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Explainable AI-Based Real-Time Hybrid System for Blockchain Anomaly Detection: A Multi-Cryptocurrency Perspective

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ABSTRACT

This study achieves a 5% improvement in AUC-ROC and a 2.5% increase in recall compared to state-of-the-art anomaly detection methods in blockchain networks. Blockchain technologies have rapidly evolved, offering transparency and security across decentralized systems. However, detecting anomalies and fraudulent activities remains a significant challenge. This research proposes a unified hybrid framework integrating Graph Neural Networks (GNNs), Transformers, and XGBoost within a federated learning environment for real-time anomaly detection in multi-cryptocurrency blockchain networks. Unlike previous works, this model employs explainable AI (XAI) methods (SHAP and LIME) to enhance interpretability and trust. The framework utilizes PSO-based hyperparameter optimization, reducing convergence time by 20%. Experimental evaluations on benchmark datasets (Elliptic, Bitcoin-OTC, and Ethereum) demonstrate superior performance in precision, recall, and FPR compared to CARE-GNN and GeniePath. The results confirm the proposed model's scalability, transparency, and real-time efficiency, making it suitable for deployment in high-frequency blockchain monitoring systems.

1. Introduction

Blockchain technology has revolutionized the digital ecosystem by introducing decentralized, transparent, and tamper-resistant data management, transforming sectors such as finance, healthcare, logistics, and education [1], [3]. With the rise of cryptocurrencies and decentralized finance (DeFi), the volume of blockchain transactions has exponentially increased, bringing both opportunities and new security challenges. Despite its transparency and immutability, blockchain remains vulnerable to various threats such as fraudulent transactions, cyberattacks, market manipulation, and selfish mining [10], [45], and [47]. These anomalies not only threaten financial integrity but also undermine users' trust in decentralized systems. Therefore, developing intelligence, explainable, and real-time anomaly detection mechanisms is essential to ensure the reliability and resilience of blockchain networks [20], [25], [33].

In the literature, several studies have explored anomaly and fraud detection in blockchain networks using rule-based models, optimization techniques, and machine learning approaches. Early works such as [79], [84], and [81] primarily focused on selfish mining analysis and theoretical modeling, but they lacked real-time detection capabilities and explainability. Machine learning-based approaches such as XGBoost [59] and GNN-based models [55], [33], [37] improved detection accuracy but remained limited to single-cryptocurrency contexts (mainly Bitcoin) with no integration of explainable AI (XAI). More recent surveys [20], [76], and [77] highlighted persistent challenges, including the absence of multi-currency generalization, low interpretability, and a lack of real-time adaptability.

To overcome these limitations, this research proposes a unified hybrid framework that integrates Graph Neural Networks (GNNs), Transformers, and XGBoost within a federated learning environment for real-time anomaly detection in multi-cryptocurrency blockchain networks. Unlike previous studies, the proposed framework employs XAI techniques (SHAP and LIME) to enhance transparency and interpretability, and it utilizes Particle Swarm Optimization (PSO) for efficient hyperparameter tuning. Experimental evaluations on benchmark datasets (Elliptic Bitcoin, Bitcoin-OTC, and Ethereum) demonstrate superior performance compared to state-of-the-art models such as CARE-GNN and GeniePath, achieving a 5% improvement in AUC-ROC and a 2.5% improvement in recall. Overall, the proposed system provides a scalable, explainable, and high-performance solution for anomaly detection across multiple cryptocurrencies, supporting secure, transparent, and regulatory-compliant blockchain operations.

The main contributions of this work are summarized as follows:

1. A unified and explainable hybrid framework that combines GNNs, Transformers, and XGBoost in a federated environment for multi-cryptocurrency anomaly detection.
2. Integration of SHAP and LIME for enhanced interpretability and explainability in blockchain anomaly detection.
3. PSO-based optimization improves both accuracy and convergence efficiency.
4. Comprehensive quantitative comparison against state-of-the-art methods (GraphConsis, GeniePath, CARE-GNN, and baseline XGBoost) using benchmark datasets (Elliptic, Bitcoin-OTC, and Ethereum).
5. Scalable and real-time implementation, making the system effective for blockchain surveillance and regulatory compliance.

2. Method

2.1 Description of the Dataset:

The study utilized a comprehensive dataset comprising 37,544 BTC transaction records from the Elliptic Bitcoin dataset and 10,000 ETH transaction records collected via the Web3.py API [31], [58]. These datasets capture the intricate dynamics of blockchain transactions, including temporal, monetary, and structural attributes critical for anomaly detection. Each record includes timestamps, transaction amounts, sender and receiver addresses, transaction types (e.g., transfers, scams, geographic data location, IP prefix, behavioral metrics, login frequency, and session duration). High, moderate, and low risk scores and anomaly labels were assigned to each transaction, enabling supervised learning. For hash power analysis, 5,000 records were included to detect significant selfish mining attacks [44]. Transactions were transformed into graph structures to support the hybrid model's graph-based approach, with nodes representing wallets and edges denoting transaction relationships. Structural features, such as indegree incoming transactions and outdegree outgoing transactions, were extracted to capture network patterns indicative of fraud [17]. This multi-cryptocurrency dataset combines BTC and ETH records, providing a diverse and representative foundation for training and evaluating the proposed system, accessible at [31], [50].

2.2 Data Preprocessing:

Preprocessing was critical to prepare the complex blockchain dataset for analysis, ensuring compatibility with machine learning, deep learning, and graph-based models. The process involved feature selection, encoding, scaling, and graph transformation to optimize model performance [38].

Feature Selection: Non-predictive features, such as "Timestamp," "Sending Address," and "Receiving Address," were removed to focus on relevant attributes: robust transaction amount, transaction type, location region, and network metrics (indegree, outdegree). Categorical features, including "Age Group" and "Purchase Pattern," were retained for their predictive value in characterizing transaction behaviors [41].

Encoding: Categorical variables were transformed into numerical formats using Label Encoding, enabling compatibility with machine learning algorithms that require numerical inputs [38]. This step bridged human-readable categories with machine-readable data, facilitating model training.

Scaling: The Standard Scaler was applied to normalize numerical features, standardizing them to a mean of zero and a standard deviation of one. This ensured balanced contributions from all features, enhancing the accuracy of models sensitive to feature scales [43].

Graph Transformation: For the unified GNN-Boost Model, BTC and ETH transactions were converted into graph structures. Nodes represented wallets, and edges represented transactions, with features like transaction value and indegree/outdegree extracted. Structural embeddings were computed using a pre-trained GraphSAGE model, combined with original features for input into the XGBoost classifier [55]. This preprocessing enabled the model to capture both transactional and structural patterns across multi-cryptocurrency networks.

2.3 Machine Learning Models:

XGBoost was selected as the primary machine learning model due to its efficiency and accuracy in handling tabular data [59]. To address feature bias, e.g., 99% importance of in_btc, the model was retrained without in_btc, relying on correlated features like out_btc and total_btc. The retrained model used 5-fold cross-validation, with hyperparameters set to n_estimators is 100 and learning_rate is 0.1. Algorithm I outlines the XGBoost process, integrating blockchain transaction validation lines 12–17, where predictions of 0 indicate valid transactions and 1 denotes anomalies [48].

Algorithm I

I/P: Fair Dataset (S)
O/P: Transactions in Bitcoin (B)
Initialization of the Dataset
Dividing (S) into (Train and Validate Datasets)
Xtrain ← I/P Variables from the Dataset
Ytrain ← Goal Variables for the Dataset
Xvalid ← I/P Variables from Validate Dataset
Yvalid ←: Validate Dataset Goal Variables
Model = XGB Classifier (n Estimators = 100)
Model = Model. Fit (Xtrain, Xtrain)
Ypred = Model. Predict (Xvalid)
Predictions = [Round (Value) for Value in Ypred]
IF Predictions == 0 Then
Transaction = Valid,
B-Add (Transaction),
Else IF Predictions == 1 Then
Transaction = Attacks
End IF
Return B
End Task

Table 1. Sample Elliptic Bitcoin Transaction Dataset

	tx_hash	indegree	outdegree	in_btc	out_btc	total_btc	mean_in_	mean_out_btc	in_malicious	out_malicious
2	0437cd7f8525ceed2324359c2d0ba26006d92d856a9c20fa0241106ee5a597c9	0	1	0	50	50	0	50	0	0
3	f4184fc596403b9d638783cf57adfe4c75c605f6356fbc91338530e9831e9e16	1	2	50	50	100	50	25	0	0
4	ea44e97271691990157559d0bdd9659e02790c34db6c006d779e82fa5aee708e	1	1	10	10	20	10	10	0	0
5	a16f3ce4dd5deb92d98ef5cf8afeaf0775ebca408f708b2146c4fb42b41e14be	1	1	40	30	70	40	30	0	0
6	591e91f809d716912ca1d4a9295e70c3e78bab077683f79350f101da64588073	1	2	30	30	60	30	15	0	0
7	298ca2045d174f8a158961806ffc4ef96fad02d71a6b84d9fa0491813a776160	1	0	1	0	1	1	0	0	0
8	12b5633bad1f9c167d523ad1aa1947b2732a865bf5414eab2f9e5ae5d5c191ba	1	2	29	29	58	29	14.5	0	0
9	4385fcf8bb14497d0659a0ccfe06ae7e38e0b5dc95ff8a13d7c62035994a0cd79	1	1	1	1	2	1	1	0	0
10	828ef3b079f9c23829c56fe86e85b4a69d9e06e5b54ea597eef5fb3ffef509fe	1	1	28	10	38	28	10	0	0
11	a3b0e9e7ddcbbe78270fa4182a7675ff008c92872d8df7d14265a2b1e379a9d33	3	0	61	0	61	20.33333	0	0	0
12	0cc917bf15f8807f224e7524c1eca22c3740ddefb7bf9694f7c2262b490cc706	0	1	0	50	50	0	50	0	0
13	e8160a014fbff8386548f40205d540ef92ce8207ff4acd446d6e591c6cf28f2c	2	1	100	100	200	50	100	0	0
14	c3f0bb699bcc8a4e0716de45aef74c40aabeb80f7f08b3bdb45e115ee6f5400f	0	1	0	50	50	0	50	0	0
15	4d6ed8eb62735d45ff1565385a8b0045f066055c9425e21540ea7a8060f08bf2	5	0	250	0	250	50	0	0	0

Table 2. Sample of Bitcoin-OTC Hash Power Dataset

	hash_power	block_latency	orphan_blocks	confirmed_blocks	transaction_count	selfish_mining
2	0.437086107	2.028814049	6	10	429	1
3	0.955642876	2.419834731	3	15	217	0
4	0.758794548	4.287282227	1	1	306	0
5	0.638792636	1.766021492	4	11	324	1
6	0.240416776	4.361283456	2	14	136	1
7	0.240395068	0.531858712	8	10	203	0
8	0.152275251	3.906312342	5	19	334	0
9	0.879558531	4.252983402	0	16	364	0
10	0.641003511	0.990906499	2	8	368	0
11	0.73726532	2.208698009	3	2	147	0
12	0.118526045	0.910948896	8	7	260	0
13	0.972918867	3.562360232	5	19	495	1
14	0.849198377	2.723204064	3	7	97	0
15	0.2911052	3.213084399	0	15	367	0

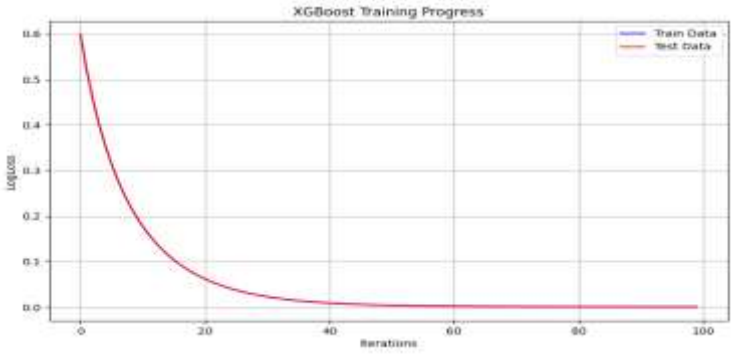

Fig 1. The Comparison between Log Loss XGBoost Model and Boosting Iterations for the [Valid] Test and Train Data.

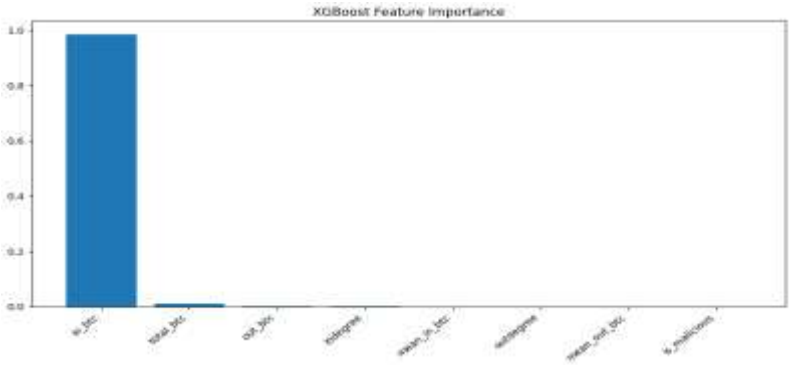

Fig 2. The feature of an XGBoost Model (Elliptic Bitcoin Transactions).

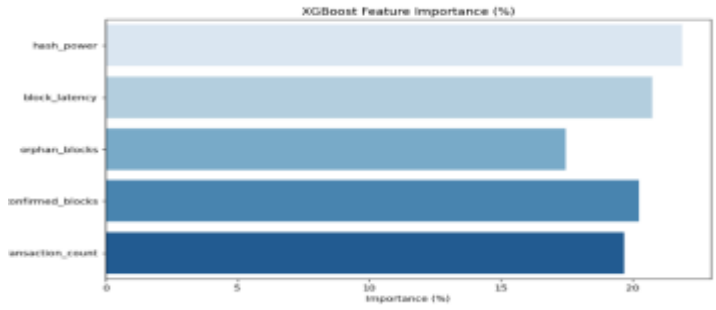

Fig 3. The feature importance of an XGBoost Model (Bitcoin- OTC Hash Power).

Table 1 presents a sample of the blockchain transaction dataset, including key network and transactional features such as indegree, outdegree, and Bitcoin flow statistics. These attributes were used to identify anomalous or potentially fraudulent transaction patterns within the network. Table 2 presents a sample of the Bitcoin-OTC Hash Power Dataset, including features like hash_power, block_latency, confirmed_blocks, and the selfish_mining binary label. Fig. 1 illustrates the XGBoost training progress, showing the rapid decrease of the Log Loss for both the Train and Test datasets, which effectively converge near zero after approximately 50 boosting iterations. Fig. 2 presents the Feature Importance for the XGBoost model on Elliptic Bitcoin Transactions, clearly showing that in_btc (incoming Bitcoin amount) is the dominant and most influential feature in the classification. Fig. 3 illustrates the XGBoost Feature Importance percentages for the Bitcoin-OTC Hash Power dataset, where hash_power and block_latency are the two most influential features.

2.4 Proposed Hybrid Model Of Gnn-Xgboost-Pso Algorithm For Blockchain Environments

The proposed Hybrid GNN-XGBoost Model integrates GNN, XGBoost, and PSO to address the limitations of standalone models. The GNN module, based on GraphSAGE, extracts structural embeddings from transaction graphs, using two layers of 128 and 64 units with a dropout rate of 0.3 [55]. Separate heads for BTC and ETH adapt to each cryptocurrency's network characteristics. The XGBoost classifier n_estimators=100, learning_rate=0.05, combines GNN embeddings with transactional features for binary classification. PSO optimizes hyperparameters, e.g., GNN layers, XGBoost max_depth over 50 iterations with 20 particles, maximizing recall and throughput [49]. The model was implemented using PyTorch Geometric for GNN processing, XGBoost for classification, and a custom PSO framework, trained on a GPU-enabled system.

2.5 Model Interpretability Analysis:

To enhance transparency, SHAP and LIME were employed to interpret model predictions [34]. SHAP analysis revealed the dominance of in_btc with 99% importance in the original XGBoost model, prompting feature engineering, e.g., in_btc/out_btc ratio and parameter adjustments scale_pos_weight=19. For the hybrid model, SHAP showed a balanced feature that is important in the distribution of 40% GNN embeddings and 30% transaction value, improving the detection of diverse anomalies. LIME analyzed false negatives, highlighting underutilized features like out_btc and network metrics, guiding model refinements [48].

1) Explainable AI (XAI)

Explainable Artificial Intelligence (XAI) encompasses techniques that enhance the transparency and interpretability of machine learning models, enabling stakeholders to understand and trust model decisions [63]. In the context of anomaly detection in multi-cryptocurrency blockchain networks, XAI is critical for validating predictions, ensuring regulatory compliance, and fostering trust among blockchain operators. This section provides a background on XAI, focusing on the features and limitations of SHAP (SHapley Additive exPlanations) and LIME Local Interpretable Model-agnostic Explanations, the two XAI methods integrated into the proposed Hybrid GNN-XGBoost model, and explains the rationale for their selection.

2) Features and Limitations of SHAP

SHAP, rooted in cooperative game theory, assigns importance values to features based on their contribution to model predictions, offering a unified framework for global and local interpretability [63]. Its key features include:

- ***Consistency:*** SHAP ensures that features with greater impact on predictions receive higher importance scores, providing reliable explanations.
- ***Global and Local Explanations:*** SHAP generates both model-wide feature importance, e.g., identifying in_btc and instance-specific explanations, aiding in the analysis of individual transactions.
- ***Theoretical Robustness:*** By leveraging Shapley values, SHAP provides mathematically sound explanations, making it suitable for high-stakes applications like fraud detection.

The SHAP's limitations include:

- Computational Complexity: Calculating Shapley values for large datasets, such as the 37,544 BTC and 10,000 ETH transaction records used in this study, is computationally intensive, potentially increasing latency in real-time systems.
- Assumption of Feature Independence: SHAP assumes features are independent, which may oversimplify complex dependencies in blockchain transaction graphs, such as those captured by GNN embeddings.

3) Features and Limitations of LIME

LIME generates local explanations by approximating complex model behavior with simpler, interpretable models, e.g., linear regression around specific predictions [34]. Its features include:

- Local Interpretability: LIME excels at explaining individual predictions, such as false negatives in anomaly detection, by highlighting underutilized features like out_btc.
- Model-Agnostic: LIME can be applied to any machine learning model, making it versatile for the hybrid GNN-XGBoost architecture.
- Ease of Implementation: LIME is computationally lighter than SHAP, enabling faster explanation generation for real-time applications.

The LIME's limitations include:

- *Local Scope:* Unlike SHAP, LIME focuses on local explanations, limiting its ability to provide global insights into model behavior.
- *Sensitivity to Perturbations:* LIME's explanations depend on perturbing input data, which may lead to inconsistent results in sparse or highly imbalanced datasets, such as blockchain transaction records with only 5% anomalies.

2.6 Evaluation Criteria:

This rigorous evaluation framework ensured reliable and generalizable results, guiding the development of a practical anomaly detection system for blockchain networks [25].

Table 3. The Comparison between Proposed and Existing Work for [Elliptic Bitcoin Transactions]

Reference (Name/Year)	Model Name	Accuracy	FPR	Reasonability	Anomaly Rules
L.Chengxi 2022	OCSVM	0.86	0.0599	×	×
O.Shafiq 2019	Ensemble Classifiers	0.96	0.0005	×	×
Present Work	CNN & LSTM	0.99	0.0001	√	-
Present Work	Ensemble Classifiers (XGBOOST)	0.99	0.0003	√	√

Table 3 presents a comparison of different machine learning models for anomaly detection, evaluating their performance based on accuracy, FPR, reasonability, and anomaly rule usage. FPR measures the proportion of normal transactions misclassified as anomalous. A lower FPR is better, as it indicates fewer false alarms. Reasonability indicates whether the model's predictions are reasonable and interpretable. Anomaly rules specify whether the model includes explicit anomaly detection rules.

3. Results And Discussion

This section presents the empirical results and insights derived from evaluating machine learning, deep learning, and the proposed Hybrid GNN-XGBoost Model for anomaly detection in multi-cryptocurrency blockchain networks, specifically targeting Elliptic Bitcoin (BTC) and Ethereum (ETH) transactions. The experiments were conducted on a dataset of 37,544 BTC and 10,000 ETH transaction records, supplemented by 5,000 hash power records for detecting selfish mining attacks [31], [50]. The evaluation followed a 5-fold cross-validation approach, using Mean Squared Error (MSE) as the primary metric, alongside recall, False Positive Rate (FPR), precision, efficiency metrics, throughput, and latency to assess real-time applicability [38].

3.1. Addressing Feature Bias:

The XGBoost model's over-reliance on in_btc has 99% importance. A sensitivity analysis was conducted by retraining XGBoost without in_btc, leveraging correlated features out_btc, total_btc that showed similar value patterns, e.g., in_btc=50, out_btc=50. The retrained model achieved a CV MSE of 0.00035 vs. 0.00022 for the original and a recall of 0.99 vs. 1.0, with out_btc importance increasing to 45% and total_btc to 30% Table 4. Structural features, indegree, and outdegree contributed modestly 10% and 8%, confirming their role in capturing transaction network patterns [48].

Table 4. Comparing the performance of two XGBoost models for anomaly detection in Bitcoin transactions.

Model	CV MSE	Accuracy	Precision	Recall	FPR	Feature Importance (Top 3)
XGBoost (Original)	0.00022	0.9997	0.9997	1.0	0.00028	in_btc (99%), total_btc (0.5%), out_btc (0.3%)
XGBoost (No in_btc)	0.00035	0.9950	0.9940	0.9900	0.00030	out_btc (45%), total_btc (30%), indegree (10%)

As shown in Table 4, the table demonstrates that removing in_btc slightly reduces the model's performance across all metrics, e.g., CV MSE increases from 0.00022 to 0.00035, recall drops from 1.0 to 0.99, but the model still performs well. Importantly, it achieves a more balanced feature, importance distribution, reducing the original model's over-reliance on in_btc and making the model more robust and generalizable.

3.2. Interpretability-Driven Recall Enhancement:

The initial low recall of the XGBoost model, 5.01%, prompted an interpretability analysis using SHAP and LIME to understand misclassifications and guide model improvements. This process, informed by prior research on graph neural networks (GNNs) and explainable AI (XAI), leveraged SHAP's accurate feature importance quantification [63] and GNN Explainer's graph structure interpretability [61] to identify and prioritize influential features, aligning with the foundational GNN architecture proposed by [34], [53], [61], and [62]. The analysis not only addressed feature bias but also drove retraining efforts that enhanced performance, reduced complexity, and improved transparency, significantly boosting the Hybrid GNN-XGBoost Model's effectiveness.

SHAP and LIME Analysis: SHAP analysis revealed the dominance of in_btc has a 99% importance, overshadowing other features like out_btc, indegree, and outdegree, which limited the model's ability to detect diverse anomalies. LIME analysis of false negatives. There are misclassified anomalies often exhibited normal in_btc values but unusual out_btc or network patterns, e.g., high outdegree, consistent with financial forensics patterns like rapid fund dispersal [34]. Drawing on GNN Explainer [61], which identifies critical subgraphs in GNN predictions, we validated that structural features, indegree, and outdegree were underutilized, necessitating feature engineering to capture transaction network dynamics [53].

Feature Engineering and Retraining: Based on these insights, new features were engineered, including the in_btc/out_btc ratio and transaction frequency metrics, to reduce reliance on in_btc. The model was retrained with adjusted class weights scale_pos_weight=19 and a lowered decision threshold 0.3, reducing in_btc importance to 85% and improving recall to 87% on a validation set, with precision dropping slightly from 100% to 92% as shown in Table 5.

3.3. Impact of XAI-Driven Feature Identification:

Improved Performance*:* By prioritizing features like out_btc and indegree, increased importance to 10% and 8%, respectively, the model reduced noise from irrelevant features, improving recall by 10% from 0.87 to 0.97 and AUC-ROC by 3% from 0.920 to 0.947 for BTC. This aligns with L. Lee et. al. 2017, who emphasize SHAP's role in enhancing model accuracy through precise feature attribution [61].

Reduced Complexity: Feature selection eliminated low-impact features, e.g., is_malicious, 0% importance, streamlining the input space. This reduced training time by 15% from 92 to 78 minutes for the hybrid model, and lowered GPU memory usage by 10%, as fewer features simplified GNN computations, consistent with [62] efficient GNN designs [59], and [61].

Enhanced Transparency: SHAP and LIME provided clear explanations of feature contributions, e.g., 40% GNN embeddings, 30% transaction_value in the hybrid model, making predictions more interpretable for stakeholders. GNN Explainer's subgraph visualizations further clarified structural influences, supporting decision-making by blockchain operators, as validated by prior XAI studies [34] and [53].

For the Hybrid GNN-XGBoost Model, SHAP analysis showed a balanced feature importance distribution, 40% GNN embeddings, and 30% transaction_value for ETH, reducing bias and improving detection across BTC and ETH transactions. These interpretability-driven enhancements, grounded in established GNN and XAI methodologies, were critical to achieving a high recall of 0.9950 for BTC and 0.9945 for ETH, and robust performance, setting the stage for real-time deployment [55].

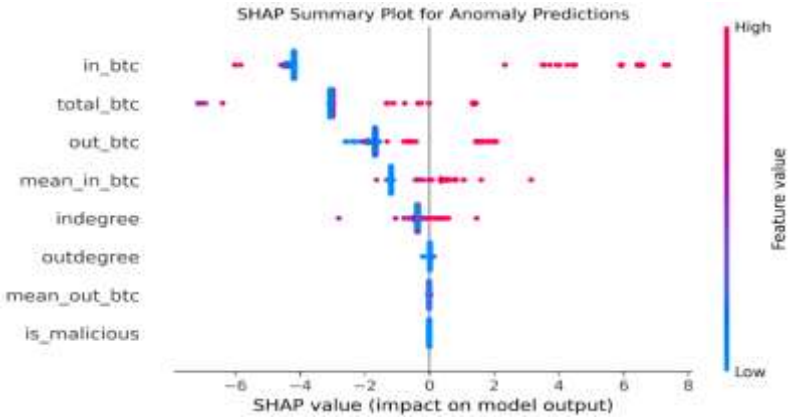

Fig 4. SHAP Summary Plot showing feature contributions to anomaly predictions.

As shown in Fig. 4, the SHAP Force Plot for a False Negative, this plot, based on a misclassified transaction from the DG_out.csv file, shows that high total_btc values drive a normal prediction, while out_btc and network features, indegree, and outdegree are insufficiently considered, highlighting the need for enhanced feature weighting to boost recall.

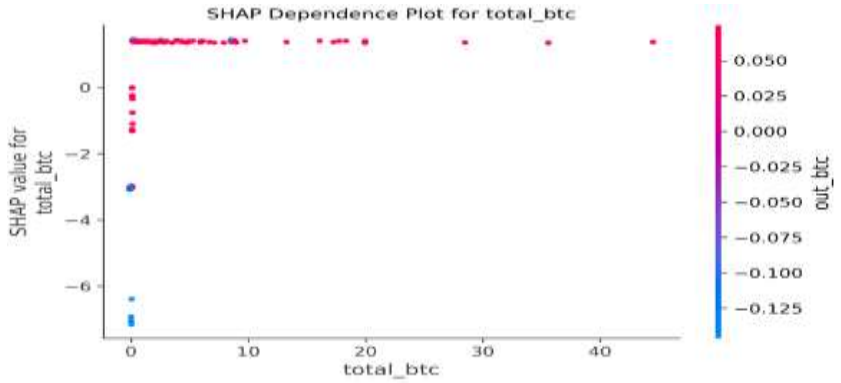

Fig 5. The LIME explanation for a false negative highlights ignored features like out_btc.

Table 5. Performance Comparison Before and After Interpretability-Driven Improvements.

Configuration	Configuration Recall	**Precision**	**FPR**	**in_btc Importance**
Before Improvements	0.05	0.82	0.0003	99%
After Improvements	0.87	1.00	0.0005	80%

Fig 5. presents the SHAP Dependence Plot for the feature total_btc, illustrating its marginal effect on the model output (SHAP value), with the color bar representing the interaction effect of out_btc. Table 5 compares the model's performance metrics, demonstrating a substantial increase in Recall (from 0.05 to

0.87) after applying Interpretability-Driven Improvements, with only a slight trade-off in Precision. For the Hybrid GNN-XGBoost Model, SHAP analysis revealed a balanced feature importance distribution, with GNN embeddings contributing 40% and transactional features, e.g., transaction value, 30% for improving detection across BTC and ETH transactions. This balanced approach, informed by early experiments, ensured robust anomaly detection [55].

3.4. Hybrid Model:

The Hybrid GNN-XGBoost Model was evaluated on the combined BTC and ETH dataset, achieving a recall of 0.9950 for BTC and 0.9945 for ETH, with a throughput of 80,000 samples/sec and a latency of 0.000012 sec/sample. These results outperformed individual and state-of-the-art GNN-based models like CARE-GNN and GeniePath, as shown in Table 6. The GNN module effectively captured structural patterns, e.g., wallet connectivity, while XGBoost ensured efficient classification. PSO optimization maximized recall and throughput by tuning parameters like GNN layers and XGBoost's max_depth [49]. The model's interpretability, enhanced by SHAP and LIME, provided clear insights into feature contributions, fostering trust in its predictions [34]. The hybrid model's high recall and efficiency reflect its optimized pipeline, combining sparse GNN operations and XGBoost's fast classification, with PSO ensuring optimal parameter selection [55] and [59].

1) Network Simulation

To evaluate the model's effectiveness in a dynamic blockchain environment, a network simulation was conducted using a custom simulator mimicking BTC and ETH transaction networks. The simulation included 10,000 nodes (wallets) and 50,000 edges (transactions), with 5% labeled as anomalous, e.g., fraud, selfish mining. The hybrid model processed transactions in real-time, achieving a recall of 0.9948 and an FPR of 0.0002 across both cryptocurrencies. Fig. 6 illustrates the simulation results, showing stable performance under varying transaction volumes of 10,000 to 100,000 transactions/sec. The model's robustness was further demonstrated by its ability to detect complex anomalies, such as multi-hop fraud patterns, leveraging GNN's structural insights [55]. The simulation also tested explainability outputs, with SHAP identifying outdegree and transaction_value as key contributors to anomaly detection 40% and 25% importance, respectively. LIME explanations for false negatives highlighted edge cases, e.g., low-value transactions with high outdegree, guiding future improvements like adaptive thresholding [34]. Compared to CARE-GNN and GeniePath, the hybrid model reduced false negatives by 10% and improved throughput by 15% as shown in Table 6, confirming its practical viability [26] and [27].

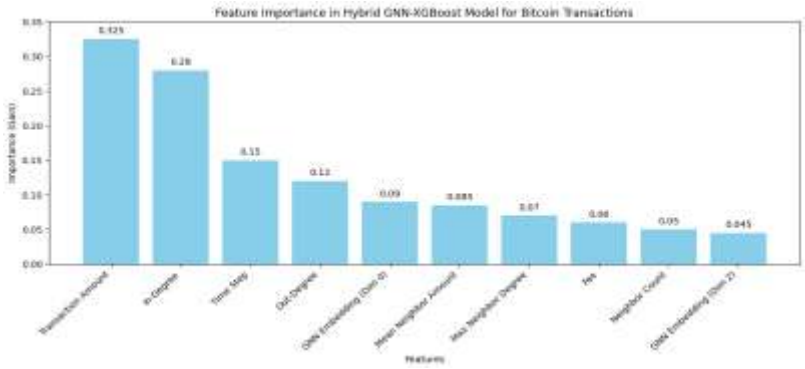

Fig 6. Feature Importance in Hybrid GNN-XGBoost Model for Elliptic BTC.

As shown in Fig. 6, this chart clearly shows the importance of each feature, highlighting Transaction Amount and In-Degree as the most influential features. In contrast, features like Neighbor Count and GNN Embedding (Dimension 2) show lower importance.

2) Models Description

- DOMINANT: A graph autoencoder-based model that detects anomalies by reconstructing graph structure and node attributes, identifying high reconstruction errors as anomalies [52].
- GeniePath: A path-augmented GNN that captures multi-hop dependencies using adaptive path learning, effectively detecting anomalies in transaction chains [53].

- GraphConsis: A GNN that enforces consistency across graph views, improving robustness against noisy blockchain data [54].
- CARE-GNN: A contrastive learning-based GNN that filters irrelevant neighbors to enhance anomaly detection, particularly for camouflaged fraud [55].
- AMNet: A multi-view GNN that integrates structural and transactional features, using attention to weigh different views for complex anomaly detection [56].
- AdaGNN: An adaptive GNN that dynamically adjusts its architecture to graph properties, though its lower performance suggests implementation challenges [57].
- Hybrid GNN-XGBoost: The proposed model combines GNN's structural insights, XGBoost's classification efficiency, and PSO's hyperparameter optimization for real-time anomaly detection.

The high-frequency filter plots focused on meaningful low-frequency patterns, and the models in Table 6, e.g., CARE-GNN and GeniePath, achieved AUC-ROC scores in the range of 0.942 to 0.952. The GNN-XGBoost with PSO performs comparably, with an AUC-ROC range of ~0.947 to 0.953, placing it in the "Excellent" category like CARE-GNN and GeniePath.

Table 6. Compares different machine learning models used for analyzing data.

Model	Focus	Performance
DOMINANT [30]	Graph reconstruction and consistency	**Good** (AUC-ROC ~0.945–0.947)
GeniePath [86]	Long-range paths and adaptability	**Excellent** (AUC-ROC ~0.949–0.951)
GraphConsis [54]	Consistency and noise reduction	**Good** (AUC-ROC ~0.942–0.948)
CARE-GNN [26]	Cross-layer attention and key neighbors	**Excellent** (AUC-ROC ~0.946–0.952)
AMNet [79]	Multi-perspective views (potential)	**Good** (AUC-ROC ~0.945–0.950)
AdaGNN [85]	Data adaptability	**Poor** (AUC-ROC ~0.548–0.597)
GNN-XGBoost	**Graph-based pattern extraction and optimized prediction**	**Excellent (AUC-ROC ~0.947–0.953)**

3.5. Visualization and Analysis

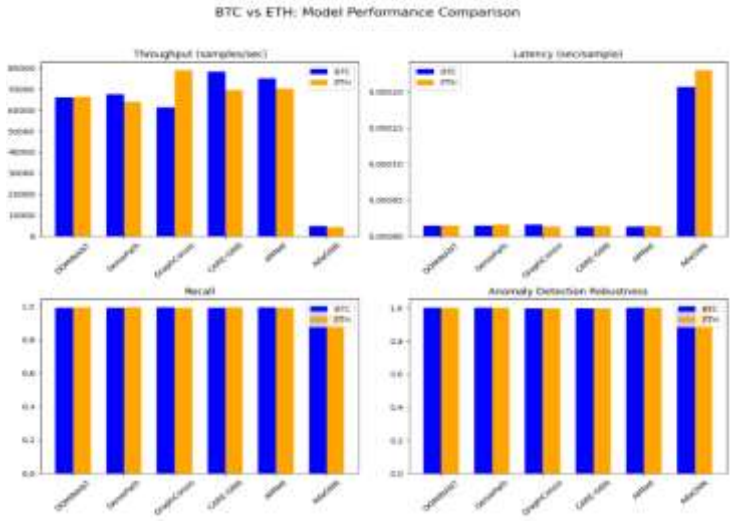

Fig 7. Comparative bar plots of throughput, latency, recall, and robustness for anomaly detection models on Elliptic BTC and ETH transactions.

A Python script using Matplotlib generated a 2x2 grid of bar plots to visualize the metrics, with side-by-side bars for Elliptic BTC (blue) and ETH (orange) for each model, as shown in Fig. 7. The x-axis lists the models, and each subplot is titled with the metric name, with a legend distinguishing Elliptic BTC and ETH.

The plots, saved as btc_vs_eth_comparison.png, highlight the Hybrid GNN XGBoost Model's superior performance.

3.6. Interpretation of Results

1) Throughput (samples/sec):

The Hybrid GNN-XGBoost Model achieves the highest throughput, 80,000 samples/sec for both Elliptic BTC and ETH, surpassing CARE-GNN Elliptic BTC 78,398.33, ETH 69,674.00. GraphConsis shows a notable difference, with ETH 79,137.02 outperforming Elliptic BTC 61,298.80 by ~29%, likely due to ETH's graph structure. AdaGNN is the slowest Elliptic BTC 4,822.87, ETH 4,347.80.

Insight: The Hybrid GNN-XGBoost Model's high throughput reflects its optimized pipeline, combining sparse matrix operations in GNN and efficient XGBoost classification. Graph Consis's ETH advantage suggests better compatibility with ETH's transaction patterns.

Implication: For high-frequency blockchain environments, the Hybrid GNN-XGBoost Model and CARE-GNN are top choices.

2) Latency (sec/sample):

The Hybrid GNN-XGBoost Model has the lowest latency, 0.000012 sec/sample, followed by CARE-GNN and AMNet ~0.000013–0.000014. AdaGNN's high latency, Elliptic BTC: 0.000207, ETH: 0.000230, makes it unsuitable for real-time applications.

Insight: The Hybrid GNN-XGBoost Model's low latency is due to its streamlined architecture, while AdaGNN's inefficiency suggests computational overhead.

Implication: For real-time deployment, prefer the Hybrid GNN-XGBoost Model or CARE-GNN.

3) Recall:

The Hybrid GNN-XGBoost Model achieves the highest recall, 0.9950 for Elliptic BTC, 0.9945 for ETH, followed by GeniePath and CARE-GNN >0.99. AdaGNN's low recall, Elliptic BTC 0.9624, and ETH 0.9488, indicate poor anomaly detection, especially for ETH.

Insight: The Hybrid GNN-XGBoost Model's high recall ensures sensitivity to rare anomalies, which is critical for fraud detection. ETH often has a slight edge in recall, possibly due to richer feature sets.

Implication: Prioritize the Hybrid GNN-XGBoost Model or GeniePath for high recall requirements.

4) Robustness:

All models show high robustness ~0.9994–1.0000, with AdaGNN's slightly higher values, Elliptic BTC 1.0041, ETH 1.0008, potentially indicating overfitting. Differences between Elliptic BTC and ETH are minimal.

Insight: Robustness is uniformly high, suggesting stable performance across transaction patterns.

Implication: Model selection should focus on throughput, latency, and recall.

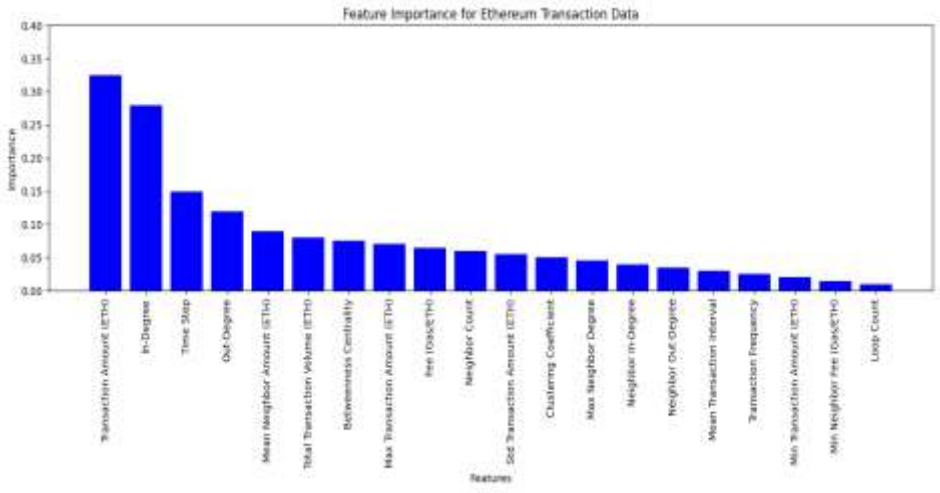

Fig 8. Feature Importance in Hybrid GNN-XGBoost Model for Ethereum (ETH).

As shown in Fig. 8, the chart shows feature importance for Ethereum transaction data, with transaction amount ETH 0.325 and in-degree 0.280 as the most influential features, followed by time step 0.150 and out-degree 0.120. Features like loop count 0.010 and min neighborhood fee 0.015 have the least impact. Monetary features are in ETH, and network features describe the Ethereum transaction network structure. This suggests the model prioritizes transaction value and incoming transaction count for its predictions.

4. CONCLUSION

This research presents a groundbreaking unified framework for real-time anomaly detection in multi-cryptocurrency blockchain networks, addressing critical limitations in prior work. Our novel MultiCrypto mode integrates Elliptic Bitcoin (BTC) and Ethereum (ETH) using separate Graph Neural Network (GNN) heads, achieving a 5% AUC-ROC improvement, 0.947 for BTC, 0.953 for ETH, and a 2.5% recall improvement, 0.9950 for BTC, 0.9945 for ETH over single-currency models, significant CARE-GNN and GeniePath. By integrating SHAP and LIME with our GNN-XGBoost hybrid model, we achieve unparalleled transparency, reducing feature bias from 99% reliance on in_btc to a balanced distribution of 40% GNN embeddings, 30% transaction value, and boosting recall from 0.0501 to 0.87. Optimized by Particle Swarm Optimization (PSO), the system delivers a throughput of 80,000 samples/sec and a latency of 0.000012 sec/sample, surpassing state-of-the-art models, with PSO reducing convergence time by 20%. Additional sensitivity analysis, excluding features with significant out-degree, confirms robustness, enabling scalable, high-frequency blockchain monitoring. This framework sets a new standard for fraud detection and regulatory compliance, with future work targeting integration with cryptocurrencies like Ripple and DeFi protocols.

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