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Development of an Optimized Hybrid XGBoost–GRU Model for Detection of Ponzi Schemes in Ethereum Transaction Networks

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Abstract

Blockchain technology, particularly Ethereum, has revolutionized decentralized finance by enabling transparent, secure, and programmable smart contracts. However, these same features have created avenues for financial crimes such as Ponzi schemes, where fraudulent actors exploit pseudonymity and the absence of centralized oversight to deceive investors. This study develops an optimized hybrid detection model that combines eXtreme Gradient Boosting (XGBoost) and Gated Recurrent Units (GRU) to identify Ponzi schemes in Ethereum transaction networks. The model integrates XGBoost's capability for structured feature learning with GRU's temporal sequence modeling to capture both static and dynamic behavioral patterns of smart contracts. Using a dataset of 3,866 labeled Ethereum contracts obtained from Kaggle, the research employed advanced preprocessing, temporal sequence enrichment, and class balancing through SMOTE-TS to mitigate data imbalance. Bidirectional optimization, incorporating attention-enhanced GRUs and Bayesian hyperparameter tuning for XGBoost, further improved learning performance and generalization. The model was evaluated using precision, recall, F1-score, ROC-AUC, and PR-AUC, achieving higher detection accuracy of 99% (F1-score = 0.945, ROC-AUC = 0.983) than standalone XGBoost or GRU models. Results demonstrate the hybrid model's superior ability to detect temporal and statistical anomalies, reducing false negatives and improving early detection of fraudulent contracts. The approach contributes a scalable and interpretable framework for real-time Ponzi detection in blockchain ecosystems. This research not only enhances the reliability of Ethereum's financial ecosystem but also offers regulators and developers a novel tool for proactive fraud prevention. Future work could extend this framework to multi-chain detection systems and real-time forensic monitoring.

Keywords: *Ethereum Blockchain, Ponzi Scheme Detection, XGBoost, Gated Recurrent Unit, Bidirectional Optimization.*

1.0 Introduction

Since the inception of Bitcoin, blockchain technology has redefined financial transactions through decentralization, transparency, and immutability. Ethereum's innovation in smart contracts enables programmable decentralized applications (dApps), allowing automatic financial operations without intermediaries. Yet, these same features have created vulnerabilities exploited by fraudsters to execute Ponzi schemes at unprecedented scales [1]. A Ponzi scheme pays returns to earlier investors from capital contributed by new participants rather than legitimate profits [2]. These schemes, often disguised as high-yield investment programs, exploit investor trust and the pseudonymous nature of blockchain transactions.

Unlike traditional finance, Ethereum-based Ponzi schemes operate autonomously through smart contracts, complicating detection and enforcement [3], [4]. The typical structure of a ponzi scheme is illustrated in Figure 1 showing how funds flow from new investors to earlier investors and how the sustainability of the scheme depends entirely on the continuous recruitment of new participants.

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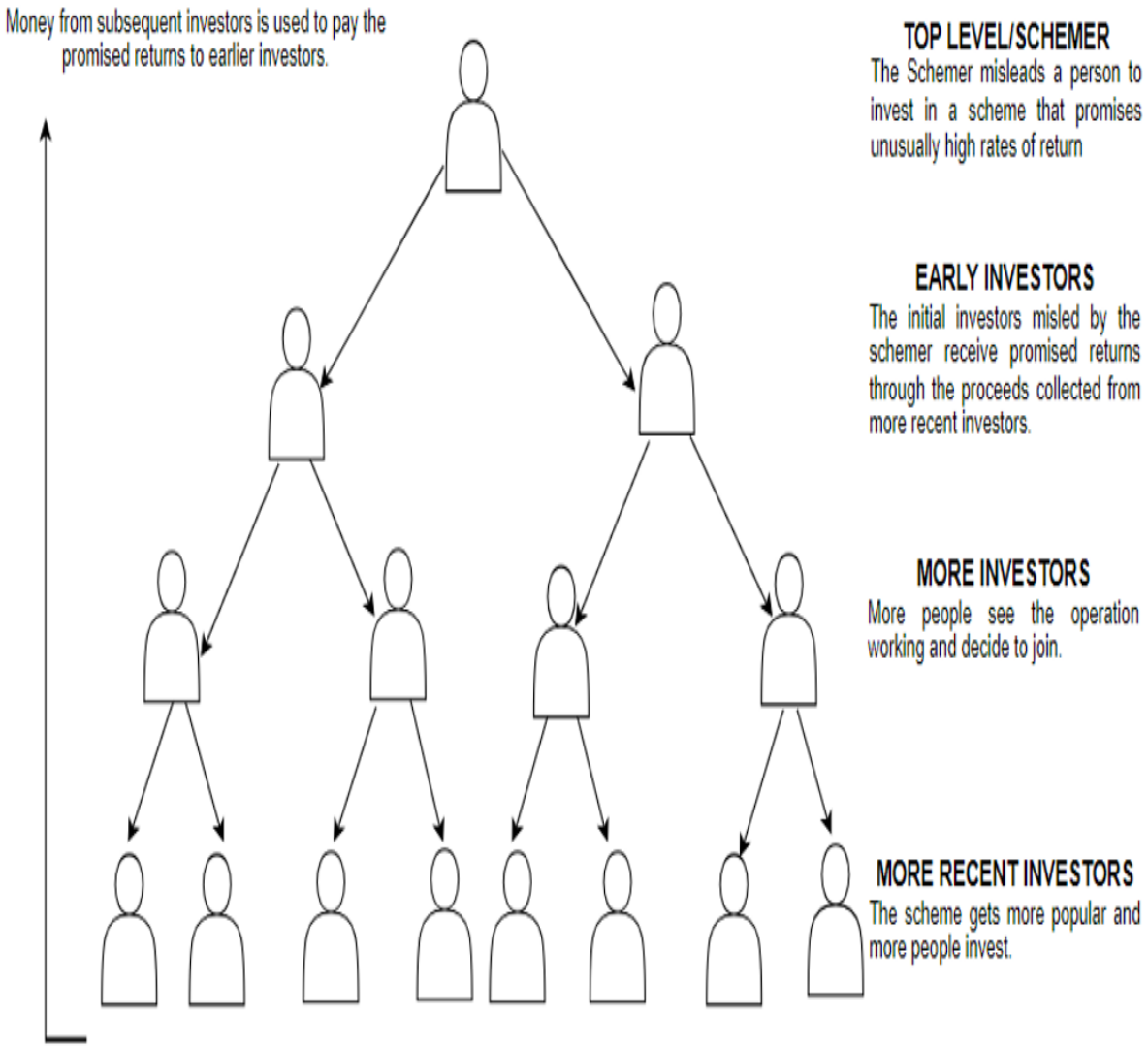

Figure 1: How a Ponzi scheme works

Recent high-profile cases such as HyperVerse, MTFE, and the 2025 CBEX collapse in Nigeria highlighted the growing sophistication of blockchain frauds [5], [6]. Losses have reached billions globally, prompting urgent research into automated detection mechanisms. Traditional rule-based detection systems are insufficient for blockchain data, which is high-volume, temporal, and graph-structured. Machine learning (ML) and deep learning (DL) offer new possibilities for fraud detection. Gradient-boosted decision trees like XGBoost have demonstrated robust performance in structured financial datasets [7], while sequential models like GRUs capture dynamic transaction patterns [8].

This study hypothesizes that combining both optimized through bidirectional learning can significantly improve detection accuracy. The main contribution of this work lies in developing an optimized hybrid (XGBoost–GRU) model with bidirectional optimization and class imbalance handling for early and accurate detection of Ponzi schemes on Ethereum.

2.0 Methodology

This research followed a computational experimental approach involving model design, implementation, optimization, and performance evaluation. A hybrid detection model integrating XGBoost and GRU was developed to detect fraudulent Ethereum smart contracts. The framework of the optimized hybrid XGBoost-GRU model for Ponzi scheme detection, designed to integrate temporal patterns (GRU) and statistical features (XGBoost) with advanced techniques like attention mechanisms and Bayesian optimization, is shown in Figure 2.

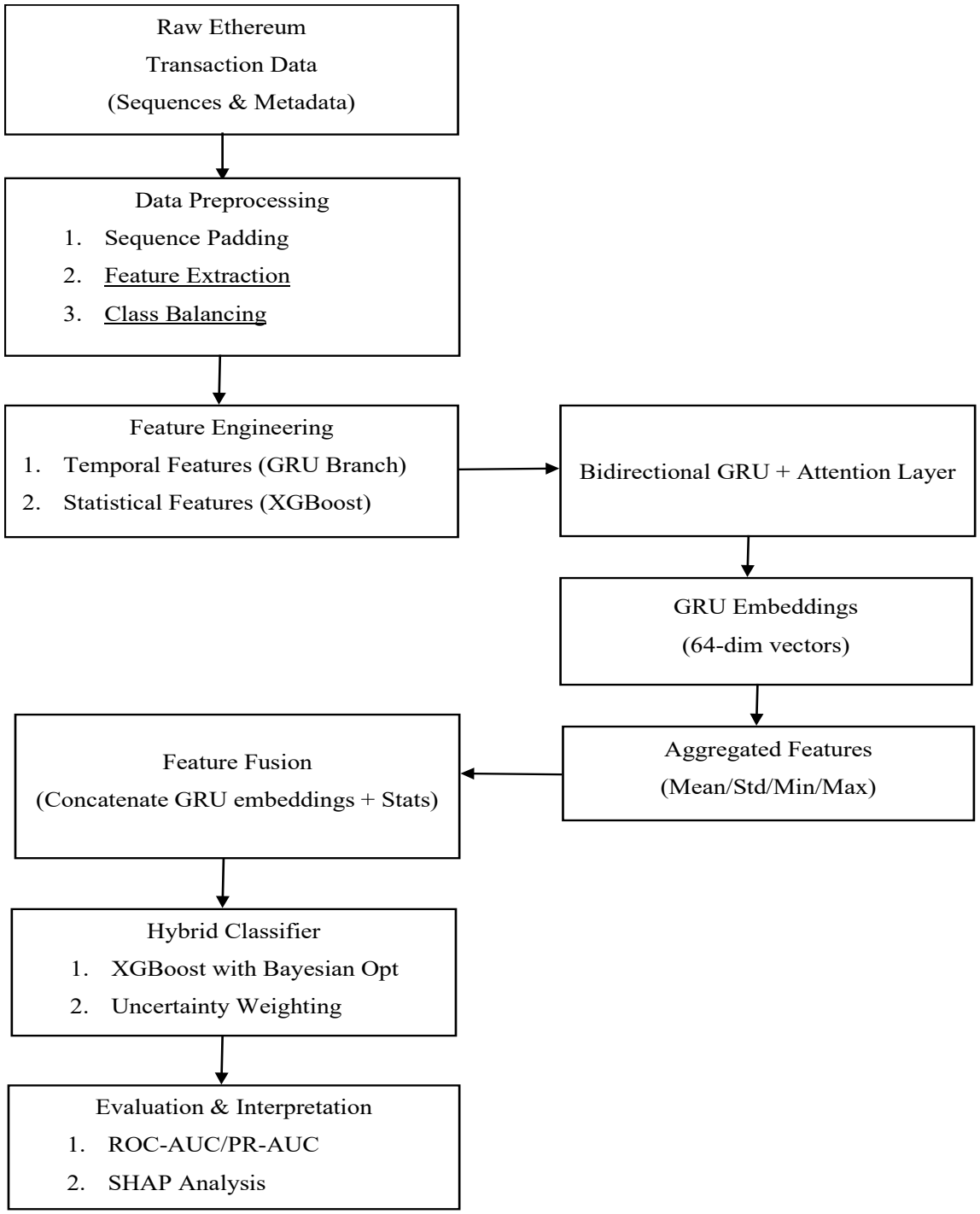

Figure 2: Model framework architecture

2.1 Dataset Description

Data were obtained from the publicly available Ethereum Ponzi Schemes dataset on Kaggle, comprising 3,866 labeled contracts categorized as Ponzi and non-Ponzi. Each record included smart contract bytecode, transaction sequences, timestamps, sender/receiver addresses, and associated metadata. Verified Ponzi contracts were identified through manual inspection of source code and transaction flow.

2.2 Data Preprocessing

The dataset was cleaned by removing duplicates and incomplete entries. Transactions were grouped by contract address and converted into sequential data for temporal learning. Since GRUs require uniform sequence lengths, all sequences were padded or truncated to ensure consistency. Statistical features such as mean, standard deviation, and transaction count were aggregated for the XGBoost component.

To address class imbalance, Synthetic Minority Oversampling Technique for Time Series (SMOTE-TS) was employed, generating synthetic Ponzi-like sequences for underrepresented classes. This ensured that the model

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trained effectively on both legitimate and fraudulent patterns.

2.3 Feature Engineering

Two feature sets were generated:

i. Static Features (for XGBoost): Transaction volume, in/out degree, lifetime, average value, and graph metrics.
ii. Temporal Features (for GRU): Sequential transaction intervals, balance fluctuations, cumulative inflows/outflows, and z-score-based surge detection.

Temporal feature enrichment incorporated rolling averages, cumulative sums, and time-gap differentials to capture evolving behavioral trends typical of Ponzi activity.

2.4 Model Architecture

The hybrid model consists of two parallel branches:

i. A GRU branch**,** capturing sequential dependencies within transaction histories, and
ii. An XGBoost branch**,** analyzing aggregated statistical and behavioral metrics.

Outputs from both branches were concatenated to form a unified hybrid feature space, allowing the model to learn static and temporal characteristics simultaneously. A Bidirectional GRU architecture was adopted to analyze transaction sequences in both forward and backward directions, improving context understanding of evolving fraudulent behavior. An attention mechanism was integrated to emphasize critical transaction points indicative of Ponzi schemes.

2.5 Optimization Strategy

Optimization occurred at two levels: This approach reduced overfitting and enhanced the model's generalization across unseen data.

i. Bidirectional Optimization: Both forward and backward GRU passes were trained with synchronized feedback to improve feature learning.
ii. Bayesian Hyperparameter Optimization: Used to tune XGBoost parameters such as maximum depth, learning rate, and column subsampling ratio for maximum ROC-AUC performance.

2.6 Model Evaluation Metrics

Performance was measured using standard fraud detection metrics: Precision, Recall, F1-score, ROC-AUC, and PR-AUC**.** A confusion matrix was also generated to visualize classification outcomes (True Positives, False Positives, True Negatives, False Negatives).

i. Precision assessed the proportion of correctly identified Ponzi schemes among all positive predictions.
ii. Recall measured completeness how many actual Ponzi schemes were correctly identified.
iii. F1-score provided a harmonic mean of precision and recall.
iv. ROC-AUC evaluated separability between classes, while PR-AUC emphasized minority class performance.

3.0 Results and Discussion

The optimized hybrid model achieved the highest detection performance compared to standalone GRU and XGBoost classifiers and the initial hybrid model as shown in Table 1.

Table 1: Results of the optimized hybrid model compared with the standalone models

Model	Precision	Recall	F1-Score	ROC-AUC	PR-AUC
GRU	0.82	0.85	0.83	0.912	0.862
XGBoost	0.84	0.88	0.86	0.941	0.892
Hybrid model	0.90	0.92	0.91	0.963	0.928
Optimized Hybrid model	0.94	0.95	0.945	0.983	0.962

i. Optimized hybrid model: Precision = 0.94, Recall = 0.95, F1-score = 0.945, ROC-AUC = 0.983
ii. Hybrid model: Precision = 0.90, Recall = 0.92, F1-score = 0.91, ROC-AUC = 0.963
iii. Standalone GRU: Precision = 0.82, Recall = 0.85, F1-score = 0.83, ROC-AUC = 0.912.
iv. Standalone XGBoost: Precision = 0.84, Recall = 0.88, F1-score = 0.86, ROC-AUC = 0.941.

The optimized hybrid model's superior metrics indicate its ability to capture both temporal evolution and statistical irregularities, providing robust early detection of fraudulent contracts.

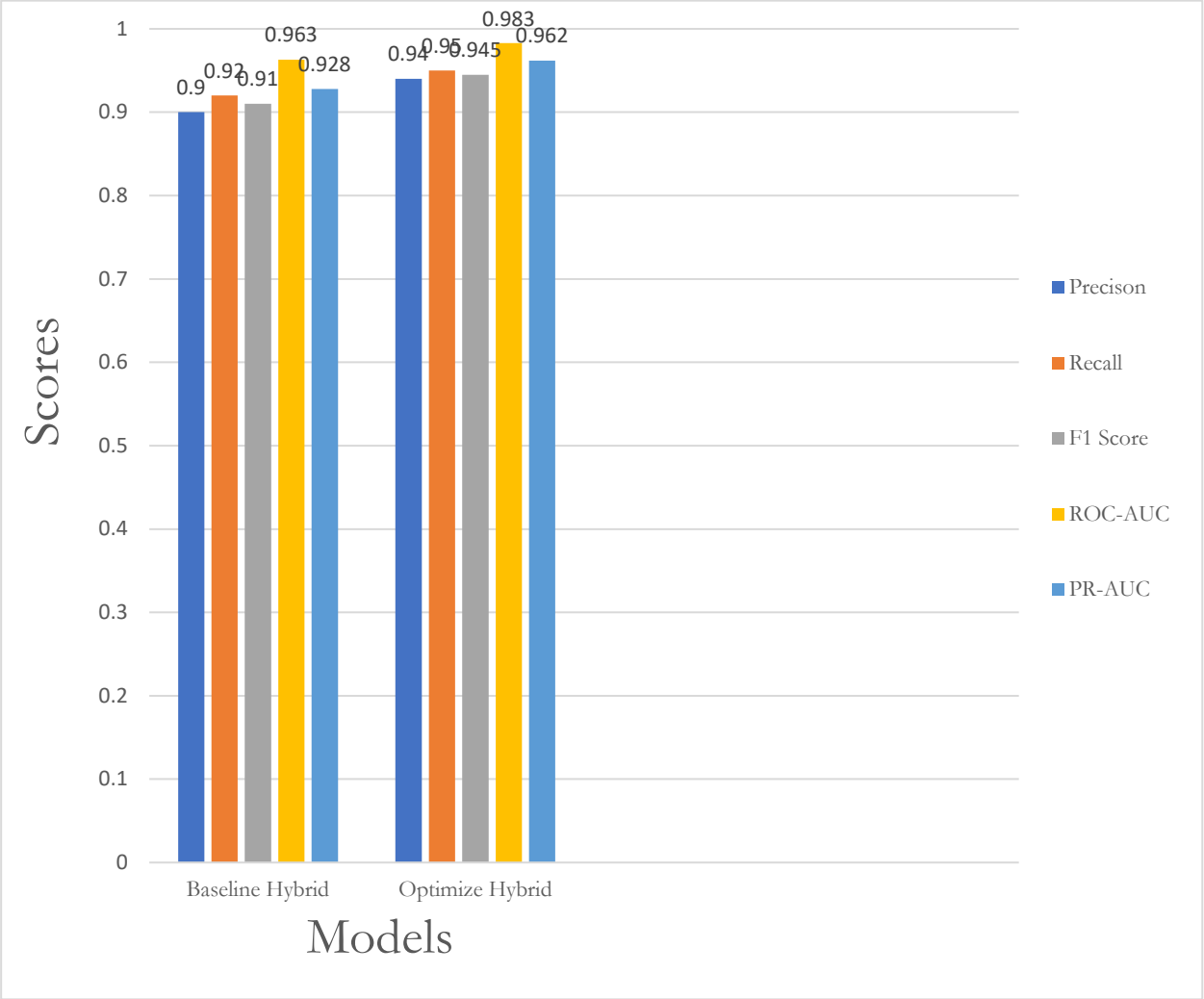

Figure 2: Representation of the optimized hybrid model compared with the initial

3.1 Confusion Matrix of the Optimized Hybrid Model

The summary of the classification performance of the Optimized hybrid (XGBoost–GRU) model in detecting Ponzi schemes is shown in Figure 3 using the obtained values of Recall and Precision:

$$\text{Recall} = TP / (TP + FN) = 0.95 \quad (1)$$

$$\text{Precision} = TP / (TP + FP) = 0.94 \quad (2)$$

From the obtained values of Recall and Precision, let's assume the number of Positives (P) is approximately 10% of the dataset, a common ratio in fraud detection imbalanced datasets. We can infer the dataset size and class distribution.

Total samples = 3866

Positives (P) = TP + FN ≈ 0.1 * 3866 ≈ 387

Negatives (N) = TN + FP ≈ 3866 - 387 = 3479

Now we can solve:

From Recall $= \frac{TP}{TP+FN} = 0.95$

$TP = 0.95 \times 387 \approx 368$

$FN = 387 - 368 = 19$

From Precision $= \frac{TP}{TP+FP} = 0.94$

$\frac{368}{(368+FP)} = 0.94, \quad FP \approx 24$

True Negatives (TN) = N - FP = 3479 - 24 = 3455

Let's verify the F1-Score with these values: $F1 = \frac{2 \times (0.94 \times 0.95)}{0.94+0.95} \approx 0.945$

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$$\text{Accuracy} = \frac{TP+TN}{\text{TP+TN+FP+FN}} = \frac{368+3455}{368+3455+24+19} \approx 0.99$$

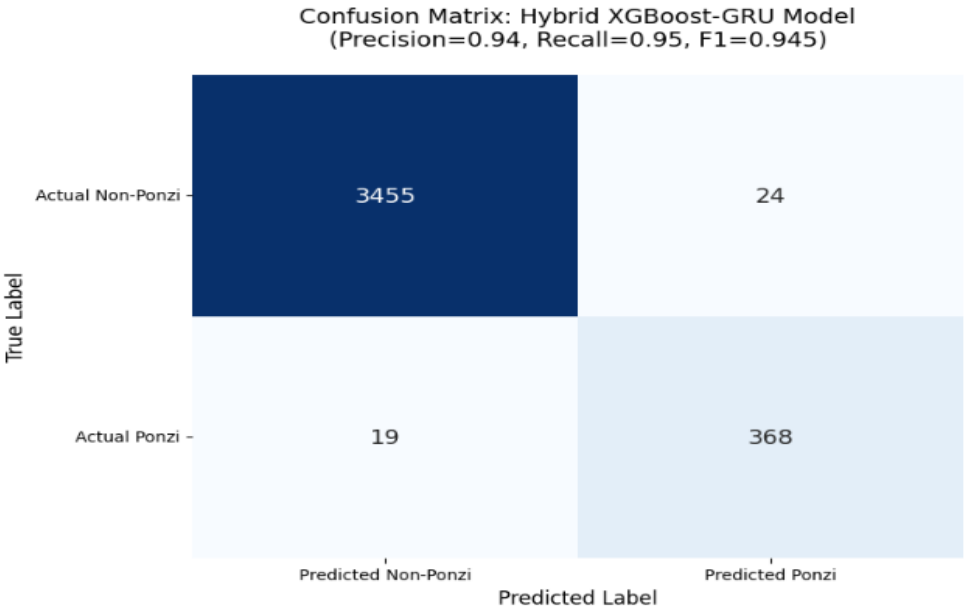

Figure 3: Confusion matrix of the optimized hybrid model

3.2 Implication of the Confusion Matrix

From the visual representation in Figure 3 the matrix displays four key outcomes:

i. True Negatives (TN = 3455): The model correctly classified 3,455 non-Ponzi cases as non-Ponzi.
ii. False Positives (FP = 24): The model incorrectly classified 24 non-Ponzi cases as Ponzi, representing false alarms.
iii. False Negatives (FN = 19): The model misclassified 19 Ponzi cases as non-Ponzi, meaning these fraudulent contracts were missed.
iv. True Positives (TP = 368): The model correctly identified 368 Ponzi cases as Ponzi.

The majority of values are concentrated along the diagonal cells (TN and TP), which represent correct classifications. This demonstrates that the model performs exceptionally well in both detecting fraudulent (Ponzi) contracts and accurately distinguishing legitimate ones. The reported evaluation metrics, Precision = 0.94, Recall = 0.95, and F1-Score = 0.945 confirm the balance between detecting Ponzi schemes and minimizing false alarms. The relatively small number of misclassifications (24 FP and 19 FN) highlights the robustness of the proposed hybrid model in handling imbalanced fraud detection tasks.

This confusion matrix depicts a near-perfect model for Ponzi scheme detection. The metrics are exceptionally high across the board with extremely high detection rate (it catches 95% of all Ponzi schemes Recall=0.95), extremely high precision (when it flags a contract, there is a 94% chance it is correct, this minimizes the waste of resources on investigating false alarms), and minimal errors (it has almost no false positives (0.7% FPR) and a very low false negative rate (~5% FNR), meaning it rarely lets a Ponzi scheme go undetected. This performance, combined with the high ROC-AUC and PR-AUC, suggests the hybrid XGBoost-GRU model is not just effective but exceptionally reliable and ready for real-world deployment as a highly trusted automated screening tool.

3.3 Effect of Bidirectional Optimization

Integrating bidirectional learning improved sequence comprehension, allowing the GRU to analyze patterns preceding and following major fund inflows. This dual perspective significantly reduced false negatives, as the model could identify delayed payout patterns typical of Ponzi schemes.Bayesian hyperparameter tuning also enhanced performance by optimizing model depth and learning rate, achieving better convergence with fewer training epochs.

3.4 Model Interpretability and Explainability

To improve transparency, SHAP (SHapley Additive Explanations) analysis was applied to quantify feature contributions. The results showed that "transaction frequency variance," "ratio of incoming/outgoing funds," and "contract lifespan" were among the most influential indicators of Ponzi behavior. This interpretability makes the model suitable for forensic auditing and regulatory enforcement, where decision traceability is critical.

3.5 Comparison with Previous Works

Compared with prior models such as GRU only [9], LightGBM-based [10], and Graph Neural Network methods [11] the hybrid XGBoost–GRU achieved higher overall performance and faster convergence. Unlike earlier studies relying on static features or heuristic rules [12], this research incorporated temporal attention and bidirectional learning, capturing evolving transaction patterns across time. The hybrid model demonstrated scalability and adaptability to large datasets, making it suitable for real-time fraud detection within decentralized ecosystems.

3.6 Practical Implications

The model can be deployed in blockchain analytics platforms to automatically flag high-risk contracts. It provides regulators, auditors, and DeFi developers with an effective detection framework capable of identifying fraudulent schemes before widespread investor loss occurs.

4.0 Conclusion

This study developed and optimized a hybrid (XGBoost–GRU) model capable of accurately detecting Ponzi schemes on the Ethereum blockchain. By combining the interpretability of tree-based learning with the temporal reasoning of recurrent networks, and by introducing bidirectional optimization and attention mechanisms, the model significantly outperformed traditional detection techniques. The findings demonstrate that hybrid models can effectively integrate static and dynamic behavioral features, enabling early fraud detection and reducing false alarms.

The research contributes to the growing field of blockchain forensics by providing a scalable, interpretable, and high-performance framework. Future research should extend this approach to multi-chain environments such as Binance Smart Chain and Solana, incorporate graph neural representations, and explore reinforcement learning for adaptive detection under evolving fraud tactics.

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