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

# Research Question

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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 a common 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, which represents one of the most significant and frequent daily operations, based on the increment of daily online purchases around the world after COVID-19. At the same time 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 results to improve the 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 encouraged that recent technology breakthroughs offer new benefits and effective techniques for banks, financial institutions, and credit card issuers to efficiently lower the risk of significant losses and monitor and detect fraud scenarios.

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 training dataset and model efficiency.

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, we will use machine learning techniques to create automated credit card fraud detection, much like actual banks.

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

Credit risk management has increased greatly in the previous several decades, both in terms of scholarly 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).

Body

Millions of credit card transactions are done every second, and people are unable of analysing and processing 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, we rely on 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 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 address 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 bureau data. Their 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. Their 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, their approach is somewhat 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 their 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 our 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 robots. 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 utilising his or her own abilities or by collaborating with others. So, should we employ machine intelligence to approve credit cards automatically? Instead of full automation, we believe that machine intelligence may be leveraged to aid people in the credit card acceptance process. (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 sceptical about the trustworthiness of such a recommendation. It may be more prevalent in sensitive areas like finance, healthcare etc. Significantly, it is not possible for a machine to correctly recommend the approval of all credit card applications. Even if a machine is tested to be sufficiently accurate, unexpected behaviour could be possible in a real banking environment. The availability of recommendation confidence can help in such circumstances. (Toreini, E. 2020)

According to the credit card statistics presented by the Central Bank of Ireland in April 2022, it is noteworthy how the use of credit cards has increased compared to the previous year, due to the recent pandemic affecting consumer behaviour. 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 model, 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 behaviour; therefore, a different treatment should be given to those who meet certainly profitable, this is becoming increasingly challenging for banks, especially for the credibility that a new customer must build by proving to the financial institution that they can be responsible with the debt acquired, at the same time the system will assign a score to the customer according to how the client managed the debt, as a bank record for future applications.

There are different studies about credit card prediction, however, it’s a topic that is still improving to achieve the ideal performance for banks, this makes it a trending topic since the fact that it will always look to develop new technologies. The research suggests using machine intelligence to automatize processes, nevertheless, this procedure is still depending on a final decision from a human to analyse and determine if the applicant is suitable for the financial portfolio, which means the machine cannot take the decision to trust or not based on the result, there are many factors which can help to consider or refused the applicant.

* 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).

* Credit Card Fraudsters

There are many credit card fraudsters; some of them are listed below. (J. Akhilomen. 2013)

1. Credit Card Information Buyers: These are a group of fraudsters with limited IT abilities who obtained stolen or hacked credit card information from an illicit website in order to purchase goods and services digitally.
2. Black Hat Hackers: They are essentially fraudsters who get unauthorised access for malevolent motives, particularly for personal gain; they employ the "pre-hacking stage" procedure, which includes targeting, research, information gathering, and concluding the attack.
3. Physical credit card thief: This category includes fraudsters who steal credit cards for illicit reasons. This is the simplest method for a fraudster to obtain the cardholder's information without investing in contemporary technology.

* 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 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

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*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.

* 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.

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*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 replete with many 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 information used for this research includes a large number of transactions over time, transactions by category amount, and the distribution of fraudulent and non-fraudulent transactions. This study also includes an explanation of how the information was pre-processed, and the EDA describes each characteristic evaluated for the analysis to provide a feasible practical financial business viewpoint. It also discusses the many approaches that were used, data engineering and as well as the constraints that were imposed in order to fulfil the goals that were set forth at the outset.

# Dataset

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 amounts. The data was released to the public each transaction had already been labelled as fraud or not fraud. Therefore, there is no identified noise in the dataset.

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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

* **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.

For these reasons, experimentation is considered a supplement to the research, and if people refuse to attend the interview, 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.

# Conclusions and Future Research

* **References**