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Deep Learning and Ensemble Models for Multi-Country Cryptocurrency Prediction and Automated Smart-Contract Trading

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Abstract
This study presents a unified framework that integrates deep learning architectures and ensemble machine learning models to enhance cryptocurrency price prediction across multiple countries and regulatory environments. Leveraging LSTM, GRU, hybrid recurrent networks, Random Forest, XGBoost, PCA, and Z-score anomaly detection, the system captures nonlinear market dynamics and cross-jurisdictional policy impacts. SHAP-based explainability improves transparency, while smart-contract automation enables real-time, trust-free trading execution via oracle-driven price updates. Regulatory ablation experiments reveal significant country-specific sensitivities, highlighting the importance of tailored policy design. The proposed approach demonstrates strong predictive accuracy and practical feasibility, offering a robust foundation for next-generation crypto-market intelligence.

Keywords: Cryptocurrency Forecasting, Deep Learning, Ensemble Models, Smart-Contract Trading, Explainable AI

1. Introduction

The rapid expansion of digital asset markets has transformed cryptocurrencies from speculative curiosities into globally traded financial instruments with significant economic and technological implications. As of 2024, the global cryptocurrency market has exceeded trillions in market capitalization, with countries such as the United States, Russia, and Indonesia demonstrating varied adoption rates, regulatory philosophies, and trading behaviors. Despite this growth, cryptocurrency markets remain notoriously volatile, nonlinear, and sensitive to regulatory shocks, macroeconomic shifts, investor sentiment, and high-frequency structural patterns. This unpredictability poses significant challenges for traders, researchers, policymakers, and automated trading platforms seeking reliable forecasts and transparent decision-making frameworks.

Traditional statistical models such as ARIMA, SARIMA, and GARCH often struggle to capture the complex, time-varying dependencies and irregular fluctuations that characterize digital asset markets. To address these limitations, recent research has increasingly focused on machine learning (ML) and deep

learning (DL) approaches that can learn intricate temporal dynamics and nonlinear relationships. Ensemble learning techniques such as Random Forest and XGBoost have gained prominence for their robustness and superior performance across diverse datasets. At the same time, recurrent neural networks, particularly LSTM, GRU, and hybrid LSTM-GRU architectures, have become essential for modeling long-range dependencies and high-frequency patterns in cryptocurrency price movements.

At the same time, the emergence of blockchain-based automation through smart contracts has opened new opportunities for decentralized, transparent, and autonomous trading systems. Integrating AI-driven price prediction models with smart-contract execution frameworks enables trust-free portfolio management, automated risk mitigation, and real-time strategy adjustments powered by oracle-based market feeds. This integration not only democratizes access to advanced trading tools but also helps create highly efficient, verifiable financial ecosystems.

However, the majority of existing forecasting systems remain limited in scope, focusing primarily on price and technical indicators while overlooking broader multi-country regulatory factors, macroeconomic conditions, energy-market influences, and anomaly detection. Studies on regulatory policy effects highlight how country-specific regulations, such as AML/KYC enforcement, taxation policies, payment bans, and licensing requirements, significantly shape trading volume and market behavior. Yet, most prediction frameworks do not systematically integrate such regulatory variables or simulate their interactive impacts across jurisdictions. Furthermore, the interpretability of many DL and ML models is limited, creating barriers to adoption for institutional investors, regulators, and financial analysts who require transparent, explainable decision-making frameworks.

This research addresses these gaps by presenting a comprehensive multi-factor cryptocurrency forecasting system that combines the strengths of deep learning, ensemble learning, and explainable AI. The proposed framework integrates LSTM, GRU, hybrid recurrent architectures, Random Forest, XGBoost, PCA, and Z-score anomaly detection to capture diverse market signals. SHAP-based interpretability provides transparency into model behavior, while smart-contract automation facilitates on-chain, oracle-driven, real-time trading execution. Multi-country regulatory features enable cross-jurisdictional simulations, revealing differentiated policy sensitivities and highlighting the importance of regulatory design.

Overall, this study provides a unified, interpretable, and deployment-ready architecture that effectively operates in highly volatile global cryptocurrency environments. It lays the foundation for more intelligent, adaptive, and transparent trading ecosystems powered by machine learning, deep learning, and decentralized technologies.

2. Literature Review

Islam et al. (2025), This study explains how predicting cryptocurrency prices is difficult because most models ignore market liquidity, which strongly affects price movement. The research uses XRP/USDT data and adds two liquidity measures, VVR and VWAP, to improve prediction accuracy. Four machine learning models were tested, and the LSTM consistently gave the best results, both with and without these liquidity signals. The findings show liquidity must be included for better forecasting and safer trading decisions. [1]

Islam et al. (2025) Note That Cryptocurrency markets move extremely fast and fluctuate heavily, making price forecasting challenging. This research analyzes Bitcoin, Ethereum, and major altcoins using large

datasets of prices, volumes, and indicators like RSI and moving averages. Three models, Logistic Regression, Random Forest, and XGBoost, were tested to predict market direction. Logistic Regression performed the best. The study highlights how AI-based forecasting can improve trading, support regulatory oversight, and inspire deeper research using models such as LSTMs for time-series prediction. [2]

Olutimehin (2025), This study investigates how AI can strengthen cybersecurity in cryptocurrency platforms by detecting fraud and risky smart contract activity. Using datasets such as Elliptic, CryptoScamDB, and SolidiFI, the authors apply Logistic Regression, Random Forests, and Reinforcement Learning to identify suspicious patterns. Their approach offers stronger protection for transactions and helps financial institutions and regulators better track illegal activities. The research shows AI can significantly improve the safety of digital currency systems. [3]

Pinky et al. (2025) note that, with more than 23,000 cryptocurrencies and significant volatility, accurate price prediction is essential. This chapter reviews machine learning methods used from 2014 to 2024, including linear models, tree-based algorithms, transformers, and large language models. It also highlights how sentiment analysis from news and social media helps capture market mood. Industrial engineers play a significant role by optimizing data pipelines and improving computational efficiency. The review outlines challenges, new technologies, and future improvements for more reliable prediction systems. [4]

Gwala (2025), This research reviews how artificial intelligence and blockchain together are transforming medicine, technology, and cryptocurrency systems. Blockchain supports AI by offering secure data sharing, trusted storage, and decentralized coordination across IoT devices. It also enables new digital economies and cryptocurrencies. These advancements help address AI trust and security issues, promote safer applications, and accelerate innovation in medical systems and digital markets. The study shows how both technologies strengthen and accelerate each other's growth. [5]

Ashok et al. (2025), This study examines how difficult it is to predict cryptocurrency prices because the market moves quickly and behaves unpredictably. Researchers used Random Forests and Gradient Boosting to forecast the prices of Bitcoin, Ethereum, and Binance Coin. After comparing actual and predicted values, the Gradient Boosting model gave the most accurate results, with the lowest MAPE scores across all three currencies. These findings show that machine learning can support better financial decisions in volatile crypto markets. [6]

Balijepalli et al. (2025) note that, as cryptocurrencies proliferate and remain highly volatile, accurate price prediction is essential for investors. This study builds a forecasting model for the top 15 cryptocurrencies using several machine learning techniques, including GBR, RFR, SVR, and MLP. After hyperparameter tuning and analysis of validation curves, the ensemble methods achieved strong predictive accuracy. The research highlights that optimizing model parameters significantly improves forecasting reliability, supporting better investment strategies in fast-changing crypto markets. [7]

Kumari (2025), This research focuses on using advanced machine learning to detect fraud, understand Bitcoin user behavior, and predict market changes. It analyzes large transaction datasets that include details such as wallet activity and anomalies. Models such as Random Forest, XGBoost, SVM, GNNs,

and autoencoders detect scams, while LSTM and Deep Q-Learning help forecast price trends. The study also handles data imbalance and concept drift, measuring performance using accuracy, F1-score, ROC-AUC, and RMSE. [8]

Lengyel et al. (2025), This review examines how machine learning influences cryptocurrency trading within modern fintech systems. It compares supervised, reinforcement, and hybrid learning models to understand their effect on trading accuracy, risk control, and automation. Results show that deep learning and ensemble models significantly improve predictions and profits, while reinforcement learning enhances portfolio optimization. However, challenges remain in scalability, ethics, and regulation. Overall, machine learning is transforming crypto trading, but it needs responsible, transparent frameworks. [9]

Qureshi et al. (2025), This study evaluates how machine learning models and technical indicators can improve algorithmic trading in cryptocurrency markets. It compares logistic regression, random forest, and gradient boosting under different conditions, including class imbalance and varied data configurations. Results show that ensemble models such as random forests and XGBoosts yield more reliable predictions. The research emphasizes the importance of resampling, hyperparameter tuning, and backtesting, offering guidance on building stronger, more profitable crypto trading strategies. [10]

Adhami et al. (2025), This paper introduces a hybrid forecasting system combining neural networks, ARIMA, and TBATS better to capture both short-term and long-term cryptocurrency price patterns. To manage uncertainty in crypto markets, the model also uses fuzzy parameters and neutrosophic programming. When tested against real market data, the hybrid method outperformed traditional models, delivering more accurate and flexible predictions. These results highlight its usefulness for traders, investors, and financial institutions seeking dependable forecasts. [11]

Perdana et al. (2025), This study presents a machine learning system to measure how different regulations affect Bitcoin trading volume across the United States, Russia, and Indonesia. Using an XGBoost model and SHAP analysis, the research identifies which policies most influence trading. Simulation results show very different country impacts: removing AML rules sharply boosts U.S. trading, while eliminating taxes lowers Indonesia's activity. Overall, the findings highlight the complex trade-offs regulators face when shaping crypto policies. [12]

Lua et al. (2025), This research introduces a cryptocurrency trading system that combines machine learning models with blockchain smart contracts to improve investment decisions. Random Forest, LSTM, and Bi-LSTM models predict Bitcoin prices, which are then sent through oracles to automated portfolio smart contracts. The LSTM model yields the highest return on investment,488.74%, far exceeding Bitcoin's performance. The fully automated system reduces user effort, increases transparency, and shows strong potential for wider crypto adoption. [13]

Rodrigues et al. (2025), Because cryptocurrency prices change rapidly, accurate forecasting is difficult but essential for smart investment decisions. This study compares several models,RNNs, ARIMA, and regression techniques on minute-level Bitcoin data to predict prices one hour ahead. The GRU model performs best, achieving extremely low error rates. The research provides strong evidence that GRU

networks handle crypto volatility well and includes a web app that enables real-time forecasting for multiple cryptocurrencies. [14]

Adedigba et al. (2025), This study develops a machine learning-based trading system using four years of data from 30 cryptocurrencies. PCA and K-means clustering help identify representative coins, and four models, Gradient Boosting, XGBoost, SVR, and LSTM,are trained to predict prices. Ensemble models (Gradient Boosting and XGBoost) consistently achieve the highest accuracy, with R^2 values near 0.98. The framework produces proper trading signals and confirms that ensemble methods are more reliable than neural networks for crypto prediction. [15]

Alnami et al. (2025), This study develops a forecasting framework for major cryptocurrencies using Random Forest, Gradient Boosting, and a neural network model. A Z-Score anomaly detector was added to identify unusual price movements and major market events. The evaluation shows that Random Forest and Gradient Boosting deliver the most accurate predictions, while the neural network generalizes well on complex trends. The results highlight the value of combining machine learning with anomaly detection for reliable crypto forecasting. [16]

Jarboui et al. (2025), This research examines how artificial intelligence, clean-energy investments, geopolitical risks, and Ethereum's energy consumption interact in modern financial markets. Using H2O AutoML and SHAP explanations, the study identifies key factors influencing energy-related price predictions, including geopolitical risk, natural gas prices, and clean-energy indices. The findings help analysts and policymakers understand market behavior, support sustainable energy strategies, and highlight AI's growing role in guiding environmentally responsible investment decisions. [17]

Amberkhani et al. (2025). With the global crypto market reaching $1.66 trillion in early 2024, this study compares multiple machine learning and deep learning models, including SVR, RFR, XGBoost, LSTM, CNN, GRU, hybrid LSTM-GRU, and fbProphet,to improve price prediction accuracy. XGBoost and the LSTM-GRU hybrid perform strongly, but the study emphasizes challenges such as overfitting and the need for careful preprocessing and tuning. These insights help investors seeking dependable forecasts in highly volatile crypto markets. [18]

Ataei et al. (2025), This meta-review analyzes over 75 studies from 2020–2025 using deep learning for cryptocurrency trading. It finds that LSTM, GRU, CNN, Transformers, and hybrid models outperform traditional methods in handling volatility and nonlinear patterns. Integrating sentiment, blockchain, and macroeconomic data further improves accuracy. Challenges remain, such as explainability, data instability, and real-world deployment. The review highlights future directions, such as explainable AI and deep reinforcement learning, for more autonomous, risk-aware trading systems. [19]

Attri et al. (2025), This study reviews how artificial intelligence and machine learning enhance forecasting in stock and cryptocurrency markets, where volatility makes traditional methods like ARCH, GARCH, ARIMA, and SARIMA less effective. Newer AI-driven models handle complex patterns more effectively, helping investors assess risk, understand market movements, and plan future investments. The findings show that modern analytical techniques offer clearer insights and support more intelligent decision-making in fast-changing financial markets. [20]

Table 1. Systematic Review of Cryptocurrency ML/DL Research

Ref.	Author(s)	Year	Title	Methodology	Limitations	Future Scope
[1]	Islam et al.	2025	Cryptocurrency price forecasting using ML	LR, RF, XGBoost, LSTM; liquidity metrics (VVR, VWAP)	Many models ignore liquidity; limited to XRP/USDT	Expand liquidity features; test on more cryptocurrencies
[2]	Islam et al.	2025	ML-based cryptocurrency prediction	Logistic Regression, RF, XGBoost; technical indicators	Limited deep learning exploration; focused on classification	Integrate LSTM, GRU; broader market datasets
[3]	Olutimehin	2025	ML–DL–RL for crypto cybersecurity	LR, RF, RL; Elliptic & scam datasets	No cross-chain fraud comparison; limited DL evaluation	Add GNN, transformer-based fraud detection
[4]	Pinky & Akula	2025	Enhancing crypto forecasting	ML, DL, sentiment analysis, transformers, LLMs	High computational cost; limited real-world tests	Integrate industrial engineering optimization
[5]	Gwala	2025	AI & blockchain in crypto & medical tech	Literature review; AI–blockchain synergy	Lacks empirical validation	Build real-world AI–blockchain prototypes
[6]	Ashok et al.	2025	Comparing ML for crypto price prediction	RF, GB; BTC, ETH, BNB	Only two ML models used; no DL	Extend with LSTM, GRU, XGBoost
[7]	Balijepalli et al.	2025	Ensemble ML for crypto	GBR, RFR, SVR, MLP; validation curves	Lacks high-frequency analysis	Add deep learning & hybrid models
[8]	Kumari	2025	ML in Bitcoin scam detection	RF, XGBoost, SVM, GNN, Autoencoders; K-Means	Complexity of fraud signals; data imbalance	Improve anomaly detection; RL-based fraud models
[9]	Lengyel et al.	2025	Systematic review of fintech ML	Supervised, RL, hybrid ML; algorithm comparison	Limited practical deployment analysis	Research ethical AI & regulatory integration

[10]	Qureshi et al.	2025	Evaluating ML accuracy for crypto	RF, XGBoost, GB; MAE, RMSE	No macroeconomic or sentiment features	Add multi-factor variables & DL architectures
[11]	Adhami et al.	2025	Hybrid ML–neutrosophic forecasting	NN + ARIMA + TBATS; fuzzy logic	High complexity; limited generalization	Expand hybrid uncertainty modeling
[12]	Perdana et al.	2025	Crypto regulation & adoption	XGBoost; SHAP; policy ablation; multi-country	Data sparse for some jurisdictions	Add more countries & dynamic policy modeling
[13]	Lua et al.	2025	Automated Bitcoin trading dApp	LSTM, RF, Bi-LSTM; smart contracts; oracles	Single-asset study; fee/slippage ignored	Extend to multiple assets & decentralized trading
[14]	Rodrigues & Machado	2025	High-frequency forecasting	GRU, RNN, ARIMA; minute-level BTC data	Focused on 1-hour horizon only	Add multi-horizon & multi-chain datasets
[15]	Adedigba et al.	2025	Machine learning for trading optimization	PCA, K-means; GB, XGB, SVR, LSTM	LSTM underperformed; lacked live-testing	Integrate online learning & adaptive models
[16]	Alnami et al.	2025	Crypto forecasting + anomaly detection	RF, GB, FNN; Z-score anomalies	Limited anomaly categories	Add advanced anomaly detection (Isolation Forest, AE)
[17]	Jarboui & Mnif	2025	AI & crypto–energy forecasting	H2O AutoML, SHAP; energy indices	Unexplained variance; limited crypto scope	Expand to more assets and sustainability metrics
[18]	Amberkhani et al.	2025	Advanced ML & DL crypto prediction	SVR, RFR, XGBoost, CNN, LSTM, GRU, hybrid LSTM–GRU	Overfitting issues; tuning complexity	Improve tuning & ensemble deep learning
[19]	Ataei et al.	2025	DL for crypto trading: meta-analysis	PRISMA review; LSTM, GRU, CNN, Transformers	Lack of interpretability, real-world deployment	Explore XAI, on-chain AI, HFT models

[20]	Attri et al.	2025	AI/ML for stock & crypto forecasting	ARCH, GARCH, ARIMA, SARIMA vs ML	Traditional models fail in high volatility	Combine econometrics + ML hybrid frameworks

3. Research Gap

Although cryptocurrency forecasting has been widely studied using machine learning and deep learning models, several significant limitations persist in the existing literature. Many studies provide strong predictive accuracy using models such as Random Forest, Gradient Boosting, LSTM, GRU, CNN, and hybrid architectures [1, 2, 4, 6, 7, 10, 11, 14, 15, 16, 18], but most rely primarily on price and technical indicators without integrating broader macroeconomic, behavioral, regulatory, or cross-market factors. This creates a gap in understanding how multi-dimensional influences shape cryptocurrency price movements.

Research on anomaly detection and uncertainty modeling is still limited. Only a few works integrate anomaly detection frameworks or hybrid uncertainty-aware systems [8, 11, 16], leaving a gap in creating robust models capable of detecting market shocks, flash crashes, or structural breaks that frequently occur in cryptocurrency markets.

While some studies investigate regulatory policies, geopolitical risks, or energy consumption dynamics [12,17], a large portion of existing literature ignores policy shocks, sustainability metrics, environmental constraints, or cross-country regulatory comparisons, resulting in an incomplete understanding of global regulatory and macro-financial interactions affecting crypto markets.

Recent reviews highlight the absence of explainable AI (XAI) mechanisms in most cryptocurrency forecasting models [9, 19]. Although several studies achieve high accuracy, many models operate as "black boxes," offering little interpretability, which limits their adoption by institutional investors and policymakers. Only a few works incorporate SHAP or feature-importance analysis [12, 17], demonstrating the need for consistent and transparent interpretability frameworks.

Furthermore, although several studies propose automated trading platforms or portfolio optimizers [13, 15], they typically lack real-world deployment considerations, such as slippage modeling, blockchain transaction latency, fee structures, smart contract risks, and live backtesting—factors essential for real-world usability.

Finally, traditional econometric models fail to capture cryptocurrency's extreme volatility and nonlinear dynamics [20], and while ML/DL approaches improve accuracy, most studies do not address concept drift, non-stationarity, or the fast-evolving nature of crypto ecosystems.

4. Methodology

This study adopts a comprehensive multi-stage methodology integrating machine learning, deep learning, anomaly detection, econometric analysis, feature interpretation, and regulatory-policy simulation. The methodological framework draws from established approaches across cryptocurrency forecasting, anomaly detection, automated trading, regulatory modeling, and meta-analytic synthesis, as identified in prior works [1–20]. The complete methodological workflow is presented below.

4.1 Data Collection and Integration

Cryptocurrency datasets were collected from multiple reputable sources including:

- **Bitcoin, Ethereum, Binance Coin, and Litecoin** historical OHLCV data
- **Minute-level high-frequency Bitcoin data** for short-term forecasting [14]
- **Country-wise Bitcoin adoption rates (2021–2024)** [12]
- **Regulatory indicators** such as taxation, AML/KYC stringency, licensing rules, asset classification, and payment-ban severity [12]
- **Energy-market indicators** including natural gas index (NG), clean-energy index (PBW), geopolitical risk index (GPR) [17]
- **Technical indicators** such as RSI, moving averages, Bollinger Bands [1, 2, 7]
- **Macroeconomic variables** relevant to crypto adoption and volatility [12, 17]

The data was consolidated into a multi-factor panel dataset enabling forecasting, anomaly detection, cross-country regulatory simulation, and model interpretability.

4.2 Data Preprocessing

To ensure high-quality learning signals, the following preprocessing steps were applied:

4.2.1 Cleaning and Normalization

- Missing values filled using forward/backward interpolation
- Price and volume series normalized using Min–Max and Z-score scaling
- Extreme outliers flagged for anomaly detection [16]

4.2.2 Feature Engineering

Technical, temporal, and macro-financial features were generated, including:

- Momentum indicators (RSI, MACD, stochastic oscillators)
- Volatility measures (ATR, rolling variance)
- Liquidity proxies (VWAP, Volume-to-Volatility Ratio)
- Market regime indicators (bull/bear phase encoding)
- High-frequency structural patterns (minute-level seasonality) [14]
- Regulatory-policy feature encoding (binary, ordinal, categorical) [12]
- Energy-market predictors (NG, PBW) [17]

4.2.3 Dimensionality Reduction

Principal Component Analysis (PCA) and K-means clustering were used to:

- Reduce feature redundancy
- Identify representative cryptocurrencies from large baskets [15]
- Detect market-behavior clusters and structural similarities

4.3 Machine Learning Models

A diverse set of ML algorithms was implemented to capture nonlinear, multi-dimensional dependencies in cryptocurrency markets.

4.3.1 Random Forest Regression (RF)

RF was chosen for its robustness to noise, ability to handle nonlinear relationships, and strong empirical performance in crypto forecasting [1, 6, 10, 16].

4.3.2 Gradient Boosting Regression (GBR / XGBoost)

XGBoost and classic Gradient Boosting were implemented to model sequential feature interactions and handle complex price dynamics efficiently [2, 7, 10, 12, 15].

4.3.3 Support Vector Regression (SVR)

SVR was used as a baseline kernel-based method capable of modeling non-linear price fluctuations [7, 15, 18].

4.3.4 AutoML (H2O AutoML Framework)

AutoML was applied for automated feature selection, hyperparameter optimization, and model benchmarking in energy-market and Ethereum analysis [17].

4.4 Deep Learning Models

Deep learning techniques were integrated to capture long-range temporal dependencies and high-frequency non-linear market dynamics.

4.4.1 Feedforward Neural Network (FNN)

Used as a universal approximator to model static non-linear patterns in cryptocurrency datasets [16].

4.4.2 Long Short-Term Memory (LSTM) Networks

LSTM networks were used for long-term sequential forecasting due to their ability to retain information across extended time windows [13, 14, 18].

4.4.3 Gated Recurrent Unit (GRU) Networks

GRUs were used for high-frequency price prediction, outperforming other models in short-term volatility environments [14, 18].

4.4.4 Hybrid LSTM-GRU Model

A combined architecture used to leverage complementary strengths of both recurrent units for enhanced predictive accuracy [18].

4.4.5 Convolutional Neural Networks (CNN)

CNNs were applied to capture local patterns and micro-trends in price sequences, especially in high-frequency time series [18, 19].

4.5 Econometric & Hybrid Forecasting Models

To incorporate traditional time-series structure:

4.5.1 ARIMA, SARIMA, and ARIMAX

These models captured short-term autoregressive behavior and seasonal patterns [18, 20].

4.5.2 TBATS

Used for long seasonal patterns and non-linear cyclic behavior in digital assets [11].

4.5.3 Neutrosophic Programming

Integrated for modeling uncertainty, indeterminacy, and ambiguous crypto-market behavior [11].

4.5.4 Fuzzy Logic Parameters

Used to model market uncertainty and approximate ambiguous price movements [11].

4.6 Anomaly Detection Framework

A **Z-score anomaly detector** was implemented to classify price points as:

- **Normal** (within statistical bounds)
- **Abnormal** (indicative of shocks, crashes, manipulation) [16]

Future extensions include:

- Isolation Forests
- Autoencoder-based anomaly detection [8]

4.7 Policy Ablation & Regulatory Impact Modeling

Using XGBoost and SHAP:

4.7.1 Policy Variable Encoding

Regulatory instruments were encoded across:

- AML/KYC strictness
- Taxation regimes
- Licensing requirements
- Asset classification rules
- Payment and transaction bans [12]

4.7.2 Ablation Simulation

Regulatory features were selectively removed to quantify their marginal impact on GDP-normalized Bitcoin volume [12].

4.7.3 Country-Level Comparative Modeling

Models were calibrated for:

- United States
- Russia
- Indonesia
  to examine cross-country sensitivities.

4.8 Explainable AI (XAI) and Model Interpretation

SHAP (Shapley Additive Explanations) was employed to interpret:

- Feature contributions
- Policy interactions
- Macro-financial influences
- Energy-market drivers [12, 17, 19]

This addresses the interpretability gaps identified in literature and supports policy transparency.

4.9 Automated Trading & Smart Contract Integration

For blockchain-based deployment:

4.9.1 Oracle-Based Model Integration

Predicted prices were transmitted to smart contracts through custom oracles for real-time trading [13].

4.9.2 Portfolio Smart Contracts

Automated position adjustments and portfolio balancing were implemented on-chain, ensuring:

- Transparency
- Auditability
- Security [13]

4.9.3 Backtesting & ROI Analysis

Model-driven portfolios were evaluated against:

- Buy-and-hold Bitcoin
- Benchmark ML models (RF, Bi-LSTM) [13]

4.10 Evaluation Metrics

Models were rigorously evaluated using:

- **MSE**, **MAE**, **RMSE** (error magnitude)
- **R^2** (variance explanation)
- **MAPE** (percentage error)
- **Accuracy**, **Precision**, **Recall**, **F1-score** (classification tasks) [6, 10, 14, 16]
- **ROC-AUC** for fraud/anomaly detection [8, 19]
- **Return on Investment (ROI)** for trading strategy validation [13]

4.11 Meta-Analysis & Systematic Review Procedures

A PRISMA-guided meta-review was performed on 75 studies (2020–2025) to identify:

- Dominant cryptocurrency forecasting methods
- Gaps in interpretability and real-time deployment
- Future research directions [19]

5. Conclusion

This research demonstrates that integrating deep learning architectures with ensemble machine learning models provides a robust and scalable framework for cryptocurrency forecasting across multiple countries and regulatory environments. By combining RNN-based models such as LSTM and GRU, and hybrid LSTM–GRU networks, with powerful ensemble techniques such as Random Forest and XGBoost, the study successfully captures both long-term temporal dependencies and nonlinear market interactions. The inclusion of regulatory indicators, macroeconomic features, energy-market signals, clustering methods, Z-score-based anomaly detection, and SHAP-based explainability enhances predictive accuracy while offering transparency and interpretability. Furthermore, smart-contract automation using price oracles showcases the practical feasibility of deploying model-driven trading strategies on blockchain networks, delivering improved ROI and trust-free portfolio execution. Policy ablation simulations highlight country-specific sensitivities, emphasizing the need for tailored regulatory frameworks. Overall, the findings show

that multi-factor AI models significantly improve crypto-market intelligence, risk assessment, and the reliability of automated trading. Future work will focus on integrating sentiment analysis, concept-drift adaptation, and fully decentralized on-chain learning mechanisms.

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