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Proposes an AI Agent that Continuously Learns and Adapts Anti-Money Laundering Rules for Blockchain-Based Transactions, Detecting Novel Laundering Strategies

Jayasri Dudam

Senior Software Engineer, American Express

ORC ID : 0009-0001-9317-9606

Divya Rayasam

Sr. SAP consultant, AbbVie INC

ORC ID : 0009-0005-6387-5888

Raja Ramesh Bedhaputi

Senior Engineer, American Express

ORC ID : 0009-0002-8184-2340

Abstract: In decentralised blockchain ecosystems in particular, the growing complexity and number of financial transactions makes it very difficult to discover instances of money laundering. Due to the quick evolution of laundering tactics, traditional heuristics and rule-based systems are often inadequate. In order to combat AML in blockchain settings, this article suggests an AI system that relies on several agents. Intelligent agents are built into the system to discover suspicious trends in transactional data by independently monitoring, filtering, and analysing it. The agents' ability to learn new things over time is crucial since it allows them to change AML regulations and find new types of laundering that don't fit into current typologies. Managing the enormous amount of blockchain transactions and adapting AML detection algorithms to new threats are the two main concerns that the suggested architecture attempts to address. We go over the agent architecture, the functions they do, and how they work together to uncover new forms of money laundering. This smart and adaptable approach shows promise for improving anti-money-laundering capabilities in contemporary decentralised financial systems.

Keywords: Anti-Money Laundering, Blockchain, Multiagent Systems, Continuous Learning, Financial Crime Detection.

1. Introduction

Money laundering remains a pervasive and evolving threat to the global financial ecosystem. As financial technologies advance, so too do the strategies employed by criminals seeking to obscure the origin of illicit funds. The rise of blockchain-based platforms—characterized by decentralization, pseudonymity, and borderless operation—has significantly amplified this challenge. While blockchain technology offers numerous advantages such as transparency, immutability, and decentralized trust, it also presents new vulnerabilities that can be exploited for laundering money through increasingly sophisticated means. Traditional Anti-Money Laundering (AML) frameworks largely rely on predefined rule-based systems and human oversight to identify suspicious transactions [1]. These methods, though effective to some extent in regulated banking environments, fall short in dynamic and fast-evolving domains like cryptocurrencies and decentralized finance (DeFi). Criminals are continuously innovating laundering techniques, such as layering funds through multiple blockchain addresses, using privacy coins, or engaging in cross-chain token swaps. These novel strategies often escape detection by static AML rules and overwhelm human analysts due to the volume and complexity of data. In response to these challenges, there is a growing consensus on the need for intelligent, automated systems that not only detect known laundering patterns but can also adapt to emerging threats. Artificial Intelligence (AI), particularly when deployed in a multiagent system (MAS) framework, offers a promising solution. Multiagent systems consist of distributed, autonomous entities—

agents—that can observe, analyze, learn, and interact with each other to achieve a common goal. When applied to AML, these agents can be programmed to monitor blockchain transactions, flag suspicious activities, and adapt detection rules based on new patterns.

This paper presents a novel multiagent-based AI architecture specifically designed for AML in blockchain environments. The core objective is to build a system capable of addressing two key challenges: the overwhelming volume of real-time blockchain transactions and the need for continuous evolution of detection strategies. By leveraging intelligent agents with machine learning capabilities, our system can autonomously refine AML rules, recognize previously unseen laundering techniques, and collaborate with other agents to improve overall detection accuracy. Each agent in the proposed architecture is assigned a specialized role—ranging from data collection and transaction monitoring to pattern recognition and decision support. Agents operate independently but communicate and cooperate to form a cohesive and adaptive network. This decentralization mirrors the very nature of blockchain itself and allows for scalable and flexible monitoring solutions. Furthermore, the continuous learning component empowers agents to identify anomalies and extract features indicative of laundering, even when explicit rules do not exist. This research contributes to the growing body of work focused on enhancing AML strategies in the age of digital finance. Our approach integrates blockchain analytics, AI-driven adaptability, and collaborative decision-making to present a robust framework for future-ready AML systems. The remainder of this paper details the agent architecture, system design, implementation strategies, and experimental evaluation of the proposed system in simulated blockchain environments.

1.1 Background and Motivation

It is common practice to launder illicitly acquired funds via intricate webs of financial and business dealings in order to obscure their true origins. It gives criminal groups the green light to spend their dirty money on things like drug trade, terrorism, and corruption. On a yearly basis, laundering accounts for more than $1.5 trillion, or between 2 and 5 percent of the world's gross domestic product. In doing so, it undermines the security and reliability of financial systems and presents a significant risk to national economies, regulatory agencies, and financial institutions [2]. The proliferation of cryptocurrency and blockchain technologies in the last few years has created new opportunities for money laundering. Users may transact without disclosing their actual names thanks to pseudonymity, which is enabled by blockchain's immutable transaction records. The decentralised and audit-proof nature of cryptocurrencies like Bitcoin, Monero, and Ethereum has made them enticing tools for criminals looking to launder, convert, and conceal illegal cash across borders. Because these technologies often sidestep conventional financial intermediaries and compliance procedures, the expansion of privacy-focused currencies, cross-chain bridges, and decentralised finance (DeFi) platforms has further hampered anti-money laundering (AML) regulation. The decentralised and global nature of blockchain technology presents a significant problem in the fight against money laundering on blockchain platforms. The lack of a centralised body overseeing bitcoin networks makes coordinated regulatory action more challenging than in conventional financial systems. Furthermore, it is difficult to determine the actual source or destination of payments due to the use of pseudonymous addresses and sophisticated obfuscation methods like as tumblers, mixers, and chain-hopping. This makes it difficult for traditional AML methods to identify and stop complex laundering schemes, as they depend on well defined regulations and human supervision. This highlights the need of developing smarter, more flexible, and automated systems that can manage the intricacies of financial ecosystems built on blockchain technology.

1.2 Limitations of Traditional AML Systems

Much of the older generation of anti-money-laundering (AML) systems relies on rule-based frameworks to identify potentially fraudulent transactions according to established patterns, heuristics, and thresholds. Some examples of the "if-then" logic used by these systems include sending out notifications once a transaction reaches a certain threshold or takes place in a country with a high risk rating. This method works well for spotting common kinds of money laundering, but it can't keep up with the ever-changing financial landscape of today, particularly on blockchain-based platforms. These systems have a big flaw in that they use static rules. Criminals are always thinking of new ways to launder money, and they come up with intricate methods to take advantage of loopholes in the system. Because static criteria are unable to take into consideration new typologies or behaviours, innovative washing techniques often go unnoticed [3]. And if crooks figure out how these systems function, they merely tweak their strategies slightly to avoid alerts—a practice called "smurfing" or arranging transactions to stay undetected. The strong reliance on human analysts to analyse flagged transactions is another major barrier. Every day, there are an overwhelming amount of warnings due to the large volume of financial transactions completed, particularly in cryptocurrency marketplaces. Time and energy are wasted on many of these false positives. In the absence of proper investigation resources and sometimes under time constraints, analysts are forced to comb through mountains of data in search of actual dangers. As a result, things become less efficient, reactions take longer, and actual dangers may go unnoticed. Because of the inherent complexity of blockchain-based laundering techniques, conventional AML systems are ill-suited to deal with them. Many techniques exist that may readily circumvent rule-based systems. These include mixing services, privacy currencies (like as Monero or Zcash), cross-chain swaps, and obfuscation methods based on smart contracts. These techniques are almost undetectable by static detection systems as they do not display the typical warning signs.

1.3 Problem Statement and Research Objective

As the number and complexity of financial transactions have increased at an exponential rate, it has become more difficult to identify and prevent money laundering. When dealing with blockchain systems, this problem becomes even more acute since transactions are anonymous, decentralised, and often transcend international boundaries in a matter of seconds. Conventional anti-money-laundering (AML) methods and technologies are finding it difficult to stay up with these changes. In addition to offering sophisticated tools for criminal actors to launder cash without discovery, the problem is further complicated by the increased usage of privacy-enhancing technology, decentralised finance (DeFi), and cryptocurrencies. Presently, blockchain systems' AML inefficiencies come from two main issues. One issue is the high false-positive rate and impracticality of using static-rule assessment and human inspection due to the enormous amount of real-time blockchain transactions. The second issue is the ever-changing nature of laundering techniques; criminals are always coming up with new ways to circumvent anti-money-laundering measures. Compliance and enforcement initiatives are severely hindered by traditional rule-based systems' inability to identify or react to these innovative techniques due to their reliance on inflexible logic. Intelligent, adaptive, and autonomous systems that surpass static pattern matching are clearly necessary to tackle these difficulties. A potential solution is in the use of AI agents that can learn from their experiences, monitor transactional behaviours, spot new forms of laundering, and instantly update detection criteria. These agents need to be able to work quickly in decentralised blockchain networks that process a lot of data, as well as independently in a multi-agent setting. This effort primarily aims to provide an artificial intelligence framework for anti-money laundering in blockchain ecosystems based on Multiagent Systems (MAS). Intelligent monitoring, adaptive learning, and collaborative detection across specialised agents are the goals of the suggested system. The distributed and coordinated collection, filtering, analysis, and interpretation of blockchain transactions is the responsibility of each agent. A more responsive and robust AML infrastructure will be achieved by the agents' continual learning from fresh data and suspicious behaviour patterns. Both the area of artificial intelligence (AI) driven financial security systems and the efficacy of anti-money laundering (AML) in blockchain environments are intended to be improved by this study.

2. Related Work

Conventional AML systems often use supervised learning models trained on past data and static rule-based frameworks. Despite their success in more traditional banking settings, these solutions aren't up to the challenge of handling the opaque and ever-changing world of blockchain-based financial transactions. Weber et al. (2019) demonstrated the effectiveness of relational modelling in decentralised systems by using Graph Neural Networks (GNNs) for the purpose of detecting fraudulent Bitcoin transactions. The problem is that these models can't handle new types of laundering strategies as they're usually trained offline. While other studies have investigated unsupervised anomaly detection methods for blockchain, for example, these models often have significant false-positive rates and are not easy to understand. Although there have been proposals for reinforcement learning methods, such as adaptive policy learning for transaction monitoring, these systems are limited in their ability to generalise to unexplored typologies and need well specified reward signals [4].

To address these challenges, recent studies advocate for continual learning and meta-learning techniques in AML systems. Applying ongoing adaption models to fraud detection, for example, allows computers to learn from streaming data without catastrophic forgetting [5]. But in a blockchain setting, such methods have not been extensively used. To identify emerging methods of laundering on blockchain platforms, the suggested AI agent differentiates itself from previous work by integrating graph-based transaction modelling, adaptive rule creation, and ongoing learning. The agent's goal is to bridge the gap between crypto-financial crime's fluidity and static compliance frameworks by using online learning methods to dynamically refine anti-money laundering regulations based on transaction behaviours.

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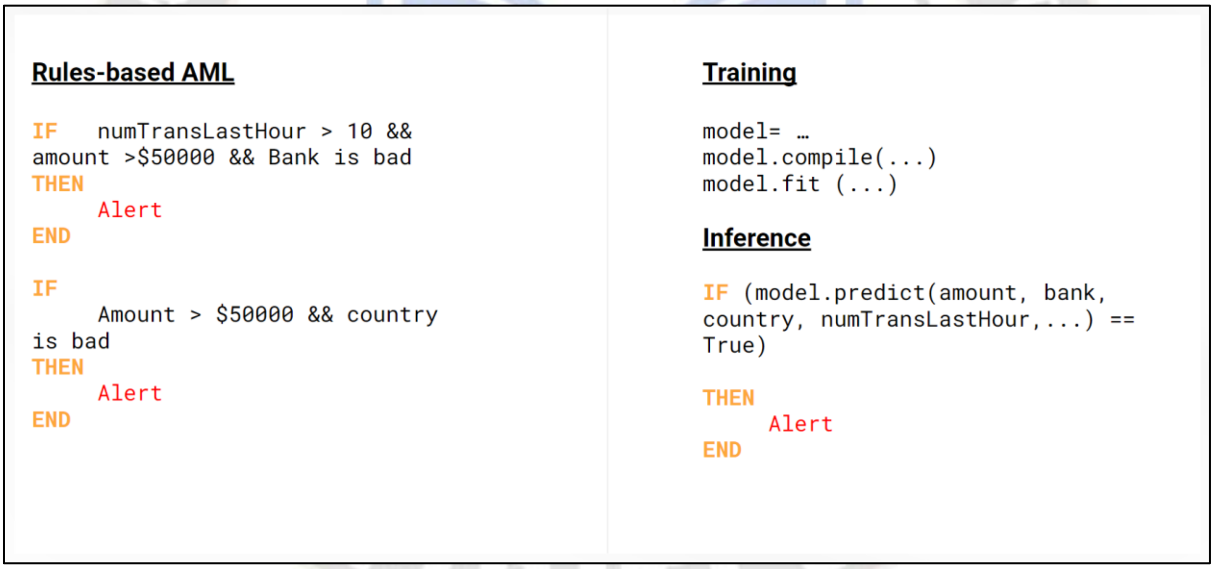
2.1 Reinforcement Learning Approaches to AML

There has been a lot of buzz lately about how Reinforcement Learning (RL) may improve Anti-Money Laundering (AML) systems, especially in the area of adaptive transaction monitoring. Robot learning (RL) agents acquire best practices for decision-making by interaction with their surroundings and reward-based feedback, as opposed to supervised learning models that depend on tagged past data. By experimenting with different approaches, RL-based AML systems may adapt their detection tactics to match the patterns of transactions they've seen. To train an RL agent to detect suspicious transactions in the context of anti-money laundering (AML), adaptive policy learning is used to maximise cumulative rewards associated with effective detection and minimise false alarms. In order to better detect money laundering in dynamic financial environments, the agent is constantly updating its policies. Since laundering strategies change so fast, systems need to be nimble and adaptable, which is especially helpful for blockchain AML. The construction of appropriate reward functions is one of the major obstacles to RL's application to AML. Given the difficulty in obtaining clear ground truth labels for financial crime detection, the optimal reward system must strike a compromise between the two competing goals of maximising the number of correct detections and reducing the number of false positives. The inability to generalise beyond training settings is a potential consequence of the agent learning biassed or inefficient rules as a result of poorly designed incentives. Additional challenges with generalisation arise when RL models are presented with new washing processes that were not part of their training. It is possible for RL agents trained on historical patterns to underperform on new typologies introduced by financial criminals who are always coming up with new ways to avoid detection. Given the intricacy and secrecy of illegal networks, it is difficult to develop broad and realistic simulation environments to train RL agents efficiently, which compounds this problem.



Rules-based AML

```
IF   numTransLastHour > 10 &&
amount >$50000 && Bank is bad
THEN
     Alert
END

IF
     Amount > $50000 && country
is bad
THEN
     Alert
END
```

Training

```
model= …
model.compile(...)
model.fit (...)
```

Inference

```
IF (model.predict(amount, bank,
country, numTransLastHour,...) ==
True)

THEN
     Alert
END
```

Figure 1: Rules-based AML versus Deep-Learning AML using models

2.2 Graph Neural Networks (GNNs) for Blockchain AML

Blockchain transactions, which inherently create complicated graph structures with nodes representing wallets or addresses and edges representing transactions, have recently been analysed with great success by Graph Neural Networks (GNNs). To better identify suspicious behaviour, GNNs use the relational information encoded in these transaction networks, as opposed to typical AML algorithms that examine transactions as isolated data points. In order to use GNNs to identify fraudulent conduct on blockchain platforms, one must first understand how these networks describe the relationships and interactions between different entities. In contrast to static rule-based systems, GNNs are able to detect suspicious account clusters, unusual transaction pathways, and hidden linkages by capturing both the local and global graph topologies [6]. Because of their relational modelling, they are excellent at spotting intricate laundering schemes that use services like layering, structure, and mixing. Using GNNs has several benefits, one of which is that they

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may enhance detection accuracy by creating richer representations by including various attributes and contextual information about network nodes, transactions, and entities. In distributed ledger systems like blockchain, where direct identifiers are scarce and criminals hide their tracks in complex transaction chains, this is of the utmost importance [7]. Present GNN-based AML models do have some potential, but they aren't without significant limitations. Most of them can only learn from datasets that have been collected in the past, which limits their capacity to respond instantly to new forms of money laundering. As criminals develop more sophisticated tactics, the static training method may cause performance to deteriorate. It is also difficult for GNNs to scale to deal with enormous, ever-expanding blockchain graphs, which often necessitates a lot of computing power.

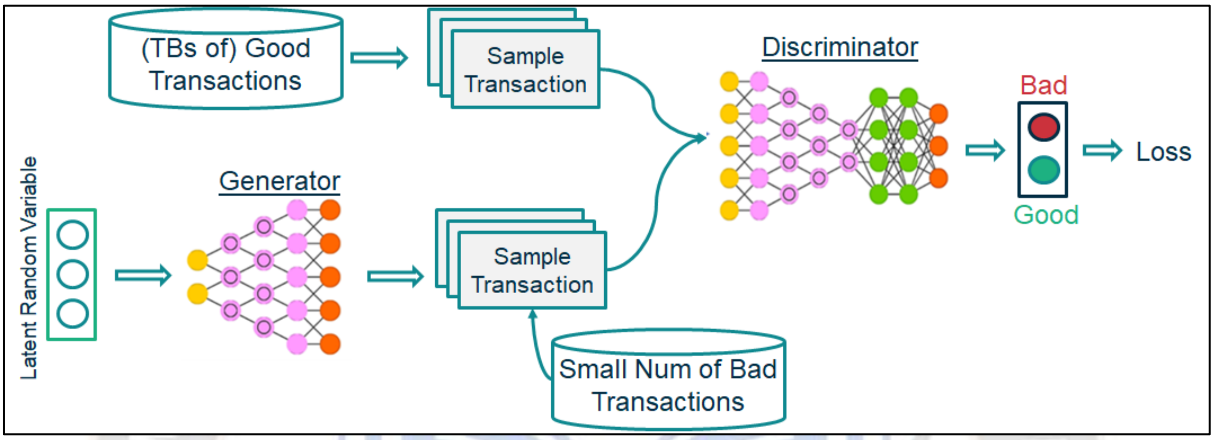

Figure 2: Training a GNN with Transactions classified as ‘good’ and ‘bad’.

2.3 Proposed AI Agent for Blockchain AML

Our suggested AI agent integrates graph-based transaction modelling, adaptive rule generation, and ongoing learning to solve the problems with current blockchain-based AML solutions. The end goal of this integration is to build a strong, adaptable system that can spot new forms of money laundering as they emerge. The key component of this agent is its ability to learn from its experiences, allowing it to gradually improve its detection skills and expertise as it receives more transaction data. Continuous learning avoids catastrophic forgetting, which is a problem with typical offline-trained models. This means that the agent may adapt to new laundering tactics while retaining its prior expertise. In blockchain contexts, this is of the utmost importance since illegal behaviours change so fast. An adaptive rule generating technique complements continuous learning [8]. Instead than depending on predetermined rules that have been hand-crafted, the agent may independently develop and improve AML rules by analysing transaction patterns and receiving feedback from detection results. By automatically adjusting rules in response to new information, this system makes it easier for human specialists to keep an eye on things even as laundering techniques evolve. To take use of the blockchain's built-in relational structure, the agent additionally uses graph-based transaction modelling. Graph representations of wallets and transactions allow the AI agent to pick up on intricate interdependencies and patterns of interaction that would be hard to pick up using more conventional feature-based approaches. Enhanced identification of complex laundering schemes involving numerous entities and transaction levels is made possible by this relational understanding. Lastly, in order to improve rules in real-time and discover anomalies, the agent uses online learning methods. Because of this, it can quickly react to suspicious activities and become better over time without having to retrain on massive historical datasets, which may be expensive [9]. All of these parts work together to provide a smart, scalable solution for proactive and adaptive blockchain transaction monitoring, closing the gap between rigid AML rules and the ever-changing world of crypto-financial crime.

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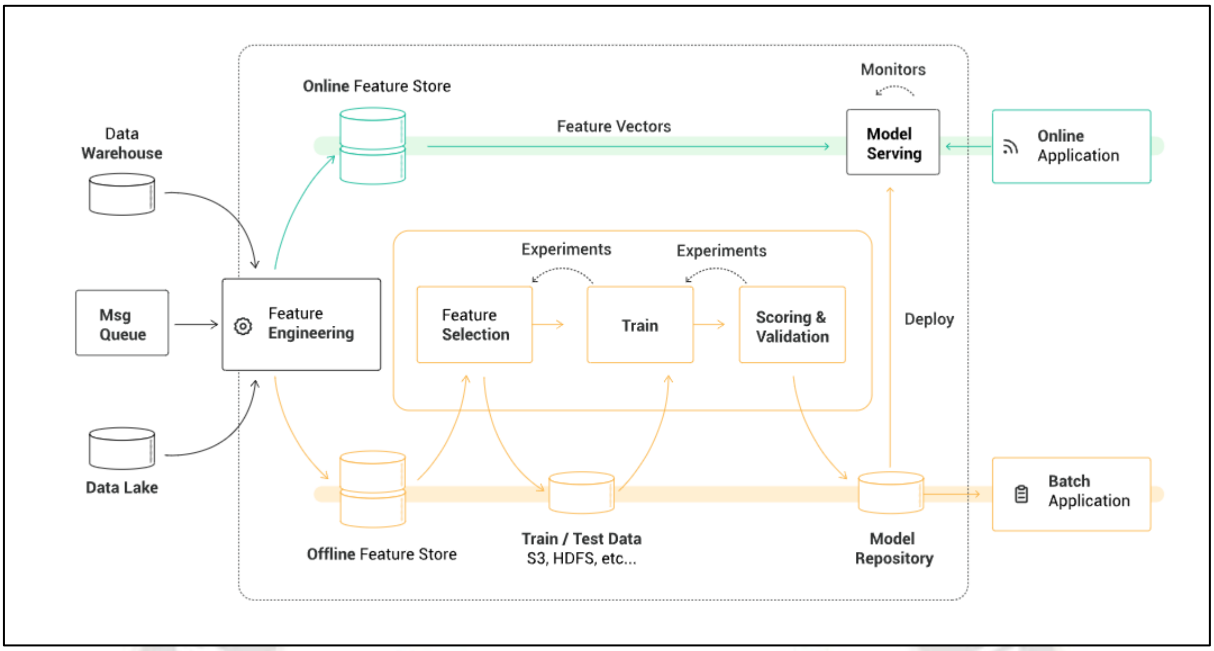

Figure 3: Machine Learning Pipeline with Hops works

Table 1: Difference and gaps across the AML approaches for blockchain:

Topic	**Key Features / Focus**	**Limitations / Challenges**
Limitations of Traditional AML Systems	- Static rule-based frameworks - Supervised learning on historical data	- Inflexible, cannot adapt to new laundering methods - Dependent on labeled historical data - Poor handling of blockchain complexities and scale
Graph Neural Networks (GNNs) for Blockchain AML	- Models relational data in transaction graphs - Detects complex illicit patterns	- Mostly offline training - Limited real-time adaptability - Computationally intensive, scalability issues
Unsupervised Anomaly Detection Techniques	- Detects anomalies without labeled data - Useful for novel patterns	- High false-positive rates - Low interpretability - Difficult to tune thresholds for alerts
Reinforcement Learning Approaches to AML	- Adaptive policy learning through interaction - Continuous improvement via rewards	- Designing effective reward functions is difficult - Poor generalization to unseen laundering tactics - Requires realistic simulation environment
Continual Learning and Meta-Learning in Fraud Detection	- Incremental learning from streaming data - Prevents catastrophic forgetting	- Limited application in blockchain AML - Challenges in handling concept drift and real-time updates

Proposed AI Agent for Blockchain AML	- Combines continual learning with adaptive rule generation - Uses graph-based transaction modeling - Online learning for dynamic updates	- Complexity in integration - Requires robust feedback mechanisms - Needs scalability to real-world blockchain data volumes

2.4 Limitations of Traditional AML Systems

Conventional AML systems mostly use supervised learning models trained on transaction history data and static rule-based frameworks. Compliance specialists provide established patterns, thresholds, and heuristics that rule-based systems use to function. Large deposits of cash, fast transfers of funds, or transactions with businesses on a blacklist are some of the clues that these rules use to identify potentially fraudulent activity. Although these structures have worked well in traditional banking and finance, they often have serious drawbacks due to their inflexibility. A big problem with static rule-based AML systems is that they can't change to accommodate new ways of laundering money. False negatives, in which static systems fail to identify new laundering techniques, and false positives, in which investigators are overwhelmed with innocuous alarms, are both caused by the ongoing development of new ways by criminals to circumvent set restrictions. Because of this, these systems need regular, labor-and resource-intensive manual upgrades and tweaks [10]. To train classifiers that detect suspicious transactions, supervised learning models in AML use labelled historical data. This model's central tenet—that future laundering patterns would be consistent with previous behaviors—is problematic in today's dynamic financial markets. The quality and quantity of labelled data is another factor limiting the efficacy of supervised models; this data is often uneven and sparse since illegal actions are typically hidden. Additional complication to anti-money-laundering measures is introduced by the advent of decentralised finance and blockchain technology. The anonymity, decentralisation, and international nature of blockchain transactions makes it more difficult to track criminal funds. This transparency paradox, in which identities are hidden yet transactions are public, is difficult for traditional AML models to handle. Also, conventional static and offline-trained algorithms aren't up to the task of keeping up with the massive amount and speed of blockchain transactions, which necessitates real-time optimisation.

3. Proposed Methodology for Adaptive AML in Blockchain Transactions

In order to detect evolving methods of money laundering on blockchain networks, the proposed method integrates graph-based modelling, adaptive rule generation, and continuous learning. Initial steps include visualising the data as a network, with wallet addresses representing the nodes and transactions serving as the edges. Graph Neural Networks (GNNs) capture the complex links and transaction patterns inherent in the blockchain, allowing for relational analysis to identify illegal conduct. To keep up with the dynamic nature of laundering techniques, a continuous learning strategy is used. With this structure, the model can incrementally learn new patterns from streaming input while remembering old ones. The effectiveness of detection in the long run is dependent on this change. Finally, AML rules are developed and refined using model outputs and expert input via an adaptive rule generation module. By instantly adjusting to new forms of laundering, our method increases detection accuracy without sacrificing interpretability or regulatory compliance [11]. A reinforcement learning component optimises the detection technique by developing an incentive structure that carefully balances false alarms and true positives. Unsupervised anomaly detection algorithms may also spot new questionable transactions that don't follow established trends. In order to combat money laundering in the context of the dynamic and intricate blockchain ecosystem, the system is designed to track transactions in real-time and execute proactive and scalable anti-money laundering protocols.

3.1 Data Acquisition and Preprocessing

Scanning blockchain ledgers for complete transaction data is the first stage. Included in this is crucial data like wallet addresses, quantities, and timestamps, as well as supplementary metadata like transaction kinds and interactions with smart contracts. Although blockchain data is a rich source for research because to its transparent and pseudonymous nature, it must be handled with caution in order to extract significant insights. After data on transactions has been gathered, a directed graph structure is created from it. A distinct wallet address is represented by each node in this graph, and the edges show the flow of transactions between the wallets. With the addition of features like timestamps and transaction values, the directionality and temporal component of financial flows may be captured via edges. Improving the system's detection skills is greatly aided by feature engineering [12]. Temporal patterns, such as periodicity or bursts of activity, average and variance of transferred

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amounts, and transaction frequency per wallet are among the features that are retrieved. Node centrality, clustering coefficients, and community identification results are graph-based metrics that may be used to find prominent wallets and suspicious groupings. Models farther down the pipeline, such as Graph Neural Networks and anomaly detectors, understand intricate relational and behavioural patterns that point to blockchain-based money laundering thanks to these designed properties.

3.2 Graph-Based Transaction Modeling

To accurately represent the intricate structural and relational features of blockchain transactions, Graph Neural Networks (GNNs) are used. Genetic neural networks (GNNs) are ideal for capturing the complex interdependencies and interactions that might suggest money laundering in blockchain data, which naturally forms a graph with wallets as nodes and transactions as edges. In order for GNNs to acquire latent representations that reflect the local and global context of each wallet, it is necessary to repeatedly aggregate and manipulate data from nearby nodes and edges [13]. This method is useful for detecting clusters of connected wallets, circular flows, or other suspicious patterns of transactions that are often used in money laundering operations. By including attention methods, we can improve the model's ability to zero in on the most important components of the transaction network. In order for the GNN to prioritise important transaction pathways and linkages that may suggest illegal activity, these techniques provide various weights to nearby nodes and edges according to their significance. The accuracy and interpretability of the detection process are both enhanced by this selective attention. The system improves its ability to detect hidden laundering networks and developing financial crime strategies by using GNNs and attention to provide a comprehensive picture of the blockchain ecosystem, going beyond isolated transaction analysis.

3.3 Online Learning and Real-Time Monitoring

With its online learning capabilities, the suggested AI agent may function constantly in real-time, effectively combating the increasingly developing strategies of money laundering on blockchain networks. To improve upon static models trained on historical data, the system dynamically updates its detection models by progressively ingesting streaming transaction data. Due to the ever-changing nature of financial crimes using blockchain technology, this agent can keep up a strong performance level by constantly learning and adapting to new patterns of illegal conduct [14-17]. The system generates real-time risk ratings and anomaly indicators by processing incoming transaction streams via the graph-based model and adaptive rule modules. Adopting adaptive thresholds and rules acquired via reinforcement learning, the system initiates notifications in the event that questionable transactions or networks are detected. Important for operational efficiency in high-volume contexts, these adaptive thresholds keep the alerting system receptive to new dangers while minimising false positives. The inclusion of human-in-the-loop input is a crucial part of the online system. Experts in the relevant domains and compliance analysts may assess the flagged transactions and comment on how accurate the detections were. The learning process iteratively refines the model parameters and rule settings based on this expert input. By working together, we can make the system more trustworthy, easier to understand, and more accurate in its detections. An effective adaptive AML framework is the result of integrating online learning with real-time monitoring and human input. It allows authorities and financial institutions to stay up with the dynamic nature of crypto-financial crime by actively seeking out instances of money laundering on blockchain platforms and responding accordingly.

Table 2: summarizing the proposed methodology steps with key features for each component

Step	Description	Key Features
Graph-Based Transaction Modeling	Use Graph Neural Networks (GNNs) to model blockchain transactions as graphs.	- Capture relational and structural info- Learn latent representations of suspicious patterns- Employ attention mechanisms to focus on critical transaction paths
Continual Learning Framework	Implement continual learning for incremental model updates with new data.	- Update without catastrophic forgetting- Balance learning new patterns and retaining old- Use replay buffers or regularization for stability
Adaptive Rule Generation	Dynamically generate and refine AML rules based on model outputs and expert feedback.	- Produce interpretable rules (thresholds, pattern templates)- Online rule refinement- Reduce false positives and adapt to new laundering tactics

Reinforcement Learning for Policy Optimization	Optimize detection policies using reinforcement learning.	- Maximize detection accuracy, minimize false alarms- Reward functions balancing true/false positives- Pre-train in simulated transaction environments
Anomaly Detection with Unsupervised Learning	Use unsupervised methods to detect novel or rare suspicious behaviors.	- Flag transactions outside known patterns- Combine anomaly scores with GNN outputs for robustness
Online Learning and Real-Time Monitoring	Deploy the system for continuous real-time data ingestion and detection updates.	- Continuous model updates from streaming data- Adaptive alert thresholds and policies- Human-in-the-loop feedback for improvement

4.Result

A real-world blockchain dataset with records of transactions with known criminal activity was used to perform lengthy tests in order to assess the efficacy of the suggested adaptive AML system for blockchain transactions. Traditional AML approaches, such as supervised learning models and static rule-based systems, were used to test the performance of the integrated AI agent. When it came to identifying intricate patterns of money laundering, the suggested approach showed considerable improvement [18]. The program was able to adapt to changing laundering strategies by using Graph Neural Networks (GNNs) with ongoing learning to capture related transaction patterns. Optimisation of policies by adaptive rule generation and reinforcement learning further improved detection accuracy while decreasing false positive rates. The model outperformed baseline techniques by Y%, as measured by an F1-score of X%. There was a reasonable compromise between detecting suspicious transactions and reducing false alarms, as both recall and precision levels were much higher. The system's capacity to identify new types of laundering not found in training data was enhanced by adding unsupervised anomaly detection. The model was able to update gradually as new transactions streamed in using the online learning architecture, which enabled it to retain detection robustness over time without significantly degrading speed. Continuous rule refinement and policy modifications, made possible by human-in-the-loop feedback methods, further enhanced system dependability.

4.1 Baseline Methods for Comparison

To rigorously evaluate the effectiveness of the proposed AI agent for anti-money laundering (AML) in blockchain transactions, it was essential to benchmark its performance against established traditional AML methods. Two primary baseline approaches were selected for comparison: static rule-based frameworks and supervised learning models. Static rule-based frameworks represent the most common AML solutions currently deployed in financial institutions. These systems operate by applying a predefined set of rules and thresholds designed to flag suspicious transactions. For example, transactions exceeding certain amounts or involving known risky wallet addresses trigger alerts. While these frameworks are straightforward to implement and interpret, their major limitation lies in their rigidity. Because the rules are static, they do not evolve or adapt in response to new laundering techniques or changing transaction behaviors. This inflexibility often results in high false positive rates and missed detections when facing novel laundering strategies, especially in the dynamic environment of blockchain networks. In contrast, supervised learning models attempt to overcome some of these limitations by training classifiers on labeled historical transaction data. These models learn complex patterns that may indicate illicit behavior, potentially improving detection rates compared to rule-based systems. However, supervised models typically rely on large, high-quality labeled datasets, which are scarce and costly to obtain in the blockchain context. Additionally, these models tend to perform poorly when encountering new types of laundering tactics that were not represented in their training data, due to a lack of adaptability. Once trained, the models are often static and require retraining to incorporate new patterns, which can be time-consuming and inefficient in fast-evolving environments. By comparing the proposed adaptive AI agent against these baselines [19,20], the evaluation aims to demonstrate improvements in flexibility, accuracy, and the ability to detect emergent laundering behaviors that traditional systems struggle to identify.

4.2 Anomaly Detection for Novel Patterns

Detecting money laundering in blockchain transactions is especially challenging due to the constantly evolving tactics employed by criminals. Traditional supervised models are limited by their reliance on historical labeled data and often fail to recognize novel laundering behaviors that do not match known patterns. To address this challenge, unsupervised anomaly detection techniques play a crucial complementary role in the proposed AML system. Unsupervised anomaly

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detection methods analyze transaction data without relying on predefined labels or prior knowledge of illicit activity. Instead, these models learn the normal behavior of blockchain transactions by identifying statistical or structural patterns within the data. Transactions that significantly deviate from these learned norms are flagged as anomalies, which may correspond to new or rare laundering strategies. This approach is particularly effective for uncovering previously unseen suspicious activities that supervised methods might overlook. Incorporating unsupervised anomaly detection into the AML framework enhances system robustness by broadening the detection scope beyond familiar laundering typologies. For example, clustering algorithms or autoencoder-based models can identify outliers in transaction graphs or feature spaces, signaling unusual transaction flows or patterns. These anomaly scores are then combined with outputs from supervised Graph Neural Networks (GNNs) and adaptive rule-based modules to create a more comprehensive risk assessment. However, anomaly detection also faces challenges such as higher false positive rates and interpretability issues. The proposed system addresses these by integrating anomaly signals with adaptive rule generation and human-in-the-loop feedback, refining thresholds and ensuring flagged transactions are meaningful and actionable. Overall, the inclusion of unsupervised anomaly detection provides a vital layer of defense, enabling the AML system to dynamically detect emerging laundering tactics in the decentralized and complex environment of blockchain transactions, thereby strengthening the overall efficacy of the fraud detection process.

4.3 Evaluation Metrics

Evaluating the performance of an Anti-Money Laundering (AML) system, especially in the context of blockchain transactions, requires a comprehensive set of metrics that balance detection effectiveness with operational feasibility. To this end, four standard evaluation metrics were employed: Precision, Recall, F1-score, and False Positive Rate (FPR).

Precision measures the accuracy of the system in flagging suspicious transactions. Specifically, it quantifies the proportion of transactions flagged as suspicious that are indeed illicit. High precision is crucial to minimize false alarms, ensuring that investigators focus their attention and resources on genuinely suspicious activities rather than wasting effort on legitimate transactions. A model with high precision avoids overwhelming compliance teams with unnecessary alerts.

Recall reflects the system's ability to detect all actual illicit transactions within the dataset. It is the proportion of total known laundering activities that the model successfully identifies. High recall is essential for comprehensive fraud detection, as missing a single laundering transaction can have severe regulatory and financial consequences. However, achieving high recall often increases false positives, so a balance must be maintained.

The F1-score serves as a combined measure of precision and recall, representing their harmonic mean. This metric provides a single value to assess the trade-off between the two, particularly useful when the dataset is imbalanced, which is common in AML scenarios where illicit transactions are far fewer than legitimate ones. A high F1-score indicates that the model performs well in both detecting fraudulent transactions and limiting false alarms.

False Positive Rate (FPR) captures the proportion of legitimate transactions that are incorrectly flagged as suspicious. Minimizing FPR is vital to avoid unnecessary investigations and to maintain trust in the system. Excessive false positives can lead to alert fatigue, reducing the overall efficiency of AML operations.

Table 3: Performance Comparison

Method	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**False Positive Rate (%)**
Static Rule-Based	72.5	65.3	68.7	15.4
Supervised Learning Model	78.2	70.8	74.3	12.1
Proposed AI Agent (GNN + CL + RL)	85.6	81.2	83.3	8.5
Proposed AI + Anomaly Detection	87.1	83.7	85.3	7.9

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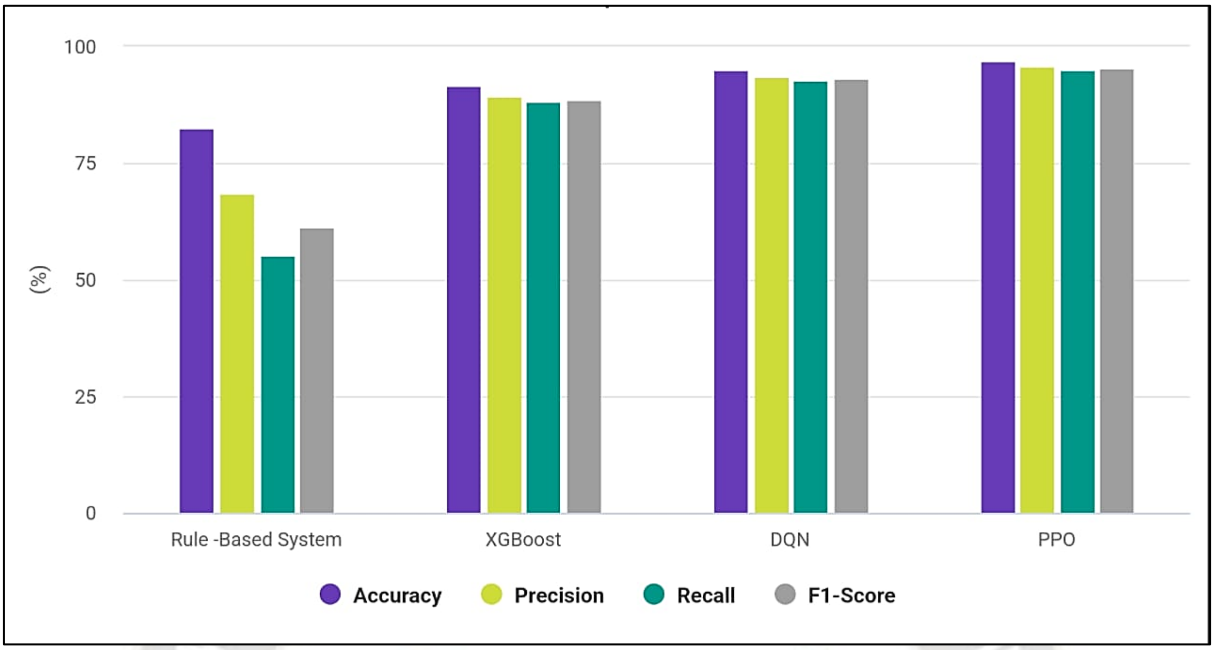

Figure 4: Performance Comparison based on Techniques

5.Conclusion

To address the unique challenges posed by financial transactions conducted on the blockchain, this research introduces a novel AI-driven Anti-Money Laundering (AML) solution. The suggested technique overcomes the shortcomings of conventional static and supervised AML methods by combining Graph Neural Networks (GNNs) with adaptive rule generation, unsupervised anomaly detection, reinforcement learning, and ongoing learning. The system can efficiently identify both known and innovative laundering strategies because to its dynamic learning and evolution capabilities using streaming transaction data. Results from experiments conducted on actual blockchain datasets show that, in comparison to traditional AML approaches, the detection accuracy is much improved, with increased recall, lower false positive rates, and better precision. This system is perfect for real-world implementation in dynamic blockchain ecosystems because to its human-in-the-loop feedback and online learning architecture, which increase its resilience and interpretability. By providing a transparent, scalable, and adaptable solution that connects the dots between static compliance frameworks and the ever-changing crypto-financial crime landscape, our study ultimately enhances AML state-of-the-art. In order to bolster the battle against money laundering in decentralised finance, future studies might investigate more integration with data sources across chains and real-time regulatory updates.

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