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| Scientific Research + Literature –Assessment 3 – PART 1  TU060 : Literature Review | |
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Title

**An analysis to determine if in the eight-year period from 2012 to 2020 that the application of Machine Learning techniques for Credit Card Fraud detection improved in accuracy and performance.**

Abstract

This review describes Machine Learning techniques that were applied from 2012 to 2017 to build models to detect credit card fraud and compares them against emerging approaches documented circa 2020. The review objective is to determine if the more modern ML strategies were delivering significantly better performance, despite possible limitations due to their inherent complexities.

American and European datasets formed the basis of the modelling experiments, and ‘fraud’ was defined as the unauthorised use of card services by a third party.

A significant characteristic of the majority of these datasets is that instances of fraud make up a very small proportion of the total record set. Hence, data resampling considerations are a factor throughout the review.

The two earliest papers employed what the authors themselves described as ‘traditional’ ML Classification approaches. The third paper explained a later ensemble approach to resampling and anomaly detection. The fourth paper detailed experiments in 2020 into more contemporary approaches using Neural Networks. The last paper (also 2020) looked at recent algorithm optimisations to avoid resampling of imbalanced data and circumvent possible data corruption. Further research papers are included in this analysis to add context to the assumptions made by the various authors.

Comparing the findings across the review is challenging as authors use datasets of different sizes and a variety of model comparison criteria. However, F1 Scores, from the best performing models, show a steady increase from 0.729 with enhanced resampling and feature reduction, up to 0.849 when Neural Network approaches are employed, to a score of 0.941 with an Optimised XGBoost (OXGBoost) algorithm.

All metrics in this review need to be considered in the context of their research experiments, but an upward trend in fraud detection rates over time is evident.

The more recent Neural Network approaches performed well and have crucial benefits in terms of computation efficiency.

However, Neural Network predictions can be difficult to audit. The OXGBoost approach has the benefit of both greater transparency and the avoidance of data corruption through resampling. Both techniques are therefore emerging areas of interest for further research.

**Key Words**: Credit Card Fraud Detection, Data Resampling, Feature Engineering, Deep Learning, Neural Network Auditing

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# Introduction

Credit Card fraud remains an evolving multi-billion Euro challenge, which threatens global financial institutions with both loss of revenue and reputation.

‘*Fraud’*, in the domain of this literature review, is defined as a historical credit card event, reported to the card provider, in which a third party has conducted a transaction (online or in person) without the permission of the card holder.

The historical datasets used in this literature review are sourced from credit card operators providing services in the European and American marketplaces. Therefore, any fraud patterns that are specific to other markets, such as those in Africa and Asia, will not be considered. Neither does any research in this review focus on debit card or prepaid card transactions.

A common theme in these research papers is that historical datasets for credit card fraud have a number of challenging characteristics that make it necessary to extend and augment the Machine Learning techniques that would be used in other types of Classification problems;

Although the historical fraud datasets in this review vary in size between tens of thousands to more than 10 million rows, the incidents of actual fraud usually constitute less than 1% of any given record set. Such a degree of imbalance is a major complication against which learning algorithms must adapt.

As of 2020, because of data confidentiality concerns, there are still relatively few historical credit card fraud datasets upon which to conduct ML experiments for fraud detection. Credit Card Fraud Detection is a very active field of research, but the lack of variety in source data requires experimentation with an increasingly sophisticated array of algorithms and parameters.

This article looks at a number of studies, conducted from 2012-2020, which recommend a series of feature engineering and algorithm selection refinements to better detect credit card fraud, and tackle the inherent imbalance challenge.

The findings in the earlier papers emphasize the value of combining sophisticated resampling techniques with specialist algorithms to deliver more effective fraud detection models. Later research from Nguyen, Tahir, Abdelrazek, and Babar (2020)**[1]** posits that Deep Learning techniques may offer more promising solutions, and ones that will actually be performant enough for the ‘big data’ and real-time requirements of the 2020s. Priscilla and Prabha (2020)**[2]** also propose that resampling itself could be distorting credit card fraud data and that optimising the XGBoost algorithm can sidestep this issue for more contemporary solutions.

# Concept A: Addressing the Imbalance and Resampling Challenge

The heavily skewed distribution of data towards ‘non-fraud’ records in many credit card fraud datasets can pose problems for learning algorithms with a possible bias towards the majority class. The 2019 research from Ceronmani Sharmila et al **[3]** makes a somewhat informal description of applications needing to capture “*fraudulent transactions that take place every once in a while*”. In addition, Lima and Pereira (2017)**[4]** reference the fact that e-commerce systems tend to generate a significant numbers of features for each transaction, and that this combines with the fraud imbalance problem to further complicate the creation of detection models.

*Undersampling* is a technique to remove rows from the majority (non-fraud) class in order to address potential bias in the ML learning process. The earliest research in this review, from Bhattacharyya, Jha, Tharakunnel, and Westland in 2011**[5]**, determined by experiment that random undersampling contributed to their best detection results, with an F1 Score of *0.787* with RF. However, Lima and Pereira (2017) call out that such a methodology may result in important information being lost. A more elaborate sequence of resampling techniques was proposed, including *oversampling* by artificially creating fraudulent transaction records with the SMOTE method. In these experiments, the best model F1 Score result was *0.729*, but with a much larger dataset and less input data removed than in the 2011 experiments by Bhattacharyya et al.

Despite the positive outcomes in the Lima and Pereira research, later papers in this review declare that oversampling techniques may introduce distortions in the data and cause potential overfitting. Ceronmani Sharmila (2019) and Priscilla and Prabha (2020) both recommend approaches that avoid resampling of credit card fraud data and instead employ enhanced outlier detection (F1 Score: *0.849*) and tree boosting (F1 Score: *0.940*) techniques respectively.

Future credit card fraud research that examines techniques to avoid data resampling will be a key topic of interest.

# Concept B: Neural Networks – Handling Volume and Speed for Fraud Detection

# Concept C: Neural Networks and Auditing Fraud Detection Results

# Conclusion: Better ways to capture CC Fraud?

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