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Identifying Money Laundering Transactions Using Artificial Neural Network – A Predictive Model

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ABSTRACT: As the conventional statistical analysis failed in providing good predictions on the bank's customer transactional data in terms of legitimate or suspicious transactions, the Artificial Neural Network has gained recognition and is widely used by industries in order to get good predictions on the complex nature of customer data for triggering money laundering transactions. This paper presents an Artificial Neural Network (ANN) modeling which is meant for identifying money laundering transactions.Here the ANN is modeled with 4 input variables, 3 hidden layers and one output layer. Softmax activation function that searches for an input pattern and that produces a maximum model response for a quantity of interest is used.And this model is critically examined through case processing summary, network information, classification and model summary.
Anticipatedoutcomes**:**The proposed model is used to train the sample data from large number of customer transactions and it segregates the suspicious customer data quickly and clearly from millions of legitimate ones. It supports financial institutions to prevent money laundering transactions well in advance. Thus, Financial Institutions realize the significance of a predictive model in mitigating the risk of Money Laundering Transactions (MLTs)and also to avoid expensive fines or disruptive investigations.Overallof the data analysis,the ANN has achieved a very accurate prediction of 99% along with limitations of the present study.

KEY WORDS: Artificial Neural Network, predictive model, prediction accuracy, financial transactions and money laundering transactions

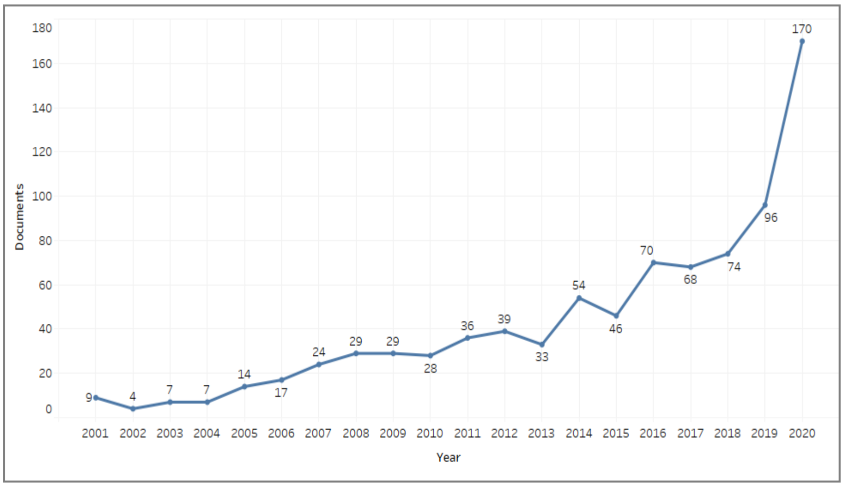
I. INTRODUCTION

Financial transparency is the criteria to evaluate the quality of the banking transactions across financial institutions. Now a days, most of the financial institutions have been facing a lot of money laundering issues which drag them to face disruptive investigations, bear the fines coupled with sanctions on their operations and on the extreme, closure of the institution itself. The results of statistical evaluations on the transactional data waslimited to just ex-post facto study on the sample of customer transactions datawhich hardly supports the decision making process. To cope with such limitation, Artificial Neural Network is increasingly beingused in identifying money laundering transactions through huge volumes of banking transactions by experiential knowledge through training the sample data. And now it has been gaining the attention of industry and is being widely applied in most of the non-linear situations and has proven to be a great success in pattern recognitions, classifications, forecasting and prediction in the areas of weather, health care, frauds and stockmarkets patterns.In this paper, the customer's banking transactional data of 2708 records is used to perform an ANN training, validation and testing in order to develop a model to predict accurately those customers who are prone to practice money laundering transactions(MLTs) across financial systems. As a whole, this paper presents an exploratory model and analyses the customer data and segregates the same into legitimate or suspicious type continuously to keep the financial systems away from illicit financial transactions. Legitimate customer is labeled as '0' and suspicious one as '1'.This paper has been organized into 4 sections; section 1 exploresconcepts and review of ANN, section 2 touchesresearch objectives and methodology, section 3 deals with ANN modeling and verification and section 4 highlights findings and conclusion.

Concepts: Money laundering is a process of converting the illegal money into legal money and alsois being freely used by miscreants in the legitimate business operations. This process enables the criminals to enjoy the un-cleaned money without jeopardizing their sources. Launderers pass funds through the financial system to make them appear legitimate. Anti-money laundering teams, meanwhile, develop and deploy monitoring programs throughout their institutions in search of behavior consistent with money laundering. A good risk detection system puts banking customers at ease and improves the bank's reputation. Failing to detect suspicious transactions leadsinstitutions to get exposed to money laundering risks. Banks will realize significant time and cost savings by using Artificial Intelligence (AI) to detect fraud activities automatically. Banking organizations can now rely on Machine Learning techniques for detecting anomalies on fraudulentfinancial transactions. One such model is known as predictive model which is based on supervised learning which is also known as Back Propagation (BP).

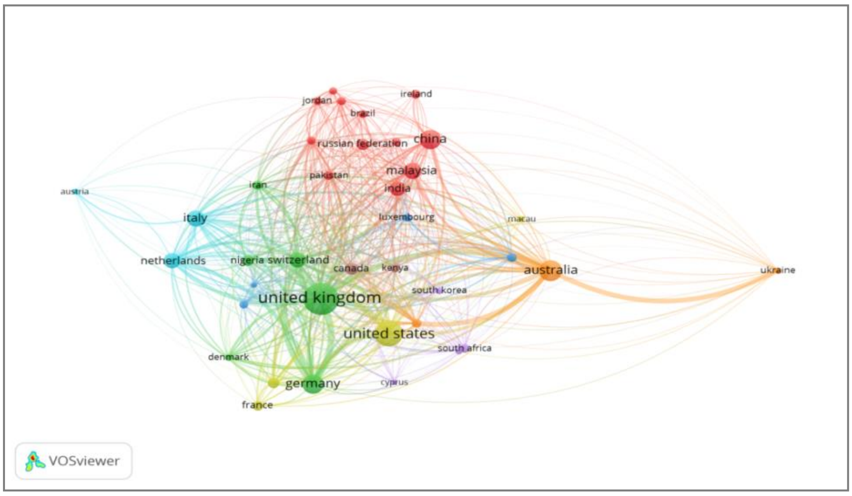
Artificial Neural Network (ANN) is a processor which has a power of storing experiential knowledge through the transactional data and making it available for future prediction of anomalies,on the customer behavioural patterns, with accuracy. It is a supervised learning in the sense that the model-predicted results can be compared against known values of the target variables in the transactional data.It works like a human thinking where identifying non-linearity events with deeper understanding about huge data and provide general solutions with good predictive accuracy. Ideally the ANN can be applied in the non-linearity situations like credit risk, financial risks, portfolio risks, fraud detection, targeted marketing, voice recognition, and face recognition etc.

Review of Literature: Seen through the Scientometric perspective, the previous studies on Money Laundering at nationalandinternational levels and the contributions of countries are reviewed here andfound a research gap to make an attempt on the proposed title "Identifying Money Laundering Transactions Using Artificial Neural Network – A Predictive Model**"** and this model would enable the financial institutions to be cautious about the potential risks which get transmitted from huge customer transactions.The research documents worldwide from 2001 to 2020 can be well assimilated from graph 1 and 2.



Graph 1:Studies on Money Laundering year wise
Source: Author compilation through VOSviewer

UK and USA have stood first and second on the Money Laundering research contributions. Australia and China are placed at third and fourth places respectivelywhereasIndian contribution is just modest. That can be understood fromgraph 2.



Graph 2: Studies on money laundering country wise
Source: Author compilation through VOSviewer

Asia Pacific Group (2014) Report on Money Laundering Typologies: Under investigation of money laundering, the proceeds of financial crimemostlyinvested into immovable properties. According to Associated Certified Anti-Money Laundering Specialists(2019), hundreds of bankers, regulators and others participatedand shared their knowledge with strategies to combat money laundering. According to Emilia Díaz-Struck and Agustin Armendariz, Institutional Consortium of Investigative Journalists (2020), it was found that there were 18153 transactions extracted from FinCEN files worth more than $ 2 trillion world wide and 406 transactions from India worth $ 482181226 received and $ 406278962 sentwhich shows how suspicious money travels across worldwide through the networks of international and local banks. The proposed research aims at building a predictive model for classifying huge customer transaction volumes into a money laundering event type(1) or not (0) with the following research objectives. Type 1 means suspicious and type '0' means legitimate.

Objectives of the study

1. To understand the concepts of Money Laundering Transactions (MLTs) and Artificial Neural Network (ANN)
2. Totrain the sample data by the trained data patterns with ANN in order to coin a predictive model for identifying those customers whoare prone to practicemoney laundering at the cost of the image of the financial institutions and the economy of the country.
3. To highlight the accuracy of the predictive model and to showhow it helps the management to curb the illicit financial transactions well in advance in order tokeep the financial systems away from these un-cleaned financial transactions.

II. RESEARCH METHODOLOGY

The sample of banking customers isof 2708 records which is retrieved from metadata. The elements of customer transaction include transaction type, transaction intense, original old balance, original new balance of the customer after transaction occurred, old balance at destinationcustomer and new balance of the destination customery.To run Artificial Neural Network (ANN) in the SPSS, the sample data has been partitioned as training sample, testing sample and holdout sample with 70%:20%:10%. And sample records assigned randomly to the trained sample, test sample and holdout sample. Standardized scaling is applied to predictive variable and predictor variables. Automatic architecture is taken as the researcher is of non-computer science background.The basic structure of a neural network contains an input layer, one or more processing layers, and an output layer. For anomaly detection, neural networks can classify financial transactions or network traffic patterns as 'normal' or 'suspicious'.The basic idea behind using ANNs is to reduce the number of false positives.

ANN modeling and verification

Table 1: Case Processing Summary

		N	Percent
Sample	Training	1885	69.6%
	Testing	560	20.7%
	Holdout	263	9.7%
Valid		2708	100.0%
Excluded		0	
Total cases		2708	

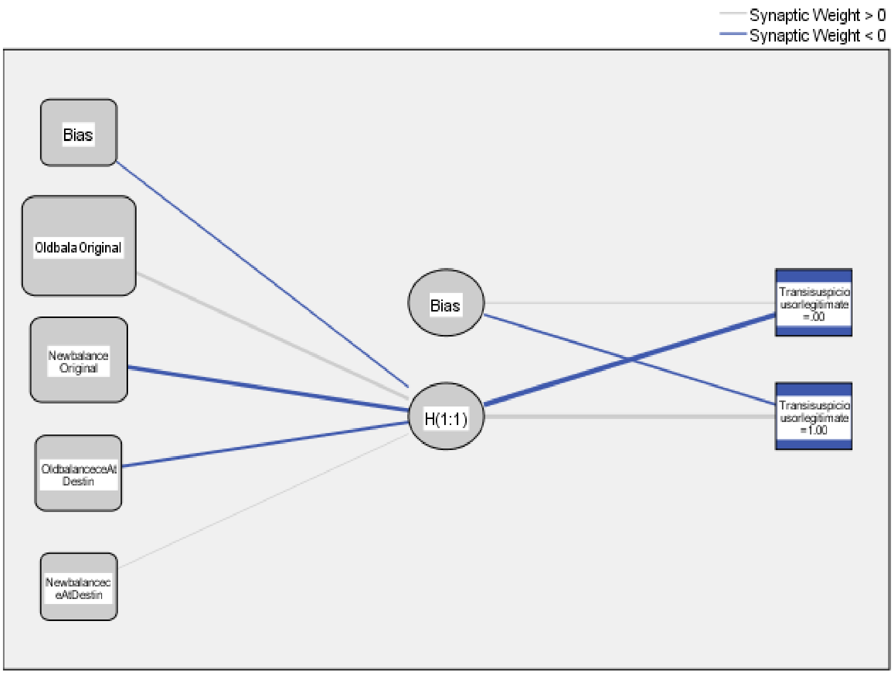
The ANN system itself assigned 69.6% of customer records for the training sample to train the neural network and the trained neurons are used to track the errors during the process of testing the sample of customer records. The network training will be considered most efficient as the testing sample is smaller than the training sample i.e20.7%.

Table 2: Network Information

Input Layer	Covariates	1	Oldbalance Original
		2	Newbalance Original
		3	Oldbalance at Destination
		4	New balance at Destination
	Number of Units[a]		4
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		1
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Is Transaction Suspicious or Legitimate
	Number of Units		2
	Activation Function		Softmax
	Error Function		Cross-entropy

Excluding the bias unit

From the Network Information, the training data set with four covariates (old balance original, new balance original, old balance at destination and new balance at destination) along the predictable output (suspicious or normal) is processed with back propagation which in turn feed forward the weights of each input to the hidden layersof network. The test sample data set is further processed with the back propagation derived from trained data set to predict output of network whose input is known. The activation function in the network is hyperbolic tangent which is an analysis framework that searches for an input pattern that produces a maximum model response for predicting the suspicious transactions.



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Softmax

There are three lines in the network viz dot lines, smaller lines and thick lines. Dot lines are the ones that are most important, smaller lines are the one which have a little impact where synaptic weight is less than 0 and bias is error and having some kind of impact on the model. Thick blue linesindicate strong polarization. These networks use single-layer perceptron.

Table 3: Model Summary

Training	Cross Entropy Error	62.106
	Percent Incorrect Predictions	0.7%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.26
Testing	Cross Entropy Error	7.270
	Percent Incorrect Predictions	0.5%
Holdout	Percent Incorrect Predictions	0.0%

Error computations are based on the testing sample
Dependent Variable: Is Transaction Suspicious or Legitimate.

Under the model summary, it is found that the incorrect predictions on the training sample is 0.7% which is pretty low in other words we achieved 99% accuracy in the training. Whatever the mathematical model we figured out in the training stage will be used in the testing sample to see the accuracy of the model. Here the calculated percent of incorrect prediction is 6.5% which means we achieved 94.5% accuracy. Further it is also noticed that the cross entropy error for sample data is 7.270 which is less than training data error. Therefore really it would be a good predictive model for identifying the money laundering transactions across financial systems.

Table 4: Classification: Correctness Report of Cases

Sample	Observed	Predicted		
		Legitimate	Suspicious	Percent Correct
Training	Legitimate	1869	2	99.9%
	Suspicious	12	2	14.3%
	Overall Percent	99.8%	0.2%	**99.3%**
Testing	Legitimate	559	0	100.0%
	Suspicious	1	0	10.0%
	Overall Percent	100.0%	0.0%	**99.8%**

Dependent Variable: Is Transaction Suspicious or Legitimate

It reveals more information about the accuracy of the classification. In the training sample,the model has predicted 1869 customer records as legitimate transactions and two records as suspicious, out of 1871 customer records. Coming to the suspicious customer records, the model has predicted 12 customers as confirmed suspicious and 2 records as false positives out of 14 customer records. The experiential knowledge of training data set can be deployed on the sample data set to get accuracy in identifying legitimate and suspicious transactions from millions of customer data.Finally the overall correct prediction for sample data is 99.8% and for training data is 99.3% and which is pretty good.

Table 5: Independent Variable Importance

	Importance	Normalized Importance
Oldbalance Original	.342	95.0%
Newbalance Original	.266	77.9%
Oldbalance at Destination	.217	63.5%
New balance at Destination	.175	51.2%

Here it would be interesting as to how each independent variable is important to predict whether the customer transaction is legitimate or suspicious. Old balance original has high importance in predicting the customer transaction legitimacy whose value is 34.2% and which has been normalised as 95%. The importance of rest of predictors is; 0.266, 0.217 and 0.182 respectively and afterwards found their normalised importance as 77.9%, 63.5% and 51.2% respectively. In other words, the old balance of the customer does have high impact on the customer transaction legitimacy followed by new balance original, old balance at destination and new balance at destination.

Findings and conclusion:

Transparency of financial transactions and governance of financial administration are most important parameters for any financial institution to win the customer loyalty. To achieve this, the ANN predictive model is need of the hour. The following findings are explored with ANN;

- The sample data predictive accuracy is not much higher than training data accuracy, therefore the model is well fitted in identifying the suspicious customer transaction with 99% accuracy.
- The Predictive Model can be used asreplica for new data to predict target variable accurately rather than prescriptive information.
- Potential risk of money laundering can be detected with an accuracy at an early stage
- Financial Institutions can keep away themselves from all these illicit financial transactions and can prevent the surprise investigations, fines, black listing etc.

III. CONCLUSION:

Overall, the ANN has achieved accurate prediction of 99% therefore the ANN as a predictive model can play a significant role not only in money laundering transactions but also useful in unearthing the frauds in claims settlements, in exploring the risks of stock market, in identifying criminals with facial recognitions, in understanding the credit risks of the borrowers etc.

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