



## SMART HYBRID SYSTEM FOR MONEY LAUNDERING DETECTION IN MODERN BANKING

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### ABSTRACT

A Hybrid Modelling Approach for Detecting Money Laundering in Banking Sectors presents an intelligent and robust framework designed to identify suspicious financial activities by combining multiple analytical techniques. Money laundering poses a significant threat to financial institutions, enabling illegal funds to be disguised as legitimate transactions. Traditional rule-based systems often fail to detect complex and evolving laundering patterns due to their static nature and high false-positive rates. The proposed hybrid model integrates machine learning algorithms such as decision trees, random forests, and support vector machines with advanced techniques like anomaly detection and network analysis to improve detection accuracy. Additionally, the system incorporates behavioral analysis and transaction pattern mining to identify unusual activities in real time. By combining supervised and unsupervised learning approaches, the model effectively captures both known and unknown fraud patterns. The system is designed to handle large-scale transactional data, ensuring scalability and efficiency in banking environments. Overall, the proposed approach enhances the capability of financial institutions to detect, prevent, and mitigate money laundering activities while reducing operational costs and improving compliance with regulatory standards.

### KEYWORDS:

Money Laundering Detection, Hybrid Model, Machine Learning, Anomaly Detection, Financial Fraud, Banking Systems, Transaction Analysis, Data Mining, Artificial Intelligence, Risk Management



## I. INTRODUCTION

Money laundering is a serious financial crime that involves disguising the origin of illegally obtained funds to make them appear legitimate. It poses a significant threat to the stability and integrity of financial systems, particularly in the banking sector, where large volumes of transactions occur daily. With the rapid growth of digital banking, online transactions, and global financial networks, the complexity and scale of money laundering activities have increased substantially, making detection more challenging for financial institutions.

Traditionally, banks have relied on rule-based systems and manual monitoring to detect suspicious activities. These systems use predefined rules and thresholds to flag unusual transactions. However, such approaches are often rigid, generate a high number of false positives, and struggle to adapt to evolving laundering techniques. Criminals continuously modify their strategies to bypass detection systems, making it necessary to adopt more intelligent and adaptive solutions.

In recent years, **machine learning** and **artificial intelligence (AI)** have emerged as powerful tools for fraud detection in the banking sector. These technologies enable the analysis of large-scale transactional data, identification of hidden patterns, and detection of anomalies that may indicate illicit

activities. Supervised learning models can identify known patterns of money laundering, while unsupervised learning techniques can detect previously unseen or suspicious behaviors.

The proposed **Hybrid Modelling Approach for Detecting Money Laundering in Banking Sectors** combines multiple analytical techniques, including machine learning, anomaly detection, and network analysis, to improve detection accuracy and efficiency. By integrating different models, the system can leverage the strengths of each approach while minimizing their individual limitations. This hybrid framework enhances the ability to detect both known and emerging laundering patterns, reduces false positives, and supports real-time monitoring of financial transactions.

## II. LITERATURE REVIEW

Recent research in money laundering detection has increasingly focused on applying data mining and machine learning techniques to improve the identification of suspicious financial activities. Early studies primarily relied on rule-based systems and statistical methods, where predefined thresholds and expert-defined rules were used to flag abnormal transactions. While these approaches were simple to implement, they lacked adaptability and often resulted in high



false-positive rates, making them less effective in dynamic financial environments [1][2].

With the advancement of machine learning, researchers began using supervised learning algorithms such as decision trees, support vector machines (SVM), and logistic regression to classify transactions as legitimate or suspicious. These models improved detection accuracy by learning patterns from historical data; however, their performance depended heavily on labeled datasets and struggled to detect new or unknown laundering patterns [3].

To address these limitations, unsupervised learning techniques such as clustering and anomaly detection were introduced. Methods like k-means clustering, isolation forests, and autoencoders enabled the detection of unusual transaction behaviors without requiring labeled data. These approaches proved effective in identifying novel fraud patterns but sometimes lacked precision and interpretability [4].

Recent studies have explored hybrid approaches that combine supervised and unsupervised learning methods to enhance detection performance. By integrating classification models with anomaly detection techniques, these systems can identify both known and unknown patterns of money

laundering, reducing false positives and improving overall efficiency [5].

In addition, network-based analysis has gained attention, where financial transactions are modeled as graphs to analyze relationships between accounts. Graph-based techniques help uncover hidden connections and detect complex laundering schemes such as layering and structuring, which are difficult to identify using traditional methods [6].

The emergence of deep learning has further advanced the field, with models such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks being used to capture sequential transaction patterns over time. These models provide improved performance in detecting temporal anomalies and evolving fraud behaviors [7].

Recent research also emphasizes real-time detection systems and the use of big data technologies to handle large-scale financial transactions efficiently. These systems leverage distributed computing and streaming data processing to provide faster and more scalable solutions for anti-money laundering (AML) applications [8].

Despite these advancements, challenges such as data imbalance, lack of labeled datasets, model interpretability, and privacy concerns remain significant. These issues highlight the need for more robust, transparent, and adaptive hybrid models to effectively detect



money laundering in modern banking systems [9].

### III. EXISTING SYSTEM

The existing systems for detecting money laundering in banking sectors are primarily based on **rule-based approaches** and basic statistical techniques. These systems rely on predefined rules and thresholds set by domain experts to identify suspicious transactions. For example, transactions exceeding a certain limit or involving high-risk regions are flagged for further investigation. While these systems are simple and widely implemented, they are rigid and unable to adapt to evolving laundering techniques.

Another commonly used approach is **manual monitoring and auditing**, where compliance officers review flagged transactions. This process is time-consuming, labor-intensive, and prone to human error. As the volume of financial transactions increases, manual analysis becomes inefficient and impractical for real-time detection.

Existing systems also incorporate **traditional machine learning models** such as logistic regression, decision trees, and support vector machines (SVM). These models analyze historical transaction data to classify activities as normal or suspicious. Although they improve detection accuracy compared to rule-based systems, they depend heavily on labeled

data and often fail to detect new or unknown laundering patterns.

A major limitation of current systems is their inability to effectively handle **large-scale and high-dimensional data**. With millions of transactions occurring daily, scalability becomes a critical issue. Additionally, these systems often generate a high number of **false positives**, leading to unnecessary investigations and increased operational costs for financial institutions.

Furthermore, existing approaches lack the ability to capture **complex relationships between entities**, such as connections between multiple accounts involved in layered transactions. They also do not fully utilize advanced techniques like network analysis or real-time anomaly detection, which are essential for identifying sophisticated money laundering schemes.

### IV. PROPOSED SYSTEM

The proposed system introduces a **Hybrid Modelling Approach for Detecting Money Laundering in Banking Sectors**, designed to overcome the limitations of traditional rule-based and single-model systems. This system integrates multiple analytical techniques, including supervised learning, unsupervised learning, and network-based analysis, to provide a comprehensive and intelligent solution for detecting suspicious financial activities.



In this approach, large-scale transactional data is collected from banking systems, including customer details, transaction history, account relationships, and behavioral patterns. The data undergoes preprocessing steps such as cleaning, normalization, and feature engineering to ensure high-quality input for analysis. Relevant features such as transaction frequency, amount patterns, geographic location, and time-based behavior are extracted to improve model performance.

The core of the proposed system is a **hybrid model** that combines multiple machine learning techniques. Supervised learning algorithms such as decision trees, random forests, and support vector machines (SVM) are used to detect known patterns of money laundering based on labeled data. In parallel, unsupervised techniques such as clustering and anomaly detection (e.g., Isolation Forest, Autoencoders) are employed to identify unusual or previously unseen transaction behaviors.

Additionally, the system incorporates **network (graph-based) analysis**, where transactions are represented as interconnected nodes and edges. This allows the system to identify complex relationships between accounts, uncover hidden transaction chains, and detect sophisticated laundering strategies such as layering and structuring.

The outputs from these different models are combined using an ensemble or weighted scoring mechanism to generate a final risk score for each transaction. Transactions with high-risk scores are flagged for further investigation. The system is designed to operate in near real-time, enabling continuous monitoring of financial activities.

## V. METHODOLOGY

The methodology of the proposed **PHARMA: AI-Driven Drug Repurposing Platform** follows a systematic pipeline that integrates data collection, preprocessing, feature extraction, model training, and prediction to identify potential drug repurposing opportunities effectively.

Initially, data is collected from multiple heterogeneous biomedical sources such as gene expression datasets, drug databases, protein-protein interaction (PPI) networks, clinical trial records, and scientific literature. This includes both structured data (drug properties, target proteins, clinical outcomes) and unstructured data (research articles and medical reports). The collected data is then preprocessed to remove inconsistencies, handle missing values, normalize formats, and ensure high-quality input for analysis.

Next, feature extraction is performed to transform raw data into meaningful representations. For structured data, features

such as molecular descriptors, gene expression patterns, and interaction networks are extracted. For unstructured textual data, Natural Language Processing (NLP) techniques such as tokenization, stemming, and embedding methods are used to convert text into machine-readable formats.

Following feature extraction, multiple AI models are applied. Machine learning algorithms such as support vector machines (SVM), random forests, and logistic regression are used for baseline predictions, while deep learning models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and graph neural networks (GNNs) are employed to capture complex biological relationships. Network-based models are used to analyze interactions between drugs, genes, and diseases, enabling link prediction and discovery of hidden associations.

The system adopts a hybrid modeling approach where outputs from different models are combined to improve prediction accuracy and robustness. Ensemble techniques or weighted scoring methods are used to integrate results from various components. The system is trained and validated using known drug-disease associations to ensure reliability.

After training, the model predicts potential new uses for existing drugs by identifying strong associations between drugs and diseases. The results are ranked based on

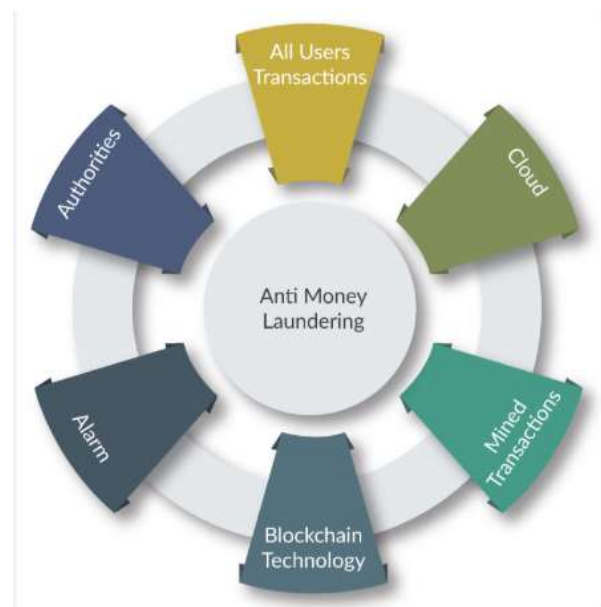
prediction confidence and relevance. Visualization tools are used to present the findings in an understandable format, aiding researchers in decision-making.

Finally, the system is evaluated using performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Continuous learning mechanisms are incorporated to update the model with new biomedical data, ensuring adaptability and improved performance over time. This methodology ensures a scalable, efficient, and intelligent approach to drug repurposing.

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## VI. SYSTEM MODEL

### System Architecture



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## VII. RESULTS AND DISCUSSIONS





integrating multiple techniques such as supervised learning, unsupervised learning, and network-based analysis, the system is capable of identifying both known and unknown patterns of money laundering with higher accuracy.

Unlike traditional rule-based systems, the hybrid approach adapts to evolving laundering strategies and significantly reduces false positives, thereby improving operational efficiency for financial institutions. The use of anomaly detection and graph-based analysis enables the system to uncover complex transaction patterns and hidden relationships between accounts that are often missed by conventional methods.

Furthermore, the system is designed to handle large-scale transactional data and supports near real-time monitoring, making it suitable for modern banking environments. The inclusion of a feedback mechanism ensures continuous learning and improvement, allowing the system to remain effective over time.

Overall, the proposed model enhances the ability of banks to detect, prevent, and mitigate money laundering activities while ensuring compliance with regulatory standards. With further advancements and real-world implementation, this approach has the potential to significantly strengthen

financial security and contribute to a more transparent and trustworthy banking system.

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## IX. FUTURE WORK:

The proposed **Hybrid Modelling Approach for Detecting Money Laundering in Banking Sectors** can be further enhanced through several advancements to improve its effectiveness, scalability, and adaptability in real-world financial environments. Future work can focus on integrating advanced deep learning models such as transformer-based architectures and graph neural networks (GNNs) to better capture complex transaction patterns and relationships between entities. These models can significantly improve the detection of sophisticated and evolving money laundering schemes.

Another important direction is the incorporation of **real-time streaming analytics**, where the system processes live transaction data using technologies such as Apache Kafka and Spark Streaming. This would enable instant detection of suspicious activities and faster response times, reducing financial risks and losses.

The system can also be extended by incorporating **explainable AI (XAI)** techniques to provide transparency in decision-making. This will help compliance officers understand why a transaction is



flagged as suspicious, thereby increasing trust and supporting regulatory compliance.

Future enhancements may include the integration of **cross-institutional data sharing frameworks**, allowing multiple banks and financial institutions to collaborate and share anonymized data. This can improve detection capabilities by identifying broader laundering networks that span across different organizations.

Additionally, incorporating **behavioral biometrics and user profiling** can further strengthen detection accuracy by analyzing user-specific patterns such as transaction habits, login behavior, and device usage. This adds another layer of security in identifying fraudulent activities.

Scalability can be improved by deploying the system on **cloud-based and distributed computing platforms**, enabling efficient handling of massive volumes of transaction data. At the same time, strong emphasis should be placed on **data privacy and security**, implementing techniques such as encryption, anonymization, and federated learning to protect sensitive financial information.

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