
Flighting Money Laundering With Statistics And Machine Learning

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ABSTRACT

Money laundering is a profound global problem. Nonetheless, there is little scientific literature on statistical and machine learning methods for anti-money laundering. In this paper, we focus on anti-money laundering in banks and provide an introduction and review of the literature. We propose a unifying terminology with two central elements: (i) client risk profiling and (ii) suspicious behaviour flagging. We find that client risk profiling is characterized by diagnostics, i.e., efforts to find and explain risk factors. On the other hand, suspicious behaviour flagging is characterized by non-disclosed features and hand-crafted risk indices. Finally, we discuss directions for future research. One major challenge is the need for more public data sets. This may potentially be addressed by synthetic data generation. Other possible research directions include semi-supervised and deep learning, interpretability, and fairness of the results.

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 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.

2 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.

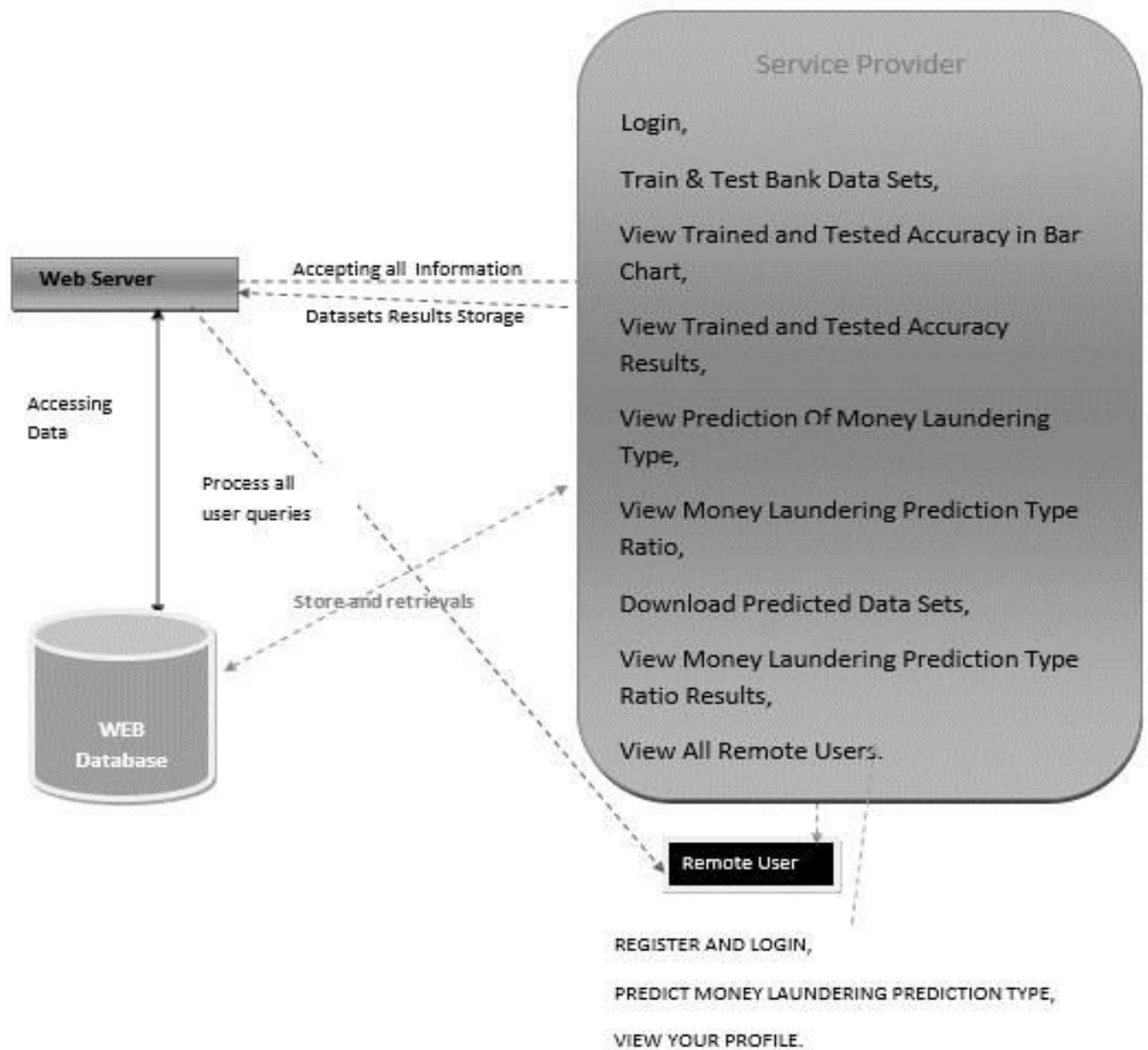


Fig1: proposed Model

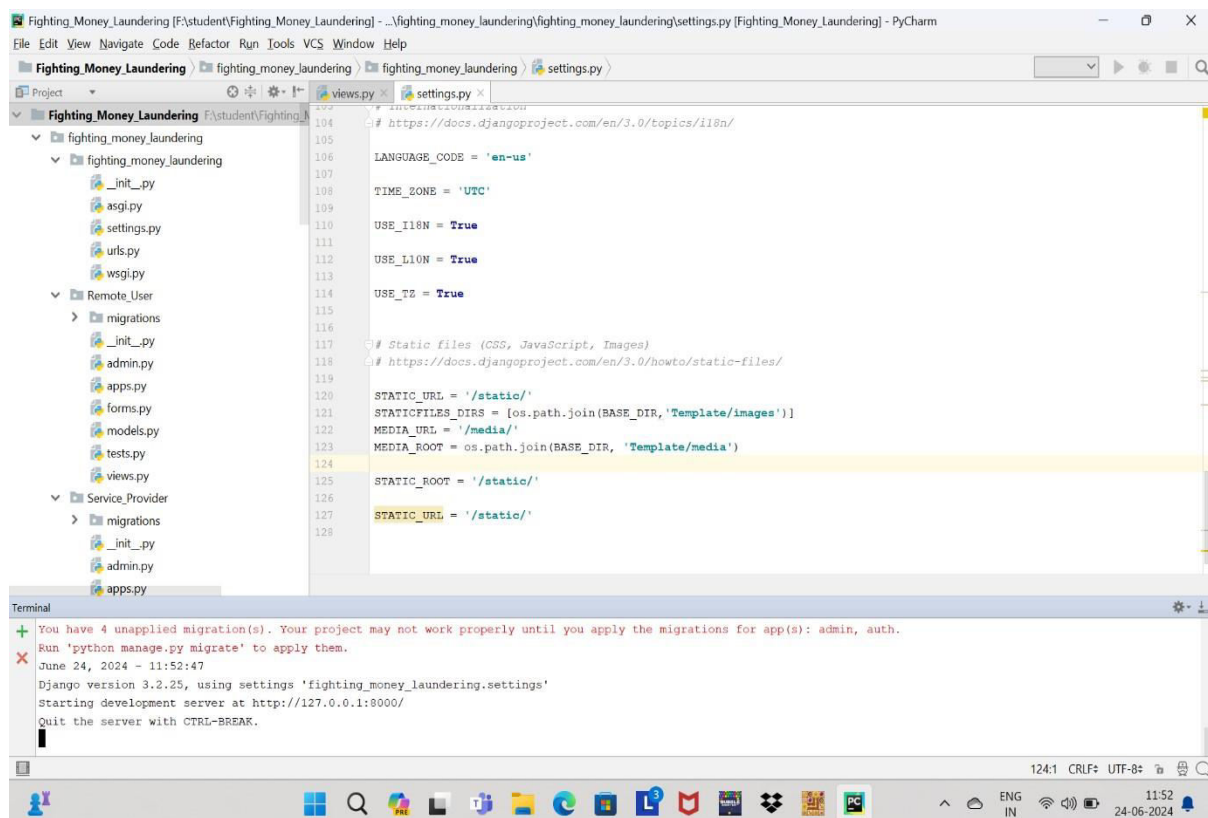
RANDOM FOREST ALGORITHM:

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.

RESULTS AND DISCUSSION



```

104 # https://docs.djangoproject.com/en/3.0/topics/i18n/
105
106 LANGUAGE_CODE = 'en-us'
107
108 TIME_ZONE = 'UTC'
109
110 USE_I18N = True
111
112 USE_L10N = True
113
114 USE_TZ = True
115
116
117 # Static files (CSS, JavaScript, Images)
118 # https://docs.djangoproject.com/en/3.0/howto/static-files/
119
120 STATIC_URL = '/static/'
121 STATICFILES_DIRS = [os.path.join(BASE_DIR, 'Template/images')]
122 MEDIA_URL = '/media/'
123 MEDIA_ROOT = os.path.join(BASE_DIR, 'Template/media')
124
125 STATIC_ROOT = '/static/'
126
127 STATIC_URL = '/static/'
128

```

```

Terminal
+ You have 4 unapplied migration(s). Your project may not work properly until you apply the migrations for app(s): admin, auth.
- Run 'python manage.py migrate' to apply them.
x June 24, 2024 - 11:52:47
Django version 3.2.25, using settings 'fighting_money_laundering.settings'
Starting development server at http://127.0.0.1:8000/
Quit the server with CTRL-BREAK.

```

**Fig2: COPY THE PROTOCOL FROM THE TERMINAL
DOUBLE PASTE MICROSOFT EDGE**



Fig3: OPEN SERVICE PROVIDER



Fig4: LOGIN PAGE FOR SERVICE PROVIDER

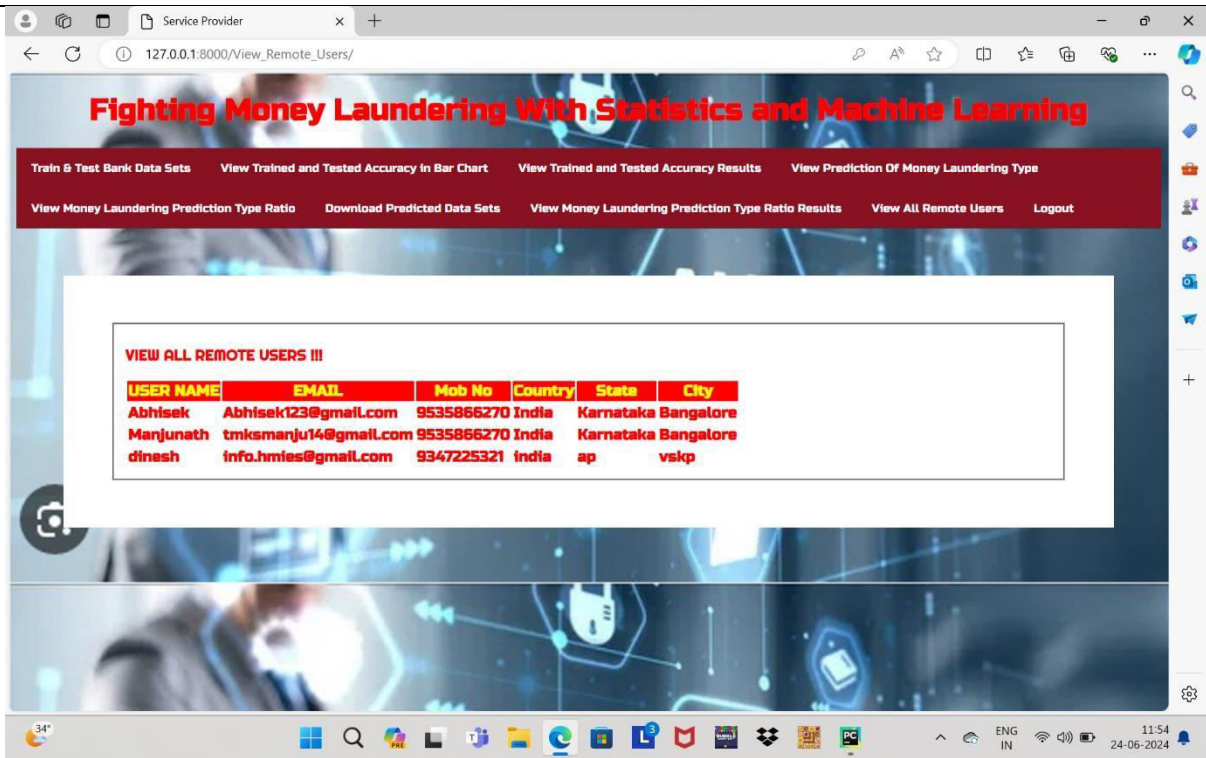
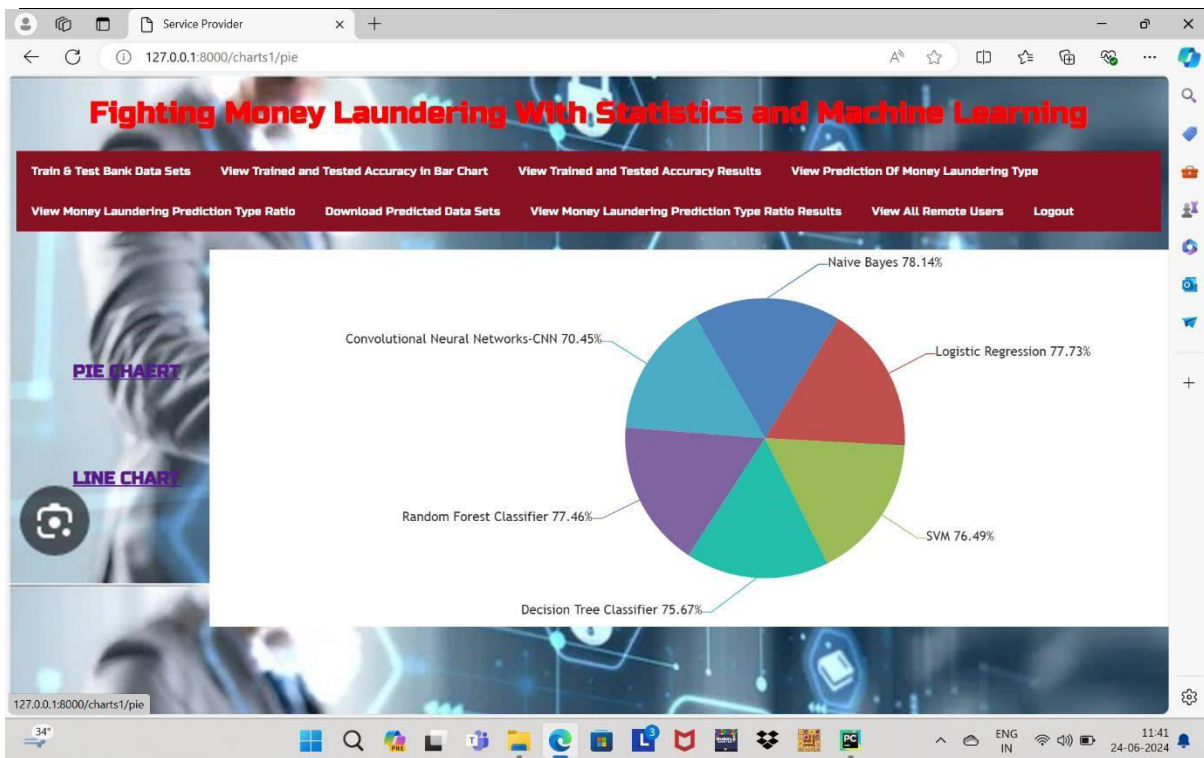


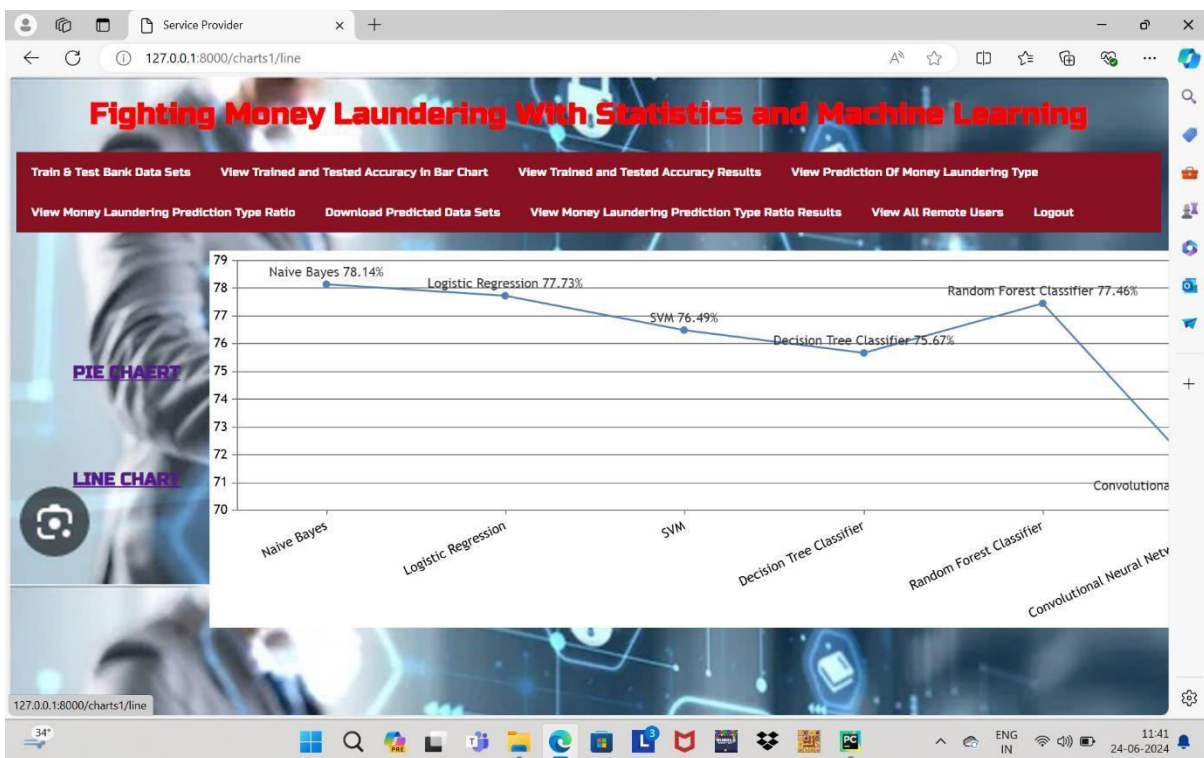
Fig5: TRAIN AND TEST BANK DATA SET



Fig6: VIEW TRAINED AND TESTED ACCURACY IN BAR CHART



VIEW TRAINED AND TESTED ACCURACY RESULT IN PIE CHART



VIEW TRAINED AND TESTED ACCURACY RESULT IN LINE CHART

View Money Laundering Prediction Type Details !!!

FId	AccOpenData	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	Goforth	616	Germany	Male	45	3	143129.41	2	0
10.42.0.211-111.206.25.159-38861-80-6	19-04-17	15811589	Metcalfe	716	Spain	Male	42	8	0	2	0
140.205.250.8-10.42.0.42-443-43717-6	18-11-2016	15634602	Hargrave	619	France	Male	42	2	0	1	1

VIEW PREDICTION OF MONEY LAUNDERING TYPE

Fighting Money Laundering With Statistics and Machine Learning

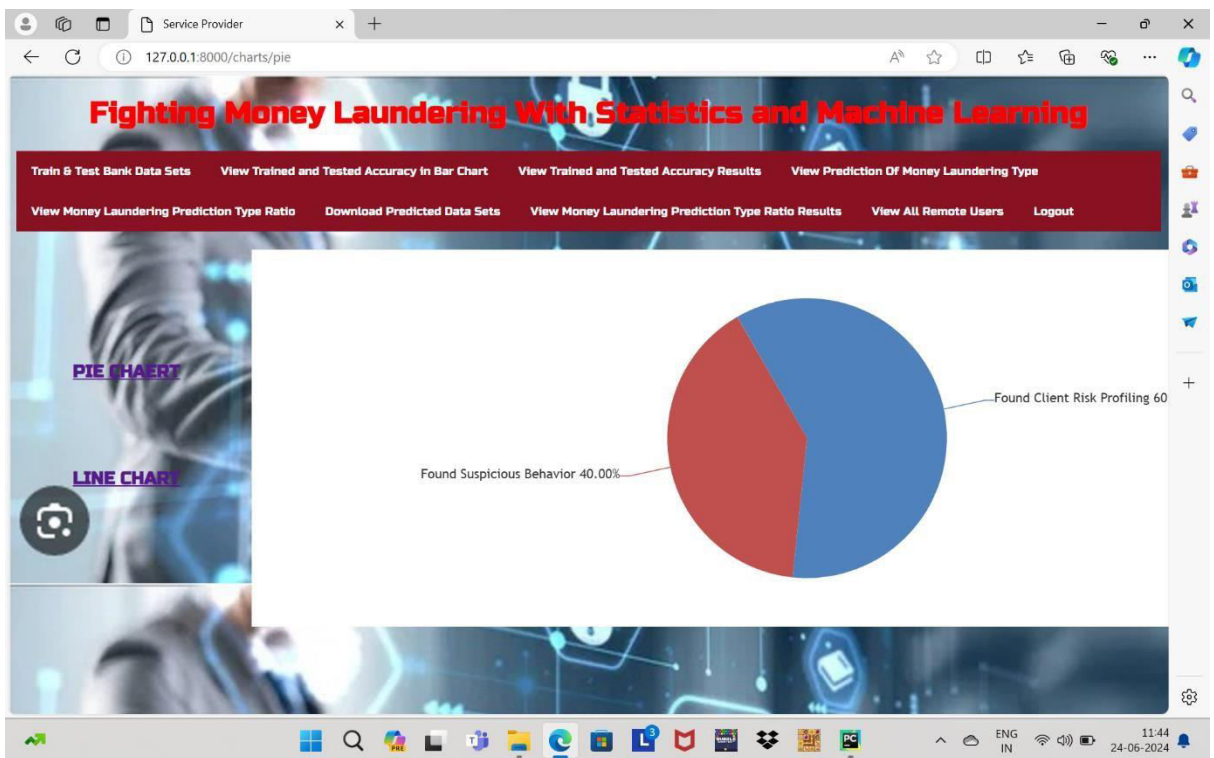
View Money Laundering Prediction Type Details

Money Laundering Prediction Type	Ratio
Found Client Risk Profiling	60.0
Found Suspicious Behavior	40.0

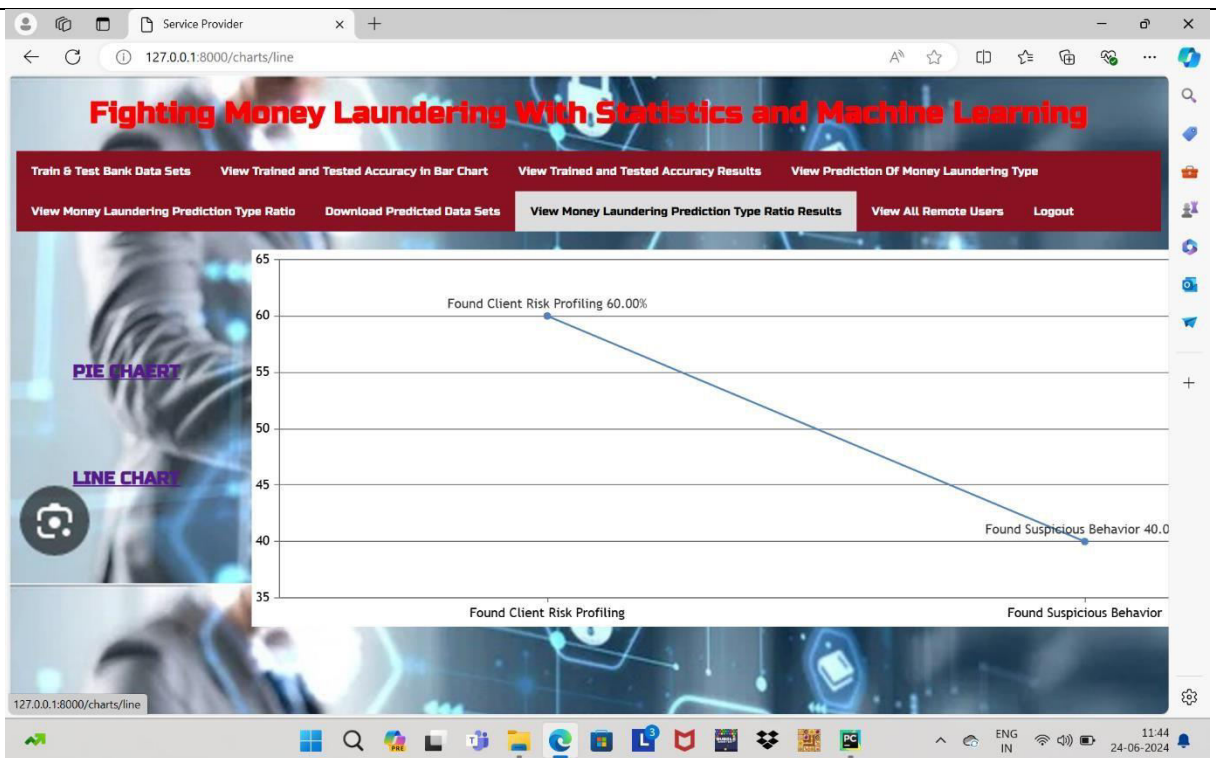
VIEW MONER LAUNDERING PREDICTION TYPE RATIO

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1																			
2	10.42.0.15	25-11-16	15656148	Obinna	376	Germany	Female	29	4	115046.744	1	0	119346.88	Found Suspicious Behavior					
3	172.217.1	30-11-16	15632264	Kay	476	France	Female	34	10	0	2	0	26260.98	Found Client Risk Profiling					
4	10.42.0.21	03-12-16	15643966	Goforth	616	Germany	Male	45	3	143129.412	0	1	64327.26	Found Client Risk Profiling					
5	10.42.0.21	19-04-17	15811589	Metcalfe	716	Spain	Male	42	8	0	2	0	180800.42	Found Client Risk Profiling					
6	140.205.2	18-11-201	15634602	Hargrave	619	France	Male	42	2	0	1	1	101348.88	Found Suspicious Behavior					
7	140.205.2	18-11-201	15634602	Hargrave	619	France	Female	42	2	0	1	1	101348.88	Found Client Risk Profiling					

DOWNLOAD PREDICTED DATA SET



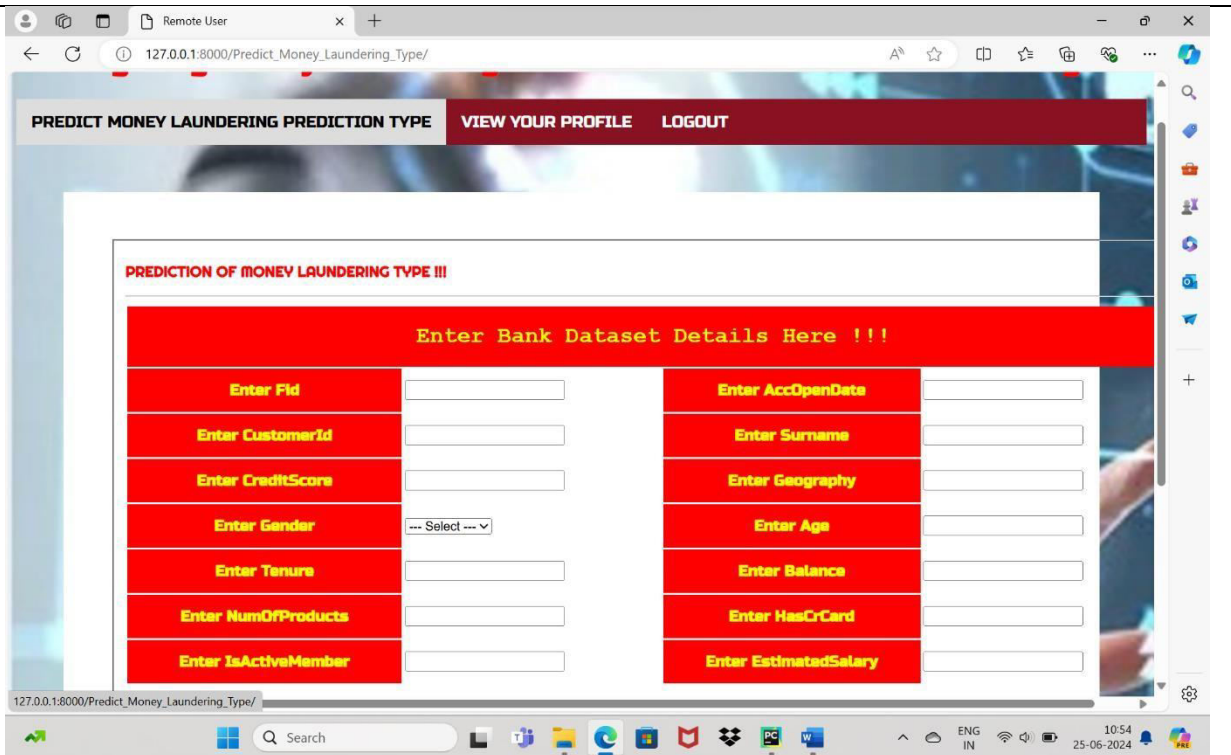
VIEW MONEY LAUNDERING PREDICTION TYPE RATIO RESULT IN PIE CHART



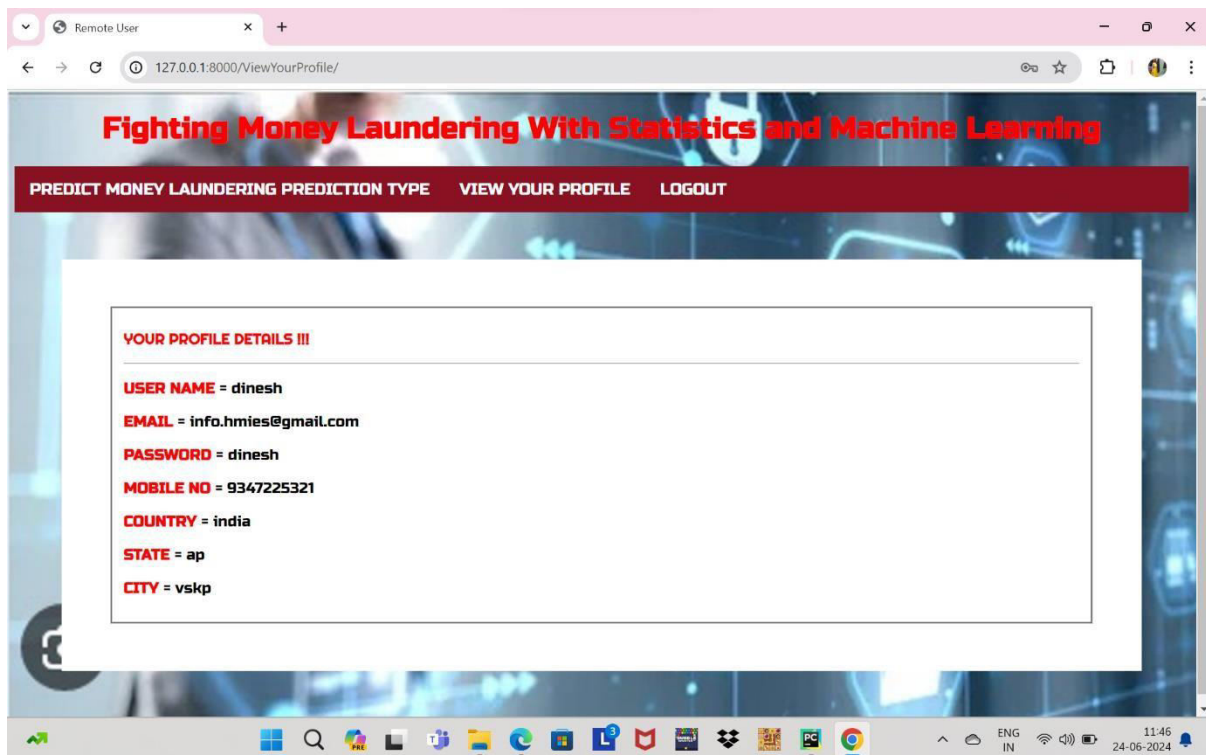
VIEW MONEY LAUNDERING PREDICTION TYPE RATIO RESULT IN LINE CHART

USER NAME	EMAIL	Mob No	Country	State	City
Abhisek	Abhisek123@gmail.com	9535866270	India	Karnataka	Bangalore
Manjunath	tmksmanju14@gmail.com	9535866270	India	Karnataka	Bangalore
dinesh	info.hmies@gmail.com	9347225321	India	ap	vskp

VIEW ALL REMOTE USERS



PREDICT MONEY LAUNDERING PREDICTION TYPE



VIEW YOUR PROFILE

6. CONCLUSION AND FUTURE WORK

Inspired by FATF's recommendations, we propose a terminology for AML in banks structured around two central tasks: (i) client risk profiling and (ii) suspicious behavior flagging. The former assigns general risk scores to clients (e.g., for use in KYC operations) while the latter raises alarms on clients, accounts, or transactions (e.g., for use in transaction monitoring). Our review reveals that the literature on client risk profiling is characterized by diagnostics, i.e., efforts to find and explain risk factors. The literature on suspicious behavior flagging, on the other hand, is characterized by non-disclosed features and hand-crafted risk indices.

7. REFERENCES

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