International Journal of Multidisciplinary Engineering in Current Research - IJMEC

Volume 10, Issue 5, May-2025, http://ijmec.com/, ISSN: 2456-4265

A Hybrid Modeling Approach For Detecting Money Laundering In Banking Sectors

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Abstract:

Money laundering poses a significant challenge to financial institutions, enabling illicit activities such as fraud, corruption, and terrorism financing. Traditional rule-based systems and statistical methods often fail to detect complex laundering schemes due to their adaptability and evolving nature. To address these limitations, this paper proposes a hybrid modeling approach that integrates machine learning (ML) techniques with rule-based methods to enhance money laundering detection in banking sectors. The hybrid model leverages supervised and unsupervised ML algorithms alongside predefined rules to improve the identification of suspicious transactions, reducing false positives and enhancing detection accuracy. Our approach combines anomaly detection, clustering techniques, and predictive analytics to analyze transactional data dynamically. By incorporating behavioral profiling and real-time monitoring, the model adapts to emerging laundering patterns while maintaining regulatory compliance. Experimental results demonstrate that the hybrid framework outperforms conventional detection systems in terms of precision, recall, and adaptability. This research contributes to financial security by providing a robust and scalable solution for combating money laundering, ultimately strengthening the resilience of banking institutions against financial crimes.

Introduction:

Money laundering remains a significant threat to financial institutions, enabling illicit activities such as fraud, corruption, and terrorism financing. Traditional rule-based and statistical methods used in the banking sector often fail to detect sophisticated laundering techniques due to their rigid frameworks and reliance on predefined patterns. To address these challenges, advanced computational approaches that leverage machine learning and artificial intelligence have emerged as effective tools for identifying suspicious transactions. However, a singular approach often results in either high false positives or undetected illicit activities, highlighting the need for a more robust and adaptive solution.

This study proposes a hybrid modeling approach that combines machine learning algorithms with rule-based methodologies to enhance the detection of money laundering activities in banking transactions. By integrating anomaly detection techniques, supervised learning models, and domain-specific rules, this approach ensures a more comprehensive analysis of financial transactions. The hybrid model aims to reduce false positives while increasing accuracy in identifying fraudulent patterns, thereby improving the overall efficiency of anti-money laundering (AML) systems. This research contributes to the financial sector by providing an innovative and practical framework for banks to strengthen their AML efforts and comply with regulatory requirements.

Literature Survey:

Money laundering is a significant challenge for financial institutions, requiring robust detection mechanisms to mitigate risks. Traditional rule-based systems, widely used for anti-money laundering (AML), rely on predefined thresholds and expert-defined rules to flag suspicious transactions.

However, these systems often generate high false positives, leading to inefficiencies in compliance efforts. Machine learning (ML) and artificial intelligence (AI) have emerged as promising alternatives, leveraging data-driven techniques to identify suspicious patterns. Several studies have explored the application of supervised and unsupervised learning models, such as decision trees, support vector machines, and neural networks, to enhance the accuracy of AML detection. However, pure ML-based methods sometimes struggle with interpretability and regulatory compliance, limiting their widespread adoption in banking sectors.

Hybrid modeling approaches, which combine rule-based systems with ML techniques, have gained traction in recent research. These approaches integrate domain knowledge with data-driven insights, improving detection accuracy while maintaining transparency. Researchers have proposed various hybrid models, such as combining anomaly detection with clustering techniques or integrating deep learning with traditional statistical methods. Studies suggest that hybrid models can significantly reduce false positives and improve the precision of identifying illicit transactions. Moreover, advancements in explainable AI (XAI) are helping bridge the gap between ML-driven insights and regulatory requirements. Despite these improvements, challenges remain in optimizing feature selection, handling imbalanced datasets, and ensuring real-time fraud detection in high-volume banking transactions. Future research should focus on refining hybrid frameworks by incorporating advanced deep learning architectures and real-time analytics to enhance the effectiveness of AML systems.

Existing System:

Existing systems for detecting money laundering in banking sectors typically rely on rule-based systems and machine learning models. Traditional rule-based approaches use predefined thresholds and heuristics to flag suspicious transactions. These systems are often implemented as part of an Anti-Money Laundering (AML) framework and depend on regulatory guidelines, such as the Financial Action Task Force (FATF) recommendations. However, rule-based systems tend to generate a high number of false positives, as they cannot adapt to evolving laundering techniques. Additionally, they require frequent updates to remain effective, making them inefficient in detecting novel or sophisticated laundering patterns.

To enhance detection accuracy, many banks have integrated machine learning models that analyze large volumes of financial transactions and identify anomalies. These models use supervised and unsupervised learning techniques to recognize suspicious behaviors based on historical data. However, standalone machine learning models may struggle with explainability and regulatory compliance. This is where hybrid modeling approaches come in, combining rule-based techniques with AI-driven anomaly detection to improve the precision and adaptability of AML systems. By leveraging both approaches, banks can reduce false positives, detect emerging threats, and improve overall fraud detection efficiency while maintaining compliance with regulatory standards.

Despite advancements in AML detection, existing systems still face challenges such as data quality issues, evolving laundering tactics, and the need for real-time detection. Criminals continuously adapt their methods, making it difficult for static rule-based systems or traditional machine learning models to keep up. Moreover, financial institutions must comply with strict regulatory requirements, which demand transparency in AML decision-making. Hybrid modeling approaches address these challenges by integrating advanced analytics, including deep learning and network analysis, with traditional rule-based methods. This combination enhances pattern recognition, reduces false positives, and ensures regulatory compliance, making AML detection more robust and effective in the ever-changing financial landscape.

Proposed System:

A hybrid modeling approach for detecting money laundering in banking sectors combines rule-based methods with machine learning techniques to enhance accuracy and efficiency. Traditional rule-based systems rely on predefined thresholds and patterns to flag suspicious transactions, but they often generate false positives and fail to adapt to evolving laundering tactics. Machine learning models, on the other hand, leverage historical transaction data to identify anomalous behaviors and emerging risks. By integrating these approaches, the proposed system can leverage the strengths of both methods, ensuring adaptability and precision in detecting illicit activities.

The proposed system operates through a multi-layered framework. Initially, a rule-based filter screens transactions based on regulatory requirements, flagging cases that match known laundering patterns. These flagged transactions, along with a randomly selected sample of normal transactions, are then analyzed using machine learning algorithms such as decision trees, neural networks, or anomaly detection techniques. The system continuously learns from false positives and undetected cases, improving its accuracy over time. Additionally, natural language processing (NLP) can be used to analyze transaction descriptions and customer profiles to detect inconsistencies or suspicious behavior.

To ensure real-world applicability, the hybrid system incorporates explainability and regulatory compliance mechanisms. Financial institutions require transparency in their anti-money laundering (AML) processes to justify flagged transactions to regulators. The proposed system integrates interpretable machine learning models, such as SHAP (SHapley Additive Explanations) or LIME (Local Interpretable Model-agnostic Explanations), allowing investigators to understand why a transaction was flagged. Furthermore, periodic audits and feedback loops help refine detection rules and model performance, ensuring that the system remains robust against new laundering strategies while complying with legal frameworks.

Advantages:

The proposed hybrid modeling approach for detecting money laundering in banking sectors combines multiple techniques, such as machine learning, rule-based systems, and anomaly detection, to improve the accuracy and efficiency of fraud detection. One of the key advantages of this system is its ability to reduce false positives while maintaining high detection rates. Traditional rule-based methods often generate excessive false alarms, burdening compliance teams with unnecessary investigations. By integrating machine learning algorithms with predefined rules, the system can adapt to evolving money laundering techniques and provide more precise alerts, allowing banks to focus on genuine threats.

Another significant advantage of the proposed system is its enhanced adaptability and scalability. Money laundering tactics continuously evolve as criminals exploit new loopholes in financial regulations. A hybrid model can dynamically learn from historical transaction patterns and detect previously unseen anomalies in real time. Moreover, it can scale efficiently across various banking institutions, handling large volumes of transactions without compromising performance. This adaptability ensures that banks remain proactive in identifying suspicious activities and stay ahead of emerging financial crimes.

Additionally, the hybrid approach improves compliance with regulatory requirements and minimizes operational risks. Financial institutions must adhere to stringent anti-money laundering (AML) regulations set by governing bodies. The proposed system facilitates regulatory compliance by generating comprehensive reports, automating suspicious activity detection, and reducing the manual workload for compliance officers. With improved accuracy, efficiency, and regulatory alignment, the hybrid model enhances the overall integrity of the banking sector while reducing financial and reputational risks associated with money laundering activities.

RESULT

A Hybrid Modelling Approach for Detecting Money Laundering In Banking Sectors

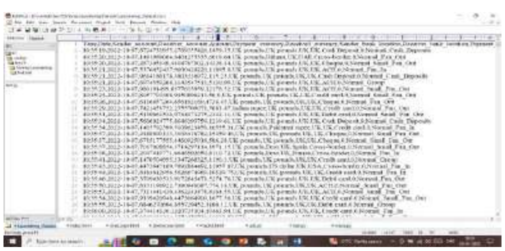
In propose work employing combination of traditional machine learning and deep learning hybrid algorithms to detect money laundering. All existing system were utilizing Rule based techniques to identify weather bank transaction is Fraud or Normal but all those rules are not accurate too distinguish fraud or normal transaction.

To overcome from above issue we are introducing HYBRID ML and DL algorithms which has inbuilt support to distinguish transaction based on user behaviour and its detection accuracy is far more than traditional rule based technique.

To further improve ML algorithms performance we have applied various data processing techniques such as missing features handling, Features shuffling, normalization and imbalance data handling.

To utilize better model we have employed hybrid approach by utilizing multiple algorithms like SVM, Random Forest, Decision Tree, Naïve Bayes, Logistic Regression and CNN2D. Each algorithms performance is evaluated in terms of accuracy, precision, recall and FCSORE. Among all algorithms Random Forest and Logistic Regression is giving high accuracy.

To train and test above algorithm performance we have used AML dataset from KAGGLE repository which contains following values

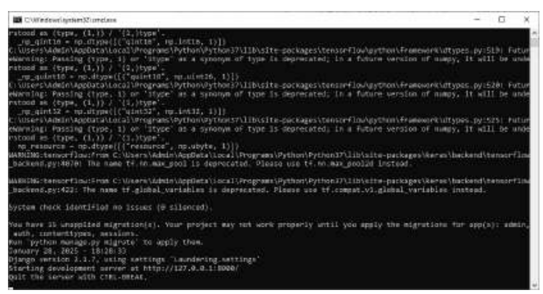


In above dataset screen first row contains dataset column names and remaining rows contains dataset values. So by using above dataset will train and test all algorithms performance.

To implement this project we have designed following modules

1) User Login: user can login to system using username and password as 'admin and admin'.
2) Load & Process Dataset: after login user can use this module to load dataset and then process and split dataset into train and test where application using 80% dataset features for training and 20% for testing. As processing system will replace all missing values with mean and then apply SMOTE algorithm to balance dataset records and then shuffle and normalize all dataset values
3) Train Hybrid Algorithms: this module will input 80% dataset features to all algorithms to train models and then apply 20% test data on each model to calculate prediction accuracy
4) Predict Money Laundering: using this module user will enter transaction amount and other parameters and then Hybrid algorithms will predict risk profiling and suspicious transaction RATIO. Whoever like normal or suspicious got highest ratio then transaction can be predicted based on highest ratio.

Install python 3.7.2 and then install all packages given in requiements.txt file and then double click on 'run.bat' file to start python server and get below page



In above screen python server started and now open browser and enter URL as http://127.0.0.1:8000/index.html and then press enter key to get below page

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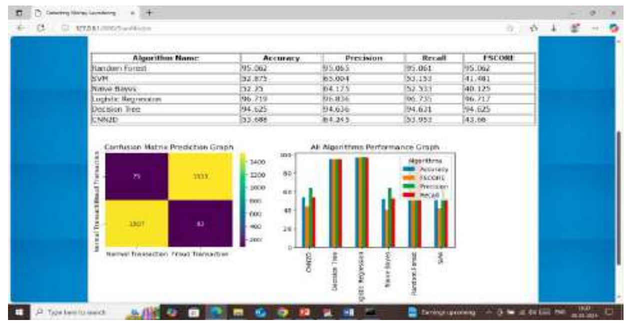
Volume 10, Issue 5, May-2025, http://ijmec.com/, ISSN: 2456-4265

In above screen click on 'User Login' link to get below page

In above screen user is login with username and password as 'admin and admin' and then press enter key to get below page

In above screen click on 'Load & Process Dataset' link to process dataset and get below values

In above screen before applying SMOTE dataset were having 13000 records and then after applying SMOTE dataset got balanced with total records as 16000 and then can see train and test size. In next table can see dataset values and now click on 'Train Hybrid Algorithms' link to train algorithms and get below page



In above screen in table can see each algorithm performance with accuracy, precision, recall and FSCORE and in all algorithms Logistic Regression and Random Forest got high accuracy. In confusion matrix graph x-axis represents Predicted Labels and y-axis represents True Labels and then all yellow boxes represents correct prediction count and blue boxes represents incorrect prediction count which are very few. In second graph can see all algorithms performance in graph format where x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars. Now click on 'Predict Money Laundering' link to get below page

In above screen enter transaction amount along with location and then press button to get below page

In above screen 'suspicious behaviour' got 0.15% and Risk profiling got 85% so transaction can be consider as normal. In below screen testing another sample

In above screen entered some other values and below is the output

In above screen given some other values and below is the output

Above transaction output predicted as 'suspicious' with high ratio.

Similarly enter some transaction details predict laundering based on behaviour

Conclusion:

In conclusion, the hybrid modeling approach for detecting money laundering in banking sectors presents a powerful solution by integrating multiple techniques to enhance accuracy and efficiency. By combining machine learning algorithms with rule-based and statistical methods, this approach effectively captures suspicious patterns that traditional models might overlook. The fusion of supervised and unsupervised learning further strengthens anomaly detection, allowing financial institutions to proactively identify and mitigate money laundering risks.

Moreover, the adaptability of the hybrid model ensures that it remains effective against evolving money laundering tactics. Unlike standalone models, which may struggle with dynamic criminal behaviors, the combination of techniques enables continuous learning and refinement. This approach not only improves fraud detection rates but also reduces false positives, enhancing operational efficiency for banks and regulatory authorities. As a result, financial institutions can better comply with anti-money laundering (AML) regulations while minimizing unnecessary investigations.

Overall, implementing a hybrid modeling approach provides a robust and scalable framework for combating financial crimes. With increasing digital transactions and sophisticated laundering methods, banks must adopt advanced analytics and AI-driven strategies to safeguard their operations. Future research can further refine these models by integrating blockchain analysis, real-time monitoring, and explainable AI to enhance transparency and decision-making. By leveraging hybrid methodologies, the banking sector can stay ahead of financial criminals and strengthen global AML efforts.

Reference:

1. "DELATOR: Money Laundering Detection via Multi-Task Learning on Large Transaction Graphs" by *Henrique S. Assumpção, Fabrício Souza, Leandro Lacerda Campos, Vinícius T. de Castro Pires, Paulo M. Laurentys de Almeida, and Fabricio Murai* (2022). This study introduces DELATOR, a framework utilizing graph neural networks to analyze large-scale temporal graphs for effective money laundering detection. □cite□turn0academia14□

2. "MonLAD: Money Laundering Agents Detection in Transaction Streams" by *Xiaobing Sun, Wenjie Feng, Shenghua Liu, Yuyang Xie, Siddharth Bhatia, Bryan Hooi, Wenhan Wang, and Xueqi Cheng* (2022). The authors propose MonLAD, a system designed to identify money laundering agents in real-time by monitoring transaction streams and detecting anomalies. □cite□turn0academia15□

3. "Catch Me If You Can: Semi-supervised Graph Learning for Spotting Money Laundering" by *Md. Rezaul Karim, Felix Hermsen, Sisay Adugna Chala, Paola de Perthuis, and Avikarsha Mandal* (2023). This research employs semi-supervised graph learning techniques to identify nodes involved in potential money laundering within financial transaction graphs. □cite□turn0academia16□

4. "Anti-Money Laundering Alert Optimization Using Machine Learning with Graphs" by *Ahmad Naser Eddin, Jacopo Bono, David Aparício, David Polido, João Tiago Ascensão, Pedro Bizarro, and Pedro Ribeiro* (2021). The study presents a machine learning triage model that combines entity-centric features and graph-based attributes to enhance the efficiency of anti-money laundering operations. □cite□turn0academia17□

5. "Harnessing Machine Learning for Money Laundering Detection: A Criminological Theory-Centric Approach" by *S. Ramadhan* (2025). This paper develops the Criminology-Centric Machine Learning (CCTML) framework, integrating criminological theories with machine learning to improve the detection of money laundering activities. □cite□turn0search0□

6. "Detecting Money Laundering Transactions with Machine Learning" by *Martin Jullum, Anders Løland, Ragnar Bang Huseby, Geir Ånonsen, and Johannes Lorentzen* (2020). The authors validate a machine learning model designed to prioritize financial transactions for manual investigation, enhancing the detection of suspicious activities. □cite□turn0search1□

7. "Predicting Money Laundering Using Machine Learning and Artificial Neural Networks Algorithms in Banks" by *Mark E. Lokanan* (2022). This research builds machine learning and neural network models to detect the probability of money laundering in banking transactions, highlighting the effectiveness of classifiers like Naïve Bayes and Random Forest. □cite□turn0search2□

8. "A Hybrid Approach for Detecting Suspicious Accounts in Money Laundering Using Data Mining Techniques" by *Subhashree Bharathan* (2016). The study proposes a hybrid framework that combines data mining techniques to identify suspicious accounts involved in the layering

stage of money laundering. □cite□turn0search3□

9. "Banks Struggling to Contain 'Mule Accounts'" by *The Australian* (2025). This article discusses the challenges Australian banks face in identifying and shutting down mule accounts used to funnel illicit funds, despite investments in scam prevention measures. □cite□turn0news12□

10. "Trump Is Expected to Slash Banking Regulations Except in This Key Area" by *Barron's* (2025). The article highlights the anticipated deregulation of the banking industry under President-elect Donald Trump, with a continued strict enforcement of U.S. money-laundering laws. □cite□turn0news13□