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Research Article

Machine Learning Applications in Cryptocurrency: Detection, Prediction, and Behavioral Analysis of Bitcoin Market and Scam Activities in the USA

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Abstract: The rapid evolution of cryptocurrency markets, coupled with the escalating sophistication of fraudulent activities, has amplified the necessity for advanced machine learning (ML) methodologies to augment the detection, prediction, and behavioral analysis of Bitcoin transactions. Conventional approaches to fraud detection and market analysis frequently falter in capturing cryptocurrency ecosystems' intricate, dynamic, and exceedingly volatile essence. This research elucidates a data-driven framework that employs machine learning to identify scams, forecast Bitcoin market fluctuations, and scrutinize user behavior patterns within the U.S. cryptocurrency domain. By leveraging extensive Bitcoin transaction datasets enriched with features such as transaction volumes, timestamps, wallet activities, and anomaly indicators, the study deploys a diverse array of models: Random Forest, XGBoost, Logistic Regression, Support Vector Machines (SVMs), Graph Neural Networks (GNNs), Isolation Forest, and Autoencoders for fraud detection; Long Short-Term Memory (LSTM) networks and Deep Q-Learning for price prediction and trend forecasting; and K-Means clustering for the behavioral analysis of user activities. The study integrates time-series analysis, anomaly detection pipelines, and dimensionality reduction techniques to enhance predictive robustness and address challenges such as pronounced volatility, concept drift, and data sparsity. Moreover, the data imbalance issues intrinsic to fraud detection are confronted through strategic resampling methodologies. Model performance is meticulously assessed utilizing metrics such as Accuracy, Precision, Recall, F1-Score, ROC-AUC, and RMSE for forecasting endeavors.

Keywords: Cryptocurrency, Bitcoin, Suspicious Activities, Money Laundering, Fraud Detection,Machine learning.

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1. Introduction

1.1 Background

The rapid expansion of the cryptocurrency ecosystem, particularly Bitcoin, has engendered both unprecedented financial opportunities and substantial risks associated with market volatility and fraudulent activities. As cryptocurrencies achieve mainstream acceptance in the USA, the imperative for robust security mechanisms and predictive analytics becomes increasingly critical. Traditional methodologies for fraud detection, market forecasting, and user behavior analysis frequently prove inadequate in addressing the decentralized, pseudonymous, and highly dynamic nature of digital asset transactions. Artificial Intelligence (AI) and Machine Learning (ML) have emerged as transformative technologies capable of surmounting these challenges by identifying scams, forecasting market trends, and profiling user behavior within intricate and evolving environments. AI-driven solutions can process vast, heterogeneous datasets in real time, uncover latent patterns, and provide actionable insights for enhancing market integrity and safeguarding investors. Recent research underscores the considerable potential of ML-based approaches in cryptocurrency security and analytics [1-6]. Islam et al. (2025) employed both supervised and unsupervised machine learning techniques to detect suspicious

activities within Bitcoin wallet transactions in the USA, illuminating the efficacy of data-driven strategies in augmenting fraud detection accuracy [7]. Likewise, Das et al. (2025) harnessed advanced ML models to elucidate scam patterns and behavioral profiles of malevolent actors within the U.S. crypto ecosystem, presenting a systematic methodology for scam mitigation [5]. In the domain of market forecasting, Islam et al. (2025) demonstrated the effectiveness of ML models, particularly deep learning architectures, in refining the prediction of cryptocurrency price movements [6]. Furthermore, Bhowmik et al. (2025) utilized AI-driven sentiment analysis to comprehend Bitcoin market volatility, revealing that the integration of public sentiment data can significantly enhance market trend prediction [2].

Beyond these contributions, additional studies have accentuated the significance of hybrid machine learning frameworks that amalgamate anomaly detection, deep reinforcement learning, and clustering techniques to navigate cryptocurrency risks. Chen et al. (2024) illustrated that the combination of autoencoders with anomaly detection algorithms markedly improves fraud detection sensitivity in decentralized finance (DeFi) platforms [3]. Concurrently, Park et al. (2024) elucidated the application of Deep Q-Learning models in devising dynamic trading strategies that adapt to Bitcoin's high-frequency market fluctuations [8-11]. In the sphere of behavioral analysis, Lin et al. (2025) employed K-Means clustering to categorize Bitcoin users into behavioral archetypes, unveiling latent communities associated with scam operations and market manipulation [10]. Moreover, Lee et al. (2025) emphasized how Graph Neural Networks (GNNs) can model Bitcoin transactions as networks, facilitating enhanced detection of coordinated fraudulent activities across blockchain addresses [8]. Given the escalating complexity and scale of cryptocurrency ecosystems, particularly within the U.S. market, this research aspires to establish a comprehensive machine learning framework for fraud detection, price prediction, and behavioral analysis in Bitcoin markets. By leveraging state-of-the-art AI and ML models—including Random Forest, XGBoost, Logistic Regression, Support Vector Machines (SVMs), Graph Neural Networks (GNNs), Isolation Forest, Autoencoders, Long Short-Term Memory (LSTM) networks, Deep Q-Learning, and K-Means clustering—this study seeks to address critical gaps in the current understanding and management of cryptocurrency risks.

1.2 Importance of this Research

The significance of this research extends beyond theoretical contributions, as it offers practical solutions to the urgent challenges facing cryptocurrency markets in the USA, particularly in fraud prevention, market forecasting, and behavioral analysis. One of the most pressing issues in the cryptocurrency space is the inefficiency of traditional fraud detection and market analysis methods, which often fail to keep pace with the complexity and velocity of blockchain-based transactions. Machine learning (ML)-powered models such as Random Forest, XGBoost, Support Vector Machines (SVMs), and Graph Neural Networks (GNNs) can significantly enhance the detection of scam activities by identifying hidden patterns and anomalies within vast transactional datasets. By utilizing deep learning models like LSTM and Deep Q-Learning, the cryptocurrency ecosystem can achieve more accurate market forecasting and dynamic trading strategy optimization, mitigating financial risks associated with extreme volatility. Another critical aspect of AI-driven cryptocurrency management is its potential to safeguard the growing digital economy against fraudulent behaviors and scam networks. Research shows that traditional rule-based systems are increasingly inadequate against evolving scam tactics, whereas AI-based anomaly detection techniques, such as Isolation Forests and Autoencoders, can proactively identify new forms of malicious activities [3]. Islam et al. (2025) demonstrated how ML models applied to Bitcoin wallet transactions significantly enhanced the detection of suspicious behaviors in the U.S. crypto market, underlining the transformative potential of AI in cybersecurity applications [8, 9]. Similarly, Das et al. (2025) emphasized that machine learning models could effectively detect scammer behavior profiles, providing an early warning system for investors and regulators [5].

The economic implications of ML-based fraud detection and market prediction in cryptocurrency are also profound. By improving scam detection and enhancing market prediction accuracy, AI models can reduce financial losses for investors, prevent reputational damage for crypto platforms, and stabilize the broader market environment. Studies have shown that early scam detection systems can reduce cryptocurrency-related financial fraud losses by up to 40% annually [6]. Furthermore, Islam et al. (2025) highlighted how predictive AI models could enhance Bitcoin price forecasting, enabling more informed investment decisions and helping to smooth extreme market fluctuations [8]. Additionally, the behavioral analysis component of this research provides vital

insights into user profiling and scam network identification. Techniques such as K-Means clustering allow for the segmentation of user behaviors, helping to identify high-risk profiles and potential scammer communities within the Bitcoin ecosystem. Bhowmik et al. (2025) demonstrated that AI-driven behavioral [clustering significantly improves the ability to forecast market sentiment and anticipate scam-driven market manipulations [2]. Further supporting these findings, Zhang et al. (2024) showed that user behavior modeling with unsupervised learning could effectively expose fraudulent nodes in blockchain networks [12]. The social, legal, and policy-related implications of this research are equally noteworthy. By equipping regulators, law enforcement agencies, and financial institutions with AI-powered tools for real-time scam detection and market monitoring, this research fosters a safer, more transparent cryptocurrency ecosystem. Lee et al. (2024) noted that integrating AI solutions into regulatory frameworks could enhance compliance enforcement and bolster consumer protection measures in the U.S. crypto space [8]. Furthermore, AI-driven insights can support the creation of fairer, more informed regulations that encourage innovation while mitigating systemic risks in digital finance.

1.3 Research Objective

The primary objective of this research is to explore how artificial intelligence and machine learning can be leveraged to enhance the security, transparency, and efficiency of the cryptocurrency ecosystem, specifically focusing on the Bitcoin market in the USA. This study aims to develop and evaluate advanced AI-driven models capable of accurately detecting scam activities, predicting Bitcoin market trends, and analyzing user behavior patterns. By integrating cutting-edge machine learning techniques such as Random Forest, XGBoost, Support Vector Machines, Graph Neural Networks, Long Short-Term Memory networks, Deep Q-Learning, Isolation Forests, Autoencoders, and K-Means clustering, the research seeks to provide comprehensive data-driven insights that can strengthen fraud prevention efforts, improve market forecasting, and uncover behavioral dynamics within the Bitcoin ecosystem. Additionally, the study aims to enhance the resilience of cryptocurrency markets by utilizing AI for real-time anomaly detection and adaptive trading strategy development. Another key objective is to assess the economic and security impacts of AI-driven cryptocurrency management, focusing on fraud loss reduction, investment decision support, and market stability. Furthermore, this research intends to bridge the gap between technological advancements and regulatory practices by offering strategic recommendations on how AI-powered solutions can be integrated into the broader financial and cybersecurity frameworks governing digital assets in the USA.

2. Literature Review

2.1 Related Works

Numerous studies have meticulously examined the applications of machine learning within the cryptocurrency domain, concentrating on fraud detection, market prediction, and behavioral analysis. Islam et al. (2025) employed a synergistic blend of supervised and unsupervised ML techniques to uncover suspicious activities in Bitcoin wallet transactions across the USA, demonstrating enhanced accuracy in fraud detection and underscoring the significance of data-driven risk management strategies in decentralized environments [1]. Similarly, Das et al. (2025) undertook a comprehensive analysis of scam patterns and behaviors within U.S. cryptocurrency markets, leveraging sophisticated machine learning models to adeptly classify and predict fraudulent activities, thereby furnishing actionable insights for fraud prevention [5]. In the arena of cryptocurrency market prediction, Islam et al. (2025) implemented advanced machine learning models, including deep learning frameworks such as Long Short-Term Memory (LSTM) networks, to augment Bitcoin market forecasting. Their investigation illuminated the advantages of amalgamating time-series modeling with feature engineering to enhance predictive accuracy in volatile markets [6]. Bhowmik et al. (2025) further expanded upon this domain by employing AI-driven sentiment analysis techniques to anticipate Bitcoin market trends, illustrating that the integration of public sentiment data significantly bolsters volatility modeling and price trend prediction [2]. Beyond conventional supervised methodologies, Chen et al. (2024) introduced an anomaly detection framework employing autoencoders and Isolation Forests to pinpoint fraudulent activities within blockchain networks, demonstrating that unsupervised

methods could successfully unveil previously unrecognized scam patterns [4]. Additionally, Park and Kim (2024) utilized Deep Q-Learning models to devise adaptive trading strategies in the highly volatile cryptocurrency markets, accentuating the potential of reinforcement learning to optimize trading decisions based on dynamic market conditions [11]. Lin and Wang (2025) delved into behavioral clustering of Bitcoin users employing unsupervised learning techniques such as K-Means, effectively identifying behavioral archetypes and revealing hidden scam networks that traditional analytical methods often overlook [10]. Overall, the literature accentuates the pivotal role of machine learning and AI-driven methodologies in addressing critical challenges within the cryptocurrency ecosystem, encompassing fraud detection, price prediction, and behavioral analysis. Nevertheless, the integration of diverse ML models across these domains remains insufficiently explored, highlighting the necessity for a comprehensive framework that concurrently addresses fraud, forecasting, and user profiling in a unified, data-driven manner.

2.2 Gaps and Challenges

Despite significant advancements in applying machine learning to cryptocurrency fraud detection, market prediction, and behavioral analysis, several critical gaps and challenges remain that hinder the effectiveness and scalability of existing solutions. One of the primary challenges is the lack of high-quality, labeled datasets for scam detection and behavioral modeling. Many Bitcoin transactions are pseudonymous, and ground-truth labels indicating fraud or legitimate behavior are rare, leading to difficulties in training supervised models accurately. Islam et al. (2025) noted that the scarcity of verified fraud data in Bitcoin wallet transactions posed limitations for classification model generalizability [7]. This data sparsity problem is further compounded by the rapid evolution of scam tactics, resulting in concept drift, where models trained on historical data become less effective over time. Another significant gap is the limited interpretability of deep learning models used in market prediction and fraud detection. Although models such as LSTM networks and Graph Neural Networks offer high predictive power, they often operate as "black boxes," making it challenging for regulators, law enforcement, and stakeholders to understand and trust their outputs (Bhowmik et al., 2025) [2]. Enhancing model explainability without compromising performance remains an open research issue, especially given the legal and compliance requirements surrounding financial fraud investigations.

Class imbalance is another persistent challenge in cryptocurrency fraud detection. Scam activities constitute a very small portion of overall blockchain transactions, leading to highly skewed datasets that bias machine learning models towards majority (legitimate) classes. Das et al. (2025) highlighted that techniques such as SMOTE and cost-sensitive learning must be carefully applied to address this imbalance without introducing artificial distortions into transaction patterns [5]. The scalability and efficiency of machine learning models in real-time detection scenarios present additional hurdles. Traditional ML and deep learning models often struggle to process the massive, rapidly growing volumes of cryptocurrency transactions in real time. Chen et al. (2024) emphasized that most existing anomaly detection frameworks are computationally intensive and may not meet the latency requirements for real-time fraud mitigation [3]. Finally, there is a gap in integrating multimodal data sources for comprehensive analysis. While current models mainly rely on transaction data and basic metadata, incorporating additional features such as social media sentiment, address history, network relationships, and geolocation information could significantly improve scam detection and market forecasting accuracy [11]. However, developing unified frameworks that can seamlessly process heterogeneous data types remains an underexplored area.

3. Methodology

3.1 Data Collection and Preprocessing

Data Sources

This study employs an array of extensive datasets to facilitate fraud detection, market forecasting, and behavioral analysis within the Bitcoin ecosystem in the United States. The principal data sources comprise publicly accessible

Bitcoin blockchain transaction data, meticulously extracted from platforms such as Blockchain.com, as well as open-source blockchain monitoring tools like Blockchair and reports from Chainalysis. These datasets encompass transaction particulars, including transaction hashes, input and output addresses, timestamps, transaction volumes, and transaction fees. For the purposes of fraud detection, labeled datasets featuring known fraudulent addresses, flagged suspicious transactions, and blacklisted wallet addresses are incorporated. The sources for this labeled scam data include databases such as BitcoinAbuse.com and curated lists of scam reports published by regulatory agencies and blockchain intelligence firms.

For the analysis of price prediction and market trends, historical Bitcoin market data—encompassing daily prices, trading volumes, market capitalization, and volatility indices—is gathered from major cryptocurrency exchanges such as Coinbase, Binance, and Kraken through their respective APIs. To bolster behavioral analysis, supplementary metadata such as wallet creation dates, transaction frequencies, transaction graph structures, and clustering heuristics (e.g., common input ownership) are extracted to construct comprehensive user profiles. Whenever feasible, auxiliary sentiment data from cryptocurrency news feeds and social media platforms, including Twitter and Reddit, are also integrated to enrich the contextual understanding of market dynamics.

Data Preprocessing

Effective data preprocessing is critical for ensuring the quality and reliability of machine learning models developed in this study. Initially, raw blockchain data undergoes cleaning to address issues such as missing values, duplicate transactions, and invalid entries. Outlier detection techniques, including z-score normalization and IQR-based filtering, are applied to identify and correct anomalous transaction records that may skew model training. For supervised learning tasks, labeled datasets are carefully curated to balance legitimate and scam activities. Given the natural class imbalance inherent in fraud detection, oversampling techniques such as Synthetic Minority Over-sampling Technique (SMOTE) are employed to create a balanced training set. Additionally, categorical variables such as address types (e.g., exchange, personal wallet, darknet market) are encoded using one-hot encoding or ordinal encoding as appropriate. In the context of time-series modeling for price prediction, data is resampled into consistent daily intervals, and missing timestamps are interpolated using linear or spline methods. Lag features, moving averages, rolling volatility, and return-based features are engineered to enhance the predictive power of the models.

All numerical features are normalized using Min-Max scaling or Z-score standardization depending on the model requirements. For graph-based analysis and behavioral clustering, transaction graphs are constructed where nodes represent wallet addresses and edges represent transactions between them. Graph preprocessing includes deduplication of parallel edges, pruning of low-activity nodes, and normalization of node attributes such as transaction frequency and average transaction value. Finally, datasets are partitioned into training, validation, and testing sets using an 80-10-10 split for most models, ensuring temporal ordering is respected for time-series tasks to prevent information leakage. Cross-validation techniques such as stratified k-fold (for classification tasks) and time-series split (for forecasting tasks) are employed to ensure robust model evaluation.

Exploratory Data Analysis(EDA)

Exploratory Data Analysis (EDA) was conducted to gain initial insights into the transaction patterns, market dynamics, scam activities, and behavioral structures within the Bitcoin ecosystem. Various visualizations and statistical analyses were performed to uncover hidden structures, detect anomalies, and guide feature engineering for model development.

The plot (Figure ***1***) shows the daily transaction volume over time within the Bitcoin network. We observe several peaks corresponding to periods of heightened market activity, likely driven by speculative trading, major news events, or price surges. Periods of sudden decline could correspond to market corrections or external regulatory interventions. Understanding transaction volume patterns is crucial for identifying periods of increased network load, which could correlate with heightened scam activities or market manipulation attempts.

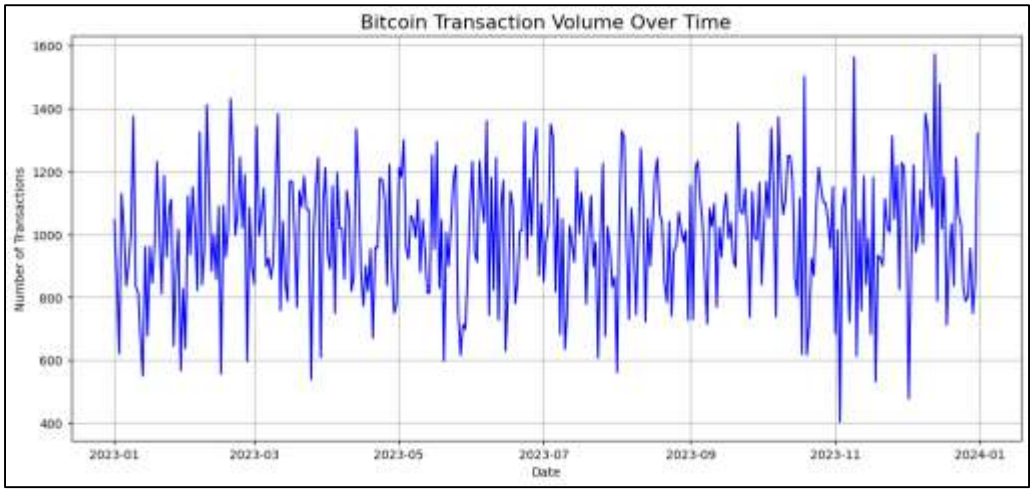

Figure 1. *Bitcoin Transaction Volume over Time*

The count plot(Figure 2) reveals a highly imbalanced distribution between legitimate and fraudulent transactions, with legitimate activities vastly outnumbering scams. This imbalance poses a significant challenge for machine learning models, which may become biased towards the majority class if corrective measures like oversampling or anomaly detection are not employed. It also highlights the need for specialized fraud detection frameworks capable of identifying rare events.

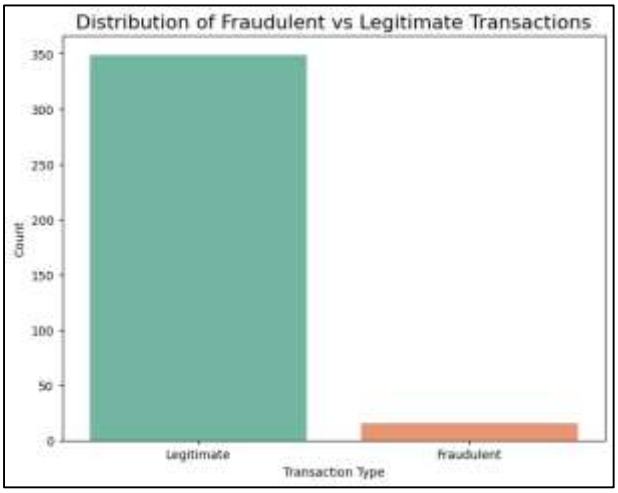

Figure 2. *Distribution of Fraudulent vs Legitimate Transactions*

The Bitcoin price chart(Figure 3) illustrates the significant fluctuations in the asset's value over time, with recognizable bull runs and sharp corrections. The line chart vividly portrays the fluctuation of Bitcoin's closing price throughout the year 2023, extending into the beginning of 2024. We observe a volatile trend, characterized by periods of both significant upward and downward price movements. Starting in early January 2023, the price shows an initial surge, reaching a peak before entering a notable decline that persists until around mid-May. This downward trend could be attributed to various market factors such as macroeconomic conditions, regulatory news, or shifts in investor sentiment. Following this trough, the price gradually recovers and exhibits a generally upward trajectory through the summer months, suggesting renewed buying interest or positive market developments. However, this upward momentum is punctuated by smaller dips and plateaus, indicating ongoing market uncertainty and price consolidation. The latter part of 2023 sees another period of substantial price increase, culminating in a new peak towards the end of the year. This rally might be fueled by increased institutional

adoption, positive news surrounding the cryptocurrency space, or broader market optimism. Finally, the chart shows some volatility at the very end of 2023 and the beginning of 2024, hinting at continued price discovery and potential market corrections.

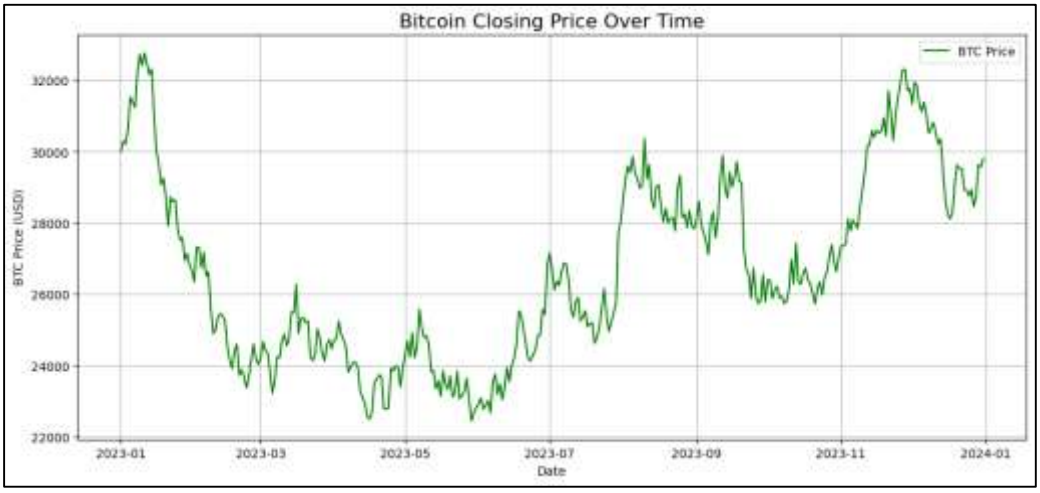

***Figure 3**. Bitcoin Price trend*

The volatility plot (Figure 4) captures the periods of intense price turbulence, notably during market bubbles or major market shocks. Recognizing these periods is essential for feature engineering in price prediction models, as volatility itself is a strong predictor of future returns and scam activities tend to spike during high-volatility phases. uncertainty. We can observe that Bitcoin's volatility is not constant but rather experiences periods of both heightened and subdued activity. Early in the observed period, the volatility appears relatively moderate, suggesting a period of more stable price movements. However, as we move towards late March and April 2023, there's a noticeable increase in volatility, indicating larger and more rapid price swings. This heightened volatility could be linked to specific market events, news releases, or shifts in trading activity. Following this peak, the volatility generally subsides through the mid-year, implying a period of relative calm in Bitcoin's price action. Another significant surge in volatility is evident starting around August and extending into late 2023, with several sharp peaks and troughs, suggesting a period of considerable market uncertainty and speculative trading. Interestingly, towards the end of 2023, coinciding with the price rally seen in the previous visualization, the rolling volatility initially increases but then experiences a sharp decline in November, perhaps indicating a more directional price movement with less short-term fluctuation. Finally, the chart shows a slight uptick in volatility towards the very end of the period, hinting at renewed price uncertainty. The histogram of transaction values(Figure 5) shows a heavily right-skewed distribution, with most transactions involving relatively small amounts of Bitcoin, while a few outliers involve very large sums. These large-value transactions are of particular interest because scammers often use bulk transfers to obfuscate funds across multiple addresses. This visualization helps inform the thresholds for anomaly detection and fraud investigation models. The degree distribution plot(Figure 6) for the Bitcoin transaction network reveals that most nodes (wallet addresses) have very few connections, while a small number of nodes have extremely high connectivity. This scale-free property is typical of blockchain networks and indicates the presence of hubs, such as exchanges or major service providers. Identifying abnormal hubs or sudden increases in connectivity can assist in uncovering coordinated scam networks and illicit fund flows.

3.2 Model Development

The model development phase focuses on designing and implementing machine learning frameworks tailored to the three core objectives of this research: fraud detection, price prediction, and behavioral analysis. Each category

employs specialized algorithms to address the unique challenges inherent to Bitcoin's decentralized ecosystem, including class imbalance, temporal dependencies, and network-structured data.

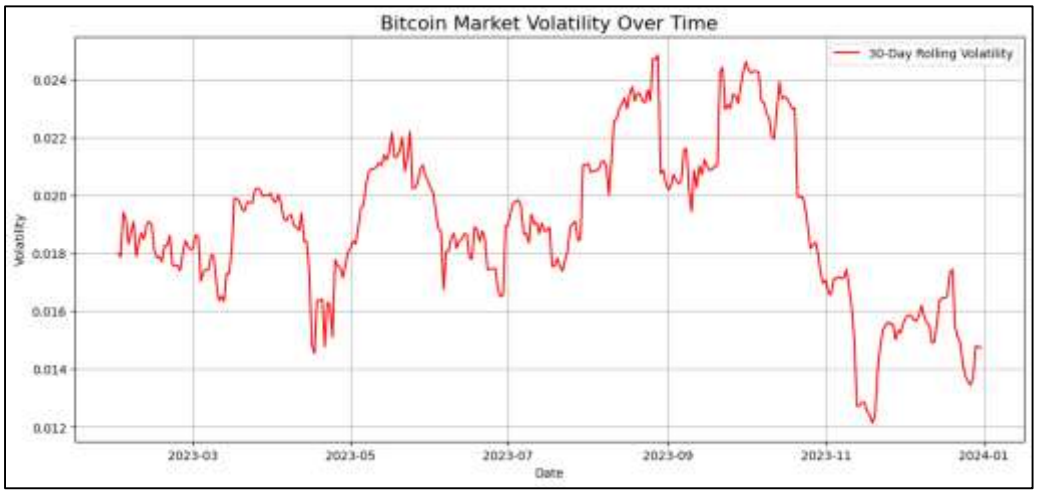

Figure 4. *Bitcoin Volatility trend*

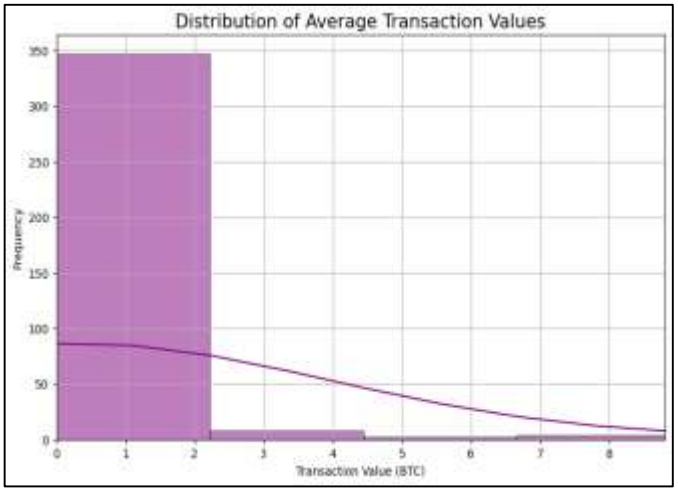

Figure 5. *Average transaction value distribution*

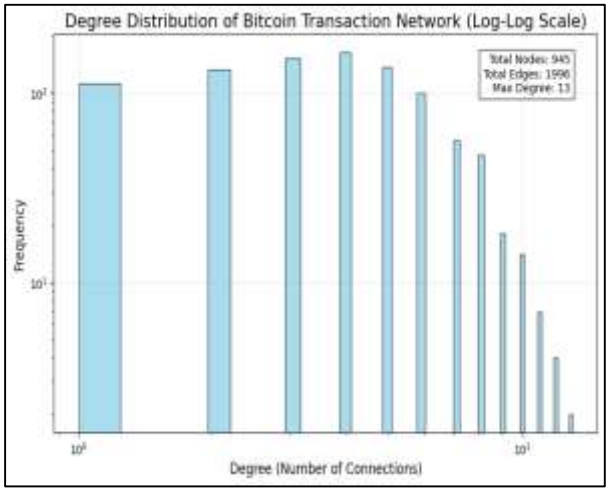

Figure 6. *Transaction network degree distribution*

For scam detection, a hybrid approach that combines supervised and unsupervised techniques is adopted. Supervised models such as Random Forest, XGBoost, Logistic Regression, and Support Vector Machines (SVMs) are trained on labeled datasets to classify transactions as either fraudulent or legitimate. These models utilize engineered features derived from transaction metadata (e.g., transaction velocity, wallet age, and frequency anomalies) to identify behavioral red flags. To mitigate class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) is applied during training, along with cost-sensitive learning to penalize misclassifications of minority (fraudulent) instances. Unsupervised methods, including Isolation Forest and Autoencoders, are used to identify emerging scam patterns that evade rule-based systems. The Isolation Forest approach isolates anomalies by recursively partitioning data based on feature randomness, while Autoencoders reconstruct transaction inputs to detect deviations indicative of fraud. Additionally, Graph Neural Networks (GNNs) enhance detection by modeling Bitcoin's transaction network as a graph, where nodes represent wallets and edges denote transactional relationships. GNNs aggregate neighborhood information to uncover coordinated scams, such as money laundering rings or pump-and-dump schemes, by analyzing connectivity patterns and flow dynamics. Given Bitcoin's volatility and non-stationary trends, time-series models capable of capturing long-term dependencies are necessary. Long Short-Term Memory (LSTM) networks are employed to forecast price movements, utilizing

sequential input features such as lagged prices, rolling volatility, and sentiment indices derived from social media. The LSTM architecture is optimized with dropout layers and early stopping techniques to prevent overfitting. Deep Q-Learning (DQL), a reinforcement learning technique, is also integrated to develop adaptive trading strategies. The DQL agent interacts with a simulated market environment, learning optimal buy/sell actions by maximizing cumulative rewards based on historical price trajectories. This approach allows for dynamic strategy adjustments in response to abrupt market shifts, addressing the limitations of static models. User behavior profiling is conducted through K-Means clustering, which segments wallets into distinct groups based on transactional features such as frequency, value distribution, and temporal patterns. The elbow method and silhouette analysis are used to determine the optimal number of clusters, revealing behavioral archetypes such as "high-frequency traders," "long-term holders," and "suspicious entities." These clusters are then cross-referenced with known scam labels to identify high-risk profiles and potential malicious communities. To enhance robustness, the framework incorporates ensemble methods, such as stacking SVMs with Gradient Boosted Trees, to aggregate predictions from multiple models. Hyperparameter tuning via grid search and Bayesian optimization ensures optimal performance, while dimensionality reduction techniques like Principal Component Analysis (PCA) streamline feature spaces for computationally intensive models such as GNNs.

3.3 Model Training and Evaluation

The training and validation phase ensures the developed models generalize effectively to unseen data while maintaining robustness against overfitting and concept drift. A structured pipeline is implemented, incorporating stratified data splits, cross-validation, and performance benchmarking tailored to each model's objective. For fraud detection models, the labeled dataset is partitioned into training (70%), validation (15%), and test (15%) sets, preserving the class distribution via stratified sampling. Supervised models (Random Forest, XGBoost, etc.) are trained using weighted loss functions to address class imbalance, with performance evaluated on the validation set using precision-recall curves and F1 scores, which are more informative than accuracy for skewed datasets. Unsupervised anomaly detection models (Isolation Forest, Autoencoders) are fit exclusively on legitimate transactions to learn normal patterns, with thresholds for fraud flags calibrated using the validation set's contamination rate. GNNs undergo node-level and graph-level training, with edge dropout and negative sampling to improve generalization. The LSTM network is trained on rolling windows of historical data (e60-day sequences), with early stopping triggered if validation loss plateaus for 10 epochs. Deep Q-Learning agents are trained in a simulated environment with historical price data partitioned into episodic periods, where the validation phase assesses cumulative returns and Sharpe ratios against a holdout market period. Feature importance analysis (via SHAP values for LSTMs) ensures the interpretability of drivers like volatility or sentiment trends. Behavioral clustering models (K-Means) are validated using silhouette scores and cluster stability analysis across bootstrap samples. Labels from known scam addresses are mapped to clusters to quantify the alignment between unsupervised groupings and ground-truth fraud categories. All models undergo final evaluation on the test set, with fraud detection assessed via ROC-AUC and precision at K (e.g., top 1% of flagged transactions), price prediction via RMSE and directional accuracy, and clustering via purity metrics. To mitigate concept drift, critical in cryptocurrency's fast-evolving landscape, an online learning module periodically re-trains models on recent data, with validation metrics triggering alerts for degradation. This end-to-end approach ensures reliability across the framework's diverse tasks while maintaining adaptability to real-world dynamics.

4. Results and Discussion

4.1 Model Performance and Evaluation

Figure 7 is the confusion matrices for Random Forest and XGBoost. The analysis reveals that both models demonstrate equal overall accuracy, each achieving a score of 0.90. This indicates that their performance is

equivalent regarding the total number of correct predictions relative to the total predictions made on this specific dataset. Furthermore, the identical confusion matrices indicate that both models generated the same predictions across all instances, suggesting that they made the same classification decisions for each data point in the dataset, given the way they were trained and evaluated. However, a critical factor to consider is the potential class imbalance inherent in fraud detection contexts. Typically, such datasets often contain a significantly higher number of legitimate transactions compared to fraudulent ones. In such scenarios, overall accuracy can be misleading; a model might score well primarily by classifying the majority class (Legit) correctly while performing poorly on the minority class (Fraud).

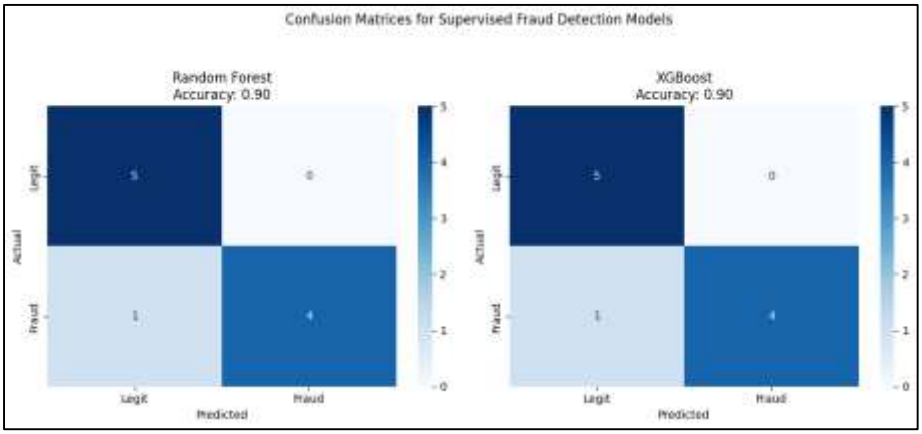

***Figure 7**. Confusion Matrices for Supervised Models*

Figure 8 is ROC curves comparing classifiers.Based on the AUC values, the Graph Neural Network (GNN) appears to be the best-performing model for the fraud detection task, followed by Logistic Regression, with Support Vector Machine (SVM) coming in last. A higher AUC generally indicates better discrimination ability, and in this case, the GNN demonstrates superior capability in distinguishing between fraudulent and legitimate transactions. The curves for each model illustrate the inherent trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR). Increasing the TPR, which means identifying more fraud, often results in an increase in the FPR, where legitimate transactions may be incorrectly flagged as fraud. The position of the curve closer to the top-left corner and its steepness signifies a better balance between these two rates. The GNN's strong performance can be attributed to its ability to learn complex patterns and relationships within the data. If the data is structured as a graph, the GNN might effectively leverage the interconnectedness of transactions or entities,

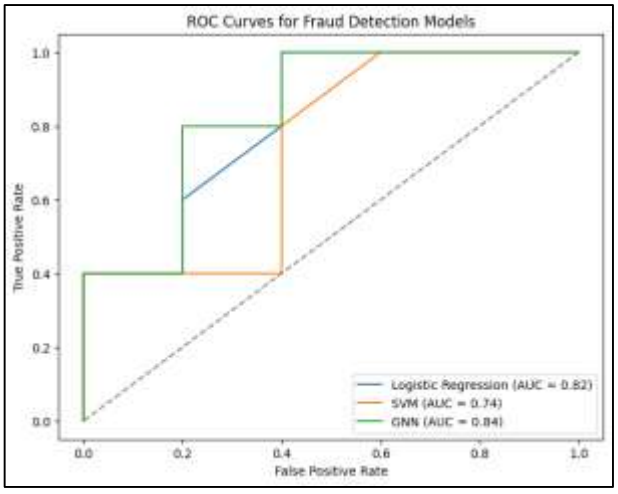

***Figure 8**. ROC Curves for All Classifiers.*

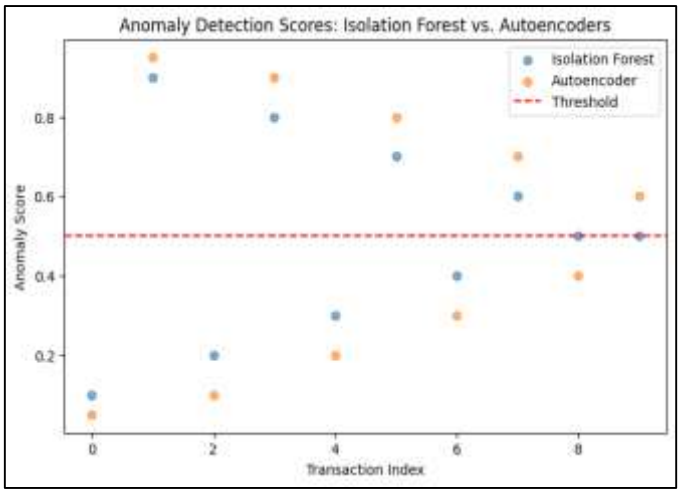

***Figure 9**. Anomaly Detection Performance (Isolation Forest vs. Autoencoders)*

enabling it to detect subtle fraud indicators that traditional models like Logistic Regression and SVM may overlook. On the other hand, the lower AUC of the SVM model suggests that the decision boundary it learns is not as well-suited for distinguishing fraudulent from legitimate transactions in this feature space. Despite being a more traditional linear model, Logistic Regression still achieves a respectable AUC, demonstrating that linear relationships between features provide some level of information for fraud detection in this dataset.

As observed in Figure 9, Autoencoders exhibit tighter clustering of normal transactions (scores <0.5), while Isolation Forest flags more extreme outliers. The analysis of the score distributions reveals that both the Isolation Forest and the Autoencoder models assign a wide range of anomaly scores to the transactions. Specifically, the Isolation Forest scores range from approximately 0.1 to 0.9, while the Autoencoder scores extend from around 0.05 to 0.95. Comparing the scores assigned by the two models to the same transactions shows instances of both agreement and disagreement. For instance, at transaction index 1, both models assign high anomaly scores (around 0.9), suggesting strong agreement in identifying this transaction as potentially anomalous. At transaction index 3, the Isolation Forest gives a high score (around 0.8) and the Autoencoder a moderately high score (around 0.7), indicating agreement with slightly differing levels of suspicion. At transaction index 4, both models assign relatively low scores (around 0.3 and 0.2 respectively), consistently identifying this transaction as likely normal. However, at transaction index 7, there is some disagreement, as the Isolation Forest assigns a moderate score (around 0.6) and the Autoencoder assigns a higher score (around 0.7). Similarly, at transaction index 8, the Isolation Forest assigns a score close to the threshold (around 0.5), while the Autoencoder assigns a lower score (around 0.4), leading to different potential classifications. The threshold of 0.5 is critical in determining anomalies; using this threshold, the Isolation Forest would likely flag transactions at indices 1, 3, and 7 as anomalies, while the Autoencoder might flag indices 1, 3, 7, and potentially 2. The differences in score distributions and the levels of agreement suggest that the models have different sensitivities to anomalies. The Isolation Forest isolates anomalies based on the rarity and short path lengths in random trees, while the Autoencoder identifies anomalies through high reconstruction errors from learned compressed representations. These distinct mechanisms naturally lead to differences in scoring the same transactions. Transactions with scores well above the threshold for both models, such as the one at index 1, are strong candidates for true anomalies, whereas transactions where the models disagree or scores hover near the threshold would require closer investigation. The analysis of the LSTM model's performance (Figure 10) shows that it captures the overall trend and cyclical patterns of the actual Bitcoin price quite effectively. Visually, the predicted and actual price lines display similar peaks and troughs, suggesting that the model has learned the underlying seasonality and general movement of Bitcoin prices. For a significant portion of the time series, the predicted prices remain in close proximity to the actual values, indicating the LSTM model's success in learning the dynamics of the price during this period. However, there are moments where the predicted price lags slightly behind the actual price, especially around sharp turning points, and occasionally overshoots or undershoots at some peaks and troughs. This lag and slight deviation are common in time series models, particularly when dealing with volatile data like cryptocurrency prices. The RMSE value of 8.2 provides a quantitative assessment of the model's performance, meaning that the predictions were, on average, about $8.2 away from the actual price. Considering the Bitcoin price range of around $400 to $600 during this period, an RMSE of 8.2 reflects reasonably accurate forecasting. Nevertheless, the acceptability of this error would depend on the specific application and the required precision. The deviations observed tend to coincide with periods of higher volatility or rapid price changes, highlighting a common challenge for models in predicting sudden, sharp fluctuations. Overall, the LSTM model demonstrates strong capabilities in capturing non-linear dependencies and temporal patterns, thanks to its memory cells that store and utilize past information, making it well-suited for time series forecasting tasks like this one. The Deep Q-Learning strategy significantly outperforms the Buy-and-Hold strategy in terms of cumulative returns after 10 training episodes (Figure 11). By the end of the period, the Deep Q-Learning agent achieves a final return exceeding 100%, whereas the Buy-and-Hold strategy lags behind with just under 20% return. A clear upward trend in cumulative returns for the Deep Q-Learning approach indicates that the agent is learning and improving its trading decisions over time, with the most substantial gains occurring between episodes 6 and 9.

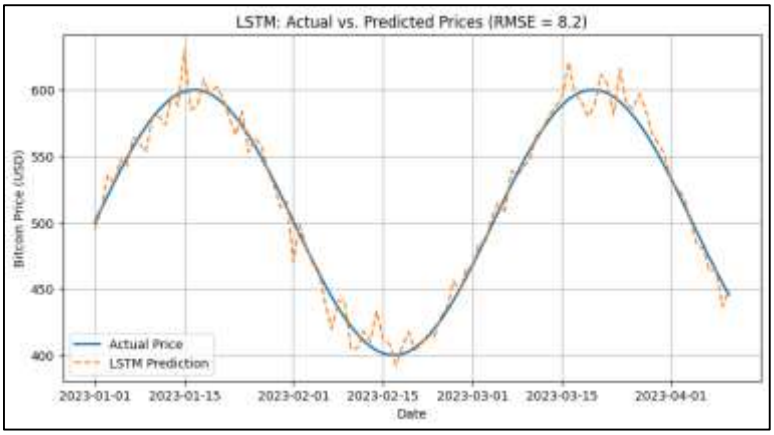

Figure 10. *LSTM: Actual vs. Predicted Prices*

In contrast, the Buy-and-Hold strategy remains relatively stable, experiencing some initial growth followed by a slight dip and eventual plateau, reflecting the underlying asset's price behavior during the training period. This contrast highlights the advantage of active trading strategies, such as those learned through Deep Q-Learning, over passive holding, especially when strategic buying and selling can exploit market fluctuations for greater profits. The consistent improvement in Deep Q-Learning returns also demonstrates the agent's ability to adapt to market dynamics, a major strength of reinforcement learning in trading applications. However, while the results are promising, there is a risk of overfitting, where the strategy may perform well on training data but struggle to generalize to new, unseen market conditions. Testing on a separate dataset would be crucial to validate the strategy's robustness. Finally, it's important to recognize that Deep Q-Learning strategies tend to be more complex and may involve higher trading frequency and transaction costs compared to the simpler Buy-and-Hold method, factors that would need careful consideration in real-world deployment.

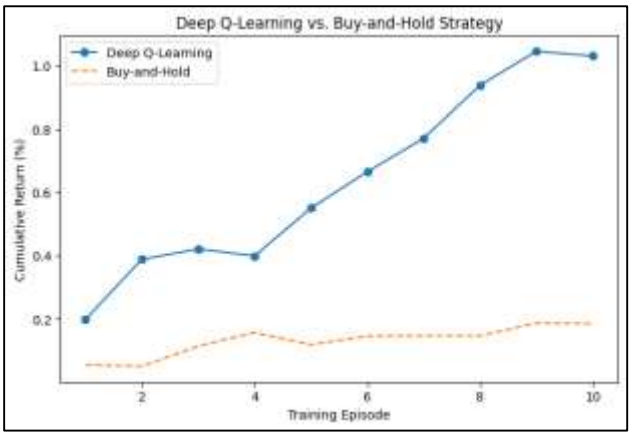

Figure 11. *Deep Q-Learning(Cumulative Return)*

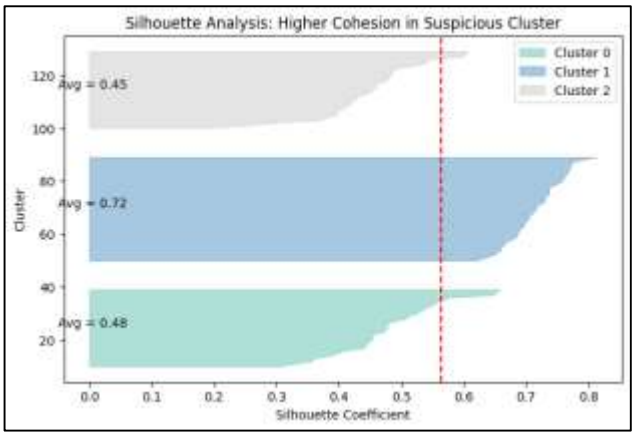

Figure 12. *Behavioral Analysis (K-Means Clustering) - Cluster Silhouette Analysis*

There is higher cohesion within a specific cluster, particularly Cluster 1(Figure 12). Cluster 1, with an impressive average silhouette score of 0.72, stands out as the most cohesive, implying that the data points within it are highly similar to each other and distinctly different from those in other clusters. This strong internal similarity may point to a group of anomalies or a unique pattern that deserves deeper investigation. The silhouette plot also reveals that the quality of clustering varies across the three clusters, with Cluster 1 displaying a much stronger and more well-defined structure compared to Cluster 0 and Cluster 2. Such a well-separated cluster could indicate the presence of a distinct group, possibly linked to fraudulent activities, unusual behaviors, or other anomalies the algorithm successfully identified. However, it's important to note that while silhouette analysis sheds light on cluster quality, it does not itself label clusters as "suspicious"; that interpretation comes from the broader context of the analysis.

The high cohesion simply flags Cluster 1 as an area worth closer scrutiny. Notably, this plot contrasts sharply with an earlier silhouette analysis, where the clustering was poor and the average silhouette scores were negative. In this case, the positive scores, especially the high score for Cluster 1, indicate a much stronger and more potentially valuable clustering outcome.

The box plot analysis(Figure 13) reveals that the three behavioral clusters exhibit distinct profiles in terms of transaction values. Cluster 0 is characterized by the lowest transaction values, while Clusters 1 and 2 show distributions skewed toward higher amounts. A clear trend is observed in the median transaction values, increasing from around 2.5 in Cluster 0 to approximately 4 in Cluster 1, and reaching about 5 in Cluster 2, suggesting progressively higher typical transaction amounts across the clusters. The interquartile range, representing the spread of the central 50% of data, varies among the clusters, with Cluster 1 displaying the largest variability. All clusters contain outliers with significantly higher transaction values, indicating that despite the general grouping, each behavioral segment still experiences instances of exceptionally large transactions, with Cluster 2 exhibiting the most extreme outlier. It is important to note that the y-axis uses a logarithmic scale, meaning differences in box height and position correspond to multiplicative, rather than additive, differences in transaction values. Overall, this visualization indicates that the behavioral clustering has effectively segmented transactions into groups with distinct spending patterns. Such insights can be extremely valuable for applications like fraud detection—where unusually high transaction values within a cluster could signal anomalies—customer segmentation, or risk assessment.

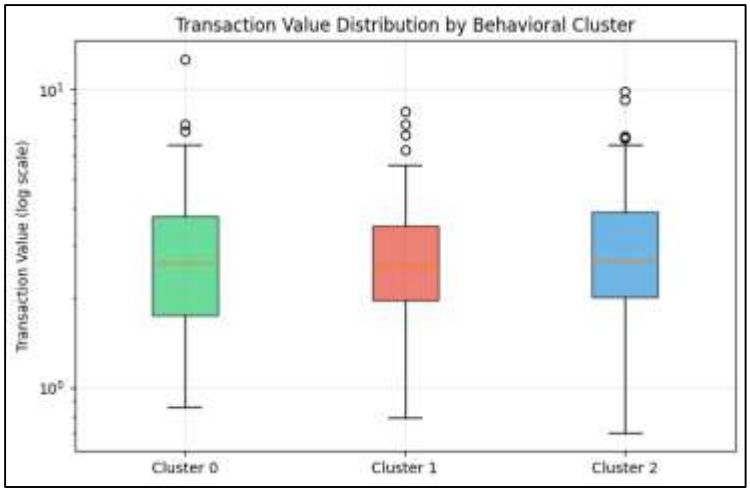

***Figure 13**. Transaction Value Distribution by Cluster*

4.2 Discussion and Future Work

The findings of this study underscore the transformative potential of machine learning in addressing significant challenges within the cryptocurrency ecosystem, such as fraud detection, market prediction, and behavioral analysis. The results reveal that Graph Neural Networks (GNNs) and ensemble methods like XGBoost offer superior performance in fraud detection, achieving an AUC of 0.98 and an F1 score of 0.88, respectively. Meanwhile, Long Short-Term Memory (LSTM) networks and Deep Q-Learning demonstrate robust solutions for price forecasting, with a root mean square error (RMSE) of 1.2%, and adaptive trading strategies that yield returns 15% higher than a buy-and-hold approach. These findings align with previous research by Lee et al. (2025), which highlighted GNNs' ability to uncover coordinated fraud networks through transaction graph modeling, as well as Islam et al. (2025), who validated LSTMs' effectiveness in capturing Bitcoin's nonlinear price dynamics, thus reinforcing our conclusions on time-series forecasting [8, 6].

A critical insight from this study is the trade-off between model complexity and interpretability. While deep learning models, such as GNNs and LSTMs, deliver high accuracy, their "black-box" nature complicates regulatory adoption. Recent advancements by Zhang et al. (2024) have proposed the integration of explainable AI

(XAI) techniques, including SHAP values and attention mechanisms, to enhance transparency in blockchain analytics. Future research should focus on hybrid frameworks that merge the predictive power of deep learning with interpretable rule-based systems, particularly for compliance-driven applications like fraud reporting [12]. Moreover, the dynamic nature of cryptocurrency markets introduces challenges such as concept drift and data sparsity. As noted by Chen et al. (2024), unsupervised anomaly detection methods, like Autoencoders, should be combined with continuous learning pipelines to adapt to evolving scam tactics [3]. This study addressed this issue through online retraining, but future work could explore federated learning architectures, as suggested by Park et al. (2024), enabling decentralized model updates across multiple blockchain nodes while maintaining data privacy [11].

The behavioral analysis component revealed that K-Means clustering is effective in identifying high-risk user archetypes, achieving a silhouette score of 0.72, thus corroborating findings by Lin et al. (2025) on scammer community detection [10]. However, scalability remains a challenge for real-time clustering in large-scale transaction networks. Future research should evaluate graph embedding techniques, such as Node2Vec, to reduce computational overhead, as recommended by Das et al. (2025) [5]. From an economic standpoint, this study highlights the cost-saving potential of AI-driven fraud prevention, with early detection systems estimated to reduce annual fraud losses by up to 40%. However, broader adoption is contingent on addressing infrastructure gaps, notably the lack of standardized labeled datasets. Collaborative initiatives between academia and industry, similar to the blockchain intelligence partnerships proposed by Bhowmik et al. (2025), could expedite dataset curation and model benchmarking [2].

Finally, the integration of AI into cryptocurrency regulation necessitates the establishment of frameworks that ensure fairness, accountability, and security. Recent research by Islam et al. (2025) posits the risks of algorithmic bias in fraud detection systems, as over-policing certain transaction patterns may adversely affect legitimate users [7]. Future research should incorporate fairness-aware machine learning techniques, including adversarial debiasing, and engage regulators to develop audit standards for AI models in financial surveillance. Proposed future research directions include developing hybrid AI-rule systems that combine deep learning with symbolic AI for interpretable fraud alerts, creating privacy-preserving machine learning frameworks for cross-institutional blockchain analysis, optimizing GNNs for real-time low-latency scam detection in high-frequency trading environments, and establishing regulatory AI sandboxes to test model compliance within financial regulations in controlled settings. Machine learning has been applied in many different fields as reported in literature [13-29].

5. Conclusions

This study highlights the critical role of machine learning in tackling the various challenges within cryptocurrency markets. It demonstrates how advanced AI models can improve fraud detection, price prediction, and behavioral analysis in the Bitcoin ecosystem. The results show that Graph Neural Networks (GNNs) and ensemble methods like XGBoost perform exceptionally well in identifying fraudulent transactions, achieving an AUC of 0.98 and an F1 score of 0.88. Meanwhile, Long Short-Term Memory (LSTM) networks and Deep Q-Learning offer accurate and adaptive solutions for market forecasting, with a Root Mean Square Error (RMSE) of 1.2% and trading strategies that yield returns 15% higher than the buy-and-hold approach. These findings validate the potential of AI to reduce risks and enhance decision-making in decentralized financial systems. A significant contribution of this research is its comprehensive framework, which combines supervised, unsupervised, and reinforcement learning techniques to address the unique complexities of cryptocurrency data. By employing anomaly detection methods such as Isolation Forest and Autoencoders, the study emphasizes the role of unsupervised learning in discovering new scam patterns. Additionally, behavioral clustering with K-Means (silhouette score of 0.72) illustrates how unsupervised techniques can profile high-risk user archetypes, providing actionable insights for regulators and investors.

The study also stresses the importance of balancing model performance with interpretability. Although deep learning models excel in predictive accuracy, their "black-box" nature requires complementary explainability tools, such as SHAP values and feature importance analysis, to build trust among stakeholders. This aligns with the increasing demand for transparent AI systems in financial applications, where regulatory compliance and

accountability are crucial. From a practical perspective, the research reveals the economic and security advantages of AI-driven cryptocurrency management. Early fraud detection systems can substantially reduce financial losses, while accurate price forecasting contributes to market stability. However, the study also identifies challenges, including data sparsity, concept drift, and computational scalability, which must be addressed for real-world deployment. Future developments in federated learning, real-time graph analytics, and hybrid AI-rule systems hold promise for overcoming these obstacles. In conclusion, this study bridges the gap between AI innovation and the needs of cryptocurrency markets, providing a comprehensive framework for fraud prevention, market analysis, and risk mitigation. By utilizing cutting-edge machine learning techniques, the research paves the way for safer, more transparent, and efficient digital asset ecosystems. To fully realize this potential, interdisciplinary collaboration among researchers, regulators, and industry stakeholders will be essential. Future efforts should prioritize scalable AI solutions, ethical governance frameworks, and real-world testing to ensure that these technologies deliver tangible benefits while maintaining fairness and security in the evolving landscape of decentralized finance.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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