Enhancing Transaction Monitoring Controls to Detect Money Laundering Using Machine Learning

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***Abstract*— Money laundering has become a great economic problem with huge consequences on society and financial institutions in the last decade. Current anti-money laundering (AML) procedures within the industry are either inefficient due to criminals' increasingly sophisticated approaches or technological advancements. This paper provides an extended abstract to identify and analyze the machine learning methods to detect money laundering through transaction monitoring in the literature. Moreover, the paper identifies research gaps and based on the observed limitations, suggests future research directions and areas in need of improvements.**

***Keywords*— Anti-money laundering, artificial intelligence, money laundering, machine learning, suspicious transactions, transaction monitoring.**

I. INTRODUCTION

Money laundering starts due to the consequences of a crime (the predicate or underlying offence) and concludes with available funds for use, securely or with minimal risk [1]. The process of converting criminal incomes into assets is money laundering. In the 21st century, money laundering has become a great economic problem with huge consequences on society and financial institutions [2]. When trying to hide the origins of funds and manipulating them to look legal, three common stages are used throughout most of the methods which are, placement, layering and integration [3]. Although it gives an idea, the three stages are solely a paradigm and should not be seen as a fixed approach.

Anti-money laundering (AML) aims to reduce money launderers converting criminal incomes into legal assets by referring to laws, techniques, and regulations. FATF (Financial Action Task Force) is an inter-governmental body that aim to prevent money laundering activities. Currently, FATF has set a risk-based framework that requires financial institutions to focus primarily on customer due diligence and transaction monitoring [4]. Transaction monitoring is conducted by financial institutes as they are required to continue risk assessment by monitoring patterns and anomalies in transactions of clients. Alerts are created in various systems by different actions, for example, strange transaction size, location, changes in client behavior or unrealistic wealth in contrast with customer reports. Suspicious Activity Reports (SAR) are filed and sent to Financial Intelligence Units (FIU) when an institution considers a customer's actions as suspicious.

Rule-based techniques for transaction monitoring is utilized by most financial institutions. Rules are set by domain experts. The false positive rate of the filed transactions are projected to be over 95% [5], hence being costly and time-consuming for financial institutions. There has been a huge increase in transactions over the years as financial institutions have used new technology to make services available to customers easier (i.e. through online banking). Rules-based methods have struggled to keep up with the increase in transactions and changes in customers behaviors giving inefficient results [6]. With large fines being issued and the complexity of identifying financial crime, financial institutions task of transaction monitoring is more expensive and difficult than even.

Due to the difficulties with rules-based methods more attention has been given to machine learning to reduce the false positives and acquire efficient results [7]. Machine learning approaches can also help upkeep the institutions reputation, reduce operational costs significantly, and satisfy regulators requirements. When applying algorithms to identify money laundering it is crucial to recognize the benefits and drawbacks of algorithms, as the effectiveness of the method is largely influences by the unique features of the transactional data. Mainly supervised and unsupervised machine learning methods have been used to detect money laundering. Supervised approaches are easier to evaluate due to having a labelled dataset, however, high quality labels are required. Unlike supervised methods, unsupervised methods can better adapt to changes in customers behavior and detect suspicious activity [8].

II. MACHINE LEARNING METHODS USED IN THE LITERATURE

Many different machine learning approaches have been proposed for transactional monitoring. Figure 1 shows the machine learning techniques used in the literature. The most popular methods are Bayesian Algorithms, SVMs, Neural Networks, Isolation Forest, and Random Forest. Transactional monitoring solutions for AML will be classified into one of the following groups, Historical AML Cases, Graph Analysis, Behavioral Analysis, Anomaly Detection, and Risk Ranking.

A. Approaches Based On Historical AML Cases

Historical AML case approaches – proposed methods that study and learn historical money laundering incidents and flag similar situations. An instance based approach. This approach is the second most popular. Neural networks (NN) and support vector machines (SVM) are some common methods that use the historical AML cases approach.

Lv *et al.* [9] built a transaction monitoring method using a type of NN called radial basis function (RBF). To calculate the parameters of the hidden layer in the RBF model the APC-III clustering was used which sped up the learning duration. However, the method was tested on a small dataset.

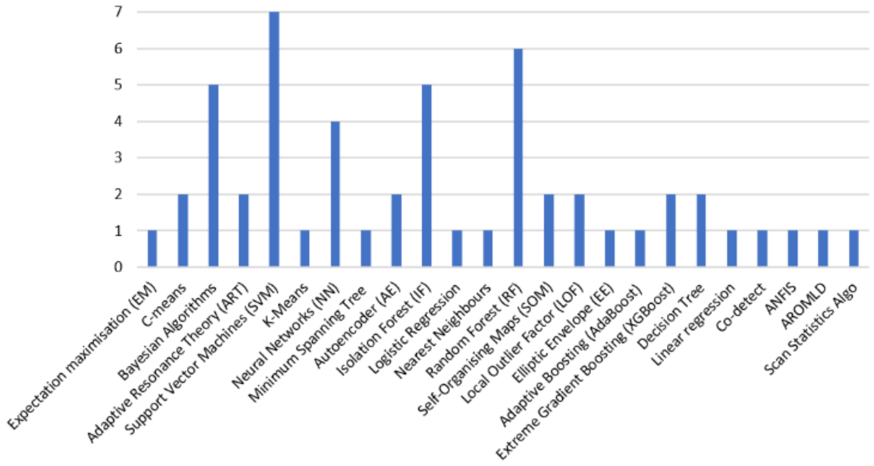

Fig. 1. Number of published studies based on the machine learning approach used.

B. *Approaches Based On Graph Analysis*

Graph analysis approach – graphs are constructed between transactions to gain further knowledge about the links between transactions to identify potential money launderers. This approach has not been researched as much as some of the others and can be explored further. Self-Organizing map (SOM) and Adaptive Resonance Theory (ART) are both unsupervised neural network-based methods [10] that have been used.

SOM is proposed in [11] with an extra step of clustering to enhance transaction monitoring. SOM produces an inter-neural distance of all neurons that range between 0 and 1. Then placed into one of the five risk level clusters. The proposed method reduces the false positive rate drastically (6.2%) compared to existing rules-based methods, however, the true positive rate (65.5%) suffers. This has a far worse impact on financial institutions.

Desrousseaux *et al.* [12] went a step further and proposed a method that utilizes SOM and ART. A variation of ART called Fuzzy ART (fzART) is used. Combining SOM and fzART reduces the execution time of the method considerably compared to executing each method separately.

C. *Approaches Based On Anomaly Detection*

This is a popular approach that alerts transactions as suspicious when they do not correlate with most transactional data that is deemed normal. Isolation forest, local outlier factor, and one-class SVM are frequently used methods. Isolation Forest separates unusual data immediately unlike most algorithms where outliers are separated after constructing an average of the data [13]. The Isolation Forest and One-Class SVM techniques were compared in [14] to detect suspicious activities by investigating the amount and time of transactions of a synthetic dataset. Isolation Forest is better as it has a shorter computation time, uses less memory, and achieves better accuracy.

LOF is an unsupervised machine learning algorithm that calculates a local outlier score with regards to a specific instance and its k-nearest neighbors. A study [15] produced a cluster-based local outlier detection factor (CBLOF) algorithm to identify suspicious money laundering transactions. However, the study lacked evaluation making it difficult to assess the effectiveness of the detection rate.

D. *Approaches Based On Behavioural Analysis*

Behavioral analysis approach – analyses customers' individual behaviors by investigating their transactions to identify money launderers. This approach is usually highly accurate, however, difficult to scale up as its analyses the behavior of customers individually. Random forest and boosting algorithms are some commonly used techniques.

Gorkem *et al.* [16] used Random Forest to develop a transactional monitoring system focusing on the time-frequency attributes of customers. The method is trained on previously labelled money laundering transactions. A threshold is set and transactions with values above the threshold are deemed suspicious.

Boosting algorithms are an ensemble approach that is implemented alongside a weak algorithm to enhance it and attain better results. Extreme Gradient Boosting (XGBoost) and Adaptive Boosting (AdaBoost) have both been used for transaction monitoring. The study [17] proposed an XGBoost method to detect suspicious transactions and compared it to a bank's existing method. The method outperforms the bank's approach in the following metrics, AUC, Brier score, and PPP (metric created by the author).

E. *Approaches Based On Risk Rating*

Risk rating approach – transactions are classified as suspicious or normal after transactions and customers are given risk ratings. Not much research is done on the approach and can be explored further. A variation of Euclidean Adaptive Resonance Theory (called TEART) is utilized by [18] along with a transaction ranking system (called AICAF) to detect potential money laundering transactions. The method is compared to K-means and outperforms it.

F. *Overview*

Figure 2 shows the number of times a type of approach was used in the literature when producing a transaction monitoring method. The anomaly detection approach is the most popular with behavioral analysis and historical case approaches a joint second.

Although the anomaly detection approach is popular and useful a drawback is that not all anomalies are suspicious which will lead to false positives. For example, a customer receiving a loan or bonus from work. Methods based on historical cases are also proposed a large amount as they can be easily evaluated (due to using labelled data) and produce accurate results. However, the method relies heavily on the quality of the dataset (how accurate are the labelled transactions) and cannot identify new money laundering strategies.

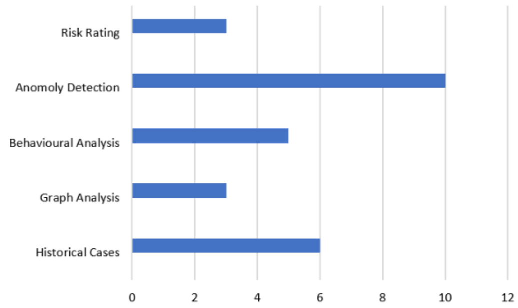

Fig. 2. Number of published studies according to the type of approach.

III. Key shortcomings and future research directions for transaction monitoring

Many papers over the last demi-decade have applied various machine learning techniques to improve money laundering detection. Review papers such as [19], [8], [6], [20] have summarized the general AML methods in the literature, but it's apparent that the methods are untrusted by financial institutions and consequently unused as fines are increasing. In 2018 fines totaled $4 billion, increasing to $8 billion in 2019, and in the first half of 2020 was $6 billion [21]. A low level of trust by institutions may be due to studies lacking information or reproducibility. Several papers present the application of the detection methods but the evaluation is limited and information on the datasets is minimal. Also, it is difficult to compare methods as they have been experimented on different datasets. Most papers' feature selection methods have not been analyzed thoroughly and explanations on the chosen features are insignificant. Solutions to detect money laundering are still an ongoing research area. There is an insufficient amount of research in machine learning methods for transactional monitoring especially using a real dataset. Research lacks ensembled learning, reinforcement, and deep learning methods which could be studied further.

IV. Conclusion and future work

This research aims to enhance transaction monitoring systems in Anti-Money Laundering (AML) to reduce false positives using machine learning. Previous research has shown that rules-based systems are mainly used by financial institutions to detect money laundering activities, which cannot identify hidden and complex money laundering activities effectively and efficiently, resulting in high false-positive alerts. Therefore, increasing human capital cost, fines from authorities and processing time for financial institutions. This paper identifies what has been done in literature as well as the key shortcoming and directions for future research. As for future work, interviews will be conducted with AML specialists to identify the problems and requirements of transaction monitoring methods. Then a method to detect suspicious transactions will be produced and evaluated that reaches the requirements identified. Reducing the number of alerted false positives compared to rules-based methods will be a major objective as this is a primary concern in the AML domain.

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