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# Abstract

Internet banking and online shopping have grown significantly in today's world; therefore, the risk of fraudulent actions is studied: because of the number of fraud cases in daily transactions. Credit card fraud is becoming a higher problem for banks in recent years, resulting in financial losses on a global scale. When an unauthorised individual uses another person's credit card details to make transactions, this is referred to as credit card fraud, however, there are many cases when the credit card holder doesn’t recognise in an early stage the transaction until receives a notification from the financial institution and probably are more than one operation already. Credit card fraud is a significant and growing issue for institutions and people worldwide, this is the reason why the following project was considered. This thesis applies different techniques and models for machine learning in order to detect fraudulent transactions in an initial act. The datasets applied were obtained from different platforms: the first dataset is from Datacamp, which contains a total of 339607 rows from which 337825 are legit and 1782 are fraudulent transactions with a total of 15 features per operation, the second dataset is from Deloitte with a total of 6362620 rows, from which 6354407 are legit and 8213 are fraudulent transactions with a total of 10 features per act, the third dataset applied for this thesis is from Datagov, with a total of 9464 and 8 columns, this dataset doesn’t provide the label of fraud or legit transactions.

In the first analysis, the supervised models performed acceptably. The XGBClassifier Model performed the best with high accuracy, however, it’s important to mention that this is a model trained with label data. In the second analysis oversampling was functional as part of the approaches and the model applied is RandomForestClassifier, which did a good performance, even though just an amount of 100,000 entries were trained because takes a lot of time to perform the model, however, it achieved good accuracy. And finally, the third analysis is with a dataset that holds many limitations, the aim with this analysis is to perform a robust model in order to predict fraud transactions, neuronal networks were applied, and the score obtained is not the best, nevertheless, it provided different outcomes which are going to help for personal knowledge and future researchers.

# Introduction

Credit card fraud represents an important fact to be considered for financial institutions, because of the large amount of reports that banks receive from customers regarding unknown transactions, which could be mentioned online purchases, withdraws, or transactions to other’s accounts, etc. As it could be identified the use of technology and the internet in general is increasing dramatically. (A. Banarescho, 2015).

This is an important factor to consider because people have access to buy online anytime, anywhere. At the same time, financial institutions need to be prepared and contemplate the risk of fraudulent transactions which could be immersed in daily transactions. This requires developing an updated effective model, being able to give solutions, and mainly detecting the fraudulent transaction in an immediate stage. (A. Patcha, J. M. Park, 2007). Therefore, it will be possible to help banks and cardholders decrease the risk of large amounts of losses effectively and safely.

Considering that every second a massive number of transactions are made, banks require efficient technologies to process the information on time, as for humans wouldn't be possible to process and analyse such an amount of data in a limited time, also to investigate customer behaviour and identify possible patterns related with credit cards fraud detection. (K. Muameleci, 2022).

Credit card fraud detection is a difficult challenge that banks, and credit card issuers are attempting to solve by adopting fraud detection systems. In today's financial system, rule-based technologies are frequently used for fraud detection. However, the advancement and development of machine learning algorithms allows banks and financial organisations to recognise an unusual scenario faster for large financial data sets, as machine learning requires as many entries as possible to learn and predict with better accuracy.

Different approaches were considered in this thesis. In the first analysis, a dataset from Datacamp is employed, which are 339607 transactions, which occurred from 01/01/2019 to 31/12 /2020. The second dataset is from Deloitte, starting on 19/3/2018, and finishing in 31 days. The dataset doesn’t contain a date column, it contains a step column, which represents the hour of time. The third dataset is from DataGov, with entries from 01/03/2020 to 01/02/2021.

According to (H. Bodepudi, 2021). The three methods studied, Isolation Forest (IF), Local Outlier Factor (LOF), and One-Class SVM, to discover the highest performing unsupervised algorithms. The author chose an unsupervised technique for credit card fraud detection since the labelled data would be unavailable in the actual world. (K. Vishwakarma, 2020*)*. The author investigated the performance of supervised algorithms, K-Nearest Neighbour (KNN), Decision Tree (DT), Logistic Regression (LR), and Random Forest (RF), for credit card fraud detection, and concluded that RF had the best performance for detecting fraud in credit card fraud transactions.

(M. Ummul Safa, R. M. Ganga, 2019 and C. Navamani, M. Phil, 2018). Compared the performance of three classification methods used for credit card fraud detection: Naive Bayes, K-Nearest Neighbour, and Logistic Regression, and their results revealed that the LR approach performed better than the other two. Further research on closest neighbor algorithms for anomaly detection.

For this thesis, an extensive analysis of credit card transactions is employed to detect credit card fraud. To achieve a good performance, it is necessary to apply different models which help to detect fraudulent transactions, The models considered in the analysis are, KNeighborsClassifier, SVC, GaussianNB, DecisionTreeClassifier, RandomForestClassifier, XGBClassifier, LGBMClassifier, GradientBoostingClassifier, AdaBoostClassifier, LogisticRegression, RandomForestClassifier, OverSampling, Neuronal Networks and SMOTE. This aims to identify which machine learning model performs the best according to the dataset applied, and the approaches that are crucial for each model.

# Using big data to detect financial fraud and predict risk management for the credit card industry.

# Research Question

# The main objective of the following thesis is the detection of credit card fraud transactions in financial institutions. How effectively can different machine learning models predict credit card fraud transactions?

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# Contribution

This thesis's major contribution is to offer a better understanding of the importance for financial institutions to identify credit card fraud transactions in the early stage of the transaction, since the fact that this has become an enormous problem around the world, the project aims to identify distinct patterns connected to fraudulent transactions to aid in their identification. According to the latest surveys and studies, consumer behaviour changed dramatically after Covid 19, because of the facility and access to purchase whenever it needed it. On the other hand, this represents an essential activity for banks, since March 2020, buying patterns have shifted significantly, including how credit cards are used for online buying. Almost efficiently, scammers identified new methods of exploiting this with clever schemes and frauds, causing a significant increase in fraud cases.

Numerous nations are currently confronting a crisis of credit card fraud. It has become an important cause of concern for many countries. 459,297 cases of fraud involving credit cards have been recorded up to the year 2020. (Ian Wright. 2022). As technology advances, fraudsters now use complex schemes to acquire sensitive personal information from cards and then use that data to seize control of existing accounts or create new accounts for fraudulent identities. Most scammers use emails known as phishing to get control of people's bank accounts by obtaining confidential and private information.

# Objectives

1. Evaluate appropriate machine learning models, to recognise patterns for credit fraud detection.

2. Apply different sampling techniques to undertake the class imbalance problem for machine learning algorithms.

3. Provide different approaches based on findings to improve the early identification of fraudulent acts in financial institutions, resulting in a reduction in payment fraud losses.

# Literature Review

Introduction.

The use of credit cards is considered one of the most important actions for banking transactions, since the fact that they deliver high profits and customer loyalty, however, the decision to approve a credit card is high risk for banks, nevertheless, with the appropriate application and use of the customer information the risk can be mitigated. The growing number of new card applications and the enormous outstanding amount of credit card bills during the recent pandemic make this even more challenging for banks to identify patterns for credit card approval. At the same time because of the high use of online purchases in daily life. Banks are even more exposed to risky transactions because of the facility for customers to obtain a credit card without difficulty, which results in a significant risk for losses and monitoring of detection in fraud transactions.

The importance of efficiency and prompt answers to customers is considered crucial at the moment of a fraud report from customers; the usage of machine intelligence for automating the detection process to moderate this challenge is recommended, however, the productivity of such automation may depend on the richness of the model competence.

In-depth data analysis and preparation for the right training will determine if the model performs accurately for credit card fraud detection, and the availability of showing confidence for the machine learning which in turn can enhance the detection efficacy of fraudulent transactions.

Banks obtain a large number of credit card transactions every minute. Several of them are not complete for a variety of reasons, such as large amounts, lower amounts in the account, or too many queries on an individual's record. Manually analysing these programs is time-consuming, and errors risk, which means losses for the institutions, fortunately, with the power of machine learning, this work can be automated, and almost every commercial bank does so nowadays. In this project, are going to be used machine learning techniques to create automated credit card fraud detection, much like actual financial institutions.

To effectively ensure the effect of credit risk detection in science and technology finance, a credit risk prediction algorithm based on cloud computing is presented. To predict, the logistic regression model and increase the risk prediction capacity employing financial indicators in science and technology credit are chosen as a model of variables. (Li, Guiping. 2022)

A deep learning and machine learning model of credit prediction is built using industry data and enterprise data from tens of thousands of small and medium-sized businesses via data set division, processing, and model integration. First, using two characteristic selection strategies, multiple subsets of the dataset are evaluated using a convolutional neural network as the coarse prediction. (Zhang, Lei. He, Jie. Zhao, Zihao. 2022).

Body

Credit risk management has increased considerably during the last decades, in terms of knowledgeable papers and the availability of methods for measuring and managing credit risk (Altman and Saunders 1998).

Current trends in credit risk management advocate the use of parametric, non-parametric, and ensemble models for credit default prediction, which are suitable for analysing large sample size data and provide better ways to capture complex relationships from the data (Figini et al. 2017; Lessmann et al. 2015; Butaru et al. 2016; Alaka et al. 2017).

Millions of credit card transactions are done every second, and people are unable of analyse and process such massive amounts of data in order to analyse fraudsters' behavioural patterns. This is where credit card fraud detection utilising machine learning algorithms comes in handy. There are two sorts of credit card fraud: online and offline fraud.

However, Fragoso et al. (2018)'s typical method to prediction does not provide a single optimum model for tackling classification, a restriction in data for various probable combinations of predictors. Breiman (1996), and the availability of several modelling methodologies makes selecting the appropriate model challenging (e.g., Hastie et al. 2009; Kuhn and Jhonson 2013; Chipman et al. 2010).

The model averaging technique (Graefe 2014; Bates and Granger 1969), an approach that provides high discriminatory power and precision compared to other traditional statistical methods. (Granger and Ramanathan 1984; Hansen 2007; Nelder and Wedderburn 1972), is one way to address such a limitation.

Even though the model is an average of successful ways for handling issues, experimental implementation of model-be near to methods is difficult owing to model parametrisation. This paper tackles this issue by offering a model average approach for linearly combining a series of biased models based on correlated-variate model prediction. To avoid any criticism, the proposed model does not emphasise parametrization. (Higgs and Banner 2017).

To apply the plan, it is considered a novel methodology based on the solution of a quadratic equation compelling challenge. The proposed technique is based on the idea that the best average model is the one that minimises the covariance between the errors of the individual models (parametric models, non-parametric models, and mixed models).

The proposed model's robustness is evaluated using a variety of key performance measures, including a measure (H), the area under the receiver operating characteristic curve (AUC), the area under the convex hull (AUCH), minimum error rate (MER), and minimum cost weighted error rate (MWL. This allows it to analyse the results' predictive capabilities, discriminatory power, and stability. When compared to well-known models, the suggested model's findings show superior performance.

In theory, the findings produced from the presented notion on a financial institution's dataset may be generalised to other groups of organisations for credit risk assessment (chance of default), because practically all entities have a dataset with a class imbalance of default risk even if there is a difference in the set of explanatory variables for the different dataset.

Most classification algorithms, which can be broadly classified as machine learning and artificial intelligence systems, are frequently not used by financial institutions due to stricter regulatory Committee requirements that support the use of parametric models for a simple and clear interpretation of the results. Despite the regulatory preference for adopting the statistical framework. (Ewanchuk and Frei 2019), a growing body of evidence supports the employment of sophisticated models in credit risk assessment (Leo et al. 2019).

(Alaka 2017), gives a comprehensive assessment of tool selection for analysing bankruptcy prediction models and addresses more advanced models for credit risk calculation.

(Chakraborty and Joseph 2017) advocate the use of a machine learning model to detect financial distress using balance sheet information, and their study concludes that the machine learning model outperforms the logistic regression model, which is the preferred classical approach of financial institutions.

(Khandani et al. 2010), used state-of-the-art non-parametric machine learning models to predict consumer credit risk default by combining transaction and credit data. The research shows that machine learning techniques may increase risk prediction more than traditional statistical approaches and that any subsequent lender loss can significantly be improved.

(Albanesi and Vamossy 2019), used a deep learning strategy based on a neural network and gradient boosting for high-dimensional data to forecast customer risk default. The work outperforms logistic regression models in terms of performance and adaptability to the aggregate behaviour of default risk.

(Bacham and Zhao 2017), compared the performance of machine learning models to industry-developed algorithms such as Moody's proprietary algorithm and proposed a 2-3 percentage point improvement in machine learning model performance. Although credit-behavior-related factors boost the discriminating strength of the studied models, the approach is slightly challenging to associate with the underlying company characteristics in forecasting credit risk default.

In estimating credit risk default of small-medium firms, (Fantazzini and Figini 2009) suggested a non-parametric technique based on random survival forests. The performance comparison of the proposed model with the traditional logistic regression model reveals a weak relationship of performance between training and testing samples, implying an over-fitting problem, which is primarily due to contrasting logistic regression testing sample performance better than their proposed random survival models.

Several more research, including (Kruppa 2013; Yuan 2015, Barboza 2017; Ampountolas 2021 and Addo 2018); demonstrate that machine learning outperforms any other statistical technique for credit risk prediction.

The literature on the non-statistical model frequently argues that the discrepancy between the expectation of the averaged forecasts and truth is dependent on the bias of contributing models as well as their weights. The underlying assumption for statistical model averaging literature, however, is that there is no bias, therefore their contribution is frequently less interesting (Burnham and Anderson 2002).

Reducing bias is frequently highlighted as the major motivation for model averaging in many of the literature publications, particularly those linked to process models (Solomon et al. 2007; Gibbons et al. 2008; and Dietze 2017).

Weights are quadratic in terms rather than linear due to the nature of predictions, since knowing completely the correct approach to calculating weights is essential. (Breiman 1997) adds several advantages to the model averaging technique. Apart from the inaccuracy of the estimate, obtaining a decent estimator for the optimal weight in the first place is an open problem, and there is no such closed solution accessible, even in the case of linear models (Liang et al. 2011).

The literature generally supports parametric, non-parametric, and ensemble model-averaging methodologies. Model averaging appears to be of importance for reducing prediction error as well as better reflecting model selection uncertainty (Buckland 1997; Madigan and Raftery 1994).

(Claeskens 2016) assumed that estimated model weights are beneficial in general since they are bias-free and have identical prediction variance, but this does not indicate that calculated equal weights are preferable. This field of study, to the knowledge, might be expanded by offering numerous suggestions for selecting weights, and the methodological approach outlined in this work is an effort in this direction to improve model predictive performance.

It is critical to understand that machines are not born intelligent. In general, supervised learning algorithms are trained to be clever by employing information gained from previous data. As a result, the historical data and learning algorithms are likely to prejudice the machines. The bias might render a computer incapable of dealing with undesirable scenarios for which it has not previously been taught. A human, on the other hand, can deal with such a problem, either by its own abilities or by collaborating with others. (Mehrabi, N. 2019).

Existing machine learning approaches generally assist the decision-making process by predicting or recommending the output of an observation. However, it is quite often reported in the literature that the end-users are unreliable about the trustworthiness of such a recommendation. It may be more prevalent in sensitive areas like finance, healthcare etc.

Overtime banks build an extensive customer database that can be analysed to evaluate the bank’s performance and make strategic decisions based on customers’ experience behaviour. This is a process that is still improving to find better accuracy and precise models, and this is the reason why banks are always working on their customer experience and adapting to changes and new trends. Not all customers behave similarly regarding financial actions; therefore, a different treatment should be given to those who meet certainly profitable, this is becoming a big challenge for banks, especially for the credibility that a new customer must build, proving consistency to the institution so that, can be considered for upcoming applications.

Credit card companies utilise rule-based systems and other tools to identify fraud. One method is to utilise sophisticated fraud detection software. The programme examines the transactions and determines whether they are fraud or legit based on past knowledge. Another method used by credit card issuers is to look for patterns used by credit card holders, which means that if the card holder always uses the card in the same way, but suddenly a transaction falls outside of the card holder's normal pattern, the credit card company investigates whether that transaction is valid or not.

* Types of electronic frauds.

These are some cases of credit cards that are related to electronic fraud, either directly or indirectly.

1. Credit Card Fraud: Credit cards, both virtual and real, are used to purchase supplies and services.

Virtual cards are used to commit fraud online, typically through the internet or phone, by getting credit card information illegally. Physical cards are used to commit fraud offline; the attacker must take the credit card.

1. Bankruptcy Fraud: Using a credit card while absent; concealing him; or engaging in other activities that cheat his creditors. Because of its intricacy, this form of fraud is difficult to foresee. (L. Delamaire, and J. Pointon. 2009).
2. Computer intrusion: the act of pushing one's way in getting unauthorised access to information with the intent of subverting the protection and detection mechanism.
3. Theft fraud / Counterfeit fraud: theft fraud is the use of a credit card without the owner's authorization, which may be checked as soon as the owner reports it to his financial institution. While credit card fraud offers the greatest risk, simply the credit card's data are necessary. (K. Chaudhary and B. Mallick, 2012).
4. Telecommunications: the use of telecommunication services to perpetrate various sorts of fraud is constantly changing; businesses, communication service providers, and consumers are all victims of this fraud. (K. Chaudhary and B. Mallick, 2012).

* Different techniques used by credit card fraudsters.

Some of the most common credit card theft schemes are detailed below:

1. Credit card fraud generating software: this is a computer software that creates genuine credit card numbers as well as expiration dates. These generators provide a list of credit card account numbers based on a single account number. The programme operates by utilising the mathematical Luhm method, which is used by card issuers to produce additional acceptable card number combinations. This allows the user to generate as many numbers as he wants in the shape of any credit card format (T. P. Bhatla 2013). Black hat hackers sell compromised credit card information to criminals via illicit websites. (J. Akhilomen. 2013).
2. Physically stolen credit card information: A fraudster steals the card and uses the information for illicit purposes. It is possibly the most difficult type of traditional credit card fraud to combat.
3. CC/CVV2 shopping website: Fraudsters utilise stolen credit card information obtained from an illicit website to purchase goods and services. (J. Akhilomen. 2013).
4. Site cloning and merchant sites: fraudsters clone a full site, including only the pages where the client made transactions. Because the page seems like those of the genuine site, the customer feels they are dealing with the firm from whom they desire to acquire products and services. Cloned site receives this information and sends an email acknowledging receipt of the purchase, just like the original firm.

Cloned site receives this information and sends an email acknowledging receipt of the purchase, just like the original firm. The thieves have all the information they need to perpetrate credit card theft. (T. P. Bhatla 2013). While merchant sites provide low-cost services to users and ask them to fill out their personal information, a fraudster can obtain a large number of credits cards.

1. Key-loggers and sniffers: The fraudster harms the user's computer by sending infected spam emails and requesting that the user download free games and software; this automatically installs a key-logger program that logs all keyboard input made into the computer on a file with the sole purpose of retrieving personal information over a network. Most of the time, this software is sold or shared on the internet among frauds.

* Difficulties of credit card fraud detection.

Several problems stated below must be solved in order to properly accomplish fraud detection solution and best practise performance (S. Sorournejad, Z. and A. H. Monadjem 2016).

1. Overlapping data: whether fraudulent transactions appear to be real or genuine transactions appear to be fraudulent; this is a significant difficulty that can lead to incorrect model design. (S. Sorournejad, Z. and A. H. Monadjem 2016.) (S. Maes K. Tuyls and B. Manderick 2002). (L.P. Andreas and J.S Salvatore. 2000).
2. Inability to adapt: Classification algorithms have the issue of recognising new patterns of fraudulent or normal behaviour. Most supervised or unsupervised fraud detection systems are incapable of detecting fraud.
3. Specifying a parameter: A lot of parameters, including a pit-set by the user, are required in the fraud detection task, which might lead to problematic model performance. This parameter has varying relevance, which increases the model's complexity. (T. P. Bhatla 2013).
4. A lack of standard metrics: The need of standardising access to and comparing good and negative results of fraud detection systems cannot be overstated.
5. Overfitting: This occurs when the algorithm used in model development attempts to learn as much information from the training data set as possible, even minor fluctuations that do not represent the real situation. This resulted in low prediction accuracy. (T. P. Bhatla 2013).

* Credit card fraud detection techniques.

Fraud detection techniques are classified into two broad categories: fraud analysis (misuse detection) and user behaviour analysis (anomaly detection). (S. Maes K. Tuyls and B. Manderick 2002).

In anomaly detection, typical user behaviour is utilised to create a normal profile of the user, which is then used to check for large deviations from the normal user profile, which are deemed fraudulent transactions. This is an unsupervised pattern based on user account profile behaviour because each user, as well as the fraudsters, has their unique profile behaviour.

Incoming transactions are compared to a categorised supervised model of a known fraudulent transaction, which is programmed into a pattern to detect genuine and fraudulent transactions. To determine if a transaction is real or fraudulent, historical data is utilised to develop a categorization model. (S. Maes K. Tuyls and B. Manderick 2002). Briefly describes some of the most recent credit card fraud detection systems.

A diagram of a model

Description automatically generated with low confidence

*Figure 1. Data processing*

* Dealing with Fraud Detection Approaches

When dealing with fraud detection systems, there are many difficulties to address, but four primary concerns are frequently addressed:

To begin, idea drift is an issue that arises when a model has been trained and has learned a specific pattern of the consumer or imposter's activity, but then the behaviour changes. That is, the model is not successfully dynamic and does not adapt as quickly as the behaviour changes. As a result, it is critical for the efficiently recognise and categorise fraudulent activities as well as valid transactions. Second, there is a skewed class distribution. One of the most crucial difficulties confronting FDS is the highly unbalanced data.

There are several techniques to solve this challenge, including data-level and algorithmic-level approaches. Third, the vast volume of data and its high dimensionality make data mining and detection extremely difficult [18]. As a result, data reduction technologies such as dimensionality and numerosity reduction are commonly used. Principal Component Analysis (PCA) is a popular method for reducing dimensionality. Finally, the difficulty of real-time detection demonstrates the need of the system detecting fraud early in order to stop it or take action quickly. Various strategies, including Very Fast Decision Tree (VFDT) [35] and Self-Organization Map (SOM), have been used to improve real-time detection.

* Supervised Machine Learning

Supervised learning is the process of categorising a new data point in the presence of labelled data. In other words, it use labelled data to train models for categorization of fresh data sets. Labelled data, for example, implies that we know which occurrences are anomalies in areas where classification algorithms are utilised for anomaly identification.

KNearest Neighbour (KNN), Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF) are some categorization algorithms used in fraud detection.

One of the most basic machine learning classifiers is the KNN algorithm. A data point is categorised by its nearest neighbours in this technique.

KNN was proposed as an efficient algorithm for credit card fraud detection and was offered as a precise way for reducing the amount of false alerts and detecting fraudulent transactions.

The approach is a discriminative algorithm for partitioning the data space for a given labelled data set by finding an ideal hyperplane (a decision boundary in binary case). The authors examined the usage of SVM as a credit card fraud detection approach in high dimensional data sets and determined that this algorithm produces better results when utilising small data sets.

* Clustering Methods.

Suggests two clustering techniques: peer group analysis and break point analysis. (R. Bolton, & D. Hand. 2002), Peer group analysis refers to earlier accounts that were acting similarly but suddenly began behaving noticeably differently; the system finds these accounts and flags them as suspicious. While break point analysis takes a different technique, when a large quantity is transferred, an account might be identified as suspicious and examined.

* Imbalanced Dataset

This section discusses numerous techniques for resolving the class imbalance problem. The techniques may be divided into three categories: resampling approaches, ensemble-based approaches, and cost-sensitive learning approaches. This thesis only addresses the resampling strategy and the ensemble-based approach, which will be discussed in detail in the next parts. Cost-sensitive learning considers misclassification costs. In the medical diagnosis of cancer, for example, the cost of misclassifying a malignancy is substantially higher than the cost of projecting that a healthy individual has cancer. As a result, by weighting the misclassification cost of the minority class more severely than that of the majority class, the model's true positive rate may be increased.

* Resampling approach

Most prediction models perform poorly in the context of an uneven class distribution. As a result, some data preparation must be conducted prior to delivering data as input to the model. In the event of a class imbalance problem, such data pretreatment is carried out utilising a data level method known as resampling. There are three types of resampling methods: under sampling, oversampling, and hybrid.

The majority class is decreased in the undersampling procedure to balance the dataset. When the size of the dataset is large, eliminating the bulk of samples can considerably increase performance and decrease storage issues. The oversampling method is the inverse of the undersampling approach. This strategy is effective with the minority population. It duplicates minority class observations to equalise the ratio of majority and minority sample. Finally, for rebalancing, a hybrid method employs both undersampling and oversampling techniques. In the next sections, we will go through some of the resampling methodologies.

* SMOTE stands for Synthetic Minority Over-sampling Technique.

SMOTE is a famous approach for rebalancing datasets that was created by Chawla BCHK02. Rather than oversampling with replacement, it seeks to generate new minority class examples (synthetic instances) by interpolating between multiple nearby minority cases. As a result, it reduces the problem of training data overfitting. The nearest neighbors of minority cases are chosen at random depending on the degree of oversampling necessary.

* SMOTE and Tomek Link removal combined.

SMOTE is an effective method for balancing class distributions. However, the minority class cluster may infiltrate the majority class space while spawning new synthetic minority cases. Providing such information to the model may result in overfitting. As a result, both the SMOTE and Tomek Link elimination procedures may be used to balance the class distribution. The original training dataset is oversampled using SMOTE in this method, and then Tomek Link removal is performed to the resultant dataset to produce a balanced dataset.

* HMM (Hidden Markov Model).

Hidden Markov Model is a limited set of states, each with its own probability distribution. To administrate transition between these states, a set of probabilities known as transition probability is employed (A. Singh and D. Narayan. 2012). The central concept is to construct a multilayer model of programme behaviour based on both HMM and enumerating approaches for anomaly detection (T. Lane 1997). This methodology (HMM) does not require a fraud signature and may successfully identify fraud based just on the credit card owner's spending behaviour. The HMM examines the cardholder's spending habits based on a threshold value of high (h), medium (m), or low (l). This threshold value is dynamically determined by the clustering algorithm of each cardholder's personal expenditure routine.

The most important advantage of the HMM-based technique is that it considerably minimises the number of valid transactions (false positives) identified as suspicious by the fraud detection system.

A picture containing text, screenshot, diagram, font

Description automatically generated

*Figure 2. Classification of fraudulent transactions.*

* SVM stands for Support Vector Machine.

This technique is appropriate for detecting credit card fraud since it just requires two classes: valid and fraudulent. SVM attempts to compute an optional hyper lane that separates the sample of the two classes (D. Meyer 2012). SVMs are supervised learning models that use learning algorithms to analyse and recognise patterns for classification and regression tasks (N. Cristianini and J. Shawe-Taylor. 2000). Kernel representation and margin optimisation are two critical components of SVM. The optimal kernel for any given problem is a massive research challenge; speed and size (large training set), which decreases the demand computational for testing poses a key restriction to SVM.

* The Decision Tree.

The decision tree is a diagram that depicts the potential consequences of a set of connected selections. It is used to create an algorithm that accurately predicts the optimal option. A decision tree may also be used to develop automated prediction models with many applications in data mining, machine learning, and so on. This approach can consider an item observation to forecast the value of that element. The advantage of this strategy is that it adds additional choices to an existing tree, is simple to grasp, and requires no data preparation. However, this approach has drawbacks in that it might grow very complicated and verify each operation one by one for better accuracy; several trees are frequently employed simultaneously in the ensemble method. (W. Fan,, M.Miller, S. Stolfo. 2001).

* Algorithm Genetic.

Genetic algorithms are heuristic search and optimisation methods that are encouraged by natural selection and belong to the wider family of evolutionary algorithm methods; these evolutionary algorithms have a propensity to get better solutions as time progresses. The challenge of fraud detection is a classification problem; GA has been applied in credit card fraud detection to minimise the amount of transactions incorrectly categorised. (E. Duman, and H. M. Ozcelik 2011). GA is effective in detecting credit card fraud due to the ease with which programming languages may be implemented. It does, however, have a memory limitation and is time demanding.

* The Artificial Neural Network.

This simulates how the human brain operates in certain circumstances, in order to accomplish the operations of nodes known as neurons. Neurons are computing units that process incoming data and generate output data. (E. Ngai, Y. Hu., Y. Wong 2011). A neural network is an interconnected network of nodes that reflect the linking functions of the human brain. (S. Ghosh, and D. L. Reilly 1994). ANN are nonlinear statistical data modelling tools that may build supervised/unsupervised learning patterns by modelling the complicated link between input and output. ANN is a random function approximation tool that can learn by viewing datasets. In ANN, the terms "training" and "recognition" are frequently used. In the ANN supervised training approach, sample data from both fraudulent and non-fraudulent transactions are utilised to develop models in fraud detection systems. (T. Guo, and L. Gui-Yang 2008).

* Recurrent and LSTM Neural Networks.

RNNs (recurrent neural networks) are a subset of supervised machine learning models. They are composed of a series of cells with hidden states and non-linear dynamics. RNNs are typically applied to time series data, such as voice recognition, unsupervised anomaly detection, and automatic translation. In economics, LSTM is used as an alternative to the ARIMA model to forecast time series data. (Malhotra P. 2015).

Because credit card transactional data is temporal in nature, RNNs should be used instead of other types such as fully connected or convolutional neural networks.

This is one of the models that is more commonly used nowadays for financial risk prediction analysis. It is important to highlight that this model is widely used in economics for predicting, implying that it is used in conjunction with recognition and unsupervised learning.

Conclusion

Over the years, financial institutions have investigated, applied, and polished the detection of credit card fraud transactions, and as a result, most banks now provide an expedient service to applicants. However, detecting and trusting artificial intelligence when it comes to money risk remains tough. At the same time, the availability of banks to detect fraud transactions becoming increasingly important, particularly for those who prefer to go for online shopping, due to the ability to do it at any time. One method utilised in the research is to use feature selection on characteristics acquired from raw transactional data to compare models and decide which performs better when using machine learning.

In credit scoring difficulties, feature selection was employed. In general, feature selection is critical for applications such as knowledge discovery in databases. As a result, the study in this work is driven by the need to automatically assess fraudulent transactions to make risk judgments, as well as the usage of credit card scores to make critical financial security decisions. Banks may use such ratings to categorise consumers into "risk groups," which might aid in detecting possible bankruptcy early and blocking the customer's card in time to reduce loses.

Neuron architecture will be stimulated by the usage of Neural Networks (NN) for machine learning frameworks. These are shown to simulate the human brain's ability to recognise complicated relationships between inputs and outputs. Based on prior studies, the researchers discovered demonstrates the potential for the study and relevance to the issue since there are sufficient data resources that can be enhanced with the treatment of another predictive model. (Haykin SS. 2009).

The model averaging strategy is largely effective for minimising prediction errors, although it may not be applicable in all situations. This is because a few individual models in the pool of models do not contribute to the reduction in covariance and average bias. This may be countered by adopting a suitable or diversified weight estimation approach, which helps to adjust the excess variance from weaker models.

The literature is full of important information criteria that support the proper method of determining weights. However, none of the information requirements, in our opinion, are suitable for applying to every single case. As a result, a constant discussion on emerging information criterion theories and approaches will be a significant step in this direction.

The conventional method recommends choosing the single best model, which overlooks model uncertainty caused by model structure and assumptions. As a result, depending on the single best model with certainty is not a smart idea because it may have negative implications. When based on model average procedures, the committee of varied models improves performance. (Figini et al. 2016; Figini and Giudici 2017).

# Methodology

The strategies investigated and discussed in this section of the study are offered to contribute to the overall goal of identifying fraudulent credit card transactions. distinct models are employed in this study to detect fraudulent credit card transactions; it is important to note that three distinct analyses are utilised to achieve an improved understanding of the problem, and particularly to gain better insights for fraud detection.

The main reason why the three analyses are separate is that the datasets are completely different and there is no possibility of merging them since they all contain very different features that would cause bias to be analysed, different approaches are applied regarding the objective of each of them.

# Datasets

First analysis

The dataset applied is from Datacamp, which contains 339607 card transactions spread out over two years from 01-01-2019 to 31-12-2020. Contains an amount of 339607 rows and 15 columns.

There is no missing data and after pre-processing the date out of the 337825 transactions, only 1782 transactions are fraudulent, making the dataset highly imbalanced. Further, the principal features for the analysis are presented in the features ‘trans\_date\_trans\_time’ of the transactions and ‘amt’ which shows the amount of each transaction made. The dataset was released to the public with the transactions labelled as fraud or not a fraud.

* Data Understanding and Preparation

To train machine learning algorithms to analyse statistical patterns and correlations, sample data must be collected and stored in datasets, this step is the beginning of the findings however it is a crucial stage to achieve a good result. Before creating machine learning models. The first dataset consists of the following methods:

* Exploration of the features, identifying the principal features and the ones that need more exploration.
* Identification of columns that need to be transformed, for example, encoding categorical values into numerical values to use machine learning afterward, as machine learning performs better with numerical values.
* Prepare and convert a feature into separate ones to gain better insight.
* Verify that the dataset does not contain missing values.
* Validate that the dataset does not contain duplicate information, to prevent noise in the outputs.
* Feature Selection

Each of the characteristics obtained from the dataset may not be useful in developing a machine learning model to make the required prediction. Some of the features may increase forecast accuracy. As a result, feature correlation plays an important role in developing a stronger machine learning model. High correlation features are more likely to be linearly related and have virtually the same influence on the dependent variable. As a result, when two characteristics have a strong correlation, we can drop one of them. The correlation heatmap of the original dataset and resampled dataset.

The heatmap does not offer much information because it is a large dataset, which is why we used feature selection to assist in choosing the key characteristics. When there are many unnecessary features contributing no more helpful information than the current subset of variables, feature selection is one of the important stages in data preprocessing. It is known as a path to capture relevant features for use in the implementation of the machine learning model to expedite the training period, improve learning interpretability, and decrease model over-fitting. The dataset's excessive and verbose information may have a significant impact on the performance of our model.

The first analysis employed necessary techniques to identify the relevant features and their correlation to the target variable, such as correlation

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*Figure 3. Credit Card Fraud and Legit Transactions.*

*Figure 4. Credit Card Fraud and Legit Transactions A graph of a graph

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# Sampling Strategy

# Primary Research, Methodology and Ethics

The original plan was to set up depth interviews with professionals in the field of Credit Card Fraud, working for banks or any other financial institutions, to achieve this were contacted by email and personally professionals who are working for organizations dealing with fraud transactions, however, the answer was not successful since they don’t aloud external people to contact them regarding this matter, this is because of data protection and specially for the delicate and sensitive information could be involved.

For this reason, experimentation is considered a supplement to the research, a focus group can be gathered with people who have ever had to deal with scams or fraud, as this is valid information as well, in order to achieve a thorough understanding of the topic and address recent information.

Simultaneously, the Data Analysis gained after implementing Machine Learning models in the project will provide intriguing issues to explore with the implementations of different methodologies that assist to collect a better knowledge of how to deal with real-world circumstances.

**Primary research methodology.**

The major goal of Credit Card Return statistics is to assist national and eurozone policymaking, as well as to improve knowledge of the function of credit cards in the domestic financial system.

The main goal of this project is to identify and analyse the best approach to dealing with fraud and scams in banks, which is a big challenge nowadays, since the number of frauds and scams is increasing dramatically around the world, especially with Credit Cards users, this enables banks to anticipate situations where banks need to provide a quick response to customers, which is why the investigation is considered relevant; in order to achieve a real-time data, it was pertinent to interview professionals with experience in the field, to identify how banks proceed in determinate situations. However, this goal is not going to be possible since there are so many difficulties that involve data privacy and politics for financial institutions.

In order to achieve the primary research emails and personal visits were delivered to different financial institutions in Dublin, Ireland. However, their answer was that because of organisations policies and data protection, they cannot proceed with interviews. For this reason, the results obtained from the models trained and tested will represent a primary outcome. Different datasets are applied in order to obtain a novel result.

* **Ethical considerations for the project.**

Performing a face-to-face interview method is said to create a better response from defendants as it is a more personal approach. However, the success of face-to-face interviews depends on the interviewer’s approach, as well as the flexibility of the public invited, this is the reason why the people selected because of their knowledge and experience in the industry, so the information gathered can be relievable and representative. It’s important to mention that ethical considerations must be taken, participants possibly will avoid some questions because of The European Data Protection Board where details; in accordance with Article 70(1)(e) of Regulation 2016/679/EU of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons in relation to the processing of personal data and the free movement of such data, and repealing Directive 95/46/EC (hereinafter "GDPR").

These recommendations aim to encourage a coordinated application of data protection guidelines about the administering of credit card data within the European Economic Area (EEA), as well as to ensure standardised protection of data subjects' rights, in full compliance with the GDPR's fundamental data protection principles.

These suggestions notably address the storage of credit card data by online retailers and service providers for the single and explicit purpose of enabling future transactions by data subjects. They cover the circumstance in which a data subject purchases a product or pays for a service through a website or an application and submits his/her credit card information, often on a dedicated form, in order to complete this one-of-a-kind transaction.

# Conclusions and Future Research

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