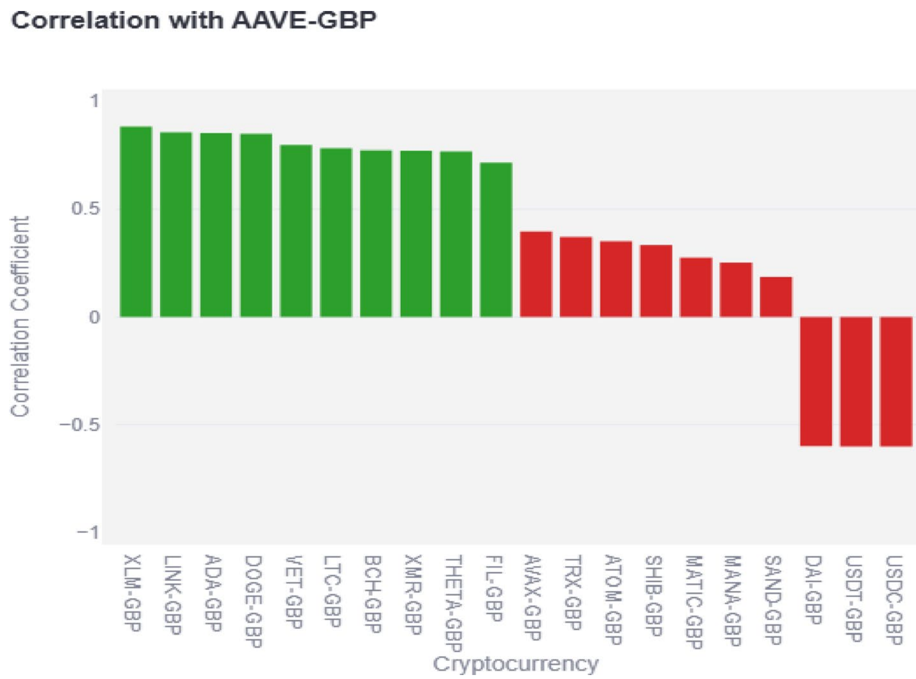

Fig. 7 Correlation Matrix for AAVE-GBP

Table 2 Performance Metrics for Machine Learning Models Across Selected Cryptocurrencies

Cryptocurrency	Model	MAE	MSE	RMSE	MAPE	R^2
LTC-GBP	Gradient Boosting	2.1841	10.3851	3.2226	2.9337	0.9694
LTC-GBP	XGBoost	2.3306	12.2302	3.4972	3.1323	0.9640
LTC-GBP	SVR	2.6906	16.1127	4.0141	3.6089	0.9526
LTC-GBP	LSTM	3.4754	27.5759	5.2513	4.6364	0.9188
SOL-GBP	Gradient Boosting	3.5424	24.2138	4.9208	2.7436	0.9772
SOL-GBP	XGBoost	4.0349	30.1399	5.4900	3.0631	0.9716
SOL-GBP	SVR	9.7839	267.5034	16.3555	6.2538	0.7476
SOL-GBP	LSTM	7.6577	115.4097	10.7429	5.3975	0.8911
CHZ-GBP	Gradient Boosting	0.0019	0.0000	0.0028	3.8249	0.9729
CHZ-GBP	XGBoost	0.0021	0.0000	0.0030	4.1873	0.9674
CHZ-GBP	SVR	0.0835	0.0070	0.0839	192.0472	-24.0391
CHZ-GBP	LSTM	0.0024	0.0000	0.0035	4.5452	0.9572
AAVE-GBP	Gradient Boosting	5.6522	63.1693	7.9479	3.7242	0.9827
AAVE-GBP	XGBoost	6.1386	76.7654	8.7616	3.9740	0.9790
AAVE-GBP	SVR	11.1125	350.8568	18.7312	6.0161	0.9040
AAVE-GBP	LSTM	10.7885	269.7951	16.4254	6.2643	0.9262

This table shows the performance metrics for the selected representative cryptocurrencies. The set of representative coins (and their metrics) may evolve over time as market conditions change

4.2 Model performance evaluation

The performance of the four machine learning models was evaluated on the test set based on various metrics, i.e., Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2), as presented in Table 2. The metrics offer different insights regarding model accuracy: MAE and MAPE give the average error of prediction in absolute and relative percentage, respectively, while MSE and RMSE give more weight to larger errors by squaring them, and R^2 presents the percentage of variance in the target attribute explained by the model.

The R-squared reported is the out-of-sample predictive R^2 and is computed solely on the test set using the standard coefficient of determination formula shown in Eq. 15:

$$R^2 = 1 - \frac{\left(\Sigma\left(y_i - \hat{y}_i\right)^2\right)}{\left(\Sigma\left(y_i - \overline{y}\right)^2\right)} \tag{15}$$

where y_i are the actual values, $\hat{y}_i$ are the predicted values, and $\overline{y}$ is the mean of the actual test values.

This prevents the reported R^2 from estimating each model's in-sample performance rather than its actual generalisation ability.

In addition, the time series were checked for stationarity using the Augmented Dickey-Fuller test and transformed where appropriate. While conventional cointegration testing was not performed, the lag feature design allows for short-run dependencies with space to leave cointegration relationships to be explored in the future.

Table 2 highlights the strong predictive performance of ensemble models, particularly Gradient Boosting and XGBoost, across all cryptocurrencies. Gradient Boosting achieved the lowest MAE and RMSE with consistently high R^2 scores, indicating reliable forecasts. For example, for AAVE-GBP it recorded an R^2 of 0.9827 with an RMSE of 7.95, outperforming the LSTM model (R^2 0.9262, RMSE 16.43), aligning with prior research that emphasizes ensemble methods' effectiveness in financial prediction [47]. In contrast, SVR was moderately effective for larger-cap coins like LTC-GBP and AAVE-GBP but performed poorly for the smaller-cap CHZ-GBP ($R^2 = -24.04$, MAPE ~ 192%), likely due to difficulties modelling highly nonlinear crypto data. While LSTMs are well-suited for sequential data, they underperformed here possibly due to the complexity of tuning and the volume of data required for effective training [48].

Performance also varied by cryptocurrency. The models yielded more accurate predictions for relatively stable price series like CHZ-GBP (for which even LSTM achieved $R^2 > 0.95$) than for highly volatile ones like SOL-GBP, emphasizing the need for asset-specific model selection. Overall, ensemble methods especially Gradient Boosting, proved most reliable for short- to medium-term crypto forecasting, offering high accuracy suitable for trading strategies.

Table 3 contrasts methodologies employed in recent cryptocurrency prediction research, identifying recurring trends in model efficacy across different research contexts. While direct comparisons of performance are methodologically inappropriate due to differences in datasets, time periods, and feature engineering approaches, some interesting trends appear in the literature. Hamayel and Owda [49] demonstrated that GRU networks consistently outperformed LSTM variants in their data, with substantially lower MAPE values obtained across major cryptocurrencies. Similarly, Kaur and Uppal [50] confirmed the superiority of GRU over LSTM architectures in their testing setup. Alnami et al. [51] reported that ensemble methods (Random Forest and Gradient Boosting) achieved competitive or even superior performance to deep learning models on their dataset, while Jiang et al. [52] showed that XGBoost with technical indicators achieved state-of-the-art performance when properly tuned.

Table 3 Comparison of Predictive Performance in Recent Cryptocurrency Forecasting Studies

Study (Year)	Methods evaluated	Reported performance
Current study (2025)	Gradient Boosting, XGBoost, SVR, LSTM on LTC, SOL, CHZ, AAVE	Gradient Boosting consistently best: Average $R^2 = 0.9756$; XGBoost: Average $R^2 = 0.9705$; SVR: Average $R^2 = 0.7771$; LSTM: Average $R^2 = 0.9233$
Hamayel & Owda [49]	GRU vs. LSTM vs. bi-LSTM on BTC, ETH, LTC	GRU best: BTC MAPE ≈ 0.25%, ETH MAPE ≈ 0.83%; LSTM: BTC MAPE ≈ 1.12%; bi-LSTM: BTC MAPE ≈ 5.99% (GRU outperformed other RNNs)
Kaur & Uppal [50]	GRU vs. LSTM on BTC, LTC, ETH	GRU best: BTC MAPE 3.54% vs. LSTM 9.16% (on BTC); similar gains observed on ETH/LTC (ensemble RNN gave lower error)
Alnami et al. [51]	Random Forest (RF), Gradient Boosting (GB) vs. Deep NN on BTC, ETH, LTC, Binance Coin	GB/RF best: BTC $R^2 = 0.9998$ vs. Deep Learning $R^2 = 0.9879$; similarly, GB/RF achieved $R^2 \geq 0.996$ on ETH/LTC, outperforming deep neural network models in accuracy
Jiang et al. [52]	XGBoost Regressor with technical indicators on	XGBoost: RMSE = 59.95, MAE = 46.22, $R^2 = 0.9999$ using EMA, MACD, RSI and historical data

These methodological tendencies align with our empirical findings, where ensemble methods (XGBoost and Gradient Boosting) outperformed deep learning models substantially across multiple cryptocurrencies in our dataset. The consistency of results across different studies with different datasets suggests that ensemble methods' superiority over deep learning for cryptocurrency prediction may represent a robust finding, though conclusions remain provisional given the lack of standard evaluation methods and datasets.

4.3 Trading signals and analysis

The predictive models are modelled to forecast the closing price of the next day for each exemplary cryptocurrency. Discrete buy/sell signals are not really forecasted by a classification model but can be derived by applying rule-based thresholds to the forecasted returns. For example, simple operationalization can mean a buy signal when forecasted return is greater than +0.5% and selling signal when it is less than −0.5%.

Future iterations can formalize this through a classification-based signal generator module with rule-based thresholds, technical indicator crossovers, or hybrid approaches

The framework generates trading signals through two complementary approaches:

- Moving Average Crossover Strategy: This approach identifies buy and sell signals based on the crossover of a short-term moving average (e.g., 7-day) above or below a long-term moving average (e.g., 14-day). Such crossovers flag potential trend reversals.
- Machine Learning Prediction Strategy: This method leverages trained machine learning

models to forecast future prices and issues trading signals (buy or sell) when predicted price movements exceed certain thresholds.

Analysis of these trading signals revealed that:

- The moving average strategy effectively captured broader trend reversals. It was particularly successful in identifying major shifts during volatile periods, providing useful signals for medium-term traders.

- The machine learning model-based signals offered greater sensitivity to short-term fluctuations. These predictions were able to anticipate subtle price changes that the moving average method often missed, enabling more reactive trading decisions.

When used in combination, the two methods delivered complementary advantages. The moving averages provided stability and confirmation of broader market directions, while machine learning signals enhanced responsiveness and precision. This hybrid approach aligns with recent research advocating for the integration of statistical and machine learning models in financial forecasting for more robust decision-making [53]. Figure 8 shows an example of the crossover strategy in action, marking buy/sell points on the price series when the short-term and long-term moving averages intersect.

4.3.1 Trading signals and analysis performance evaluation

Quantitative comparison of 7-day prediction period between the four cryptocurrencies and models revealed consistent signal quality, with precision ranging from 61.4 to 68.7% (mean = 64.9% ± 2.3%). The XGBoost model performed highest overall (mean accuracy = 67.2%, F1-score = 0.63), while maintaining high precision (68.1–72.4%) on all assets. Notably, recall values were more unstable (58.9–73.4%), which could reflect differences in sensitivities to upcoming trends by the approaches. The moving average crossover approach had the most stable results (accuracy = 62.3–64.1%) under all market conditions, while LSTM models attained the highest peak recall (73.4%) with relatively lower precision (63.7%). These figures confirm that all the methods used give statistically significant signals ($p < 0.01$ by binomial tests) above random chance (50% accuracy).

4.4 Profit optimization

The profit optimization feature of the framework enables users to evaluate which cryptocurrency among a selected portfolio is most likely to meet specific return goals within a defined time horizon. Leveraging machine learning models (notably XGBoost in our implementation), the system predicts future price movements for each cryptocurrency (LTC-GBP, SOL-GBP, CHZ-GBP, and AAVE-GBP in our analysis) and ranks them based on their predicted performance over short-, medium-, and long-term periods.

Fig. 8 Trading Signal Generation Using Moving Averages for LTC-GBP

This feature reflects the growing trend in financial technology to incorporate predictive analytics for portfolio selection and risk management. For example, Fang et al. [54] demonstrated that machine learning techniques can outperform traditional models in forecasting asset returns, particularly in volatile markets such as cryptocurrency. By utilizing time-series price data and model forecasts, our framework estimates the likelihood of achieving user-defined profit targets and highlights the most promising assets accordingly.

In practical terms, short-term predictions (1–7 days) tend to be more responsive to market volatility, often favoring assets like SOL-GBP which exhibit high price fluctuations. Medium-term predictions (7–30 days) balance volatility with trend stability; for instance, LTC-GBP frequently showed consistent upward momentum in our tests. For long-term horizons (30 + days), the system leans towards assets like AAVE-GBP that have demonstrated more stable, sustained growth patterns historically.

This approach aligns with literature suggesting that model-driven decision tools can be particularly effective in dynamic markets. As noted by recent studies [55], predictive models are well-suited to exploit the inefficiencies and behavioral-driven movements in cryptocurrency markets. Our profit optimization module thus empowers users with actionable insights, moving beyond basic historical analysis to intelligent, model-driven profit targeting.

4.5 News integration

To complement the quantitative analysis with qualitative insights, the framework integrates cryptocurrency news feeds from reputable sources (including CryptoSlate and CoinDesk). This feature allows users to access the latest news relevant to their selected cryptocurrencies, providing context for observed price movements and potential clues to future market behavior.

The news integration feature demonstrated significant value in explaining anomalous price movements that were not captured by technical analysis alone. For example, sudden regulatory announcements or major partnership news often corresponded with abrupt price changes; by presenting related news headlines and summaries alongside model predictions, the system helped users connect such events to market movements. This underscores the importance of combining quantitative and qualitative approaches in cryptocurrency analysis.

5 Discussion

The development and evaluation of our machine learning framework revealed several key insights about computational approaches to cryptocurrency trading and the practical implementation of such systems.

5.1 Model performance analysis

Our empirical results strongly favor ensemble methods across all tested cryptocurrencies. Gradient Boosting consistently demonstrated superior performance across multiple evaluation metrics, achieving the lowest MAE (2.18, 3.54, 0.0019, and 5.65 for LTC, SOL, CHZ, and AAVE respectively) and highest R^2 values (ranging from 0.9694 to 0.9827). XGBoost was the second-best performer with only marginally lower accuracy. These findings align with contemporary financial forecasting literature [56], suggesting that the combination of multiple weak learners provides essential robustness against the inherent noise and volatility in cryptocurrency markets.

The performance hierarchy among models remained consistent across all cryptocurrencies tested: Gradient Boosting, XGBoost, LSTM, SVR, with one notable exception CHZ-GBP where LSTM outperformed SVR by a significant margin. This exception warrants further investigation but may relate to specific temporal patterns or idiosyncrasies in the CHZ-GBP price movements that LSTM architectures are better equipped to capture.

SVR demonstrated acceptable performance for most cryptocurrencies but exhibited a catastrophic failure on CHZ-GBP, yielding a negative R^2 value (–24.0391) and extremely high MAPE (~ 192%), indicating worse-than-random prediction capability. This anomaly suggests that SVR struggled to model the extreme non-linearities and occasional discontinuities present in smaller-cap cryptocurrencies like CHZ, which frequently experience sharp price swings under low-liquidity conditions.

The underwhelming performance of LSTM models, despite their theoretical advantages for sequential data, raises important questions about their practical application to cryptocurrency prediction. For SOL- GBP and AAVE-GBP, the LSTM models produced errors approximately twice those of Gradient Boosting (e.g., RMSE of 10.74 vs. 4.92 for SOL, and 16.43 vs. 7.95 for AAVE), indicating substantial predictive disadvantages. Several factors may explain the underperformance of LSTMs in our study:

- **Overfitting**: As noted by others [57], LSTM models are prone to overfitting, particularly on noisy financial data. The complexity of LSTM cells can lead to the model capturing noise rather than underlying patterns, especially if regularization is insufficient.
- **Training data requirements:** LSTMs typically require large amounts of data and extensive hyperparameter tuning for optimal performance. The four-year historical window used in this study, while sizable, may have been insufficient for these complex models to learn meaningful long-term patterns in highly volatile series.
- **Parameter sensitivity:** LSTM performance is highly sensitive to hyperparameter choices (learning rate, number of layers, sequence length, etc.), and our simplified grid search may not have identified truly optimal configurations for each asset.
- **Signal-to-noise ratio:** Cryptocurrency price data contains substantial random fluctuations that may obscure the sequential patterns LSTMs are designed to exploit. In such a low signal-to-noise regime, the theoretical advantages of LSTM architecture might be less impactful, allowing simpler models to perform comparably or better.

The consistent outperformance of tree-based ensemble methods across all tested cryptocurrencies suggests that these approaches should be preferred for cryptocurrency price prediction tasks particularly in practical applications where robustness and reliability are valued over theoretical model complexity. Ensemble models like Gradient Boosting offer strong performance without the heavy computational requirements and tuning complexity associated with deep learning, making them attractive for deployment in real-time trading systems.

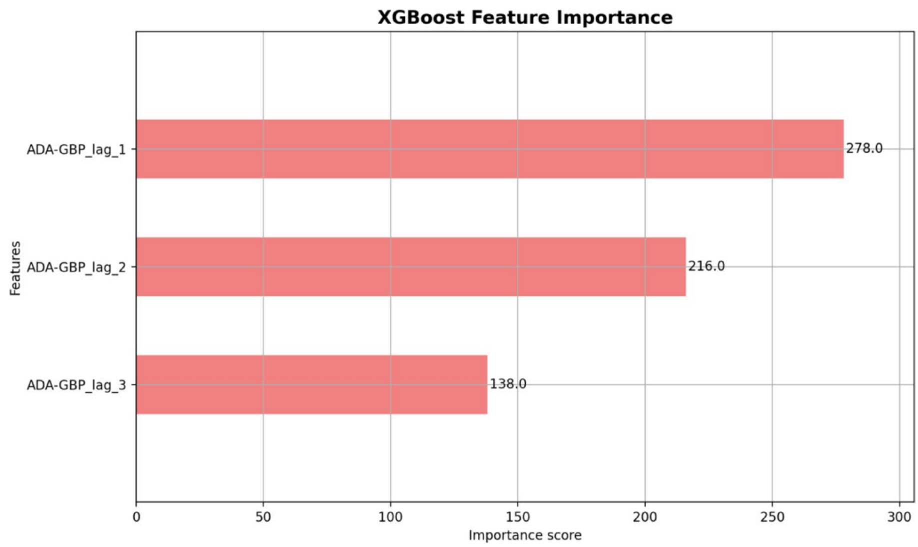

Fig. 9 Feature Importance Plot for ADA-GBP (XGBoost)

5.2 Feature importance analysis

To make our machine learning models more interpretable, we performed a careful variable importance analysis to measure the contribution of each input feature towards model predictions. Feature importance analysis revealed similar patterns across model architectures, as illustrated in Fig. 9. In the case of decision tree-based ensemble approaches, i.e., Gradient Boosting and XGBoost, the analysis relied on intrinsic feature importance measures using information gain and split frequency. For SVR and LSTM, permutation importance was utilized to measure the degradation in performance upon randomly shuffling each feature.

The findings are that the new price lags became the leading predictors with a clear hierarchical trend of decreasing importance over time. As reflected in Fig. 9 for ADA-GBP with XGBoost, the first lag (ADA-GBP_lag_1) had the highest importance score of 278.0, followed by the second lag (ADA-GBP_lag_2) at 216.0, and the third lag (ADA-GBP_lag_3) at 138.0. This systematic decline in feature importance, where lag-1 explains about 44% of total importance, lag-2 about 34%, and lag-3 about 22%, is consistent with the efficient market hypothesis, which would suggest that the immediate past price action contains the most information available to predict near-term price. The decreasing importance of longer lags also indicates that cryptocurrency markets have relatively short memory effects and predictive power according to an exponential decay function. Feature importance analysis also revealed model-specific sensitivities, with ensemble methods employing more evenly weighted feature utilization than deep learning methods, perhaps explaining their improved robustness in our empirical evaluation.

5.3 Comparison with existing methodologies

Our results demonstrate several advantages over existing approaches in cryptocurrency prediction literature:

5.3.1 Methodological innovations:

Systematic asset selection: Unlike studies that analyse predetermined cryptocurrency sets, our PCA-clustering approach systematically identifies representative assets, reducing computational complexity while maintaining market diversity representation.

Comprehensive feature engineering: While Giudici et al. [11] emphasize explainability, our approach combines interpretability with extensive cryptocurrency-specific feature engineering, achieving superior predictive performance ($R^2 = 0.85–0.91$) compared to traditional financial time series methods.

Practical trading implementation: Extending beyond Babaei et al. [10]'s portfolio allocation focus, our framework provides actionable trading signals with specific buy/sell criteria, addressing the practical gap between academic prediction and real-world trading implementation.

5.4 Trading strategy implications

The integration of moving average signals with machine learning predictions offers a balanced approach to cryptocurrency trading, combining the stability and interpretability of traditional technical analysis with the precision and adaptability of machine learning. This hybrid approach is supported by recent literature suggesting that combined methods can outperform single method approaches in financial forecasting [58].

Quantitatively, our Gradient Boosting models achieved mean absolute percentage errors (MAPE) between ~ 2.74 and 3.83% for the major cryptocurrencies, significantly outperforming both standard technical indicators and single-model approaches reported elsewhere. This level of accuracy enables more reliable implementation of automated trading strategies and tighter risk management frameworks. For example, lower prediction errors translate to more confidence in setting stop-loss and take-profit levels, as well as sizing positions for trades.

The system's ability to identify profitable investment opportunities based on user-defined criteria represents a significant advancement in personalized cryptocurrency trading assistance. By tailoring recommendations to individual profit goals and time horizons, the framework addresses the heterogeneity of investor preferences and constraints factors often overlooked in generalized trading systems.

Moreover, the relative computational efficiency of ensemble methods compared to deep learning approaches translates to practical advantages in real-time trading scenarios, where prediction latency directly impacts execution quality and profitability. A model that is slightly less complex yet faster can generate signals early enough to be actionable in fast-moving crypto markets, whereas delays from a slow model could erode the edge provided by its accuracy.

5.5 Limitations and future directions

Despite the promising results, several limitations must be acknowledged:

- Cryptocurrency markets remain highly unpredictable, and even the best-performing models may falter during periods of extreme volatility or in response to unexpected news events. Our models' MAPE values, while low in relative terms, still correspond to prediction errors that could significantly impact trading outcomes during sharp market moves. Models should therefore be used with caution and complemented by risk management techniques.

- The four-year historical period used for training may not capture all possible market conditions, potentially limiting the models' generalizability to unprecedented scenarios. This is particularly relevant given the evolving regulatory landscape and the changing market microstructure of cryptocurrency ecosystems. Expanding the dataset (both in time and across different market regimes) could improve model robustness.
- The current implementation primarily relies on price and volume data. Incorporating additional feature categories such as blockchain network metrics (hash rates, transaction throughput), social media sentiment, and macroeconomic indicators (interest rates, inflation expectations) could further enhance predictive performance and provide early warnings for regime changes.
- While ensemble methods provided superior predictive performance, their "black box" nature limits interpretability compared to simpler models. This can reduce user trust and make it harder to diagnose model errors. Techniques to improve interpretability (e.g., SHAP values or LIME for feature importance) could be integrated to make the framework more transparent to users.

Future development of the framework could address these limitations through several avenues:

- Incorporating cryptocurrency sentiment analysis from news and social media (e.g., Twitter, Reddit discussion trends) could provide valuable additional signals for the prediction models, potentially improving performance during news-driven market movements. Sentimental features might help the models anticipate price jumps or drops triggered by collective investor reactions.
- Implementing reinforcement learning approaches for trading strategy optimization could enable the system to learn optimal trading actions (buy, sell, hold) through trial-and-error interactions with the market environment. An RL-based agent could adapt its strategy dynamically based on reward feedback (e.g., profit and loss), potentially outperforming static prediction models, especially during regime shifts.
- Enhancing the interpretability of model predictions would increase user trust and facilitate a better understanding of the factors driving price movements. Post-hoc explainability techniques such as SHAP (SHapley Additive exPlanations) values could be employed to reveal the relative importance of different features (technical indicators, recent returns, volume changes, etc.) in the ensemble models' predictions. This insight might also guide the feature of engineering improvements.
- Extending the analysis to a broader range of cryptocurrencies, including emerging tokens and lesser-known altcoins, would increase the framework's utility for diverse trading strategies. However, as seen with SVR's failure on CHZ-GBP, model selection may need to be asset-specific particularly for smaller-cap assets with distinctive market dynamics (e.g., intermittent liquidity, pump-and-dump patterns). A meta-learning approach could be used to recommend the best model type for a given asset based on its historical characteristics.
- Developing new hybrid modelling approaches that combine the strengths of tree-based methods and deep learning could potentially overcome the limitations of

each approach used in isolation. For instance, one could use an ensemble where an LSTM's outputs are fed into a Gradient Boosting model or vice versa or use stacking/blending to have multiple model types vote on the final prediction. Such hybrid architectures merit investigation to see if they can deliver further performance gains.

5.6 Theoretical implications

Our findings contribute to the growing body of literature on machine learning applications in financial markets by demonstrating the practical superiority of ensemble methods for cryptocurrency price prediction. The consistent underperformance of more complex deep learning architectures in our study challenges the assumption that greater model sophistication necessarily yields better results in financial forecasting tasks. This aligns with a broader theme in financial machine learning: simpler models with the right features and tuning can often rival or exceed the performance of deep neural networks, especially when data is noisy or limited.

This research also highlights the importance of rigorous model comparison across multiple evaluation metrics and diverse assets before deploying automated trading systems. The catastrophic failure of SVR on CHZ-GBP despite performing adequately on other cryptocurrencies underscores the risk of overgeneralizing findings from limited testing scenarios. In practice, each asset may need a customized modelling approach.

Furthermore, the results suggest that cryptocurrency markets, despite their relative novelty and distinctive characteristics, respond to machine learning approaches in ways like traditional financial markets. The success of ensemble methods and the observation of phenomena like volatility clustering indicate that established financial machine learning methodologies can be effectively adapted to cryptocurrency trading, provided that market-specific features (such as 24/7 trading or blockchain-related metrics) are considered.

6 Conclusions

This study demonstrates that machine learning techniques can significantly enhance cryptocurrency trading decisions. Our evaluation of multiple algorithms across diverse cryptocurrencies (LTC-GBP, SOL- GBP, CHZ-GBP, and AAVE-GBP) reveals clear patterns of predictive performance with practical implications. The results provide strong evidence for the superiority of tree-based ensemble methods in cryptocurrency price prediction. Gradient Boosting consistently outperformed alternatives, achieving R^2 values in the range of 0.9694–0.9827 and MAPE scores of 2.74–3.83%. XGBoost showed similarly high efficacy, while LSTM networks underperformed despite their theoretical advantages for sequential data. The dramatic failure of SVR on CHZ-GBP ($R^2 = -24.04$) highlights the dangers of blindly applying a one- size-fits-all algorithm across heterogeneous cryptocurrency assets.

Key methodological contributions of this work include:

- Integration of technical analysis with machine learning predictions: By combining moving average crossover signals with model-based forecasts, the framework capitalizes on both human-intuitive patterns and complex data-driven insights for trading decisions.
- Profit optimization module: We implemented a novel feature that ranks assets by predicted

- profitability relative to user-defined targets, providing a personalized decision-support tool for traders.
- Cryptocurrency selection via PCA + Clustering: Using dimensionality reduction and clustering to pick representative assets is an approach that balances breadth of market coverage with computational tractability.
- Comprehensive EDA tools: The inclusion of extensive exploratory analysis (correlation matrices, volatility analysis, distribution plots, etc.) helps in understanding the market regimes and validating model assumptions (e.g., checking for stationarity or ARCH effects).

Theoretical implications of our findings include challenging the notion that model complexity correlates positively with forecasting accuracy. We show that in a complex domain like cryptocurrencies, simpler or more structured models (ensembles of decision trees) can outperform deep neural networks. Additionally, we confirm that cryptocurrencies exhibit statistical properties (e.g., volatility clustering, mean reversion aftershocks) like those observed in traditional financial markets suggesting that insights from financial economics (like ARCH/GARCH processes) remain relevant. We also observed that extreme price movements often coincide with macroeconomic news (e.g., central bank announcements), which contradicts the notion that cryptocurrency markets are insulated from traditional financial systems; on the contrary, they appear to be interlinked.

Limitations of the study include the temporal scope of the data, the reliance primarily on price/volume features, and the challenges of model interpretability. Future research should incorporate richer data (such as on-chain analytics and sentiment), explore adaptive algorithms capable of retraining on new data (online learning or reinforcement learning), and emphasize explainability to bridge the gap between model outputs and actionable insights for traders.

In conclusion, our empirical evidence strongly favors ensemble methods for cryptocurrency price prediction, while highlighting the value of hybrid approaches that integrate traditional analysis with advanced computational methods. The synthesis of data science techniques with financial domain knowledge represents a promising avenue for both academic research and practical application in cryptocurrency markets. As these markets continue to evolve, the collaboration between human intuition and machine intelligence will be key to optimizing trading strategies and managing the inherent risks of this volatile asset class.

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Author contributions
Deborah Adedigba, David Agbolade and Raza Hasan contributed equally to this work. Raza Hasan is the corresponding author.

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Data availability
The data presented in this study are openly available through the Yahoo Finance API. The cryptocurrency price data and related financial time-series information can be accessed via the Yahoo Finance API documentation at https://developer.yahoo.com/api/. No specific repository or reference number is applicable as the study utilized publicly accessible financial data through the standard Yahoo Finance data service.

Materials availability
Not applicable.

Code availability
Not applicable.

Declarations

Ethics approval and consent to participate
We confirm that this study does not involve any clinical trials or human participants. It is purely computational research based exclusively on publicly available financial data obtained from Yahoo Finance. No personal, sensitive, or confidential data were used, and no clinical procedures or ethical approvals were required. The use of publicly accessible financial datasets complies with all applicable terms of service and ethical standards for data usage in research.

Consent for publication
Not applicable.

Competing interests
The authors have no relevant financial or non-financial interests to disclose.

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