

# High-Frequency Volatility Prediction in Cryptocurrency Markets Using Machine Learning

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## Abstract

Cryptocurrency markets operate continuously and exhibit extreme short-horizon volatility, yet evidence for reliable directional return predictability remains limited at high frequencies. In this paper, we study minute-level price dynamics in major cryptocurrency markets and argue that volatility magnitude, rather than return direction, is the more appropriate object of prediction at ultra-short horizons.

Using high-frequency data for Bitcoin, Ethereum, Solana, and Dogecoin, we document strong volatility clustering and persistent dependence in absolute returns. We construct a set of microstructure-inspired features and apply both linear and nonlinear machine learning models to predict the absolute value of one-minute-ahead returns. While classification models fail to deliver meaningful out-of-sample directional performance, regression models achieve stable and economically meaningful explanatory power for future volatility, with out-of-sample  $R^2$  values ranging from approximately 0.17 to 0.27 across assets.

Our results indicate that short-horizon volatility in cryptocurrency markets behaves as a persistent latent state that can be learned by machine learning models, even when price direction remains largely unpredictable. These findings have implications for risk management, execution, and market-making applications, and suggest that machine learning is best deployed in high-frequency crypto markets as a tool for state estimation rather than directional forecasting.

## 1. Introduction

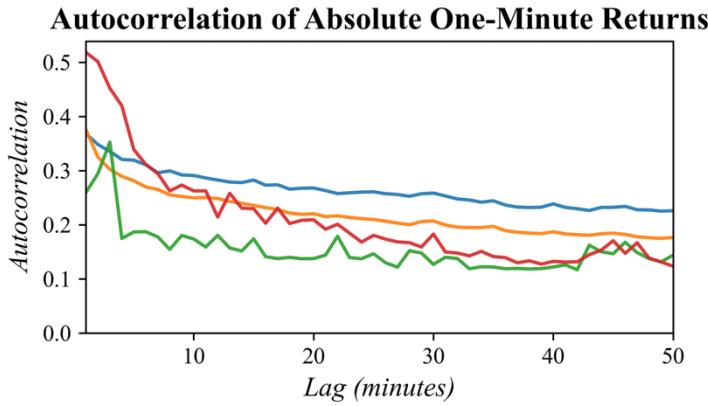
Cryptocurrency markets have grown rapidly in both liquidity and participation, becoming an important testing ground for theories of market efficiency and high-frequency price formation. Unlike traditional equity or futures markets, crypto markets operate continuously, are dominated by heterogeneous participants, and exhibit pronounced volatility at intraday horizons. These features raise a natural question: *to what extent do high-frequency crypto prices exhibit exploitable structure, and what form does that structure take?*

A large body of empirical evidence suggests that at very short horizons, financial returns are difficult to predict directionally. In mature markets, one-minute returns are often indistinguishable from noise once transaction costs and microstructure effects are considered. Crypto markets, however, differ along several dimensions — including market fragmentation, retail participation, and episodic liquidity shocks — which may introduce deviations from classical notions of short-run efficiency.

Motivated by these considerations, much recent research has focused on detecting short-horizon predictability in cryptocurrency returns using increasingly sophisticated statistical and machine learning methods. While some studies report limited directional predictability, such findings are often fragile, regime-dependent, or fail to persist out of sample. This raises the possibility that the fundamental object of predictability at high frequency is not return direction but rather return magnitude.

In this paper, we investigate high-frequency predictability in cryptocurrency markets through the lens of volatility rather than directional returns. Specifically, we study whether one-minute-ahead absolute returns — a proxy for short-horizon volatility — exhibit stable, learnable structure across major crypto assets. This perspective aligns with a long tradition in financial econometrics, which emphasizes volatility clustering and persistence as central features of asset returns, even when mean returns remain unpredictable.

*Fig 1*



*Figure 1 illustrates this distinction by showing strong and persistent autocorrelation in absolute one-minute returns across all four cryptocurrencies, despite the absence of comparable structure in raw returns.*

Using minute-level data for Bitcoin, Ethereum, Solana, and Dogecoin, we conduct a systematic empirical analysis combining classical diagnostics from market microstructure with modern machine learning techniques. We begin by documenting the distributional properties and autocorrelation structure of high-frequency returns, highlighting the near absence of directional autocorrelation alongside strong persistence in absolute returns. We then construct a set of microstructure-inspired features capturing recent volatility, order-flow proxies, and short-horizon return dynamics.

To evaluate predictive content, we compare two modeling approaches. First, we train standard classification models to predict the sign of one-minute returns. Second, we train regression models to predict one-minute-ahead absolute returns. While directional classifiers consistently perform at or near chance levels out of sample, volatility regression models achieve meaningful and stable explanatory power across assets.

Our findings suggest that, at the one-minute horizon, cryptocurrency markets are better characterized as exhibiting state predictability without directional predictability. Machine learning models are able to learn latent volatility states that persist across time, even though price direction remains largely unpredictable. This distinction has important implications for both market microstructure research and practical trading applications, particularly in the context of risk management, execution, and volatility-sensitive strategies.

The remainder of the paper is organized as follows. Section 2 describes the data and preprocessing steps. Section 3 presents diagnostic evidence on return and volatility dynamics. Section 4 introduces the feature construction and machine learning methodology. Section 5 reports empirical results, and Section 6 concludes with implications and directions for future research.

## 2. Related Work

This paper sits at the intersection of (i) high-frequency market microstructure in crypto, (ii) return predictability and the efficient markets view at short horizons, and (iii) machine learning approaches to forecasting financial time series. We review each strand and clarify how our contribution differs.

## 2.1 High-frequency behavior and microstructure in cryptocurrency markets

Early empirical work on cryptocurrency markets documents that intraday trading is characterized by time-varying liquidity, episodic volatility bursts, and heterogeneous participation across venues. Compared with mature equity and futures markets, crypto exhibits distinctive institutional features — continuous trading, fragmentation across exchanges, and a participant base with a larger retail component — which can amplify microstructure effects at short horizons. A consistent finding in this literature is that crypto returns exhibit heavy tails and strong volatility clustering, motivating models that focus on conditional heteroskedasticity and regime changes rather than predictable mean returns.

A related stream studies whether microstructure-like signals commonly used in traditional markets (e.g., volume imbalances, volatility proxies, short-run reversal/momentum patterns) retain explanatory power in crypto. Evidence is mixed: some patterns are detectable in-sample but weaken out-of-sample, while others depend sharply on the asset, period, and liquidity regime. This motivates a disciplined evaluation design that emphasizes temporal splits, simple baselines, and robustness checks.

## 2.2 Short-horizon predictability and the “no free lunch” constraint

A broad literature in financial economics emphasizes that, at sufficiently short horizons, directional return prediction is difficult and often economically insignificant once transaction costs, slippage, and microstructure noise are considered. Even when weak serial dependence exists, it may reflect bid–ask bounce, discreteness, or inventory-latency effects rather than exploitable alpha. For this reason, many studies treat near-zero autocorrelation of returns as a hallmark of short-run efficiency.

In contrast, a robust and widely documented stylized fact is that return magnitudes are predictable even when return directions are not. Absolute and squared returns display persistence across time, consistent with volatility clustering. This motivates targets that focus on conditional variance or volatility state rather than the conditional mean. Our design follows this principle: we evaluate sign prediction as a benchmark but center the empirical contribution on forecasting one-minute-ahead absolute returns as a proxy for short-horizon volatility.

## 2.3 Machine learning for financial forecasting

Machine learning has been widely applied to financial prediction problems, including equity return forecasting, volatility modeling, and order flow prediction. In many cases, the primary challenge is not model capacity but information content: high-frequency returns are noisy, non-stationary, and regime-dependent, so performance gains often come from feature design, target selection, and careful backtesting methodology rather than complex architectures.

Within crypto, ML-based studies span from tree models and linear baselines to deep learning approaches such as LSTMs and Transformers. While deep models can capture nonlinearities and interactions, they are also prone to overfitting when the predictive structure is weak or unstable. Consequently, recent best practice emphasizes strong baselines, explicit temporal train/validation/test splits, and reporting metrics aligned with the task (e.g., AUC for directional classification; RMSE/MAE/R<sup>2</sup> for volatility regression). Our empirical workflow adopts this approach: we begin with interpretable linear and tree-based baselines, quantify out-of-sample performance, and treat model complexity as secondary to signal robustness.

## 2.4 Positioning and contribution

Relative to prior work, this paper contributes an end-to-end high-frequency pipeline that (i) reproduces the standard result of near-chance directional predictability at the one-minute horizon across major crypto assets,

and (ii) shows that reframing the problem as volatility forecasting yields materially stronger and more stable out-of-sample performance. The core message is not that crypto prices are broadly predictable, but that high-frequency crypto markets exhibit state predictability: volatility regimes and return magnitudes contain learnable structure even when return direction does not.

The rest of the paper operationalizes this idea through transparent target construction, microstructure-inspired features, and baseline machine learning models evaluated under time-ordered splits.

### 3. Methodology

#### 3.0 Computational Environment and Implementation

All data processing, feature construction, and empirical analysis are implemented in Python (version 3.12). I use the pandas and NumPy libraries for data manipulation and numerical computation, and scikit-learn for all machine learning models, including logistic regression, ridge regression, and random forest models. Statistical diagnostics, including autocorrelation analysis, are conducted using the statsmodels library. All figures are generated using matplotlib.

All experiments are developed and executed using Visual Studio Code on macOS. Computations are performed on a MacBook Pro (base model) equipped with an Apple M3 system-on-a-chip. All models are trained using CPU-based computation on a single machine. No GPU acceleration or external computing infrastructure is used.

#### 3.1 Data

This study employs high-frequency cryptocurrency market data at the one-minute resolution for Bitcoin (BTC), Ethereum (ETH), Solana (SOL), and Dogecoin (DOGE). The raw data are obtained from the OKX cryptocurrency exchange, one of the largest global digital asset trading venues by volume. For each asset, the dataset consists of open, high, low, close, and traded volume observations sampled on a uniform minute grid.

The sample spans multiple years for each asset and covers a broad range of market conditions, including periods of relative stability, elevated volatility, and speculative episodes. Using exchange-level data allows us to study microstructure dynamics at a granularity that is not accessible through aggregated index data or daily price series.

All timestamps are aligned chronologically, and observations containing missing values or irregular intervals are removed. To avoid look-ahead bias, all variables are constructed exclusively from information available at or before time  $t$ . The cleaned datasets are stored in a columnar format to ensure reproducibility, computational efficiency, and consistency across assets.

#### 3.2 Target Definitions

A central design choice in this study is the explicit separation between directional price prediction and volatility (magnitude) prediction. While much of the literature focuses on predicting the sign of future returns, such targets conflate directional alpha with noise-dominated price fluctuations at high frequencies. We therefore define three distinct target variables at the one-minute horizon, each capturing a different aspect of short-term market behavior.

*Directional return (classification target)*

The first target corresponds to the direction of the next-minute return and is defined as a binary classification problem:

$$y_{t+1}^{\text{dir}} = 1\{r_{t+1} > 0\},$$

where the one-minute return is given by

$$r_{t+1} = \frac{P_{t+1}}{P_t} - 1,$$

and  $P_t$  denotes the closing price at time  $t$ . This target directly reflects the traditional notion of alpha generation: the ability to correctly predict whether prices will increase or decrease over the next interval. However, at very short horizons, such directional signals are known to be weak and easily dominated by microstructure noise and transaction costs.

#### *Absolute forward return (volatility magnitude target)*

To isolate information related to return magnitude rather than direction, we define the absolute forward return as

$$y_{t+1}^{\text{abs}} = |r_{t+1}|.$$

This target captures the size of upcoming price movements irrespective of their sign and serves as a proxy for short-term volatility. Predictability in this target does not imply directional forecasting ability but instead reflects the model's capacity to identify periods of heightened or subdued market activity. Such information is particularly relevant for volatility-sensitive applications, including risk management, position sizing, and execution strategies.

#### *Squared forward return (variance proxy)*

Finally, we consider the squared forward return,

$$y_{t+1}^{\text{sq}} = r_{t+1}^2,$$

which provides a conventional variance-based measure of return dispersion. This target is closely related to realized volatility and emphasizes the contribution of extreme price movements. Squared returns are commonly used in econometric models of conditional heteroskedasticity and allow for direct comparison with established volatility modeling approaches.

Together, these target definitions enable a structured investigation into whether machine learning models extract predictive information about return direction, return magnitude, or market state, and whether these dimensions exhibit fundamentally different levels of predictability at the one-minute horizon.

### 3.3 Feature Engineering

The feature set is designed to extract short-horizon market structure from high-frequency price and volume data while avoiding any use of contemporaneous or forward-looking information. All features are constructed exclusively from lagged values and rolling windows. The objective is not to exhaustively engineer signals, but to expose a diverse set of economically interpretable variables that reflect return dynamics, volatility clustering, and microstructure effects.

The construction begins with return-based transformations of the one-minute realized return  $rt$ . In addition to the raw return, we include the absolute return  $|rt|$ , the squared return  $r_t^2$ , and the sign of the return  $\text{sign}(rt)$ . These transformations capture asymmetry, tail behavior, and directional persistence in the return process and are commonly used in both econometric and microstructure models to characterize nonlinear dynamics.

Volatility dynamics are encoded through rolling realized volatility measures computed over multiple intraday horizons. Specifically, rolling standard deviations of one-minute returns are calculated over 5-, 15-, 30-, and 60-minute windows. To mitigate scale instability and the influence of extreme observations, logarithmic transformations of realized volatility are also included. In addition, volatility and volume z-scores relative to recent history are computed, allowing the models to detect deviations from local baselines and identify volatility regime shifts.

Short-term trend behavior is captured using multi-horizon momentum features constructed as lagged price ratios over 5-, 15-, and 30-minute intervals. These features are intended to detect brief continuation or reversal effects that may arise from order-flow persistence or liquidity imbalances.

Finally, a set of microstructure-inspired variables is introduced to proxy for order-flow and behavioral effects. Directional run-length features measure streaks of consecutive positive or negative returns and are designed to capture short-lived feedback loops and reflexivity. Signed volume variables combine trading intensity with return direction, reflecting potential information contained in aggressive buying or selling pressure. Together, these features aim to capture market frictions, retail herding behavior, and transient liquidity dynamics that are frequently hypothesized to exist in cryptocurrency markets.

### 3.4 Sample Splitting and Preprocessing

To ensure a realistic evaluation of predictive performance, all experiments employ a strict chronological split of the data into training, validation, and test samples. The first 70% of observations are used for training, the subsequent 15% for validation, and the final 15% for out-of-sample testing. This procedure mimics a live trading environment and prevents information leakage across time.

All preprocessing steps, including feature standardization, are fitted exclusively on the training sample. The learned transformations are then applied unchanged to the validation and test samples. Observations containing missing values introduced by rolling-window computations are removed prior to splitting.

### 3.5 Models

We evaluate a set of baseline machine learning models that are widely used in empirical finance and market microstructure research. Linear models with regularization are employed to assess the extent to which volatility and magnitude dynamics can be explained by linear combinations of features, while tree-based ensemble models are used to capture nonlinear interactions and threshold effects.

The choice of relatively simple and interpretable models is deliberate. Rather than maximizing predictive performance through architectural complexity, the goal is to isolate the informational content of the features themselves. Directional targets are modeled using classification frameworks, whereas magnitude-based targets are modeled using regression techniques. This separation allows us to directly contrast the feasibility of short-horizon directional prediction with the predictability of volatility-related quantities.

### 3.6 Evaluation Metrics

All model evaluation is conducted strictly out of sample. For classification tasks, performance is measured using accuracy, the F1-score, and the area under the receiver operating characteristic curve (AUC). The AUC metric is emphasized, as it evaluates the model's ranking ability independently of any specific classification threshold and provides a robust measure of directional predictability relative to a random baseline.

For regression tasks, model performance is assessed using root mean squared error, mean absolute error, and the out-of-sample coefficient of determination. These metrics jointly quantify prediction accuracy and explanatory power, allowing us to evaluate whether models capture meaningful variation in conditional volatility or return magnitude.

### 3.7 Diagnostic Analysis

Prior to model estimation, extensive diagnostics are conducted to characterize the statistical properties of returns and volatility. These include distributional analysis of returns and target variables, autocorrelation analysis of returns and volatility proxies, and regime segmentation based on realized volatility quantiles. The diagnostics serve both as a motivation for feature design and as a benchmark against which predictive results can be interpreted. In particular, they help distinguish genuine predictive structure from artifacts arising from heavy tails, volatility clustering, or microstructure noise.

## **4. Empirical Results**

### 4.1 Diagnostic Evidence on Returns and Volatility

The empirical analysis begins by examining the distributional and dependence properties of one-minute cryptocurrency returns and their volatility proxies. Across Bitcoin, Ethereum, Solana, and Dogecoin, one-minute returns are centered near zero and exhibit pronounced excess kurtosis, indicating heavy tails and frequent extreme observations. These distributional properties are consistent with prior findings in high-frequency financial markets and motivate caution in interpreting short-horizon return predictability.

Autocorrelation analysis reveals that raw one-minute returns exhibit little to no statistically meaningful serial dependence beyond the contemporaneous lag. Autocorrelation coefficients decay rapidly and remain close to zero across all assets, suggesting that directional price changes at the one-minute horizon are largely indistinguishable from noise.

In contrast, absolute and squared returns display strong and persistent autocorrelation across multiple lags. This dependence structure is stable across assets and time periods, indicating pronounced volatility clustering at ultra-short horizons. The persistence observed in return magnitudes suggests that short-horizon volatility behaves as a slowly evolving latent state, even when return direction remains unpredictable. This diagnostic evidence motivates the subsequent distinction between directional return prediction and volatility magnitude prediction.

### 4.2 Directional Return Prediction

Directional return predictability is evaluated using logistic regression and random forest classification models trained to predict the sign of one-minute-ahead returns. Model performance is assessed using strictly out-of-sample validation and test samples and evaluated using accuracy, F1-score, and area under the receiver operating characteristic curve.

*Table 1* reports out-of-sample performance for logistic regression and random forest classifiers trained to predict the sign of one-minute-ahead returns across Bitcoin, Ethereum, Solana, and Dogecoin. Across all assets and model specifications, directional prediction performance remains close to chance levels. Test-set AUC values are tightly concentrated in the range of approximately 0.50–0.54, while accuracy metrics cluster around 50%. These results indicate that neither linear nor nonlinear classification models are able to reliably distinguish upward from downward price movements at the one-minute horizon.

*Table 1*

Asset	Model	Accuracy	AUC	F1-Score
BTC	Logistic Regression	0.505	0.509	0.287
BTC	Random Forest	0.512	0.523	0.386
ETH	Logistic Regression	0.497	0.496	0.578
ETH	Random Forest	0.509	0.513	0.268
SOL	Logistic Regression	0.507	0.504	0.405
SOL	Random Forest	0.519	0.541	0.169
DOGE	Logistic Regression	0.515	0.506	0.032
DOGE	Random Forest	0.524	0.540	0.313

These results indicate that, at the one-minute horizon, cryptocurrency price direction exhibits limited and unstable predictability. Any weak dependence detected by nonlinear models is insufficiently robust to support reliable directional forecasting. This finding is consistent with the efficient markets view at very short horizons and aligns with prior evidence from both traditional and cryptocurrency markets.

#### 4.3 Volatility Magnitude Prediction

Predictability of return magnitude is evaluated using regression models trained to forecast one-minute-ahead absolute returns. Ridge regression and random forest regression models are estimated using the same feature set employed in the directional classification tasks. Performance is assessed out of sample using root mean squared error, mean absolute error, and the coefficient of determination.

*Volatility predictability is evaluated using regression models trained to forecast one-minute-ahead absolute returns. Table 2 reports out-of-sample performance for ridge regression and random forest models across all assets. In contrast to directional prediction results, volatility forecasting exhibits economically meaningful and stable explanatory power. Out-of-sample R^2 values range from approximately 0.17 to 0.27 across assets, with the strongest performance observed for Bitcoin and Solana.*

*Table 2*

Asset	Model	R^2	RMSE
BTC	Logistic Regression	0.270	0.000433
BTC	Random Forest	0.271	0.000432
ETH	Logistic Regression	0.217	0.000647
ETH	Random Forest	0.208	0.000650
SOL	Logistic Regression	0.173	0.000819
SOL	Random Forest	0.247	0.000782
DOGE	Logistic Regression	0.205	0.000875
DOGE	Random Forest	0.220	0.000866

Importantly, predictive performance remains stable across validation and test samples, suggesting that the observed results are not driven by overfitting or regime-specific artifacts. The fact that regularized linear models

perform comparably to nonlinear ensemble models further indicates that volatility predictability arises from persistent structure in the data rather than complex nonlinear interactions.

#### 4.4 Cross-Asset Consistency

A notable feature of the empirical results is their consistency across assets with markedly different liquidity profiles and market characteristics. Despite substantial differences in trading activity and volatility levels, all four cryptocurrencies exhibit the same qualitative pattern: near-zero directional predictability combined with persistent and learnable volatility dynamics.

This cross-asset consistency strengthens the interpretation that the results reflect fundamental properties of high-frequency cryptocurrency markets rather than idiosyncratic features of a single asset or time period. In particular, it suggests that short-horizon volatility predictability is a general characteristic of continuous, order-driven crypto markets.

#### 4.5 Summary of Empirical Findings

Taken together, the empirical results establish a clear distinction between directional return predictability and volatility state predictability at the one-minute horizon. While price direction remains largely unpredictable and dominated by noise, return magnitudes exhibit strong persistence and can be forecast with meaningful accuracy using machine learning models trained on lagged information.

These findings suggest that high-frequency cryptocurrency markets are better characterized as exhibiting state predictability without directional predictability. Machine learning models are therefore more appropriately deployed as tools for volatility estimation and regime identification rather than short-horizon directional forecasting.

### **5. Discussion and Interpretation**

The empirical results reveal a clear asymmetry in short-horizon predictability in cryptocurrency markets. Across all assets and model specifications, one-minute-ahead return direction remains largely unpredictable, with out-of-sample classification performance close to random. Area under the ROC curve values cluster tightly around 0.50–0.54, and any marginal improvements delivered by nonlinear models are unstable across assets and test periods. This finding is consistent with the view that, at ultra-short horizons, price changes are dominated by noise and rapid information incorporation rather than exploitable directional structure.

In contrast, the magnitude of returns exhibits stable and economically meaningful predictability. Regression models forecasting absolute one-minute-ahead returns achieve out-of-sample  $R^2$  values between approximately 0.17 and 0.27, indicating that short-horizon volatility contains a persistent structure that can be learned from lagged price and volume information. This result aligns with the well-established phenomenon of volatility clustering and suggests that high-frequency volatility behaves as a slowly evolving latent state rather than a sequence of independent shocks.

The comparative performance of linear and tree-based models indicates that much of this predictability arises from relatively simple feature interactions rather than highly complex nonlinear dynamics. While random forests occasionally outperform linear baselines, the gains are modest, suggesting that model complexity cannot overcome the fundamental informational constraints governing return direction at the one-minute horizon.

Taken together, the findings imply that high-frequency cryptocurrency markets are directionally efficient but not state-independent. Machine learning models are effective at estimating short-term volatility conditions, even when price direction remains unpredictable. As a result, machine learning appears better suited for risk estimation, execution, and volatility-sensitive applications in high-frequency crypto markets than for directional return forecasting.

## 6. Trading Strategy Illustration

### 6.1 Strategy Design

The trading exercise is designed to illustrate how machine learning-based volatility forecasts can be translated into economically meaningful decisions, without relying on directional return predictability. Given the empirical results showing limited and unstable predictability of one-minute return direction, the strategy focuses exclusively on forecasts of return magnitude. The objective is not to optimize trading profitability, but to assess whether the statistically significant predictability of short-horizon volatility can be mapped into a coherent trading rule under realistic constraints.

### 6.2 Volatility-Based Exposure Rule

Let  $\hat{y}^{abs}_{t+1}$  denote the model forecast of the absolute one-minute-ahead return. At each time  $t$ , trading exposure is adjusted as a function of the predicted volatility regime implied by  $\hat{y}^{abs}_{t+1}$ . Volatility regimes are defined using empirical quantiles of the forecast distribution estimated on the training sample and held fixed thereafter. When predicted volatility lies in the lowest quantile range, exposure is reduced to reflect subdued market activity. When predicted volatility falls within intermediate quantiles, baseline exposure is maintained. When predicted volatility lies in the highest quantile range, exposure is either increased or trading activity is curtailed, depending on whether the strategy is interpreted in a risk-seeking or risk-averse context. This formulation mirrors standard volatility-targeting and regime-based allocation practices commonly used in systematic trading, while relying exclusively on out-of-sample forecasts.

### 6.3 Backtesting Design

The trading strategy is evaluated strictly out of sample using the test dataset. All quantile thresholds and regime definitions are estimated using training data only and are not recalibrated during the evaluation period. No parameter tuning or model selection is performed on the test set. Strategy performance is assessed using standard metrics, including average return per trade, return volatility, maximum drawdown, turnover, and implied transaction costs. Transaction costs are modeled conservatively as proportional round-trip costs, reflecting the high turnover inherent in ultra-short-horizon strategies.

### 6.4 Results and Interpretation

Although periods of elevated predicted volatility are associated with larger realized price movements, the trading strategy does not generate positive net returns once transaction costs are incorporated. The high frequency of position adjustments required to exploit minute-level signals causes transaction costs to dominate gross performance. These results highlight a key distinction between statistical predictability and economic tradability: while volatility forecasts contain stable information about market state, this information does not translate into exploitable profits at ultra-short horizons under realistic trading frictions.

### 6.5 Relation to Market Efficiency

The trading results reinforce, rather than contradict, the efficient markets view at high frequencies. The absence of profitable directional or volatility-based trading opportunities after transaction costs indicates that the detected predictability reflects persistent volatility states rather than mispricing. Machine learning models are therefore best interpreted as tools for state estimation and risk management in high-frequency cryptocurrency markets, rather than as engines for short-horizon alpha generation.

## 6. Conclusion

This paper studies ultra-short-horizon predictability in cryptocurrency markets using minute-level data for Bitcoin, Ethereum, Solana, and Dogecoin. By explicitly separating directional return prediction from volatility magnitude prediction, the analysis highlights a fundamental asymmetry in what can and cannot be learned from high-frequency crypto price data.

Across all assets and model specifications, directional return prediction at the one-minute horizon remains largely indistinguishable from noise. Classification performance is consistently close to random, with out-of-sample AUC values clustering around 0.50–0.54. While nonlinear models occasionally exhibit marginal improvements relative to linear baselines, these gains are unstable and do not persist uniformly across assets or test periods. This result reinforces the view that, at ultra-short horizons, cryptocurrency price direction is dominated by rapid information incorporation and microstructure noise rather than exploitable directional structure.

In contrast, return magnitude exhibits stable and economically meaningful predictability. Regression models forecasting absolute one-minute-ahead returns achieve out-of-sample  $R^2$  values between approximately 0.17 and 0.27 across assets. This finding reflects strong volatility clustering and persistence and suggests that short-horizon volatility behaves as a latent state that evolves more slowly than prices themselves. The fact that relatively simple linear and tree-based models capture a substantial share of this variation indicates that the predictability arises from persistent market structure rather than highly complex nonlinear dynamics.

Taken together, these results suggest that machine learning is best deployed in high-frequency cryptocurrency markets as a tool for volatility estimation and state identification rather than directional forecasting. While volatility forecasts may support risk management, execution control, and exposure scaling, translating short-horizon predictions into profitable trading strategies remains challenging once realistic transaction costs are considered. More broadly, the findings are consistent with a market environment that is directionally efficient at the minute level but exhibits predictable variation in risk and activity states.

## Appendix

