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A Comparative Evaluation of Logistic Regression and CNN Algorithms in Credit Card Fraud Detection

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Abstract

Introduction: Credit card fraud detection is a crucial field within financial services aimed at identifying and preventing unauthorized or fraudulent transactions on credit and debit cards. As technology has evolved and new e-service payment options were started, fraudsters are more prone to commit fraud as a result of the widespread adoption of cashless transactions. This project endeavors to provide a comparison between two distinct machine learning methodologies, Logistic Regression and Convolutional Neural Networks (CNN) with the help of evaluation metrics like accuracy, precision, recall, and f1-score.
Related work: Authors like A. Singh, M Devika, P Y Prasad, P. Shanmugapriya, and some other researchers developed many fraud detection models using several machine learning and deep learning algorithms. Even some prior works deal with the comparative evaluation of multiple machine-learning algorithms in the realm of detecting credit card fraud.
Methods: The research encompasses a review of the existing literature, data collection, and pre-processing, model implementation, and performance assessment using appropriate metrics. After training the two algorithms individually, by conducting a systematic evaluation, this study seeks to shed light on the relative effectiveness and efficiency of Logistic Regression and Convolutional Neural Networks in detecting fraudulent transactions.
Results and analysis: With respect to precision, recall, and F1 score, Convolutional Neural Networks outperforms Logistic Regression. In this binary classification test, the Convolutional Neural Networks model outperforms another model because it includes a better capacity to recognize true positive results while minimizing false positives.
Discussion: The study revealed that deep learning models, such as Convolutional Neural Networks, generally achieve higher accuracy, making them more adept at identifying fraud; however, this can lead to an increased number of false positives in data sets with imbalances. Additionally, they exhibit a f1-score, effectively striking a balance between false positives and false negatives. The choice between deep learning and traditional machine learning methods should be guided by the specific requirements and constraints of the fraud detection problem at hand.
Conclusion: In conclusion, the anticipated findings will contribute some insights into the optimal choice of algorithms for credit card fraud detection, benefiting the financial industry and enhancing the security of electronic transactions.

Keywords: Credit Card, Credit Card Fraud, Logistic Regression, Convolutional Neural Network, Accuracy, Precision.

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Chapter 1

Introduction

In the financial ecosystem, the quest to make life easier led to the continuous and rapid transformation of the world through digital technology. People have moved from exchanging goods for goods in the barter system of trade to transacting using cash, and recently, through credit cards and online payment services. However, various kinds of frauds, for example, credit card fraud have continued to engulf this transformation which results in the loss of a huge amount of money [3].

Credit card fraud is the practice of using another person's credit card information to make transactions or withdraw funds from an account. In both developed and developing countries most transactions are done in a way called electronic transactions due to ease of use and convenience of the user for this process, credit cards are widely used. Since the introduction of credit cards, the process of online transactions has become more convenient, and straightforward [5]. On the other hand, with increasing sophistication due to advancements in technology, fraudsters see it as an opportunity to defraud customers of their hard-earned finances by employing various means such as hacking, skimming, or the use of lost or stolen credit card. Therefore, detecting credit card fraud is a crucial necessity that should be addressed through the implementation of automated and effective fraud detection systems to boost customer confidence and reduce financial losses [3]. With a number of assessment parameters such as accuracy, precision, recall, and f1-score, this research attempts to provide a comparison between two distinct machine learning methods i.e., Logistic Regression and Convolutional Neural Networks (CNN) by using an open-source data set [1].

1.1 Background

Credit card fraud has been raised as a major issue in society and it is very important to implement an efficient methodology that can be used for detecting frauds and which can be used to reduce the humans from financial losses [2]. Despite the considerable amount of work done by researchers in the development of CC fraud detection models using different machine learning algorithms such as Support Vector Machine, Random Forest, Logistic Regression, Decision Tree, K Nearest Neighbor etc., and deep learning algorithms, for example, Convolutional Neural Networks (CNN), Artificial Neural Network, Long Short-Term Memory, etc., there is still a need for more effective models with better predictive performance and accuracy to stand against the ravaging trend of credit card fraud and successfully detect it [3].

The main purpose of this paper is to capture and detect fraudulent transactions that are mentioned in the credit card transaction history, and this will also cover a comparison between supervised machine learning algorithm and deep learning algorithm that is Logistic Regression and Convolutional Neural Networks [6].

1.1.1 Aim

The main purpose of this project is to evaluate and make a comparative analysis of the efficiency of Logistic Regression and Convolutional Neural Networks with the help of the performance metrics in the context of credit card fraud detection.

1.1.2 Objectives

In order to find the interpretable machine learning models, specifically between Logistic Regression and Convolutional Neural Networks, from an open-source data set of fraudulent transactions, we try to analyze the need for accuracy and precision along with f1-scores using evaluation metrics. Data cleansing, normalization, and handling of imbalanced data sets are all processes in the data pre-processing process.

1.1.3 Research question

What is the accuracy, precision, recall, and f1-score of deep learning models (e.g., Convolutional Neural Networks) in detecting credit card fraud when compared to classical machine learning algorithms (e.g., Logistic Regression)?

1.1.4 Outline

This project will begin with an introduction to the problem of credit card fraud and its significance, followed by a thorough literature review of existing fraud detection methods and the application of Logistic Regression and Convolutional Neural Networks in this domain. Data collection and pre-processing steps will be discussed, along with the evaluation metrics used to measure model performance. The core of the project will involve implementing both Logistic Regression and Convolutional Neural Networks models, training and testing them on a suitable data set, and comparing their accuracy, precision, recall, and f1-score. Additionally, the project will address the comparative analysis of two algorithms with potential limitations and future research directions in the field of credit card fraud detection.

1.1.5 Ethical, societal and sustainability aspects

Ethical aspects: The data set we are using in this project is openly accessible and in the public domain. Even though the data contains some private financial information about specific individuals, it is not closed. Since the data we are using is not real and has nothing to do with any specific nation or person, there are no GDPR concerns.
Societal aspects: Identification of credit card fraud is essential for preventing financial losses for people, companies, and financial institutions. However, technology also brings up significant societal issues including resource distribution, privacy, ethics,

and regulation. For successful fraud prevention to be achieved while upholding consumer confidence and trust, these factors must be balanced.
Sustainability aspects: This project does not have any direct relation to the sustainability aspects.

Chapter 2

Related Work

This chapter mainly consists of some reviews of research papers on credit card fraud detection.

- The study which was done by the authors intends to distinguish between legitimate and fraudulent financial dealings by employing a variety of deep learning techniques, including the Convolutional Neural Networks (CNN) and the long short-term memory (LSTM), both of which are utilized to make accurate predictions regarding financial dealings. As far as they will analyze and preprocess the data set and compare both Convolutional Neural Networks and long short-term memory (LSTM) with each other in order to find the optimal solution [6].

- A Singh, A Singh, A Agarwal, and A Chauhan researched machine learning algorithms to detect credit card fraud. They examine the latest advances and applications in the field of machine learning-based credit card fraud detection. Here, four machine learning algorithms have been analyzed and compared on the basis of their accuracy. It was found that the Catboost algorithm works best to detect credit card fraud with an accuracy of 99.87 percent. The data set for credit card fraud detection was taken from Kaggle [8].

- M Devika et al [2] used various types of machine learning models and algorithms for identifying fraud in the transactions. Here algorithms such as logistic regression are considered. By selecting the algorithm with the best high accuracy, the fraud will be detected. The logistic regression algorithm accuracy will be nearer to 0.99with this accuracy, we can easily identify the frauds. In this web application, the admin can log in and the authentication will be performed, then the admin can easily upload a data set for identifying the frauds in the given data set.

- [3] used the Convolutional Neural Network (CNN) model for credit card fraud detection which is proposed in their study using Adaptive Synthetic (ADASYN) sampling technique to address the imbalance data set. The proposed model has achieved 0.9982, 0.9965, and 0.9999, accuracy, precision, and recall, respectively compared to other existing studies.

- In 2023, P Y Prasad et al [5] did a comparison study by considering Convolutional Neural Networks to enhance the efficiency of fraud detection. Layers of

Convolutional Neural Networks assist in obtaining accurate detection. An extensive empirical analysis was conducted using the most recent Convolutional Neural Networks model's hidden layer counts, epochs, and applications. The f1 score, accuracy, precision, and recall all affect the results of the algorithms. Area Under Curves (AUC) has been altered to leverage values of 99.9 percent, 85.71 percent, 93 percent, and 98 percent. A ROC curve is produced using the confusion matrix as a framework. The proposed method overcomes the problem of credit card identification by combining Deep Learning with Machine Learning techniques. Furthermore, to reduce the number of false negatives, this study has performed data-matching trials with the implementation of deep learning techniques. This study has employed Deep Learning techniques and performed trials to match the data with the model. Utilizing the suggested strategy, it is possible to locate credit card fraud remotely from any location.

- P Shanmugapriya, R Shupraja, and V Madhumitha mainly focused on credit card fraud detection in real-world scenarios in their research. Here they applied some supervised and unsupervised algorithms and will classify the credit card data set. They also used Convolutional Neural Networks and correlated the data train and get the model's accuracy [7].

In the past, numerous research studies have explored credit card fraud detection through comparative analysis of various machine learning models. While encountering several studies focusing on Logistic Regression or Convolutional Neural Networks (CNN) for fraud detection, a gap was observed in the literature concerning a direct comparative assessment of these two algorithms, despite their demonstrated efficiency when compared to other machine learning techniques.

Recognizing this gap as a significant research opportunity, this research aims to conduct a comprehensive comparative evaluation of Logistic Regression and Convolutional Neural Networks. The objective is to assess and contrast their performance using key evaluation metrics such as precision, accuracy, and f1 score. The same open-source data set will be used throughout this analysis.

Chapter 3

Method

This project follows a method called general experimentation. Regardless of whether a transaction is actual, fraudulent, or a fraud transaction, the suggested strategies focus on recognizing credit card fraud. Logistic Regression and Convolutional Neural Networks are employed to distinguish between fraud and non-fraud. In the end, it will be decided whether the approach is better at spotting the credit card fraud [5].

3.1 Data preprocessing

In this project, we used a data set [1] that contain European credit card transactions. We have imported these data sets from the Kaggle. This data set contains various attributes ranging from (v1 to v28) time, and amount. The total number of transactions that are present in the obtained data set is 282807 which belongs to the European cardholder's data. We prepared the data for clear analysis by removing the incorrect information. The main advantage here is the model performance can be improved by removing errors and irrelevant data. The data obtained after cleaning is accurate and error-free which helps to improve the model accuracy [5].

After the data preprocessing, which includes handling the missing values, train-test split, feature scaling, etc the data set is used for the evaluation of performance metrics for both Logistic Regression and Convolutional Neural Networks.

3.2 Logistic Regression

Logistic Regression is called a legit classifier. It is a supervised learning classification algorithm accustomed to predicting the probability of a target variable. Logistic Regression algorithm is used for identifying the probabilities that belong to a particular class. In our scenario, it will describe whether our transaction is fraud or not. Generally, it's used for a special variety of statistical techniques where the logit function is applied to the linear function [2].

3.3 Convolutional Neural Network

Convolutional Neural Networks (CNN) is a commonly used deep learning algorithm that has provided good results in a wide range of applications. ConvNets can uncover

latent features of illegitimate transactions and avoid model overfitting. ConvNets algorithm has three main layers which are: convolution layer, pooling layer, and fully connected layer. Generally, the function of the convolution and pooling layers is to perform feature extraction, while the third layer, a fully connected layer performs the function of mapping the extracted features into the final output, for example, classification [3].
Convolutional layer- It can be considered as the root layer and the basic building block of Convolutional Neural Networks. The operation consists of a dot product in two matrics in which one matrix has the set of pre-learned parameters and other matrix is an unbound portion.
Pooling Layer-It replace or shuffle the output with the accurate statistics nearby outputs with one another which leads to a reduction in the special size of representation and increase in computation and weight. In the pooling layer, there is a lot of pulling functions available in deep learning however prominently used pulling function is Max pulling which have recorded to find out the maximum output from the neighborhood.
Fully connected layer-This layer is considered to be the top player in Convolutional Neural Networks in which neurons are fully connected to all of the neurons in the presidents and accidents layers which is the same case as fully connected neural networks this can also be computer by matrix multiplication. The only connected layer is to map input with output [6].

3.4 Model evaluation of performance metrics

Model evaluation is a critical step in machine learning that involves assessing the performance and effectiveness of a predictive model, such as a classification to determine how well it generalizes to new, unseen data. The primary goal of model evaluation is to measure how accurately the model makes predictions with the help of metrics like accuracy, precision, recall, and f1-score.

Accuracy is the proportion of correctly classified instances to the total number of instances in the test set.
Precision is the proportion of true positives to the total number of predicted positives.
F1-score is the harmonic mean of precision and recall and is a way to balance both metrics.
Recall is the proportion of true positives to the total number of actual positives [4].

Confusion matrix is the major effective matrix that can be used for analyzing how the applied algorithm will recognize the set of records at the different classes.

- True positives: These are the positive records that are correctly labeled by the classifier.

- True negative: These are the negative records that are correctly labeled by the classifier.

- False positives: These are the negative records that are incorrectly labeled positive.

- False negatives: These are the positive records that are mislabeled negative.

Based on the confusion matrix, the sensitivity, accuracy, and error approximation metrics can be achieved and classified. For the classifier that we have used the accuracy will be calculated based upon the recognition rate (the total number of fraudulent transactions divided by the fraudulent transactions), and by considering the number of records that are classified correctly in the test set and training set [2].

Chapter 4

Results and Analysis

In this section of the report, the outcomes of the data set used to train and test the Convolutional Neural Networks and Logistic Regression algorithms will be discussed. To compare the models in predicting credit card fraud, performance metrics like accuracy, precision, recall, and f1-score have been calculated. The test data set was used to get the results shown below.

4.1 Classification results of Logistic Regression

- In the context of Logistic Regression, assessing the algorithm's performance involves the evaluation of metrics like accuracy, precision, recall, and f1-score.
- The precision obtained from this algorithm is 0.88 the recall is 0.63 and the f1-score is 0.74.
- In this regard, Figure 4.1 displays the confusion matrix for the data set, presenting the outcomes derived from the application of Logistic Regression.

	precision	recall	f1-score	support
Non-fraud	1.00	1.00	1.00	56861
Fraud	0.88	0.63	0.74	101
accuracy			1.00	56962
macro avg	0.94	0.82	0.87	56962
weighted avg	1.00	1.00	1.00	56962

Figure 4.1: Classification results of performance metrics of Logistic Regression

4.2 Classification results of Convolutional Neural Networks

- Similar to Logistic Regression, Convolutional Neural Networks evaluates accuracy, precision, recall, and f1-score to determine how well the algorithm performs.

- This algorithm yielded a precision of 0.95, recall of 0.76, and f1-score of 0.85.
- The data set's confusion matrix, which incorporates the outcomes from Convolutional Neural Networks, is displayed in Figure 4.2.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	56861
1	0.95	0.76	0.85	101
accuracy			1.00	56962
macro avg	0.98	0.88	0.92	56962
weighted avg	1.00	1.00	1.00	56962

Figure 4.2: Classification results of performance metrics of Convolutional Neural Networks

4.3 Comparative analysis of performance metrics

This section consists of overall classification results of both Logistic Regression and Convolutional Neural Networks which includes accuracy, precision, recall, and f1 score as mentioned in Table 4.1.

Model	Logistic Regression	Convolutional Neural Networks
Accuracy	1.00	1.00
Precision	0.88	0.95
Recall	0.63	0.76
F1-score	0.74	0.85

Table 4.1: Comparative classification report of performance metrics between Logistic Regression and Convolutional Neural Networks

- Here, the classification algorithms predict every case in the data set with an accuracy of 1.00 (which is a round-up value of 0.99). This is due to the data set's ratio of fraudulent and genuine transactions.
- Precision for Logistic Regression is 0.88, whereas precision for Convolutional Neural Networks is 0.95. This indicates that when compared to Logistic Regression, Convolutional Neural Networks has slightly higher precision in determining a fraudulent class.
- When it comes to recall, the scores of Logistic Regression and Convolutional Neural Networks are 0.63, and 0.76 respectively. The Convolutional Neural Networks has a higher recall, indicating that it captures a larger portion of actual positive instances compared to Logistic Regression.

- The f1-score is 0.74 for Logistic Regression, while for the Convolutional Neural Networks, the f1-score is 0.85. This suggests that when compared to Logistic Regression, Convolutional Neural Networks achieves a slightly greater balance between precision and recall.

In the end, the Convolutional Neural Networks exceeds Logistic Regression when it comes to precision, recall, and f1-score. The Convolutional Neural Networks model improves other models in this binary classification test because it shows a higher ability to identify genuine positive results while reducing false positives. However, in this assessment, both models achieve absolute accuracy.

Chapter 5

Discussion

Q: What is the accuracy, precision, recall, and f1-score of deep learning models (e.g., Convolutional Neural Networks) in detecting credit card fraud when compared to classical machine learning algorithms (e.g., Logistic Regression)?

This thesis stated comparison of Logistic Regression and Convolutional Neural Networks (CNN) provided a little insight into the rapidly evolving area of credit card fraud detection. The value of selecting the appropriate model for the project at issue is demonstrated by our findings, as both Convolutional Neural Networks and logistic regression possess distinct advantages. This chapter answers the research question by assessing the outcomes of the implementation.

- Deep learning models tend to achieve slightly more accuracy compared to classical methods like Logistic Regression due to their ability to learn complex patterns in data. However, better accuracy can be misleading for imbalanced data sets, where most transactions are non-fraudulent.

- Convolutional Neural Networks is better suitable for minimizing the cost of wrongly identifying regular transactions as fraudulent than Logistic Regression since they can achieve better accuracy, resulting in fewer false positives.

- By detecting more instances of fraud than Logistic Regression, deep learning models can attain a slightly more recall (sensitivity). This is necessary to make sure that genuine fraudulent transactions are not detected.

- Precision and recall may be used to calculate the f1-score. Convolutional Neural Networks makes a better f1-score over Logistic Regression, which makes it more efficient at balancing the trade-off between false positives and false negatives.

The study found that Convolutional Neural Networks algorithms outperformed Logistic Regression in term of precision, recall, and F1-score, as anticipated due to their ability to capture complex patterns in credit card transaction data. This aligns with the theoretical understanding that deep learning models, like Convolutional Neural Networks, excel in tasks where intricate, non-linear relationships are prevalent, making them more suitable for credit card fraud detection than traditional Logistic Regression, which is generally less capable of handling such complexity.

Depending on elements like data set size, quality, and feature engineering, these models' performance might vary. Deep learning models frequently require bigger data sets and more processing capacity for training. The specific requirements and constraints of the present credit card fraud detection problem should be taken into account when deciding between deep learning and traditional machine learning algorithms. Here, Table 5.1 is an assessment of the proposed model and a comparison to the results of prior related papers in the field of credit card fraud detection.

Reference	Model	Accuracy	Precision	Recall	F1-score
[7]	CNN	0.99	0.87	0.58	0.68
[2]	Logistic Regression	0.99	0.82	0.52	0.63
[3]	CNN + ADASYN	0.99	0.99	0.99	0.99
[5]	Random Forest	0.96	0.83	0.69	0.75
[5]	Support Vector Machine	0.91	0.61	0.82	0.69
[5]	Logistic Regression	0.86	0.75	0.73	0.74
Proposed model	CNN	0.99	0.95	0.76	0.85
Proposed model	Logistic Regression	0.99	0.88	0.63	0.74

Table 5.1: Comparative analysis of performance metrics between the proposed model and prior research works

In order to detect credit card fraud, a number of models are compared in the Table 5.1, including Convolutional Neural Networks, Logistic Regression, Convolutional Neural Networks with ADASYN (a method of data augmentation), Random Forest, Support Vector Machine, and proposed models combining Convolutional Neural Networks and Logistic Regression. First of all, the proposed models, Convolutional Neural Networks and Logistic Regression, both achieve high accuracy, proving their value in classification as a whole. Precision, recall, and f1-score are all significantly improved when Convolutional Neural Networks and ADASYN are used, highlighting the value of data augmentation methods.

Additionally, the proposed Logistic Regression model balances precision and recall, demonstrating its ability to reduce false positives and negatives, which is essential in fraud detection. These results establish prior research by demonstrating how a combination of data augmentation and various machine learning algorithms can be helpful in enhancing credit card fraud detection. This approach is practical, accurate, and balanced in its trade-off between precision and recall.

Limitations: Our research suggests that the linear decision boundaries of logistic regression tend to be inappropriate for capturing the complex patterns and difficulties present in credit card transaction data. This restricts the capacity to detect fraud, particularly if working with high-dimensional and nonlinear data. The other logistic regression drawback occurs when the total number of observations exceeds the number of characteristics in the data set. The objective for the future is to get over this limitation to create a system that can recognize real-time fraud transactions from streaming data.

Chapter 6

Conclusions and Future Work

6.1 Conclusion

Initially, it is essential to figure out the pros and cons of the Logistic Regression and Convolutional Neural Network (CNN) algorithms to identify credit card fraud. In the end, it defends people and organizations from potential fraud by improving the security and stability of financial transactions. By identifying the most efficient algorithm for recognizing unauthorized transactions, this project helps both financial institutions and consumers by reducing the stress and loss of money caused on by credit card fraud and developing protection in our everyday banking activities.

In conclusion, the choice of methods for modeling is essential in fraud detection, which is why our research underlines the dynamic character of this field of study. Convolutional Neural Networks and Logistic Regression provide supportive roles in this crucial sector, each with unique benefits and drawbacks. When selecting a suitable method to effectively combat credit card fraud, experts have to carefully assess their objectives, boundaries, and information properties.

6.2 Future work

Future work for this project could focus on further developing the results in various manners. Here are a few suggestions for further work:

- Look into the performance of other machine learning and deep learning models, such as Random Forest, Support Vector Machines, Recurrent Neural Networks, or Long Short-Term Memory networks. To determine if these models will yield better outcomes, compare them with Convolutional Neural Networks and Logistic Regression.

- In the field of credit card fraud,the use of ensemble methods, such as Random Forest, Gradient Boosting, or stacking, to combine the predictions of multiple models.

- Credit card fraud data sets are often imbalanced, with a majority of non-fraudulent transactions. Research and implement advanced techniques for handling imbalanced data, such as oversampling, under-sampling, or synthetic data generation methods.

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