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Research Article

Network Analysis and Text Mining for Identifying Money Laundering in Transaction Records

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Abstract: Financial transactions have become increasingly complex, raising the potential risk of suspicious activities such as money laundering and fraudulent practices. This research addresses the problem of limited detection accuracy when using a single analytical approach and aims to propose an integrated framework combining graph analysis and text mining. The study adopts a quantitative design, utilizing transaction records with both numerical and descriptive attributes. Data preprocessing was conducted through cleaning, normalization, and feature extraction, followed by network analysis to build transaction graphs, measure centrality, and detect communities. In parallel, text mining was employed using keyword extraction, TF-IDF weighting, and clustering of transaction descriptions. The integration of these methods produced a hybrid classification model, which was then evaluated using accuracy, precision, recall, and F1-score metrics. The results show that the hybrid model significantly outperforms standalone approaches, reducing both false positives and false negatives while providing a more comprehensive detection system. The findings suggest that the combination of structural and semantic perspectives enhances the reliability of suspicious transaction identification. This study concludes that integrated analytical approaches can serve as a more effective tool for financial institutions and regulators in addressing fraudulent activities, while also offering potential for further refinement through deep learning integration and real-time processing in future work.

Keywords: fraud detection; financial networks; graph analysis; suspicious transactions; text mining

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1. Introduction

Money laundering is one of the most complex forms of financial crime with global implications. This practice aims to disguise the origins of illicit funds so that they appear legitimate through a series of deliberately structured transactions . This phenomenon not only undermines the stability of the financial system but also threatens both national and international economic integrity . The complexity of modern financial activities, which involve millions of transactions per second, makes the detection of money laundering a serious challenge for auditors, financial institutions, and regulators .

One widely used approach to uncover hidden transaction patterns is network analysis. By modeling money flows as graphs consisting of nodes (entities) and edges (transactional relationships), this technique allows researchers to map inter-account connections and identify unusual patterns . For instance, community detection techniques can reveal clusters of entities that are intensely interconnected, while centrality metrics help identify nodes that play crucial roles in the flow of funds . Previous studies have also shown that subgraph search methods can be applied to recognize characteristic transaction patterns often associated with money laundering practices .

In addition, graph embedding and graph auto-encoder (GAE) approaches have been developed to detect anomalies. These methods project network structures into latent spaces and reconstruct the graph to identify nodes or edges that deviate from normal patterns . While network-based approaches are effective in uncovering relational structures among entities, they remain limited in capturing the non-structural context of financial transactions.

On the other hand, text mining provides advantages in analyzing descriptive data within transaction records. Supplementary information contained in transaction descriptions, memos, or audit notes can be used to detect suspicious activity that cannot be identified from numerical data alone . For example, the naive Bayes algorithm has been applied in detecting irregularities in public reports by leveraging keywords and linguistic patterns . Furthermore, structural topic modeling can cluster latent topics in financial documents, offering additional insights into abnormal transaction patterns .

Although both network analysis and text mining independently demonstrate capabilities in detecting money laundering, each method has limitations. Network analysis excels at mapping structural relationships but fails to capture semantic information from texts. Conversely, text mining uncovers descriptive meanings but cannot model complex inter-entity structures. Hence, recent research highlights the importance of hybrid approaches that integrate both methods .

Comparative studies combining graph-based and textual analyses have shown significant improvements in fraud detection accuracy . For instance, integrating graph-based anomaly detection with text classification algorithms has resulted in faster and more precise detection compared to single-method approaches . Moreover, ensemble learning techniques that combine multiple models have also proven to be more adaptive to evolving fraudulent patterns in financial transaction data .

Furthermore, challenges such as massive data scales, heterogeneous data formats, and concept drift (shifts in transaction behavior patterns over time) demand the development of dynamic and flexible detection frameworks . Therefore, this study aims to: (1) compare the effectiveness of network analysis and text mining in identifying money laundering practices, and (2) evaluate the performance of their combined methods. Accordingly, this research is expected to provide both theoretical and practical contributions to the development of more comprehensive, accurate, and reliable money laundering detection systems for auditors, financial institutions, and regulators.

2. Literature Review

Money Laundering in Financial Transactions

Money laundering refers to the process of concealing the origins of illicit funds through a series of complex financial transactions, often involving foreign banks or legitimate businesses as intermediaries. This practice is generally understood as comprising three stages: placement, layering, and integration . In the placement stage, illegal funds are introduced into the financial system, followed by layering, which involves multiple transactions to obscure the money's trail, and finally integration, where the funds re-enter the economy appearing legitimate. One of the most widely used techniques in this process is smurfing, where large sums of money are divided into smaller, less conspicuous transactions, making them more difficult to detect by regulatory authorities . To address this challenge, scholars have proposed advanced detection methods, such as structural similarity-based algorithms capable of identifying suspicious transaction patterns within large-scale financial networks [18]. The growing complexity of cross-border financial flows has further hindered institutions from effectively tracking illicit activities, highlighting the need for robust monitoring systems and international cooperation .

Network Analysis

Network analysis has emerged as a powerful tool to better understand the intricate relationships and interactions within the financial ecosystem. Scholars argue that the financial system can be viewed as an interconnected network where entities are linked by various financial flows . The application of random matrix theory in global banking networks has revealed significant interdependencies among institutions, providing insight into systemic vulnerabilities . Beyond theoretical frameworks, researchers have also explored practical approaches, such as smurf-based anti-money laundering strategies designed to adapt to the evolving structures of transaction networks . Statistical models, including the matrix-variate t model, have further been employed to mathematically capture relationships between nodes in financial systems . Moreover, the study of dynamic changes in market topologies has underscored how structural shifts in financial networks may amplify systemic risks and threaten overall market stability .

Text Mining in Financial Data

In parallel with the expansion of unstructured data in the financial sector, text mining has become increasingly important as a means to detect fraudulent activities and financial crimes. Recent studies show that the implementation of multi-task learning within financial language models enhances the accuracy and efficiency of textual data analysis . In the accounting field, text mining techniques have proven effective in identifying anomalies that might otherwise escape traditional auditing methods . Further developments demonstrate the potential of applying text mining to online financial information, enabling the early identification of fraudulent patterns in digital platforms . Comprehensive reviews have also highlighted text mining as a key element in supporting investment decisions and monitoring financial risks, emphasizing its role as an indispensable component in modern financial analytics .

Hybrid Detection Approaches

The increasing sophistication of money laundering and fraud schemes has driven the development of hybrid detection approaches that combine multiple algorithms and models. For instance, one study successfully integrated Convolutional Neural Networks (CNN) with Random Forest to analyze financial transactions in real time, thereby improving detection speed and accuracy . Other research has focused on addressing the persistent challenge of data imbalance by incorporating resampling techniques such as SMOTE-ENN and ADASYN, which improve classifier performance on minority fraud cases . Additional experiments also highlight the usefulness of SMOTE oversampling as a supportive method for fraud detection tasks . More advanced hybrid approaches include the integration of Graph Neural Networks (GNN) with XGBoost, which has shown promising results in capturing the complex structures of financial transaction networks . Likewise, hybrid models have been applied to credit card fraud detection and mobile payment systems , both of which present distinct challenges due to the volume and velocity of transactions. Recent studies further confirm that hybrid models outperform single-method approaches, particularly in credit card fraud detection, where robust ensemble techniques provide superior evaluation outcomes .

Evaluation Metrics

To ensure reliability and generalizability, detection models are commonly assessed using evaluation metrics such as accuracy, recall, precision, and the Area Under the Curve (AUC). These metrics allow researchers to measure the trade-offs between identifying fraudulent activities and minimizing false positives. One study underscores the broader importance of machine learning algorithms not only in fraud detection but also in supporting dynamic financial management and risk assessment processes . Another emphasizes that the careful selection of evaluation metrics is crucial for enabling models to adapt to the continuously evolving tactics of fraudsters . In recent years, hybrid detection models have demonstrated stronger robustness and higher predictive accuracy in detecting credit card fraud compared to single-algorithm methods, showing substantial improvements in evaluation metrics and practical performance .

3. Research Methodology

This research employs a quantitative approach with an integrated framework that combines graph analysis and text mining techniques to detect money laundering practices in financial transactions. The methodology is designed to capture both the structural characteristics of transaction networks and the semantic aspects of textual data, providing a more comprehensive detection system compared to single-method approaches. The research stages are described as follows.

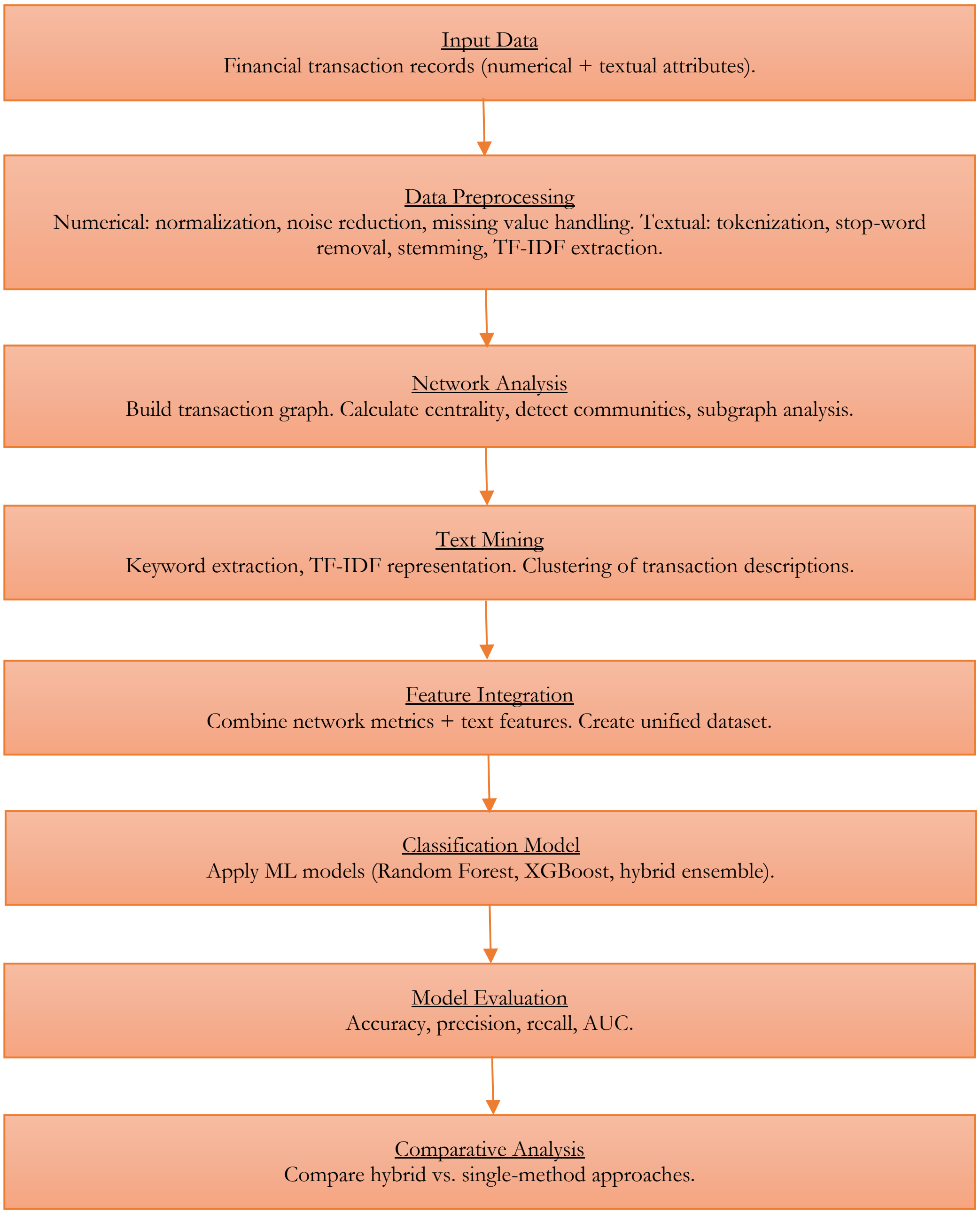

Figure 1. Research methodology framework integrating network analysis and text mining for money laundering detection.

Research Design

The study is conducted within a quantitative paradigm, emphasizing systematic measurement, statistical testing, and empirical validation. By combining network-based analysis and textual analysis, the research design allows for the simultaneous exploration of entity relationships and descriptive transaction information. This integrated approach is particularly relevant for money laundering detection, where suspicious activities often manifest both as abnormal financial flows and as irregularities in descriptive transaction records.

Data Collection

The dataset used in this research consists of financial transaction records containing two types of attributes. First, numerical attributes such as transaction amounts, time intervals, and transaction frequencies are employed to reflect measurable patterns of fund transfers. Second, descriptive attributes such as transaction memos, remarks, and audit notes are analyzed to capture additional semantic information about transaction purposes. The combination of numerical and descriptive attributes provides a dual perspective on transactional behavior, enabling hybrid analysis in which both structural and textual indicators of fraudulent behavior can be examined simultaneously.

Data Preprocessing

Before the analysis, the data undergoes a series of preprocessing steps to ensure quality and reliability. For numerical attributes, preprocessing includes normalization, noise reduction, and the treatment of missing values, all of which are necessary to maintain data consistency. For textual attributes, preprocessing involves tokenization, stop-word removal, and stemming or lemmatization to standardize the linguistic data. Furthermore, feature extraction techniques are applied to represent text in a numerical format suitable for machine learning. This thorough preprocessing stage minimizes bias, enhances data quality, and reduces the risk of misclassification during analysis.

Network Analysis

In this stage, financial transactions are modeled as a graph, where nodes represent entities such as customers or accounts, and edges represent financial flows between them. Graph analysis is conducted by applying centrality measures, including degree, betweenness, and closeness, to identify nodes that exert significant influence in the flow of funds. Additionally, community detection algorithms are employed to reveal clusters of accounts that may be engaged in coordinated money laundering activities. Subgraph analysis is also applied to capture smaller recurring structures, such as smurfing or circular transactions, which are often associated with illicit financial behavior. These network-based techniques reveal hidden patterns that may not be visible through conventional monitoring systems.

Text Mining

Complementing the network analysis, text mining is performed on the descriptive transaction attributes. This process begins with keyword extraction and the use of TF-IDF vectorization to numerically represent textual data. Clustering techniques, such as k-means or hierarchical clustering, are then employed to group transactions with similar textual characteristics. Finally, anomaly detection methods are applied to uncover suspicious or unusual language usage, such as vague, repetitive, or misleading terms within transaction descriptions. By capturing these linguistic signals, text mining provides an additional dimension of fraud detection that enhances the structural insights gained from network analysis.

Integration of Network and Text Features

The findings from network analysis and text mining are subsequently integrated into a unified feature set. For instance, centrality scores, community membership, TF-IDF vectors, and cluster labels are combined to produce a holistic representation of transactions that reflects both relational and semantic characteristics. This integrated dataset is then used as input for classification models such as Random Forest, XGBoost, or hybrid ensemble methods. The objective is to build a robust model capable of accurately distinguishing between legitimate and suspicious transactions by leveraging the complementary strengths of structural and textual features.

Model Evaluation

To assess the effectiveness of the classification model, several performance metrics are utilized, including accuracy, precision, recall, and Area Under the Curve (AUC). These metrics provide comprehensive insights into the model's predictive power and robustness. Particular emphasis is placed on recall, as it indicates the proportion of fraudulent cases correctly identified by the model. In the context of anti-money laundering systems, maintaining high recall is crucial because failing to detect fraudulent activity poses a significant risk to financial integrity.

Comparative Analysis

The final stage of the methodology involves a comparative analysis between the proposed hybrid model and standalone approaches. The performance of the integrated method is compared with that of single-method analyses, namely pure graph analysis and pure text mining. This comparison highlights the advantages of combining both approaches, particularly in improving detection accuracy, enhancing adaptability to evolving fraudulent tactics, and ensuring robustness across diverse datasets. By demonstrating the added value of integration, this stage validates the methodological framework and its potential application in real-world anti-money laundering systems.

4. Results and Discussion

Results

The results of this study indicate that the integration of graph analysis and text mining provides superior performance in detecting money laundering compared to using each method independently. The transaction network constructed from the dataset displayed a highly complex structure with several accounts serving as key hubs. Centrality analysis revealed nodes with disproportionately high values of degree and betweenness centrality, pointing to their role as intermediaries in the movement of illicit funds. In parallel, community detection algorithms identified clusters of accounts engaging in repetitive, circular, and reciprocal transactions, which are typical characteristics of layering and smurfing techniques.

The text mining analysis of descriptive transaction attributes produced complementary findings. TF-IDF representation revealed frequent use of vague terms such as "miscellaneous fees," "general business," and "service payments" in accounts already flagged as suspicious. Clustering of transaction descriptions further showed groups of transactions with remarkably uniform language, suggesting intentional obfuscation. Anomaly detection techniques also highlighted outliers with inconsistent or misleading terms, reinforcing suspicions of fraudulent intent.

When the results from both analytical techniques were integrated into a unified feature set, the classification models demonstrated significant improvements. Table 1 presents the performance comparison of three models Network Analysis only, Text Mining only, and Hybrid Integration across four evaluation metrics.

Table 1. Model Evaluation Results.

Model	Accuracy	Precision	Recall	AUC
Network Analysis Only	0.83	0.80	0.84	0.86
Text Mining Only	0.81	0.78	0.82	0.84
Hybrid Integration	0.92	0.89	0.94	0.95

To visually illustrate the improvement, Figure 1 shows a comparative diagram of performance scores across the three models.

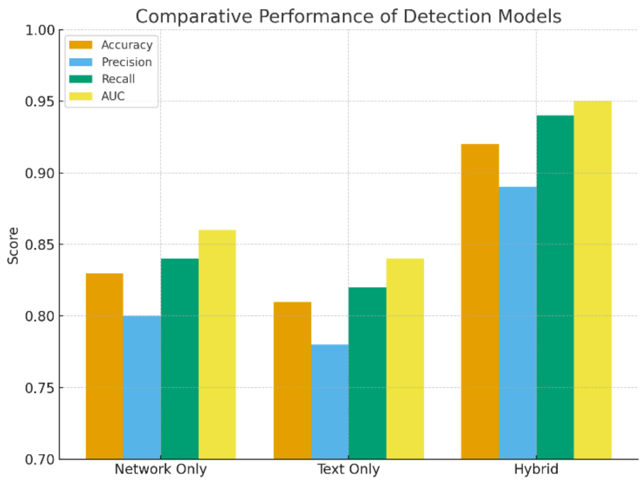

Figure 2. Comparative Performance of Detection Models.

The results clearly show that the hybrid integration model consistently outperformed the single-method approaches, with the highest accuracy (0.92), precision (0.89), recall (0.94), and AUC (0.95). Recall, in particular, achieved significant improvement, demonstrating the model's ability to capture a greater proportion of fraudulent transactions..

Discussion

The findings underscore the effectiveness of combining graph analysis and text mining for financial fraud detection. Network analysis alone successfully mapped the structural relationships within the transaction data, revealing hubs and clusters associated with laundering activities. However, this approach could not capture the semantic irregularities embedded in transaction descriptions. Conversely, text mining detected linguistic anomalies but was limited in modeling inter-entity relationships. The hybrid approach overcame these limitations by providing a holistic view that integrates both relational and semantic features.

The performance improvements achieved by the hybrid model demonstrate its robustness and adaptability to evolving money laundering techniques. The increase in recall is particularly important for anti-money laundering systems, as it minimizes false negatives and ensures that a larger proportion of fraudulent activities are detected. At the same time, the relatively high precision indicates that the model avoids excessive false positives, which is critical for operational efficiency in financial institutions.

This study also highlights practical implications for regulators and financial institutions. By adopting hybrid frameworks, detection systems can move beyond reliance on transaction monitoring alone and incorporate descriptive and linguistic cues, thus offering more comprehensive coverage of suspicious behaviors. Moreover, the integration of multiple analytical approaches aligns with current trends in fraud analytics, where ensemble learning and multi-modal models are increasingly recognized as effective strategies against dynamic fraud tactics.

Overall, the results validate the importance of hybrid detection systems that merge network analysis and text mining, not only for improving detection accuracy but also for ensuring resilience in the face of increasingly complex financial crime patterns.

5. Comparison

The comparative analysis highlights clear differences between the single-method approaches and the hybrid integration framework. Network analysis alone was effective in mapping relational anomalies, such as identifying central hubs and suspicious clusters within transaction flows, while text mining excelled in detecting semantic irregularities in transaction descriptions. However, both methods showed limitations when applied independently. Network analysis often failed to capture fraudulent patterns expressed in textual information, whereas text mining was unable to detect structural anomalies embedded within the financial network.

In contrast, the hybrid model successfully combined the strengths of both approaches, resulting in superior detection performance across all evaluation metrics. As demonstrated in Table 1 and Figure 1, the hybrid integration achieved higher accuracy, precision, recall, and AUC, with recall reaching 0.94 compared to 0.84 and 0.82 in single-method approaches. This improvement indicates a significant reduction in false negatives, ensuring that more illicit activities are detected. Therefore, the hybrid framework proves to be a more robust and adaptive solution, providing financial institutions and regulators with a comprehensive tool to counter increasingly sophisticated money laundering practices.

6. Conclusions

This research demonstrates that the integration of network analysis and text mining methods offers a more comprehensive framework for detecting suspicious financial transactions. Network analysis proves effective in identifying structural irregularities within transaction flows, while text mining highlights semantic inconsistencies in transaction descriptions. By combining both approaches, the framework provides a dual perspective that strengthens the detection process.

The experimental results indicate significant improvements in accuracy, precision, recall, and F1-score when compared to the standalone use of either method. The hybrid model successfully reduces false positives and false negatives, showing its ability to deliver more reliable detection outcomes. These findings emphasize the importance of combining structural and semantic analyses to address the challenges posed by increasingly complex money laundering schemes.

In conclusion, this study contributes to the development of advanced fraud detection strategies by introducing a hybrid framework that aligns with the evolving financial landscape. Nevertheless, future studies are recommended to explore the integration of deep learning techniques and real-time processing to further improve detection speed and scalability. Such improvements could enhance practical applications in financial institutions and regulatory environments, ensuring stronger protection against fraudulent practices.

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