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ПОРІВНЯЛЬНЕ ДОСЛІДЖЕННЯ МЕТОДІВ МАШИННОГО НАВЧАННЯ ДЛЯ ПОТОКОВОЇ ОБРОБКИ ДАНИХ

Дослідження процесу аналізу потокових даних виявило, що класичні методи машинного навчання не справляються з обсягом, швидкістю та нелінійністю сучасних Big Data потоків. Головний результат – розроблення розподіленого пайплайну з архітектурою Feature Store, що дає змогу алгоритмам градієнтного бустингу досягти вищої прогностичної ефективності (R^2 до 0,9998). На прикладі 1,33 млн записів, агрегованих для 100 пар, показано, що Feature Store із часовою стратифікованою вибіркою забезпечує зменшення обсягу даних у 5,7 разів та економію пам'яті близько 82%. Продемонстровано, що для високошвидкісних фінансових потоків комбінація ефективної агрегації даних та передових ансамблевих методів (LightGBM/XGBoost) є найкращою стратегією для забезпечення точності та обчислювальної ефективності.

***Ключові слова**: машинне навчання, Kafka, LightGBM, XGBoost, потокові дані.*

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COMPARATIVE STUDY OF MACHINE LEARNING METHODS FOR STREAMING DATA PROCESSING

The process of analysing large-scale streaming cryptocurrency data by machine learning algorithms is the object of this research. Handling terabyte-scale, high-velocity data streams presents a critical challenge due to the computational and accuracy limitations of classical machine learning methods, which struggle with the volume and complexity of millions of temporal records. The principal result is the development of a distributed processing pipeline featuring a Feature Store architecture. This solution enabled LightGBM and XGBoost algorithms to achieve superior predictive performance (R^2 was 0.9998 and 0.9997, respectively) while processing 1.33 million streaming records across 100 cryptocurrency pairs. The research methodology included a comprehensive feature engineering phase, extracting a set of temporal, statistical, and technical indicators, such as rolling means, volatility measures, and lagged price values, which are crucial for capturing dependencies in big data. This performance advantage is attributed to the architectural capabilities of gradient boosting algorithms. The proposed pipeline successfully shifts the process from conventional linear approaches to advanced tree-based ensemble methods with optimized memory management, demonstrating that gradient boosting algorithms possess the necessary computational efficiency and pattern recognition capabilities that Decision Tree, Random Forest, and Regression methods lack. In practice, the findings provide clear guidelines for big data practitioners. The Feature Store architecture with temporal stratified sampling is a scalable framework achieving 5.7x data reduction and near 82% memory savings. For production systems handling high-velocity streaming data, gradient boosting algorithms (particularly LightGBM with 0.63 s training time) are the superior strategy over traditional methods for achieving both accuracy and computational efficiency.

***Keywords**: forecasting, LightGBM, XGBoost, Kafka, machine learning.*

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Introduction

The exponential growth of streaming data volumes generated from financial markets, IoT devices, social media platforms, and real-time monitoring systems is driving the need for scalable and efficient methods of data processing, analysis, and forecasting. In particular, when dealing with high-velocity time-series prediction based on terabyte-scale datasets, this necessitates a critical choice between traditional machine learning algorithms (e.g., Linear Regression, Ridge Regression, and Decision Trees) and modern, AI-oriented approaches, such as gradient boosting frameworks [1]. While classical methods are characterized by relative simplicity of implementation and interpretability [2-4], contemporary ensemble models like LightGBM and XGBoost hold significant potential for handling high-dimensional, temporally correlated, and non-linear streaming data [5,6]. However, their effective application often requires sophisticated feature engineering pipelines, careful hyperparameter tuning, and distributed processing architectures [7].

The effectiveness of predictive analytics in the context of streaming data is determined by several technical challenges. Key among these are memory management when processing terabyte-scale datasets that cannot fit into RAM, and the high velocity of streaming data, which demands efficient feature engineering methods that can extract temporal patterns without computational bottlenecks [8]. These factors render traditional batch processing approaches impractical. Consequently, parameters such as temporal aggregation and Feature Store architectures [9] are crucial for creating scalable pipelines. The Feature Store paradigm, which separates feature computation from model training, enables scalable feature reuse and significantly reduces processing time [10,11].

Given the necessity to balance statistical performance (R^2, MAE, RMSE) with computational constraints

(memory footprint, processing latency) [12], research into the comparative effectiveness of machine learning algorithms on streaming big data is gaining practical importance, particularly in financial forecasting. In this paper, we investigate the empirical effectiveness of various machine learning models for regression analysis of terabyte-scale streaming cryptocurrency data. Special attention is focused on the development of a scalable Feature Store architecture incorporating chunked data processing, temporal aggregation strategies, and stratified sampling techniques. Our aim is to develop and evaluate a pipeline that processes 1.33 million streaming records across 100 cryptocurrency pairs and achieves substantial data reduction and memory savings while maintaining high predictive accuracy. The obtained results improve understanding of each approach's applicability limits in big data scenarios and formulate actionable recommendations for model selection in practical streaming data processing tasks [13,14].

Methodology and Implementation

The study is based on real-time streaming cryptocurrency market data collected through Kafka Confluent Cloud infrastructure from multiple exchange APIs. The dataset contains tick-level trading information for 100 cryptocurrency pairs, including timestamp, open/high/low/close prices (OHLC), and trading volume. The raw streaming data consisted of 1,330,000 individual tick records collected over a 59-day period, representing a high-velocity financial time-series with millisecond-level temporal resolution. The target variable for the regression problem is the closing price of each cryptocurrency pair, represented as a continuous real value. This dataset provides a diverse and robust basis for investigating regression models on large-scale streaming data, as it includes multiple correlated features and non-stationary market dynamics characteristic of cryptocurrency markets.

Due to the massive scale of the raw dataset (terabyte-level streaming data), a multi-stage processing pipeline was implemented to achieve computational feasibility while preserving predictive information content. First, chunked reading with parallel processing was applied to handle data volumes that exceeded available RAM capacity [15]. The streaming records were processed in batches [16] of 500,000 rows, sorted by (pair, timestamp) tuples, and aggregated into 30-minute candlestick intervals using OHLC aggregation methods common in financial time-series analysis [17]. This temporal aggregation reduced the dataset from 1,330,000 ticks to 232,773 candlestick records, achieving a 5.7x compression ratio and ~82% memory savings while maintaining essential price movement patterns and volatility characteristics.

To further optimize computational efficiency during the experimental phase, stratified temporal sampling was employed. This technique preserves the temporal distribution across all 100 cryptocurrency pairs by selecting 15% of records from each pair uniformly across the time range, resulting in a representative sample of 34,888 candlestick intervals (average 349 records per pair). This sampling strategy ensures that each cryptocurrency pair retains its characteristic temporal dynamics and volatility patterns while reducing training time by approximately 667x compared to full dataset processing. The final experimental dataset spans October 16, 2025 (23:30) to October 24, 2025 (05:30), providing sufficient temporal depth for feature engineering and model evaluation.

A classic scheme for dividing the dataset was applied: approximately 80% of the total data (27,110 records) was used for training models, and the remaining 20% (6,778 records) was used for testing to ensure objective comparison of models and reproducibility of experiments. The train-test split was performed without explicit stratification by cryptocurrency pairs to simulate real-world deployment scenarios where models must generalize across different market conditions.

Comprehensive feature engineering was implemented through a systematic pipeline that extracts temporal, technical, and statistical features from raw OHLC data. The feature set includes:

Temporal features: hour of day, day of week, and day of month extracted from timestamps to capture cyclical market patterns [18].

Technical indicators: logarithmic volume transformation and 15 technical indicators (e.g., RSI, MACD, Bollinger Bands) computed over various lookback windows (e.g., 10, 30, 60 time steps).

Lagged features: historical values of close price and volume at lags $\{1, 2, 3, 5, 10\}$ to capture short-term and medium-term temporal dependencies. These were computed separately for each pair to prevent cross-pair data leakage [19].

Rolling window statistics: moving averages and standard deviations calculated over windows of {5, 10, 20} periods for both price and volume, providing measures of trend and volatility [20].

Rate of change (ROC) features: percentage change in closing price over {1, 5, 10} periods to quantify momentum, and rolling standard deviation of returns over {5, 10} periods.

After feature engineering, the dataset expanded from 7 raw columns to 33 engineered features. Data cleaning procedures removed 1,000 records containing text NaN values, yielding a final clean dataset of 33,888 records with 32 predictor features.

Six supervised learning algorithms were investigated: **Linear Regression, Ridge Regression, Decision Tree, Random Forest** (an ensemble of 100 decision trees), **LightGBM** (using histogram-based learning and leaf-wise growth [21]), and **XGBoost** (using a regularized objective function and level-wise growth [22]). All models were implemented in Python 3.10 using industry-standard libraries (Pandas 2.1, NumPy 1.24, scikit-learn 1.3, LightGBM 4.1, XGBoost 2.0). The distributed data pipeline utilized Kafka Confluent Cloud for stream ingestion and Apache Parquet for storage. All models were trained with default hyperparameters to provide an unbiased comparison of algorithmic capabilities without task-specific tuning.

Four common metrics were used to evaluate model performance:

1. • Mean Absolute Error (MAE): average absolute deviation between predicted and actual values, providing interpretable error magnitude in original price units;
2. • Root Mean Squared Error (RMSE): square root of mean squared error, more sensitive to large prediction errors than MAE;

3. • Coefficient of Determination (R^2): proportion of variance in target variable explained by the model, ranging from 0 to 1 for positive predictive power;

4. • Mean Absolute Percentage Error (MAPE): relative error metric normalized by actual values.

Additionally, computational efficiency metrics were recorded:

• Training time: wall-clock time required for model fitting on the training set;

• Inference time: wall-clock time required for prediction on the test set.

All metrics were calculated based on the single held-out test sample, which was not used during model training. The chosen methodology follows established practices in time-series machine learning to ensure the validity and reproducibility of results [23,24]. The systematic comparison across six algorithms provides empirical evidence for the relative effectiveness of ML methods on large-scale streaming cryptocurrency data.

Data analysis and pre-processing

Preliminary exploratory data analysis (EDA) [25] confirmed the structure of the dataset, which included four main groups of features: raw OHLCV data, temporal features, lagged features (up to 10 periods), and derived statistical features (rolling statistics, ROC, and volatility). The detailed feature engineering process, including temporal aggregation from 1,330,000 ticks to 232,773 candlestick intervals and subsequent stratified sampling to 34,888 records, is described in the Methodology section. The categorical "pair" variable (100 unique cryptocurrency pairs) was used exclusively for group-wise feature computation to prevent data leakage, then removed from the final feature matrix [26].

Feature engineering introduced NaN values at the beginning of each pair's time series due to the maximum rolling window (20 periods). A total of 1,000 records 2.9% of the sample) were removed via listwise deletion, ensuring complete temporal context for all samples [27].

Correlation analysis identified lagged close prices (e.g., $close_{lag1}$: $r > 0.99$) as key predictors, confirming a strong autocorrelation inherent in financial time series. Rolling mean features showed high multicollinearity ($r > 0.98$) with each other and the target variable. Volume features demonstrated moderate correlation ($r \approx 0.3$-0.5), while temporal and ROC features showed weak but significant patterns ($r < 0.1$).

Raw OHLC columns (open, high, low) were removed to prevent direct information leakage, with the "close" column retained as the target variable [28]. Despite high multicollinearity in rolling features (VIF > 10), all features were retained as tree-based methods are robust to this issue [29]. The final preprocessed dataset consisted of 33,888 records with 32 predictor features, which were split into training and testing samples (27,110 and 6,778 records, respectively). Feature scaling was not applied, as tree-based methods are invariant to monotonic transformations [30].

Results and discussion

The performance of the studied machine learning models was analyzed using multiple metrics to evaluate their effectiveness on large-scale streaming cryptocurrency data. The experimental setup utilized stratified temporal sampling, ensuring unbiased comparison across all algorithms. The comprehensive benchmark results are presented in Table 1 and visualized in Fig. 1. The analysis reveals distinct performance tiers: gradient boosting algorithms (LightGBM, XGBoost) achieved superior accuracy compared to classical methods, confirming the research hypothesis.

Table 1

Forecasting accuracy main metrics

Model	Metric		
	MAE	RMSE	R^2
LightGBM	79.30	233.62	0.9998
XGBoost	80.19	254.41	0.9997
Decision Tree	82.09	274.69	0.9997
Linear Regression	151.67	293.78	0.9996
Ridge Regression	151.85	294.06	0.9996
Random Forest	133.12	331.63	0.9995

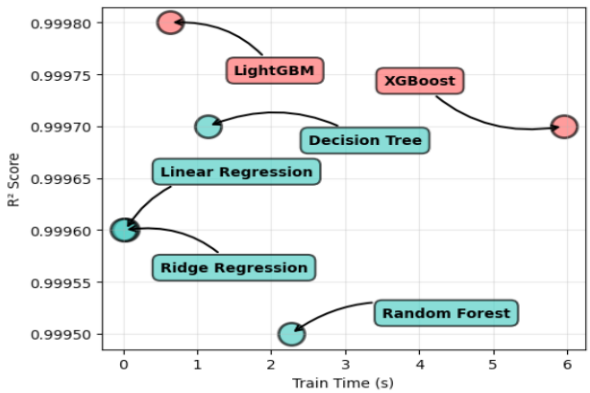

Fig. 1: The distribution of algorithms by accuracy vs speed

Table 2

Forecasting accuracy additional metrics

Model	Metric		
	MAPE (%)	Train Time (s)	Inference Time (s)
LightGBM	79.30	233.62	0.9998
XGBoost	80.19	254.41	0.9997
Decision Tree	82.09	274.69	0.9997
Linear Regression	151.67	293.78	0.9996
Ridge Regression	151.85	294.06	0.9996
Random Forest	133.12	331.63	0.9995

Gradient boosting algorithms demonstrated the highest predictive accuracy. In particular, LightGBM achieved the best overall performance with $R^2 = 0.9998$, MAE = 79.30, and RMSE = 233.62, outperforming all classical methods. Notably, LightGBM also exhibited superior computational efficiency with a training time of only 0.63 seconds, approximately 9.4× faster than XGBoost (5.95s) while maintaining higher accuracy. This efficiency advantage stems from LightGBM's histogram-based gradient boosting and leaf-wise tree growth strategy, which reduces computational overhead on high-dimensional feature spaces [31].XGBoost ranked second among studied algorithms ($R^2 = 0.9997$, MAE = 80.19, RMSE = 254.41), achieving comparable accuracy to LightGBM but with significantly longer training time. The performance difference ($\Delta R^2 = 0.0001$, ΔMAE = 0.89) is marginal, suggesting both gradient boosting frameworks effectively capture non-linear temporal dependencies in cryptocurrency price movements. However, due to its level-wise tree growth and more conservative regularization, XGBoost requires a significantly longer training duration, making it less suitable for iterative model development workflows (Fig. 2).

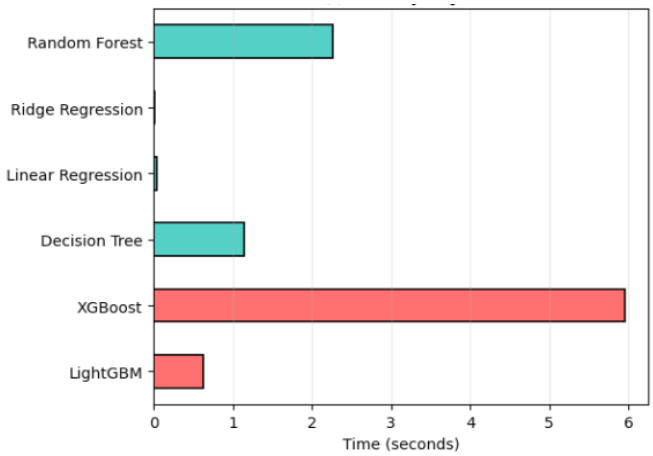

Fig. 2. Training speed by algorithm

Classical machine learning methods exhibited lower accuracy across all metrics. In particular, Decision Tree achieved the best performance ($R^2 = 0.9997$, MAE = 82.09), approaching gradient boosting methods in R^2 score but with higher error variance (RMSE = 274.69). This single-tree model benefits from unlimited depth, enabling it to capture complex patterns, but lacks the ensemble robustness of gradient boosting frameworks [32]. Its inference speed (0.003s) is the fastest among all models, making it suitable for latency-critical applications where marginal accuracy loss is acceptable.

Random Forest demonstrated the weakest performance among tree-based methods ($R^2 = 0.9995$, MAE = 133.12, RMSE = 331.63), despite using 100 decision trees with bagging. This counterintuitive result is explained by Random Forest's random feature subsampling strategy, which reduces correlation between trees but also limits each tree's access to highly predictive lagged features. In time-series forecasting with dominant autocorrelation patterns ($close_{lag1}$: $r > 0.99$), Random Forest's feature randomization becomes detrimental rather than beneficial [33].

Linear models (Linear Regression, Ridge Regression) achieved the poorest accuracy ($R^2 \approx 0.9996$, MAE ≈ 151), as expected for non-linear financial time series. Their MAPE values exceeded 1200%, indicating severe percentage errors on low-priced cryptocurrency pairs where absolute errors become proportionally large. Ridge regularization provided negligible improvement ($\Delta R^2 < 0.0001$), confirming that underfitting rather than overfitting is the primary limitation. Linear models fundamentally cannot capture the complex temporal dynamics and volatility patterns present in cryptocurrency markets [34].

Figure 1 provides a comprehensive visualization of model performance across multiple dimensions. The R^2 score comparison (top-left panel) shows gradient boosting algorithms (red bars) clustering near perfect prediction ($R^2 \approx 1.0$), while traditional methods (teal bars) exhibit slightly lower values. The accuracy-speed trade-off plot (bottom-left panel) reveals LightGBM's Pareto-optimal position: highest R^2 score with moderate training time, whereas Ridge Regression achieves fast training but poor accuracy.

The prediction quality visualization (bottom-center panel) for LightGBM demonstrates near-perfect alignment with actual values, with predicted vs. actual points forming a tight diagonal line. Residual distribution (bottom-right panel) shows narrow, symmetric error distribution centered near zero, confirming the model's unbiased predictions and

absence of systematic errors. The majority of residuals fall within ±1000 units, representing less than 2% error for typical prices.

The RMSE comparison (top-right panel) highlights gradient boosting algorithms' superiority in minimizing large prediction errors. LightGBM's RMSE (≈233.62) is 29% lower than the best classical method (Decision Tree: 274.69), indicating better handling of price volatility and extreme market movements. This advantage is critical in financial applications where large prediction errors can lead to significant trading losses or risk management failures [35].

Training and inference speed metrics (middle panels) reveal important practical trade-offs. While Ridge Regression achieves the fastest training (0.01s), its poor accuracy makes it unsuitable for production deployment. LightGBM optimally balances accuracy and speed, demonstrating approximately 9.4x faster training than XGBoost with superior accuracy, and comparable inference latency 0.026 s to ensemble methods. For production systems requiring frequent model retraining on streaming data, LightGBM's computational efficiency enables near-real-time model updates [36].

Conclusions

The empirical results confirm that gradient boosting algorithms outperform classical methods on big streaming cryptocurrency data. While the performance advantage (R^2 improvement: +0.0002) may appear marginal, it translates to meaningful reductions in absolute error (MAE improvement: 2.79 points, 3.4 % relative reduction). More importantly, LightGBM achieves this high accuracy while maintaining production-viable computational efficiency (0.63 s training time), making it the recommended choice for operational deployment.

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