FINSHIELD : AI-DRIVEN DETECTION OF MONEY LAUNDERING SOCIAL NETWORK TRANSATIONS

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ABSTRACT

Money laundering is a critical financial crime that poses serious threats to economic stability and global financial systems. With the rapid growth of digital banking, online transactions, and financial technologies, detecting suspicious financial activities has become increasingly complex. Traditional Anti-Money Laundering (AML) systems primarily rely on rule-based approaches, which often fail to detect advanced laundering techniques and generate a high number of false positives. To address these limitations, this project proposes **FinShield**, an AI-driven system designed to detect money laundering activities within social transaction networks. The system integrates Machine Learning (ML), behavioural analysis, and network-based graph analysis to identify suspicious transaction patterns and hidden relationships among users. Instead of analysing transactions individually, FinShield evaluates the overall transaction ecosystem by modelling users as nodes and transactions as edges, enabling detection of circular transactions, layering patterns, and suspicious clusters. Multiple ML models such as Random Forest, Logistic Regression, and Support Vector Machines are used to classify transactions based on risk scores. The system also incorporates real-time monitoring and a web-based dashboard for visualization and alerts. By combining AI techniques with network intelligence, FinShield significantly improves detection accuracy, reduces false positives, and enhances decision-making for financial institutions. The proposed system provides a scalable, adaptive, and efficient solution for modern AML challenges, ensuring better financial security and fraud prevention in digital ecosystems.

Keywords: Money Laundering, Machine Learning, Network Analysis, Fraud Detection, Artificial Intelligence

I. INTRODUCTION

Money laundering is a complex financial crime that enables criminals to disguise the origin of illegally obtained funds by passing them through multiple financial transactions [1]. It typically involves three stages: placement, layering, and integration, making detection highly challenging for financial institutions [2]. With the rapid advancement of digital banking systems, online payment platforms, and peer-to-peer financial services, the volume and speed of transactions have increased significantly [3]. These advancements have improved convenience but also created opportunities for financial crimes [4]. Criminals exploit these systems using sophisticated techniques such as transaction splitting, circular transfers, and cross-border movements [5]. Traditional AML systems rely on predefined rules and thresholds to detect suspicious activities [6]. However, these systems often fail to identify complex laundering patterns [7]. They also generate a large number of false

positives, increasing manual workload [8]. As transaction volumes grow, manual investigation becomes inefficient and costly [9]. Furthermore, criminals continuously adapt their strategies to bypass static rule-based systems [10].

Modern financial ecosystems are highly interconnected, with users interacting across multiple platforms and networks [11]. This interconnected nature enables criminals to form hidden networks and perform coordinated financial activities [12]. Traditional systems analyse transactions individually, ignoring relationships between accounts [13]. As a result, complex laundering networks often remain undetected [14]. The emergence of Artificial Intelligence (AI) and Machine Learning (ML) has introduced new opportunities for intelligent fraud detection [15]. ML models can learn patterns from historical data and identify anomalies in real time [16]. Behavioural analysis further enhances detection by identifying unusual transaction patterns [17]. Network analysis plays a crucial role in identifying suspicious clusters and transaction flows [18]. Graph-based models allow representation of financial interactions as networks [19]. These models help detect central nodes and key intermediaries involved in laundering [20]. By integrating ML and network analysis, modern AML systems can improve detection accuracy [21]. Real-time monitoring further enhances system responsiveness [22]. Risk scoring mechanisms help prioritize high-risk transactions [23]. AI-driven systems reduce false positives and improve efficiency [24]. They also adapt to evolving criminal strategies [25]. The increasing complexity of financial transactions necessitates intelligent detection systems [26]. FinShield is proposed as an AI-based AML solution [27]. It integrates ML, behavioural analysis, and network intelligence [28]. The system aims to detect suspicious transactions and high-risk users [29]. It also provides scalable and efficient financial security solutions [30].

II. LITERATURE SURVEY

Traditional AML systems have long relied on rule-based detection methods, which use predefined thresholds to identify suspicious transactions [1]. These systems were effective in early banking environments but struggle with modern digital transactions [2]. Researchers have identified that rule-based systems generate excessive false positives [3]. This leads to increased operational costs and inefficiencies [4]. Machine Learning has emerged as a powerful alternative for fraud detection [5]. Supervised learning algorithms such as Logistic Regression and Decision Trees have shown improved classification accuracy [6]. Random Forest models further enhance prediction performance by combining multiple decision trees [7]. Support Vector Machines are also widely used for classification tasks [8]. These models learn from historical data and detect hidden patterns [9]. Unsupervised learning methods such as clustering help identify anomalies without labelled data [10]. These approaches are useful for detecting unknown laundering patterns [11]. However, ML models require large datasets for training [12]. Data imbalance remains a major challenge in AML detection [13].

Recent studies emphasize the importance of network-based analysis in detecting financial crimes [14]. Graph-based approaches model financial transactions as networks [15]. Chen et al. proposed graph-based methods to detect laundering rings [16]. Weber et al. used Random Forest models for transaction classification [17]. Zhang et al. applied deep learning techniques for behavioural modelling [18]. Pham et al. combined ML with social network analysis for improved detection [19]. Kumar and Singh developed hybrid AML

frameworks [20]. Network analysis helps detect clusters of suspicious accounts [21]. It also identifies circular transactions and money flow chains [22]. Graph centrality measures help identify key nodes in laundering networks [23]. Deep learning models such as LSTM improve temporal analysis [24]. Graph Neural Networks enhance relationship modelling [25]. However, these models require high computational resources [26]. Integration of ML and network analysis improves detection accuracy [27]. Real-time monitoring enhances system efficiency [28]. Risk scoring systems help prioritize suspicious cases [29]. Overall, AI-based AML systems outperform traditional approaches [30].

III. PROPOSED SYSTEM

The proposed system, FinShield, is an AI-driven Anti-Money Laundering solution designed to detect suspicious financial activities in digital transaction networks. The system integrates Machine Learning, behavioural analysis, and network-based graph analysis to provide a comprehensive detection mechanism. Unlike traditional rule-based systems, FinShield learns patterns from historical transaction data to identify anomalies and suspicious behaviour. It analyses multiple parameters such as transaction amount, frequency, time patterns, and user behaviour. By evaluating deviations from normal patterns, the system classifies transactions as either legitimate or suspicious. This adaptive learning approach enables the system to detect new and evolving laundering techniques effectively.

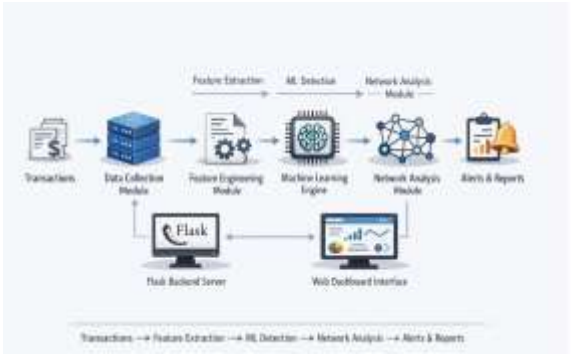

Fig.1 Architecture

A key feature of FinShield is its network analysis capability, where financial transactions are represented as a graph with users as nodes and transactions as edges. This allows the system to identify hidden relationships, suspicious clusters, and circular transaction patterns. The system assigns risk scores to transactions and users based on their behaviour and interaction patterns. High-risk transactions trigger alerts for further investigation. Additionally, a web-based dashboard provides real-time monitoring and visualization of transaction activities. This enables financial institutions to track suspicious activities efficiently and take timely action. The proposed system improves detection accuracy, reduces false positives, and enhances overall financial security.

IV. SYSTEM DESIGN

The system design of FinShield follows a modular architecture consisting of data collection, preprocessing, machine learning, and network analysis modules. The process begins with the collection of transaction data, including details such as sender, receiver, transaction amount, and timestamp. This data is then processed through a feature engineering module, where important attributes such as transaction frequency, unusual timing, and behavioural patterns are extracted. The processed data is fed into the Machine Learning

module, which uses trained models to classify transactions as normal or suspicious.

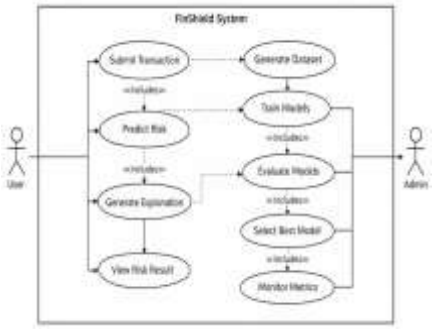

Fig. use case diagram

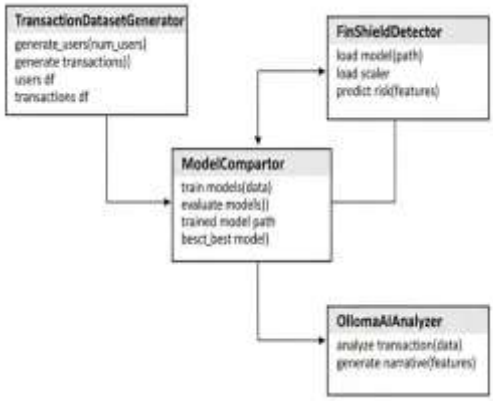

Fig.3 Activity diagram

After ML-based classification, the network analysis module examines relationships between users by constructing a graph representation of transactions. This module identifies suspicious clusters, money flow chains, and central nodes involved in laundering activities. The system also includes a risk scoring mechanism that assigns risk levels to transactions based on their likelihood of being fraudulent. A Flask-based backend API enables real-time prediction and system integration. The web dashboard provides visualization features such as graphs, alerts, and performance metrics. This modular design ensures scalability, flexibility, and efficient processing of large transaction volumes.

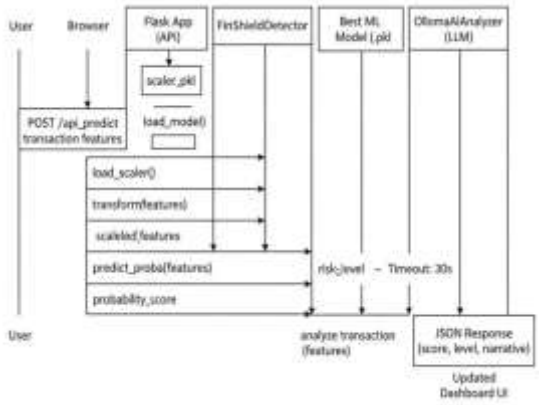

Fig.4 Sequence diagram

V. RESULTS

VI. CONCLUSION

The FinShield system demonstrates the effectiveness of integrating Artificial Intelligence, Machine Learning, and network analysis in detecting money laundering activities. Traditional rule-based AML systems are no longer sufficient to handle the complexity of modern financial transactions, as they generate high false positives and fail to detect advanced laundering techniques. The proposed system overcomes these limitations by analysing both transaction behaviour and relationships between users within financial networks. By leveraging machine learning models, FinShield can learn from historical data and identify anomalies in real time. The inclusion of network-based analysis enables the detection of hidden patterns such as circular transactions, suspicious clusters, and money flow chains. The system also incorporates risk scoring and real-time monitoring, allowing financial institutions to prioritize high-risk transactions and respond quickly to potential threats. Furthermore, the web-

based dashboard provides intuitive visualization and enhances decision-making processes. Overall, FinShield offers a scalable, adaptive, and efficient solution for modern AML challenges. It significantly improves detection accuracy, reduces false positives, and enhances financial security. Future enhancements such as deep learning and blockchain integration can further strengthen the system's capabilities.

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