

## STATISTICAL AND MACHINE LEARNING APPROACHES TO MONEY LAUNDERING PREVENTION

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### ABSTRACT

Money laundering is a serious issue on a worldwide scale. However, the scholarly literature on statistical and machine learning techniques for money laundering prevention is scant. In this paper, we review the relevant literature and provide an introduction to the topic of anti-money laundering in banks. Our proposal consists of two main components that form a unified terminology: (i) client risk assessment and (ii) reporting suspicious behavior. We discover that the diagnostics—that is, the search and elucidation of risk factors—are what define client risk profile. On the other side, non-disclosed characteristics and manually created risk indices are hallmarks of suspicious behavior flagging. Lastly, we talk about potential future study directions. The requirement for new public data sets is one of the main obstacles. Synthetic data production may be able to help with this. Additional avenues for investigation encompass semi-supervised and deep learning, as well as the interpretability and equity of the outcomes.

**Keywords:** Statistical, Machine Learning, Money Laundering, Prevention

### ,1 INTRODUCTION

Officials from the United Nations Office on Drugs and Crime estimate that money laundering amounts to 2.1-4% of the world economy. The illicit financial flows help criminals avoid prosecution and undermine public trust in financial institutions. Multiple intergovernmental and private organizations assert that modern statistical and machine learning methods hold great promise to improve anti-money laundering (AML) operations. The hope, among other things, is to identify new types of money laundering and allow a better prioritization of AML resources. The scientific literature on statistical and machine learning methods for AML, however, remains relatively small and fragmented.

The international framework for AML is based on recommendations by the Financial Action Task Force (FATF). Within the framework, any interaction with criminal proceeds practically corresponds to money laundering from a bank perspective (regardless

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of intent or transaction complexity). Furthermore, the framework requires that banks: 1) know the identity of, and money laundering risk associated with, clients, and 2) monitor and report suspicious behaviour. Note that we, to reflect FATF's recommendations, are intentionally vague about what constitutes "suspicious" behaviour.

### **Implementation study**

#### **Existing System:**

Badal-Valero et al. combine Benford's Law and four machine learning models. Benford's Law gives an empirical distribution of leading digits. The authors use it to extract features from financial statements. Specifically, they consider statements from 335 suppliers to a company on trial for money laundering. Of these, 23 suppliers have been investigated and labeled as colluders. All other (non-investigated) suppliers are treated as benevolent. The motivating idea is that any colluders, hiding in the non-investigated group, should be misclassified by the employed models.

#### **Disadvantages:**

- find that studies on client risk profiling are characterized by diagnostics, i.e., efforts to find and explain risk factors. Specifically, unsupervised methods are used to search for new "risky" observations or risk factors. On the other hand, supervised methods are used with an explanatory focus.
- We also find that studies employing unsupervised methods generally use relatively large data sets. By contrast, studies employing supervised methods use small (labeled) data sets

### **Proposed System & algorithm**

In this paper, we focus on AML in banks and aim to provide a technical review that researchers and industry practitioners (statisticians and machine learning engineers) can use as a guide to the current literature on statistical and machine learning methods for AML in banks. Furthermore, we aim to provide a terminology that can facilitate policy discussions, and to provide guidance on open challenges within the literature. To achieve our aims, we (i) propose a unified terminology for AML in banks, (ii) review selected exemplary methods, and (iii) present recent machine learning concepts that may improve AML.

#### **Advantages:**

- The proposed system reduced an UNSUPERVISED CLIENT RISK PROFILING problem.
- The proposed system eliminates SUPERVISED CLIENT RISK PROFILING problem.

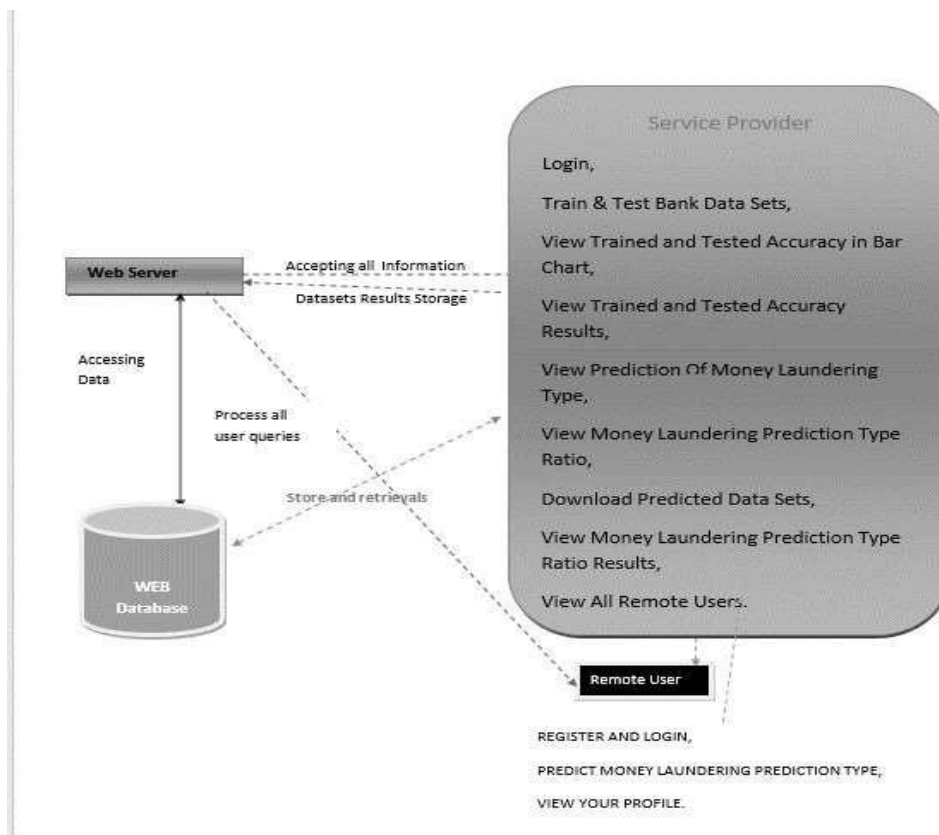


Fig1: proposed Model

### RANDOM FOREST ALGORITHM:

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of **ensemble learning**, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model.

As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

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## RESULTS AND DISCUSSION



Fig4: LOGIN PAGE FOR SERVICE PROVIDER

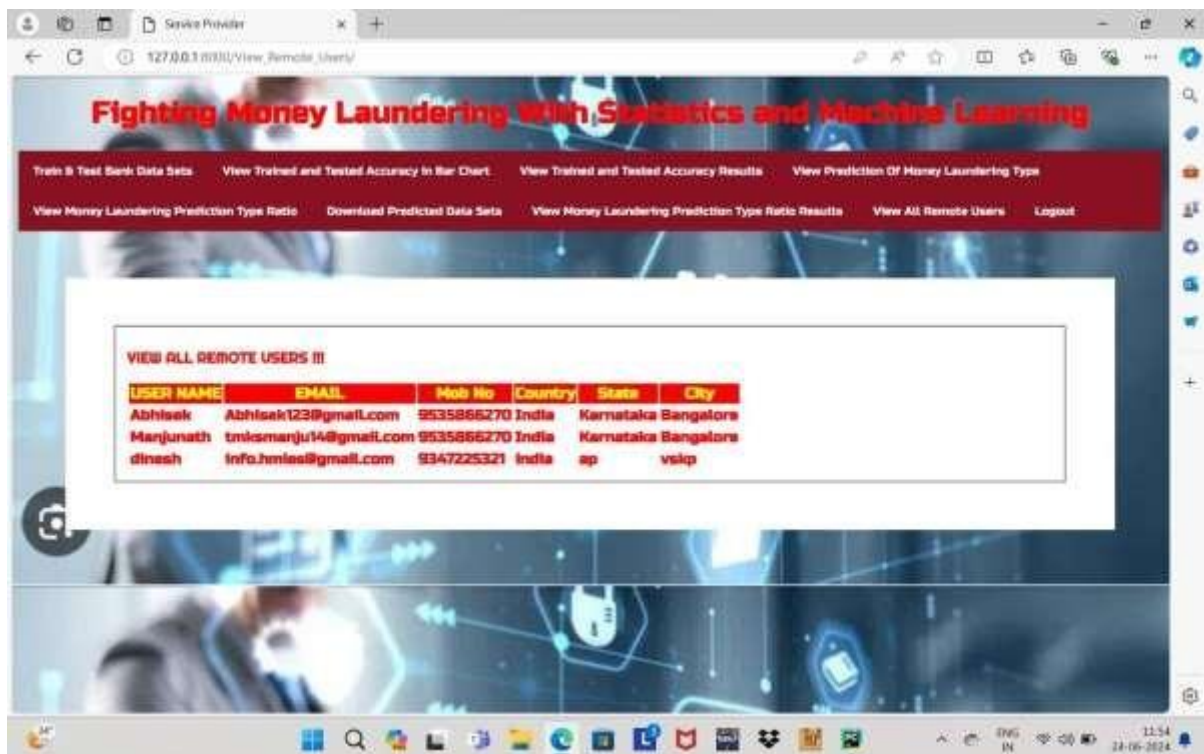
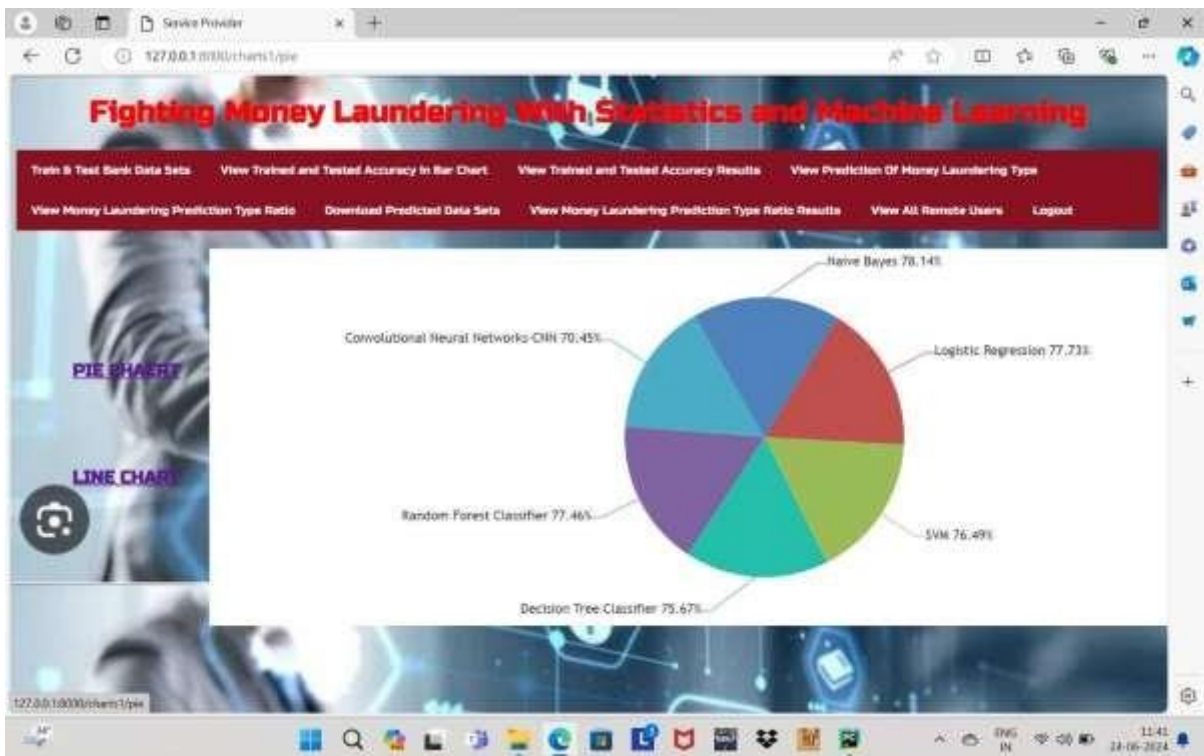


Fig5: TRAIN AND TEST BANK DATA SET

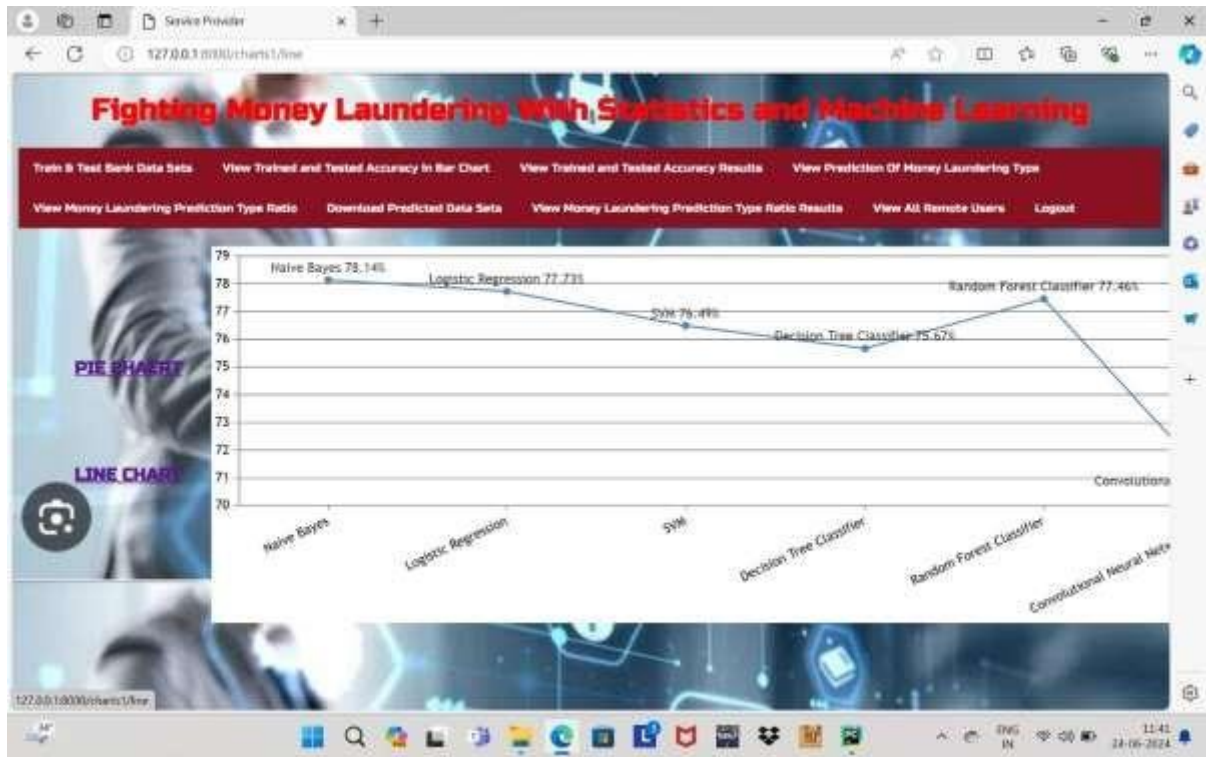


Fig6: VIEW TRAINED AND TESTED ACCURACY IN BAR CHART



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## VIEW TRAINED AND TESTED ACCURACY RESULT IN PIE CHART



## VIEW TRAINED AND TESTED ACCURACY RESULT IN LINE CHART

The screenshot shows a web application interface with a table titled "View Money Laundering Prediction Type Details III". The table contains the following data:

| Pid  | AccOpenDate | CustomerId | Surname  | CreditScore | Geography | Gender | Age | Tenure | Balance   | NumOfProducts | HasCrCard |
|--|-------------|------------|----------|-------------|-----------|--------|-----|--------|-----------|---------------|-----------|
| 10.42.0.151-31.13.80.5-58384-443-6             | 25-11-16    | 15656148   | Obinna   | 376         | Germany   | Female | 29  | 4      | 115046.74 | 4             | 1         |
| 172.217.10.110-10.42.0.151-443-58878-6         | 30-11-16    | 15632264   | Kay      | 476         | France    | Female | 34  | 10     | 0         | 2             | 0         |
| 10.42.0.211-10.42.0.1-45948-53-17              | 03-12-16    | 15643966   | Geforth  | 616         | Germany   | Male   | 45  | 3      | 143129.41 | 2             | 0         |
| 10.42.0.211-111.206.25.159-19-04-17-38861-80-6 | 19-04-17    | 15811589   | Metcalfe | 716         | Spain     | Male   | 42  | 8      | 0         | 2             | 0         |
| 140.205.250.8-10.42.0.42-843-43717-6           | 18-11-2016  | 15634682   | Bargrave | 619         | France    | Male   | 42  | 2      | 0         | 1             | 1         |

## VIEW PREDICTION OF MONEY LAUNDERING TYPE

### 6. CONCLUSION AND FUTUREWORK

We suggest a nomenclature for AML in banks that is based on two primary tasks: (i) client risk profiling and (ii) reporting suspicious behavior. This nomenclature is inspired by the FATF's guidelines. While the latter raises alarms on clients, accounts, or transactions (e.g., for use in transaction monitoring), the former assigns generic risk scores to customers (e.g., for use in KYC activities). Our analysis shows that diagnostics—that is, attempts to identify and elucidate risk factors—are what define the client risk profiling literature. In contrast, non-disclosed attributes and manually created risk indices are hallmarks of the literature on suspicious behavior flagging.

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