International Journal of Advanced and Applied Sciences, 10(7) 2023, Pages: 48-53

Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: http://www.science-gate.com/IJAAS.html

Machine learning in predicting anti-money laundering compliance with protection motivation theory among professional accountants

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ARTICLE INFO

Article history:
Received 25 January 2023
Received in revised form
9 March 2023
Accepted 10 May 2023

Keywords:
Money laundering
Professional accountants
Anti-money laundering regulations
Machine learning prediction model
Compliance behavior

ABSTRACT

Money laundering represents a significant global threat, necessitating the vigilance of professional accountants in detecting and reporting suspicious customer activities within their jurisdiction to the relevant authorities. Despite the legal obligation to comply with anti-money laundering regulations, professional accountants' adherence to these measures remains insufficient. Previous research on machine learning techniques for combating money laundering has predominantly concentrated on predicting suspicious transactions, rather than evaluating compliance behavior. This study aims to develop a machine learning prediction model to assess the inclination of professional accountants towards adhering to anti-money laundering regulations, serving as an early signal system to gauge their willingness to abide by the law in their professional responsibilities. The research elaborates on the design and implementation of machine learning models based on three algorithms: Decision Tree, Gradient Boosted Tree, and Support Vector Machine. The paper offers two types of comparisons from distinct perspectives: firstly, the performance of each algorithm in predicting real cases of anti-money laundering compliance, and secondly, the contribution of attributes measured by weights of correlation in different algorithms. Alongside demographic factors, the study evaluates the effectiveness of each algorithm in anti-money laundering compliance by utilizing five attributes derived from the Protection Motivation Theory (PMT). The findings demonstrate the significance of all attributes, including demography and PMT, in all machine learning models, with both Gradient Boosted Tree and Support Vector Machine achieving a proportion of variance of 0.8 or higher. This indicates the potential of these algorithms in effectively measuring and predicting professional accountants' intentions to comply with anti-money laundering regulations.

1. Introduction

Money laundering represents a significant financial crime that poses a substantial threat to the global economy and its overall stability (Achim and Borlea, 2020). The amount of money laundered globally in a year is estimated to be 2–5% of global GDP, or 0.8–2 trillion in US dollars (Unger et al., 2006). Briefly, money laundering is the process of concealing the source of cash or property obtained through criminal activity (Teichmann, 2018; Weber and Kruisbergen, 2019) such as human trafficking, racketeering, funding terrorism, kidnapping, cocaine dealers, weapons, corruption, bribery, theft, forgery, and counterfeiting.

The process of money laundering typically encompasses three distinct stages: placement, layering, and integration (Omar et al., 2014). During the initial stage of money laundering, known as "placement," illicit funds are typically introduced into the financial system by money launderers. This involves the infusion of substantial sums of cash into legitimate financial channels, such as structured

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deposits, investments in gold businesses, or other lawful enterprises. Subsequently, in the second stage, termed "layering," the proceeds from illegal activities undergo a process of conversion into various forms of funds, aiming to obscure the traceability of the unlawful proceeds and thus rendering the task of tracking the illicit funds considerably more intricate.

Indeed, Schneider and Windischbauer (2008) emphasized that the objective of the layering stage in money laundering is to obscure the true financial sum involved. This is achieved through multiple transfers and re-transfers of funds either within the same account or through different accounts. Additional layering techniques encompass the use of duplicate invoices for the same transaction and the re-sale of assets, such as stocks, commodities, and properties.

Subsequently, in the third stage known as "integration," the illicit proceeds merge with the legitimate economy, resulting in the generation of clean money. It is at this stage that the money laundering process is considered complete. Examples of integration include money launderers, after layering the funds, purchasing high-value items such as gold, diamonds, and luxury goods, which they subsequently sell. The proceeds from these sales contribute to producing clean money, even if the items are sold at a lower price than their current market value. Additionally, another integration approach involves money launderers engaging in legal businesses, such as restaurants or legitimate companies.

According to the report issued by Global Financial Integrity (GFI, 2019), Malaysia has been highlighted as one of the countries with the highest amount of illicit financial flows in 2015. The report shows that Malaysia lost between RM94.22 billion and RM138.66 billion in illicit outflows from 2006 to 2015. In response, the government has initiated stringent measures including the introduction of the Anti-Money Laundering, Anti-Terrorism Financing and Proceeds of Unlawful Activities Act (AMLA) (Sarif et al., 2019; BNM, 2001).

In the context of the Anti-Money Laundering Act, professional accountants encompass both accountants and auditors who play a crucial role in combatting money laundering. The Malaysian Institute of Accountants (MIA) has provided specific guidelines outlining the responsibilities of professional accountants in mitigating money laundering offenses, including the duty to report suspicious transactions and activities. To fulfill their obligations in preventing money laundering, professional accountants are required to exercise heightened vigilance towards certain client transactions and conduct assessments of the client's computer systems (Laptes, 2020).

In order to identify suspicious transactions, professional accountants should take into account the following transaction selection criteria: significant cash transactions, international transfers, transactions that deviate from the client's usual activities or income patterns, and highly intricate transactions. These criteria serve as crucial indicators that warrant careful scrutiny in the efforts to combat money laundering effectively.

Nonetheless, despite the established regulations and guidelines, recent findings, such as the Mutual Evaluation Report (MER) by Terry and Llerena Robles (2018), indicate that the level of compliance among professional accountants remains suboptimal. Disturbingly, money laundering cases have surfaced, implicating fellow professional accountants as facilitators of these illegal activities. Furthermore, the MENAFATF (2019) report highlights that a mere 2% of suspicious activity reports (SARs) have been submitted by professional accountants, suggesting a potential lack of awareness among them regarding their role as reporting entities under the Anti-Money Laundering (AML) Regime.

Compliance with AMLA regulations, including the submission of SARs, is an indispensable component in the fight against money laundering and terrorism financing. Upon receiving these reports, the Financial Intelligence and Enforcement Department (FIED) of Bank Negara Malaysia assumes responsibility for analyzing the information and providing intelligence on potential criminal activities to relevant law enforcement agencies. Consequently, law enforcement agencies leverage this vital information to initiate investigations into criminal activities that would otherwise remain undetected. This symbiotic relationship between professional accountants' compliance and the subsequent investigative actions of law enforcement agencies plays a critical role in safeguarding against money laundering and associated criminal activities.

Considering the pressing imperative to bolster anti-money laundering compliance among professional accountants, it is of utmost importance to identify more efficacious measures. Therefore, this study endeavors to contribute to the current scholarly discourse by exploring the implementation of a machine learning classification approach. The primary objective is to predict the anti-money laundering intention of Malaysian professional accountants, utilizing five distinct attributes from the Protection Motivation Theory. These attributes encompass perceived risk of noncompliance, competency, perceived effectiveness of the Anti-Money Laundering Act 2001, perceived vulnerabilities, and compliance cost.

There are two major contributions to this work. First, it attempts to extend previous work on money laundering prediction using machine learning techniques (Alkhalili et al., 2021; Canhoto, 2021; Chen et al., 2018; Chenoweth et al., 2009; Jullum et al., 2020; Lorenz et al., 2020; Zhang and Trubey, 2019) by presenting evidence on a machine learning-based anti-money laundering compliance intention prediction model among professional accountants. To the best of our knowledge, no machine learning prediction on anti-money laundering compliance intention has been published before. Second, it presents a new prediction model on professional accountants' anti-money laundering compliance based on Protection Motivation Theory's constructs (Chenoweth et al., 2009) to be observed with the machine learning performances.

The subsequent sections of this paper are organized as follows: Section 2 provides an overview of the current state-of-the-art research pertaining to machine learning in the context of money laundering issues. Following this, Section 3 elucidates the dataset employed in this investigation, along with the machine learning technique utilized. The experimental findings are presented and thoroughly discussed in Section 4. Finally, the summary and conclusions drawn from the study are presented in the concluding section.

2. Literature review

To the best of our knowledge, there have been very few studies that linked money laundering and machine learning approaches. To date, the existing research on machine learning for money laundering focus on prediction models for the detection of suspicious money laundering transactions (Alkhalili et al., 2021; Canhoto, 2021; Chen et al., 2018; Chenoweth et al., 2009; Jullum et al., 2020; Lorenz et al., 2020; Zhang and Trubey, 2019) rather than money laundering compliance. For instance, Jullum et al. (2020) developed a supervised machine learning method for discriminating between legitimate transactions and transactions that are suspicious in terms of money laundering. The data set used by the study is gathered from Norway's largest bank, DNB. A supervised machine learning model is trained by using three types of historic data: Legitimate transactions; those flagged as suspicious by the bank's internal alert system; and potential money laundering cases reported to the authorities. The model is trained to predict the probability that a new transaction should be reported, using information such as background information about the sender/receiver, their earlier behavior, and their transaction history. In addition, Zhang and Trubey (2019) used five machine learning algorithms; Bayes logistic regression, decision tree, random forest, support vector machine, and artificial neural network to predict money laundering suspicious transactions. The analysis was conducted based on actual transaction data from a U.S. financial institution. The analysis reveals the advantages of machine learning algorithms in modeling money laundering events. In particular, artificial neural networks and support vector machines consistently outperform parametric logistic regressions while random forest delivers comparable performance.

Furthermore, the existing machine learning findings on money laundering are not presenting analysis from the aspects of behavior theory as the potential factors of the prediction models. This paper provides a new insight with the inclusion of constructs from the Protection Motivation Theory (PTM) to be empirically observed with the performance of machine learning. The theory of PTM has been widely useful in research related to the prediction of human behaviors (Kothe et al., 2019; Kowalski and Black, 2021; Verkijika, 2018).

3. Research method

3.1. The dataset

This research employed a questionnaire as the data collection instrument to construct the prediction model utilizing various machine learning algorithms. The survey was distributed among professional accountants in Malaysia, specifically targeting individuals with a minimum of three years of working experience as audit and tax partners, managers, and seniors. The questionnaire consisted of two sections designed to elicit information pertaining to the demographic profile of the professional accountants and their perceptions concerning the attributes derived from the Protection Motivation Theory (PMT).

The PMT attributes encompassed in the questionnaire were risk of non-compliance, competency, effectiveness of the Anti-Money Laundering Act (AMLA) (www.agrobank.com.my), vulnerabilities, and compliance cost. Additionally, the demographic attributes captured in the questionnaire included age, work experiences, gender, and academic qualifications. Furthermore, the respondent's participation in any training or workshop related to Anti-Money Laundering (AML) (referred to as AML Training) was also included as a demographic attribute. Out of a total of 275 questionnaires distributed, 215 valid responses were considered for subsequent analysis in this study.

Fig. 1 presents the weights of correlation each of the attribute from PMT and demography to the dependent variable. The weights of each attribute were measured with Pearson Correlation test. The dependent variable is the degree of accountants' intention to comply with the AMLA2001 through three main mechanisms namely, Know Your Customer, Clients Due Diligence, Record Keeping.

The main problem of the attributes in Fig. 1 is very weak correlations to the dependent variable. Nevertheless, all were considered to contribute some degree of knowledge to the machine learning algorithms in the prediction models. Later, how each attribute was used differently in each machine learning algorithm will be discussed in the results section by looking at the weights of correlations in the different machine learning algorithms.

3.2. Machine learning

Following the initial outcomes of AutoModel in RapidMiner, three machine learning algorithms, namely Decision Tree (DT), Gradient Boosted Trees (GBT), and Support Vector Machine (SVM), have been chosen for comparative analysis. The

AutoModel in RapidMiner employed an optimization Grid Search strategy to identify the most suitable algorithms for the given dataset. From the eight suggested algorithms, the three exhibiting the best performances, with an error rate of less than 10%, were selected. Table 1 provides a comprehensive listing of the optimal hyper-parameter sets for each machine learning algorithm, as determined through preliminary hyper-parameter tuning in the machine learning process.

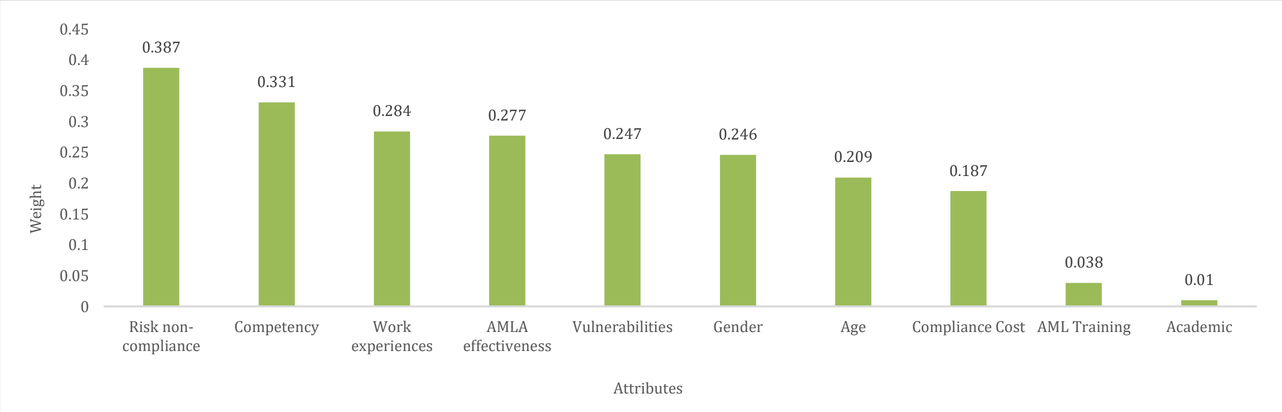

Fig. 1: Weight of correlations coefficient

Table 1: Optimal hyper-parameters

Algorithm	Hyper-parameters	Error rate
DT	Maximal depth=15	9.9%
GBT	Maximal depth=7 Number of Trees=150 Learning rate=0.1	8.1%
SVM	Kerner Gamma=0.5 C=1000	7.1%

DT has maximal depth as the most important hyper-parameter that can be referred to as the maximum level of the tree. The optimal maximal depth for DT is 15 that was able to generate the lowest error rate at 9.9 while the highest error rate was 13 when the maximal depth 2. Fig. 2 illustrates the tree as an example of DT.

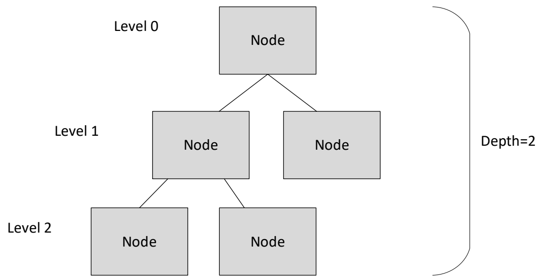

Fig. 2: DT with 2 maximal depth

GBT represents an extension of DT with two additional hyper-parameters, namely the number of trees and the learning rate. In pursuit of determining the optimal configuration, we experimented with 30, 90, and 150 numbers of trees, paired with three varying maximal depths (2, 4, 7), and three learning rates (0.001, 0.01, 0.1). The results of this investigation, presenting the optimal settings, are presented in Table 1. Notably, the highest error rate of 13.1% was observed when employing 30 numbers of trees, a maximal depth of 2, and a learning rate of 0.001, thereby constituting the least favorable combination among the hyper-parameter selections for GBT.

Conversely, SVM employs kernel gamma and C (regularization) parameters, which underwent preliminary research within the ranges of 0.005 to 5 for kernel gamma and 10 to 1000 for C. The least favorable setting for SVM was found when the kernel gamma was set to 0.005 and C was set to 100, resulting in an error rate of 39.5%. The optimal configuration for SVM is outlined in Table 1.

In order to differentiate the training and testing datasets, we adopted a split training approach with a 60:40 ratio, as recommended by the auto model in RapidMiner. Thus, out of the 215 data points, 129 were utilized for machine learning training, and the remaining 86 were allocated for machine learning testing purposes.

4. Results and discussion

This research yields two distinct sets of results that necessitate presentation. Firstly, the performance outcomes of the three machine learning algorithms in predicting professional accountants' anti-money laundering compliance are to be elucidated. Secondly, the collaborative interplay between the attributes derived from PMT and demography, influencing the efficacy of the machine learning prediction models, will be provided and discussed in the subsequent sub-section.

4.1. Performance results

Table 2 provides a comprehensive performance comparison among the three machine learning algorithms. The GBT algorithm demonstrated the lowest prediction error, with an RMSE of 0.58 and a relative error of 64%, slightly outperforming SVM. While SVM and GBT exhibited almost identical accuracy levels, it is noteworthy that GBT required significantly more processing time compared to SVM. Nonetheless, it is important to highlight that the total completion time (TCT) for GBT remained notably fast, amounting to a mere 14 seconds.

Table 2: Performances of machine learning algorithm

Algorithm	RMSE (+-std. dev)	R-squared (+-std. dev)	Relative error (+-std. dev)	TCT (ms)
DT	0.80 (0.23)	0.63 (0.10)	8.5% (1.1)	497
GBT	0.58 (0.21)	0.82 (0.08)	6.4% (2.1)	14000
SVM	0.61 (0.15)	0.80 (0.05)	6.5% (1.0)	2000

The R-squared statistic serves as a measure of the variance in the prediction model attributed to the independent variables (IVs). Among the machine learning algorithms, GBT exhibited the highest R-squared value, reaching 0.816, which was nearly identical to or marginally higher than SVM. The presence of low standard deviation values across all results indicates the reliability of the findings. To gain a more comprehensive understanding of how the variance of each attribute from the demography and PMT contributes to the prediction model across different machine learning algorithms, the subsequent sub-section presents the detailed findings.

4.2. Effect of attributes in machine learning

Table 3 lists the weights of the correlation coefficient tested with the Pearson Correlation test inside the prediction models with different machine learning algorithms. From the PMT attributes, the vulnerabilities attribute has been the most imperative attribute in DT and GBT while in SVM, competency became the first important. Earlier research has been substantiated by the results, indicating that compliance can be enhanced by competence (Verkijika, 2018). Competence refers to an individual's aptitude and ability to handle tasks or make decisions and can have a significant impact on their capacity to complete tasks (Tarmizi et al., 2022). For accountants in particular, this entails their comprehension of anti-money laundering (AML) rules, their ability to spot suspicious transactions, and their proficiency in submitting suspicious transaction reports (STRs).

Table 3: Weights of correlation coefficient in machine learning

Algorithm	DT	GBT	SVM
PMT			
Vulnerabilities	**0.129**	**0.219**	0.169
Competency	0.075	0.181	**0.204**
Compliance cost	0.055	0.173	0.108
Risk non-compliance	0.160	0.171	0.097
AMLA effectiveness	0.097	0.143	0.167
Demography			
Academic	0.027	0.032	0.055
AML training	0.042	0.045	0.042
Gender	0.034	0.034	0.036
Age	0.031	0.037	0.076
Work experiences	0.036	0.022	0.033

Comparing PMT and demography, it seems that none of the demography attributes have more than 0.1 weights of correlation in the prediction models. But, excluding the demography attributes has decreased the R-squared results of the machine learning as seen in Table 4.

Table 4: Results of R-squared with different groups of attributes

Algorithm	All attributes R-squared (+-std. dev)	PMT without demography R-squared (+-std. dev)
DT	0.630 (0.10)	0.670 (0.15)
GBT	0.816 (0.08)	0.772 (0.05)
SVM	0.802 (0.05)	0.74 (0.10)

By excluding demography, much of decremented R-squared results have been generated by GBP and SVM but a very slightly different appeared in DT. Thus, the results can be good enough to reveal the previous statement in Section A that each attribute even contributed with low weights of correlation can be beneficial to some machine learning algorithms in doing the prediction.

5. Conclusions

When dealing with real datasets for prediction models, challenges often arise due to low associations that can adversely impact the model's performance. However, in the context of the case utilized in this study, the sequence of events elucidates how the presence of low-associated attributes with the prediction target can still offer certain advantages to the machine learning models. Specifically focusing on attributes related to demography and PMT, this study presents the potential for further extensions involving various issues and machine learning methodologies to enhance the results.

Moreover, the expeditious and efficient modeling process employed by the machine learning prediction model serves as an early signal system, effectively assessing the willingness of accountants to comply with the Anti-Money Laundering Act while carrying out their duties and responsibilities. This capacity to gauge their propensity for adherence to anti-money laundering regulations proves valuable in practice.

Acknowledgment

We acknowledge the financial support granted by the Ministry of Higher Education under FRGS grant (600-IRMI/FRGS 5/3 (208/2019). We also appreciate Universiti Teknologi MARA for the full support.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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