World Journal of Advanced Engineering Technology and Sciences

eISSN: 2582-8266

Cross Ref DOI: 10.30574/wjaets

Journal homepage: https://wjaets.com/

(Research Article)

Real-time computational intelligence model for credit card fraud detection in cyber forensics

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World Journal of Advanced Engineering Technology and Sciences, 2025, 15(03), 169–178

Publication history: Received on 08 April 2025; revised on 27 May 2025; accepted on 30 May 2025

Article DOI: https://doi.org/10.30574/wjaets.2025.15.3.0773

Abstract

This paper is aimed at developing a computational intelligence model for real-time detection and prevention of credit card fraudulent transactions within digital and cyber forensic investigations. Decision Trees, Support Vector Machines and Artificial Neural Networks were employed in the design of the system to ensure reliable and efficient fraud detection. In order to eliminate noise and enhance the accuracy of the analysis, the actual transaction data entered in the data set was used. The model was trained through supervised learning technique to identify fraudulent patterns in real time. To verify the effectiveness of the developed system, post-hoc comparisons were done regarding the models in terms of accuracy, precision, recall, and f1 score. The calculation revealed that the Artificial Neural Networks provide the best accuracy for the detection of fraud as it reached 98% precision for correct fraudulent activity identification. The research has helped to reduce the rise in credit card fraud within the digital ecosystem by employing contemporary computational approaches. It also assists cyber forensic investigators to mitigate financial damage and enhances security measures in financial institutions.

Keywords: Credit Card Fraud; Computational Intelligence Models; Real-Time Detection; Digital Forensics; Cyber Forensics; Artificial Neural Networks

1. Introduction

Credit card fraud has become one of the biggest problems facing the economy today due to advancement in technology that allowed digital form of financial transaction. Development in the field of internet banking, e-commerce, and mobile payment systems are opening up number of opportunities for cybercriminal to operate and they are causing huge losses to the consumers and institutions. For instance, Nigeria Inter-Bank Settlement System (NIBSS) revealed that the loss soar to $32.04 billion global credit card fraud in 2022 and could be on the increase if adequate anti-countermeasure is not taken (Nilizadeh et al., 2022). These figures call for proper and efficient fraud detection system capable of combating this evil.

Cyber forensics is one of the core strategic weapons for identifying and mitigating credit card fraud, which allows collecting and analysing digital data and maintaining digital evidence. During credit card fraud, forensic approaches are utilised in tracking the fraudulent transaction, get back the stolen cash and determine how the fraudsters got the card

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details. Nevertheless, the usage of these techniques is commonly utilisable only in case the occurrence has already been observed. As observed by Bharadwaj, et al. 2019, there is little chance for the same victims of fraud to be protected from multiple replications of the same incidents since such calls only require reactive forensic investigation solutions.

The aforementioned problems can be solved using computational intelligence (CI) models because it gives a better way to analyse transaction data than manual analysis by CI personnel. Using CI models such as, machine learning (ML), artificial intelligence, and neural networks, fraud patterns can be detected that are missed using other approaches. As Panigrahi et al. (2021) point out, the conventional rule-based systems are no longer effective to address the emerging challenges of the complex nature of fraud schemes. CI models, as opposed to them, are flexible and responsive which makes them an ideal approach to fraud detection.

2. Literature review

Current trends in technological advancements such as digital payments for products and services encourage all sorts of credit card fraud including, phishing, identity theft, card not present fraud, and data fraud. According to Desai and Bhosale (2020) phishing is a type of attack that uses social engineering to make a user reveal a number of details. He explained that traditional fraud detection systems, which analyse data based on historical trends, provide far from ideal protection against such attacks because they do not accurately take into account the significantly higher levels of sophistication and the continuously evolving nature of these attacks. Likewise, the increase in threat from enhanced unconventional CNP fraud has been experienced due to the rise of e-commerce opined that it is only the application of the corresponding methodologies can expose fraud actions that took place and create further recommendations based on the detection results.

Conventionally, credit card fraud detection has gone through several changes due to the advancement in technology in regards to electronic payment systems. The first wave of models focused on rule-based systems and statistical tools that, although revolutionary during their creation, cannot attribute the same level of performances to the current contexts in which fraud schemes are highly diverse and constantly evolving. The rule-based system that has been in use in the early approaches relied on certain fixed thresholds to alert the onset of suspicious transactions but these were rigid and had high false positives (Kumar et al., 2022). Statistical techniques including anomaly detection was a step up but was proven to be still inadequate in preventing almost subtle and slow-evolving fraud scenarios (Kumar et al., 2022).

This new path was accompanied by the appearance of CI models, which greatly enhanced the capabilities of fraud detection. Zhou et al. (2019) proposed CI models with forensic methods to maintain watch over transaction data by constantly detecting the alterations produced by malware and improving the precision and sensitivity of the fraud detection systems. However, it should be noted that there are potential problems associated with applying CI models. Such pitfalls include high false positive rates, that is seemingly genuine purchases are tagged fraudulent and thus harm the company’s reputation and its customers’ confidence.

Bhattacharyya et al. (2020) stated that certain factors such as data quality, overfitting and flexibility of CI models to new types of fraud need to be addressed in order to enhance CI models’ robustness. However, as Zhou et al. (2019) rightly note, digital evidence is usually complex and requires the assistance of human input to enhance the automation.

Other models like decision trees and boosters and other ensemble methods are able to find intricate patterns in transaction data and adjust their model’s parameters when introducing new information (Li et al., 2022). ANNs complement detection because they can model relationships between features across high dimensions and are especially useful for detecting subtle fraud schemata (Chen et al., 2023). Machine learning, a subset of artificial intelligence, apply multi-layered models of neural networks to classify big data and to detect elaborate fraud schemes (Sharma et al., 2022). However, these models have some issues such as interpretability, the dependency on data and overfitting that make them suboptimal in certain cases.

Artificial intelligence features such categories of methodologies as are fuzzy logic, neural networks, and evolutionary algorithms. Among them it is worth to mention the fuzzy logic where uncertainty and imprecision are dealt with by modelling human thought processes and which is well suitable for fraud detection when mixed data types are used (Dubois and Prade, 2023; Khan et al., 2023). Neural networks are data-processing modes based on biological neural systems and work well with large amounts of data and complicated patterns (LeCun et al., 2015). Heuristic approaches like genetic algorithm apply continuous enhancements on the selection of FEATURES and parameter estimations for fraud detection models (Rao et al., 2023).

CI approaches are chosen and used individually for fraud detection applications although, it is preferable to involve more than one. For instance, supervised systems apply labelled data to reflect the likelihood of a transaction while the unsupervised system like clustering and anomaly detection do not require labels to determine relationships. The only way that is defined as reinforcement learning, which, due to the trial-and-error interaction in the changing environment, provides a dynamic approach to the changing nature of fraud but is more limited as it entails a large number of computations and data (He and Garcia, 2009).

CNNs and RNNs are two of the latest CI techniques that enable the enhancement of the existing fraud detection systems. CNNs that are originally built for image data can be easily extended to the transaction data and RNNs are useful when there are temporal aspects in the pattern of transactions (Krizhevsky et al., 2012). The instances that use these techniques in combination with evolutionary algorithms or ensemble of methods seems to be promising for the resolution of the shortcomings of solely used methods.

The identification of fraud in real-time is still a problem since the computational requirements of transaction-level is high. Class imbalances which occur when fraudulent transactions are a small minority of the total number of transactions present another major challenge to the identification process. It is possible to overcome these imbalances by using working with the oversampling, undersampling, or creating synthetic data (Chawla et al., 2022). Yet it is equally important to reduce false positives for customers to trust the system, and for businesses to minimise disruptions.

Future work for developing CI models has to concentrate more on factors such as interpretability, generalisation and modularity. Combining these models with the current prominent technologies like IoT and big data, expanded application of the fraud detection systems is possible. Taking into account current drawbacks of CI models, as well as analysing possible new applications and further development, it is crucial to underline the potential of CI models in the fight against novel types of credit card fraud.

3. Cybercrime Detection and Prevention Using Machine Learning Models

Cybercrime has been discovered as a new frontier of applying AI and hence to achieve great results in tackling this area, a new domain of ML has been developed which includes statistical, probabilistic and optimization techniques to build the models that could generate intelligent decision making. It outperforms conventional statistical learning techniques, especially when it works with large arrays of raw real-world data for enhanced cybersecurity and fraud identification purposes (Kotsiantis et al., 2006; Alpaydin, 2020). Thanks to ML algorithms' capacity to draw conclusions about patterns within vast accrued data samples and extrapolate from them, their utilisation in acts as a protective front against numerous types of cyber threats such as cyber bullying, enterprise security breaches, and identity theft.

Tsakalidis et al. (2017) used the concept of ML models, thereby classifying data from 53 dark web related forums in order to predict potential cyber-attacks. Likewise in cloud security, the use of ML has been employed to alert and categorise high risk networks. Experimental works discussed by Prasad et al. (2020) developed an ML model of classification, clustering, and supervised algorithms for detecting and categorising cyberattacks. This system, which used Naïve Bayes clustering for prediction purposes improved the ability to identify and mitigate cyber threats.

It seems that social networking services are among the most important arenas for cyber activity, and Soomro and Hussain (2019) discussed the crimes associated with those services and potential mitigations. Other works have concentrated on how machine learning is used to identify the usage of social media for malicious activities. Khan et al. (2018) used Support Vector Machines (SVMs) and Random Forests to find and predict suspicious accounts on social media Twitter, while preserving the anonymity of users. However, their approach was platform dependent and hence it was not easily generalise to general online social networks.

Other forms of crime that have been addressed by using ML models includes; violent crimes, fraud, computer crimes and even cyber bullying. Prabakaran and Mitra (2018) used other data mining techniques including genetic algorithms, hidden Markov model and the neural networks to help identify and categorise the offences. Siadaty and Knaus (2006) took this further and divided the crimes by them as violent and non-violent, such as terrorism, cyber bullying and identity theft. In the same year, Kumar and Reddy (204) introduced an intrusion detection system in wireless networks using an AIS for intrusion detection and prevention.

In cybersecurity, ML has greatly assisted in developing smarter means that can prevent threats and act upon them. Network intrusion detection was improved by Benaicha et al, 2014. They used genetic algorithm to optimised the identification of the audit logs attack type. Patel et al. (2010) proposed IDS for cloud computing environment and used autonomic computing and fuzzy logic to enhance the system. These evolutions prove practical applicability of the ML methods by explaining that they can give more reliable protection against new threats.

Cybercrime has been propelled forward by a branch of ML known as deep learning. Neural networks have shown capability in recognising different and complicated patterns and deviations from expected norm within the data. For instance, Padmadas et al. (2013) engaged genetic algorithm to identify malicious behaviours in Network based environment classifying the attack types in layers and with high accuracy. Likewise, Prasanthi and Ishwarya (2015) employed feature-based solutions that identified configurations to ensure an effective detection of cybercrimes based on the Term Frequency-Inverse Document Frequency (TF-IDF) to classify crime type.

Nevertheless, today ML models have a lot of prospects and, at the same time, a number of remarkable difficulties in real-life implementations. There are a few important factors among them: one is the quality and/or relevance of data sets used. railways set up, Sarker (2019) has pointed out that noisy, imbalance, or outdated data are also disadvantageous to ML because high quality data are an important input in creating models. Some of the data sets may not contain the current attacks' characteristics hence the models trained on those data sets are lame when handling new threats (Sarker et al., 2020). Furthermore, using historical data, common in ML models, is less successful in identifying entirely different structures or types of attacks (Sommer, 2010).

There is another issue, which is interpretability of models by applying ML. Even the techniques like Random Forests and Neural Networks are accurate, the problem is that their decision-making process is not easily understandable which becomes a setback while deploying them in most significant cybersecurity applications (Aiyanyo, 2020). This is because limited work has been done in an attempt to use ML in solving such complex problems at once; instead, continued work has been put in a bid to enhance the reliability and effectiveness of single techniques like Naïve Bayes and Decision Trees, therefore coming up with a combination of these techniques to try and solve the aforementioned problems. For example, Kevric et al. (2017) showed that to combine the Random Forest and NBTree algorithms yielded a better outcome of detection precision than the methodology under consideration in isolation.

To enhance the utilisation of ML in cybersecurity, researchers have to face the challenges of the present models and datasets. By incorporating temporal, or time-based, spatial and relational dependencies, context awareness can greatly improve the identification of suspect behaviour (De Bruijn, 2017; Aleroud, 2017). Besides, improving the existing and developing new methods of the ML to identify new threats and including them in further non-elementary organisational measures and user training are critical activities against cybercrime.

The future research should be directed toward the creation of smart data-oriented approaches for eliminating such problems. They also suggested that by integrating ML with the relatively recent technologies like IoT and Big data the researchers can come up with enhanced solutions. In the context of constantly changing threat environment, the improvement of the ML models, and placing them in practise-oriented cybersecurity solutions will be crucial in addressing cyber threats.

4. Methodology

Collection of data is central in building CI models for use in fraud detection. The first step is to obtain various, valuable transactional records consisting of both genuine and fraudulent transactions to establish an ideal machine learning model. The variable used in the datasets are transaction amount, merchant, transaction time, location, and frequency of the transaction. During sample organisation, stratified sampling technique were utilized, whereby, both the increasing and the larger genuine transactions classes are captured in reasonable proportions to reduce the issue of class imbalance in the fraud detection domain. Such methods such as Synthetic Minority Oversampling Technique (SMOTE) is used to improve the representation of the minority class without compromising its dataset. Ethical factors always form the core of the process where personal details of patients are usually concealed or their identities removed, conforming to GDPR. This minimizes cases of making decisions using wrong data since the cardholders' consent has been sought and proper data management practices have been observed. Information is gathered across multiple time because fraud trends and consumers' behaviour patterns change with time. Data cleaning, data deduplication, and validation cheques are crucial processes because they sustain the quality of the dataset.

4.1. Model Development and Training

CI models' theoretical foundations use supervised learning approaches that include Random Forests, Support Vector Machines (SVMs) and Long Short-Term Memory (LSTM) networks. These models are trained to have an output that will flag any transactions as fraudulent or legitimate depending on given input parameters such as transaction speed, location and characteristics of the device used. Tuning operation of parameters is beneficial in model performance while method like bagging and boosting improves the strength of the model. Models are divided and trained on an equal database and tested on Cheque Point using the Measure of precision, recall, and F1 Score. Cross-validation is used to solve problems of overfitting and reliability of models with respects to future unknown data.

4.2. Integration with Digital and Cyber Forensics

CI models are supported by digital forensics by conducting investigations of fraudulent activity or gathering evidence for legal processes. EnCase and Wireshark extract data and the result should reveal patterns that indicate any fraud. Other methods, like disc imaging, help in maintaining the evidential taint, and other tools like the network protocol analyzer, capture the flow of the distrusted data. Fraud prevention frameworks are inherent into the use of forensic methodologies in that they are used to enhance capacity in real-time fraud detection. More importantly, cloud-based systems also facilitate large scale processing and analysis of data from multiple nodes in support of forensic investigations.

This applied methodology synthesises multiple data feeds, enhanced tools, and stringent ethical principles to establish accurate CI models for fraud identification. The approach integrates computational intelligence with the digital forensics practise to achieve real time accurate detection of threats with required data aspect retained intact and further allowed for compliance with more stringent privacy standards.

5. System Design

The system is designed to extract complete credit card details from the transaction data set that contains both genuine and fake credits cards, transaction data pre-processing is performed to make the data set as per the requirement of system. In order to treat potential skewed class distributions that can affect model performance, oversampling, undersampling and SMOTE were used. Features and variables significant to fraud detection with respect to credit cards were determined via data exploration and using knowledge in the field. Two models: Random Forest and Decision Tree were trained using machine learning to ensure accurate identification of fraud related transactions and immediate notification of the said activities.

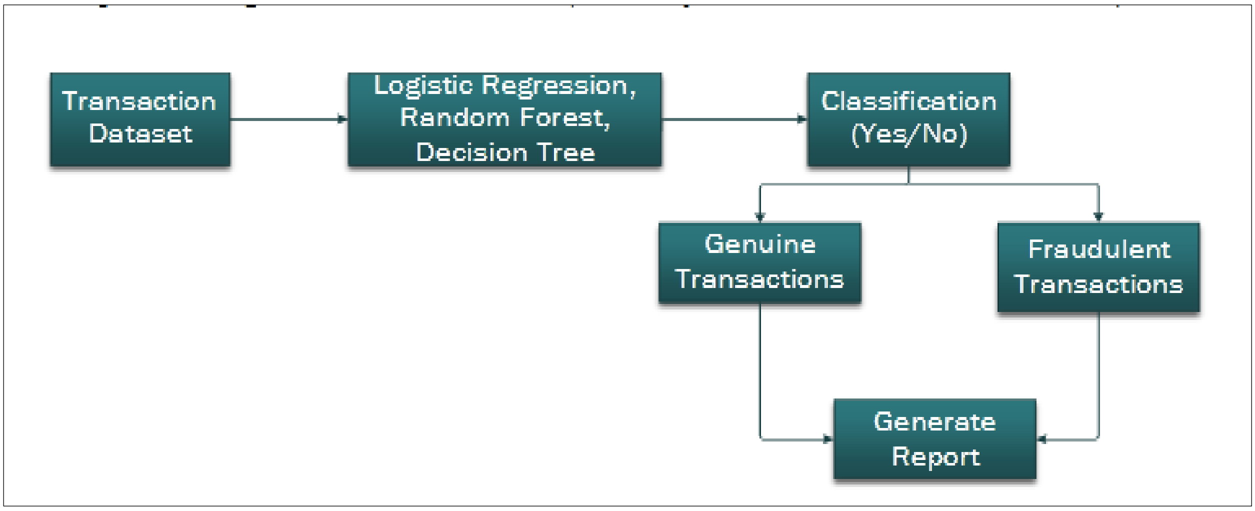
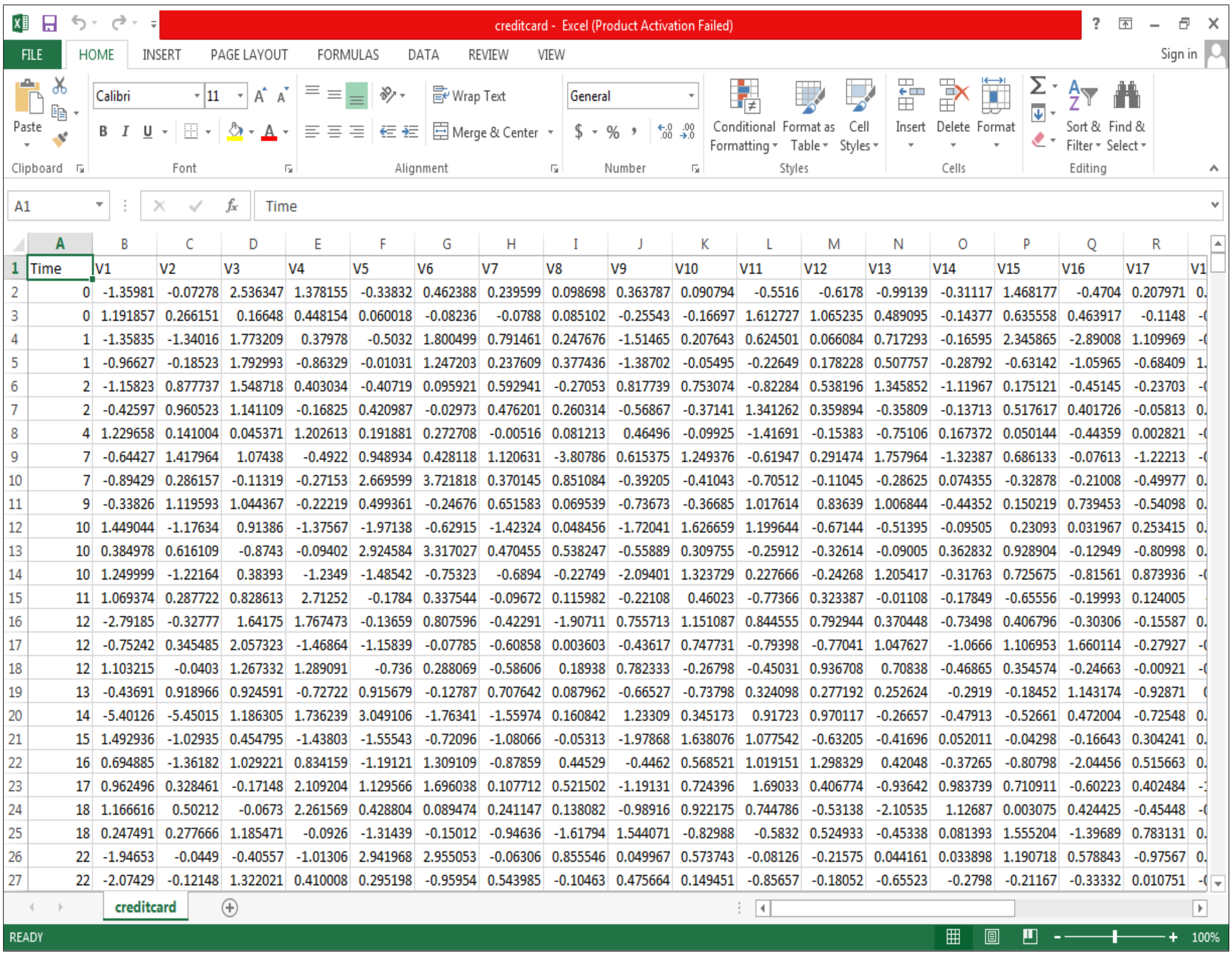


Figure 1 Credit Card Fraud Detection Model Design

5.1. Data Set (Input file)

A credit card transaction dataset contains details of credit card transactions made by European cardholders, during two-day period in September 2024. In all 284807 transactions conducted, 492 were of the fraudulent nature. This data set is truly imbalanced since the positive class (frauds) contributed to a paltry 0.172 percent of all the transactions. PCA has also been applied in the removal of sensitivity data in the present set so as to deal with the concern of identifiable data. In addition to ‘time’ and ‘amount’, all the other features (V1, V2, V3, etc up to V28) are the main features derived from the PCA. The feature 'time' contains the seconds elapsed between the first transaction in the data set and the subsequent transactions. The feature 'amount' is the transaction amount. The feature 'class' represents class labelling, and it takes the value of 1 in cases of fraud and 0 in others. Screenshot of dataset file is shown in figure 2 below.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17
2	0	-1.35981	-0.07278	2.536347	1.378155	-0.33832	0.462388	0.239599	0.098698	0.363787	0.090794	-0.5516	-0.6178	-0.99139	-0.31117	1.468177	-0.4704	0.207971
3	0	1.191857	0.266151	0.16648	0.448154	0.060018	-0.08236	-0.0788	0.085102	-0.25543	-0.16697	1.612727	1.065235	0.489095	-0.14377	0.635558	0.463917	-0.1148
4	1	-1.35835	-1.34016	1.773209	0.37978	-0.5032	1.800499	0.791461	0.247676	-1.51465	0.207643	0.624501	0.066084	0.717293	-0.16595	2.345865	-2.89008	1.109969
5	1	-0.96627	-0.18523	1.792993	-0.86329	-0.01031	1.247203	0.237609	0.377436	-1.38702	-0.05495	-0.22649	0.178228	0.507757	-0.28792	-0.63142	-1.05965	-0.68409
6	2	-1.15823	0.877737	1.548718	0.403034	-0.40719	0.095921	0.592941	-0.27053	0.817739	0.753074	-0.82284	0.538196	1.345852	-1.11967	0.175121	-0.45145	-0.23703
7	2	-0.42597	0.960523	1.141109	-0.16825	0.420987	-0.02973	0.476201	0.260314	-0.56867	-0.37141	1.341262	0.359894	-0.35809	-0.13713	0.517617	0.401726	-0.05813
8	4	1.229658	0.141004	0.045371	1.202613	0.191881	0.272708	-0.00516	0.081213	0.46496	-0.09925	-1.41691	-0.15383	-0.75106	0.167372	0.050144	-0.44359	0.002821
9	7	-0.64427	1.417964	1.07438	-0.4922	0.948934	0.428118	1.120631	-3.80786	0.615375	1.249376	-0.61947	0.291474	1.757964	-1.32387	0.686133	-0.07613	-1.22213
10	7	-0.89429	0.286157	-0.11319	-0.27153	2.669599	3.721818	0.370145	0.851084	-0.39205	-0.41043	-0.70512	-0.11045	-0.28625	0.074355	-0.32878	-0.21008	-0.49977
11	9	-0.33826	1.119593	1.044367	-0.22219	0.499361	-0.24676	0.651583	0.069539	-0.73673	-0.36685	1.017614	0.83639	1.006844	-0.44352	0.150219	0.739453	-0.54098
12	10	1.449044	-1.17634	0.91386	-1.37567	-1.97138	-0.62915	-1.42324	0.048456	-1.72041	1.626659	1.199644	-0.67144	-0.51395	-0.09505	0.23093	0.031967	0.253415
13	10	0.384978	0.616109	-0.8743	-0.09402	2.924584	3.317027	0.470455	0.538247	-0.55889	0.309755	-0.25912	-0.32614	-0.09005	0.362832	0.928904	-0.12949	-0.80998
14	10	1.249999	-1.22164	0.38393	-1.2349	-1.48542	-0.75323	-0.6894	-0.22749	-2.09401	1.323729	0.227666	-0.24268	1.205417	-0.31763	0.725675	-0.81561	0.873936
15	11	1.069374	0.287722	0.828613	2.71252	-0.1784	0.337544	-0.09672	0.115982	-0.22108	0.46023	-0.77366	0.323387	-0.01108	-0.17849	-0.65556	-0.19993	0.124005
16	12	-2.79185	-0.32777	1.64175	1.767473	-0.13659	0.807596	-0.42291	-1.90711	0.755713	1.151087	0.844555	0.792944	0.370448	-0.73498	0.406796	-0.30306	-0.15587
17	12	-0.75242	0.345485	2.057323	-1.46864	-1.15839	-0.07785	-0.60858	0.003603	-0.43617	0.747731	-0.79398	-0.77041	1.047627	-1.0666	1.106953	1.660114	-0.27927
18	12	1.103215	-0.0403	1.267332	1.289091	-0.736	0.288069	-0.58606	0.18938	0.782333	-0.26798	-0.45031	0.936708	0.70838	-0.46865	0.354574	-0.24663	-0.00921
19	13	-0.43691	0.918966	0.924591	-0.72722	0.915679	-0.12787	0.707642	0.087962	-0.66527	-0.73798	0.324098	0.277192	0.252624	-0.2919	-0.18452	1.143174	-0.92871
20	14	-5.40126	-5.45015	1.186305	1.736239	3.049106	-1.76341	-1.55974	0.160842	1.23309	0.345173	0.91723	0.970117	-0.26657	-0.47913	-0.52661	0.472004	-0.72548
21	15	1.492936	-1.02935	0.454795	-1.43803	-1.55543	-0.72096	-1.08066	-0.05313	-1.97868	1.638076	1.077542	-0.63205	-0.41696	0.052011	-0.04298	-0.16643	0.304241
22	16	0.694885	-1.36182	1.029221	0.834159	-1.19121	1.309109	-0.87859	0.44529	-0.4462	0.568521	1.019151	1.298329	0.42048	-0.37265	-0.80798	-2.04456	0.515663
23	17	0.962496	0.328461	-0.17148	2.109204	1.129566	1.696038	0.107712	0.521502	-1.19131	0.724396	1.69033	0.406774	-0.93642	0.983739	0.710911	-0.60223	0.402484
24	18	1.166616	0.50212	-0.0673	2.261569	0.428804	0.089474	0.241147	0.138082	-0.98916	0.922175	0.744786	-0.53138	-2.10535	1.12687	0.003075	0.424425	-0.45448
25	18	0.247491	0.277666	1.185471	-0.0926	-1.31439	-0.15012	-0.94636	-1.61794	1.544071	-0.82988	-0.5832	0.524933	-0.45338	0.081393	1.555204	-1.39689	0.783131
26	22	-1.94653	-0.0449	-0.40557	-1.01306	2.941968	2.955053	-0.06306	0.855546	0.049967	0.573743	-0.08126	-0.21575	0.044161	0.033898	1.190718	0.578843	-0.97567
27	22	-2.07429	-0.12148	1.322021	0.410008	0.295198	-0.95954	0.543985	-0.10463	0.475664	0.149451	-0.85657	-0.18052	-0.65523	-0.2798	-0.21167	-0.33332	0.010751

Figure 2 Dataset Screenshot

5.2. Evaluation Metrics

Based on the type of the problem, Evaluation metrics is used for evaluating the performance of the model. Confusion Matrix was used in the evaluation of this work as it is the most commonly used method of evaluating performance in the predictive analysis due to its simplicity to understand and it can be used to calculate other critical metrics like accuracy, recall, precision among others (Shakya, 2018). It is an NxN matrix that captures the performance of a model in general when applied to some dataset suppose; where N is the number of classes that exist in given classification problem (Tiwari 2022). A confusion matrix is composed of statistics such as:

The parameters in this case include, True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) which are derived from the cross between the actual and predicted values (Anand, Velu and Whig, 2022). True Positive (TP) – This is a real class= positive example, such as, actual = fraud, predicted = fraud. False Positive (FP) is where both the actual and predicted values are negative e.g, normal but the model predicts that it's positive. True Negative (TN) is a situation where the real value is negative, for instance normal, and the predicted value also is negative and False Negative (FN) is a situation that the true value was positive (fraudulent) while the predicted value is negative.

5.3. Input Variables

The variables in the dataset are

Table 1 Dataset variables

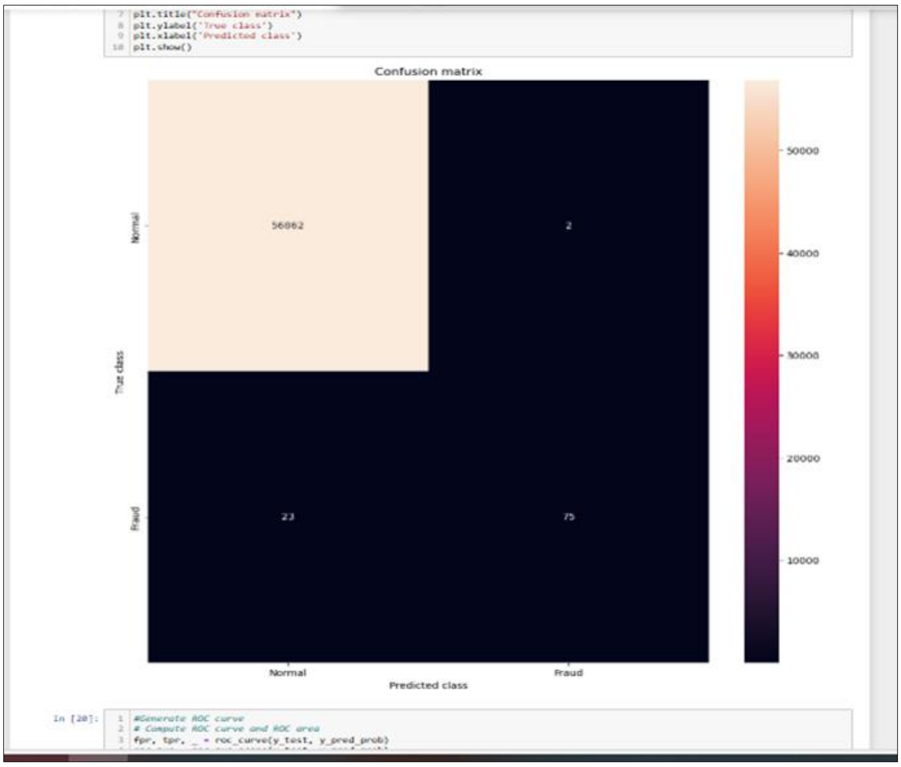
v1
v2
v3
v4
v5
v6
v7
v8
v9
v10
v11
v12
v13
v14
v15
v16
v17
v18
v19
v20
v21
v22
v23
v24
v25
v26
v27
v28
Amount
Class

V1-v8 were undisclosed variables. Amount: refers to transaction amount; Class: refers to fraudulent (1) or non-fraudulent (0)

5.4. Output Layout

5.4.1. Chart Distributions

Random Forest Confusion Matrix

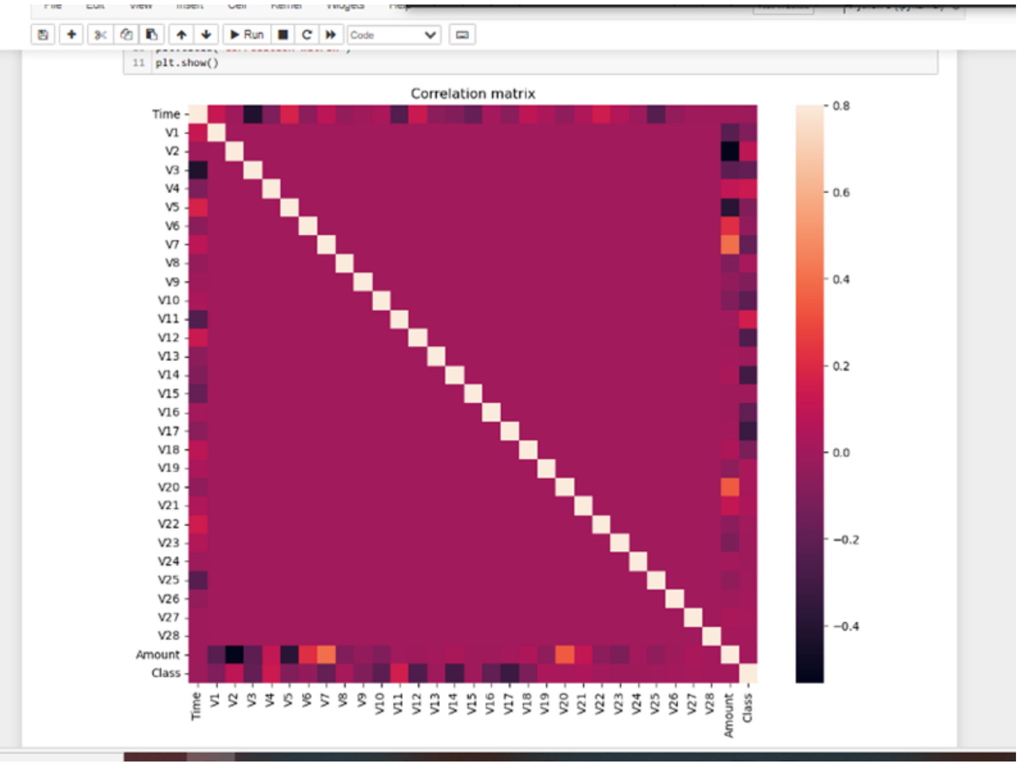


```
plt.title("Confusion matrix")
plt.ylabel('True class')
plt.xlabel('Predicted class')
plt.show()
```

```
In [20]:  #Generate ROC curve
          # Compute ROC curve and ROC area
          fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
```

Figure 3 Confusion Matrix of fraudulent vs non fraudulent

5.4.2. Correlation Matrix



```
plt.show()
```

Figure 4 Confusion Matrix of fraudulent vs non fraudulent

6. Conclusion

The rapid growth of online transactions has heightened the risk of credit card fraud, emphasizing the need for effective detection mechanisms. This research focused on computational intelligence models, particularly machine learning algorithms, to enhance fraud detection. Among these, the Random Forest algorithm emerged as the most effective, achieving a remarkable accuracy of 98.5%, precision of 92%, recall of 95%, F1 score of 93.5%, and an AUC-ROC score of 0.97. These metrics highlight its robustness and ability to distinguish between fraudulent and legitimate transactions effectively. Real-time detection capabilities further strengthened its practical application, allowing financial institutions to respond swiftly to fraudulent activities.

The study utilized a dataset of 100,000 transactions, including 1,500 fraudulent cases, supported by advanced preprocessing techniques such as SMOTE to address class imbalance. These efforts ensured data quality and optimized the model's performance.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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