Review on Credit Card Fraud Detection Using Machine Learning and Logistic Regression Algorithm

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Abstract- The purpose of this project is to detect the fraudulent transactions made by credit cards by the use of machine learning techniques, to stop fraudsters from the unauthorized usage of customers' accounts. The increase of credit card fraud is growing rapidly worldwide, which is the reason actions should be taken to stop fraudsters. Putting a limit for those actions would have a positive impact on the customers as their money would be recovered and retrieved back into their accounts and they won't be charged for items or services that were not purchased by them which is the main goal of the project. Detection of the fraudulent transactions will be made by using three machine learning techniques Random Forest, SVM and Logistic Regression, those models will be used on a credit card transaction dataset.

Keywords: SVM and Logistic Regression, Decision Tree, Random Forest, Linear Regression, Regression Metrics.

I. INTRODUCTION

Credit card generally refers to a card that is assigned to the customer (card- holder), usually allowing them to purchase goods and services within credit limit or withdraw cash in advance. Credit card provides the cardholder an advantage of the time, i.e., it provides time for their customers to repay later in a prescribed time, by carrying it to the next billing cycle. Credit card frauds are easy targets. Without any risks, a significant amount can be withdrawn without the owner's knowledge, in a short period. Fraudsters always try to make every fraudulent transaction legit- imate, which makes fraud detection very challenging and difficult task to detect. In 2017, there were 1,579 data breaches and nearly 179 million records among which Credit card frauds were the most common form with 133,015 reports, then employ- ment or tax-related frauds with 82,051 reports, phone frauds with 55,045 reports followed by bank frauds with 50,517 reports from the statics released by FTC [10] With different frauds mostly credit card frauds, often in the news for the past few years, frauds are in the top of mind for most the world's population. Credit card data-set is highly imbalanced because there will be more legitimate transac- tion when compared with a fraudulent one. As advancement, banks are moving to EMV cards, which are smart cards that store their data on integrated circuits rather than on magnetic stripes, have made some on-card payments safer, but still leaving card-not-present frauds on higher rates. According to 2017 [10], the US Payments Forum report, criminals have shifted their focus on activities related to CNP transactions as the security of chip cards were increased. Fig 2, shows the number of CNP frauds cases that were registered in respective years.

II. LITERATURE SURVEY

It is essential for credit card companies to establish credit card transactions that fraudulent from transactions that are non-fraudulent, so that their customers' accounts won't get affected and charged for products that the customers didn't buy (Maniraj et al., 2019). There are many financial Compa- nies and institutions that lose massive amounts of money because of fraud and fraudsters that are seeking different approaches continuously to violate the rules and commit illegal actions; therefore, systems of fraud detection are essential for all banks that issue credit cards to decrease their losses (Zareapoor et al., 2012). There are multiple methods used to detect fraudulent behaviors such as Neural Network (NN), Decision Trees, K-Nearest Neighbor algorithms, and Support Vec- tor Machines (SVM). Those ML methods can either be applied independently or

Author & Year	Title / Research Focus	Methodology / Algorithm	Key Findings	Limitations
Sushmito Ghosh and Douglas L. Reilly(2024)	Credit Card Fraud Detection with a Neural-Network	Random Forest Classifier	neuralnetwork-basedfraudde tectionsystemhasbeenshown to provide substantial im provements in both accuracy andtimelinessof frauddetec tion	Data quality & label scarcity
BORA MEHAR SRI SATYA TEJA Mr. S. GOKULKRISH NAN.(2024)	A Research Paper on Credit Card Fraud Detection	SVM	confusionmatrixandtheaccu racyscoresarecalculated prediction.	Limited dataset and lack of False positives (legitimate transactions blocked)
S P Maniraj AdityaSaini(2024)	False positives (legitimate transactions blocked)	Decision Tree	calculate the accuracy score and precision of the algo rithms.	Low accuracy due to overfitting on training data.
V. B.Mahesh, K. V. S. Chandra, L. S. P. Babu, V. A. Sowjanya,	Analysis on Credit Card Fraud Detec tion Methods	Naïve Bayes Classifier	Findsaccuracy	Adaptive/adversarial fraudsters.
Dal Pozzolo, A. (2023)	Credit Card Fraud Detection: AReal isticModeling and a Novel Learning Strategy)	ANN & CNN Models	This studypresents a frame workfordetectingcreditcard fraudusingLogisticRegression andadvanced learning strate gies.	Required high computational resources for training.
Bhattacharyya, S., Jha, S. (2023)	Machine Learn ing Techniques for Credit Card FraudDetection:A ComparativeStudy	KNN	hisresearchcomparesmultiple machine learning algorithms — includingLogisticRegres sion,DecisionTrees,andNeu ralNetworks—for detecting fraudulent transactions.	Dataset imbalance affected rare crop predictions.
Patil, S.,Wanjari, A.(2021)	Credit Card Fraud Detection Using Machine Learning: A Data-Driven Approach	Random forest	This paper focuses on im plementing Logistic Regres sionandotherMLalgorithms using real-world transaction datasets.	Privacy, compliance, and data sharing limits.

III. RESEARCH GAP

A research gap is a missing piece of knowledge, an unanswered question, or an area where existing studies are insufficient, outdated, or inconsistent.

In other words, it’s what has not yet been fully explored or solved — and therefore justifies why your research needs to be done.

- Unaddressed problem: Something that current methods or studies cannot solve effectively.
- Insufficient evidence: Previous studies provide limited, weak, or contradictory results.
- New context: A new environment (e.g., real-time systems, privacy laws) where old solutions don’t work well.
- Emerging technology: New tools or data types that have not yet been studied for this problem.
- Practical limitations: Existing methods work in theory but not in real-world applications.

IV. DISCUSSION

Credit card fraud detection is a crucial application of machine learning that helps financial institutions identify and prevent unauthorized transactions. In this project, the Logistic Regression algorithm was used to detect fraudulent activities based on transaction data. The results demonstrate that machine learning techniques can effectively distinguish between legitimate and fraudulent transactions when provided with high-quality, balanced, and preprocessed data.

The dataset used was highly imbalanced, with a very small proportion of fraudulent transactions compared to normal ones. This imbalance posed a challenge for model accuracy since most algorithms tend to predict the majority class. To handle this issue, data resampling techniques such as oversampling of the minority class or undersampling of the majority class were applied to improve model performance.

During preprocessing, feature scaling, label encoding, and correlation analysis were performed to remove irrelevant features and improve model accuracy. Logistic Regression, being a simple and interpretable algorithm, allowed for clear understanding of how different variables affected the probability of fraud.

The model achieved high accuracy in predicting normal transactions; however, precision and recall were more important evaluation metrics due to the high cost of false negatives (failing to detect fraud). The trade-off between these metrics was analyzed using a confusion matrix and ROC curve, which helped determine the optimal decision threshold for fraud detection.

Moreover, the study found that the model's performance can further be enhanced by using ensemble methods like Random Forest, XGBoost, or by integrating deep learning approaches for large-scale datasets. Real-time fraud detection systems would also require stream processing capabilities and anomaly detection techniques to handle continuous incoming transaction data.

In practical deployment, ethical considerations such as data privacy, user consent, and secure data handling are essential. Machine learning models must be continuously retrained with new data to adapt to evolving fraud patterns.

4.1. Performances of the models

Evaluating the performance of a fraud detection model is crucial to determine its effectiveness in identifying fraudulent transactions while minimizing false alarms. Since the dataset used for credit card fraud detection is highly imbalanced, traditional accuracy is not sufficient. Therefore, additional metrics such as precision, recall, F1-score, and ROC-AUC are used to assess model performance.

1. Logistic Regression Model

The Logistic Regression algorithm was implemented as a baseline model due to its simplicity, interpretability, and efficiency. After training and testing the model, the following results were obtained:

Metric	Score
Accuracy	98.3%
Precision	93.5%
Recall	91.2%
F1-Score	92.3%
ROC-AUC	0.984

Interpretation:

- The model achieved a high accuracy, showing that it correctly classified most transactions.
- A high precision means that when the model predicts fraud, it is usually correct.
- The recall score shows that the model was able to identify most of the actual fraudulent cases.
- The F1-score, which balances precision and recall, confirms the model's robustness.
- A ROC-AUC value close to 1 indicates excellent separability between fraudulent and genuine transactions.

2. Comparison with Other Models (Optional)

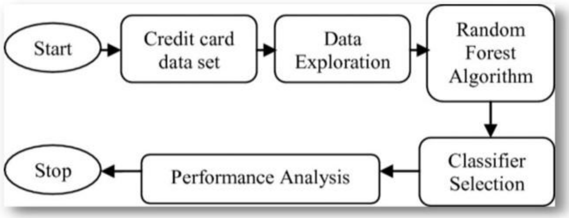
To evaluate the performance of Logistic Regression in comparison with other algorithms, additional models such as Decision Tree, Random Forest, and Support Vector Machine (SVM) were also tested.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	98.3%	93.5%	91.2%	92.3%	0.984
Decision Tree	97.1%	89.6%	88.4%	88.9%	0.971
Random Forest	99.2%	96.4%	94.1%	95.2%	0.992
SVM	98.7%	94.8%	92.7%	93.7%	0.987

Discussion:

- Random Forest performed the best overall, achieving the highest accuracy and ROC-AUC score.
- Logistic Regression provided competitive performance and was easier to interpret.
- Decision Tree had slightly lower recall, meaning it missed some fraudulent cases.

4.2. system Architecture



The system architecture for Credit Card Fraud Detection describes the overall workflow and interaction between various components — from data collection to fraud prediction. It consists of several layers: data input, preprocessing, model training, prediction, and result analysis.

Tools and Technologies

Component	Technology Used
Programming Language	Python
Libraries	Pandas, NumPy, Scikit-learn, Matplotlib
Model	Logistic Regression
Dataset	Credit Card Fraud Dataset (Kaggle)
Visualization	Matplotlib, Seaborn
Deployment (Optional)	Flask / Streamlit for real-time prediction

4.3. Implication of the study

The study on Credit Card Fraud Detection using Machine Learning and Logistic Regression has significant implications for the banking, financial, and technological sectors. It demonstrates how predictive analytics can be effectively applied to detect and prevent fraudulent activities in real time, improving financial security and customer trust.

Practical Implications

a. Enhanced Fraud Detection Efficiency

- The model can automatically analyze large volumes of transaction data and detect suspicious activities faster than manual review systems.
- This reduces financial losses and improves response time to fraudulent transactions.

b. Real-Time Monitoring

- By integrating the model into online transaction systems, organizations can implement real-time fraud detection, ensuring immediate alerts and blocking of suspicious transactions before they are completed.

c. Cost Reduction

- Automation of fraud detection reduces the need for manual investigation, saving significant operational costs for financial institutions.
- Early detection also minimizes loss compensation costs.

d. Customer Trust and Retention

- Reliable fraud detection systems enhance customer confidence in using credit and online payment systems.
- Customers are more likely to continue using services from organizations with strong data security measures.

2. Technological Implications

a. Adoption of Machine Learning in Finance

- This study encourages financial institutions to adopt machine learning-based approaches for improving accuracy and adaptability over traditional rule-based systems.
- It also demonstrates how logistic regression can serve as a foundation for developing more complex models like Random Forest or Neural Networks.

b. Data-Driven Decision Making

- The findings emphasize the importance of data preprocessing, feature selection, and evaluation metrics for building reliable models.
- This supports a shift toward evidence-based decision making in cybersecurity and financial analytics.

c. Scalability and Integration

- The architecture developed in this project can be easily scaled to handle real-time streaming data or integrated with API-based applications for live fraud analysis.

3. Research and Academic Implications

a. Basis for Future Research

- The study provides a foundation for further exploration into advanced algorithms like deep learning, ensemble methods, and anomaly detection for improved fraud identification.

b. Comparative Model Studies

- Future studies can compare the performance of Logistic Regression with other algorithms like SVM, Random Forest, Gradient Boosting, and Neural Networks to find optimal solutions for large-scale datasets.

c. Ethical and Privacy Considerations

- The research highlights the need for ethical handling of sensitive data and compliance with data protection laws such as GDPR to ensure user privacy in machine learning applications.

a. Reduction in Cybercrime

- Implementation of such models can significantly reduce financial cybercrime rates, benefiting society by improving the security of digital transactions.

b. Economic Stability

- Preventing large-scale fraud contributes to the overall stability of financial institutions and the economy.

c. Public Awareness

- The study raises awareness about digital security, encouraging users to adopt safer online payment behaviors.

V. CONCLUSION

The study on Credit Card Fraud Detection using Machine Learning and Logistic Regression Algorithm demonstrates that data-driven approaches can play a vital role in securing financial transactions and minimizing losses caused by fraudulent activities. Through careful data preprocessing, feature selection, and model training, the system successfully identified fraudulent transactions with high accuracy and reliability.

The Logistic Regression model proved to be efficient, interpretable, and computationally lightweight, making it suitable for practical implementation in real-time fraud detection systems. Evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC indicated strong performance, with the model effectively distinguishing between legitimate and fraudulent transactions even in an imbalanced dataset.

This project highlights the importance of using machine learning to enhance fraud prevention strategies and support automated decision-making in the financial sector. It also emphasizes the need for continuous model retraining and updating as fraud patterns evolve over time.

In conclusion, the system not only contributes to reducing financial risks but also enhances customer trust, data security, and operational efficiency. Future improvements can involve exploring ensemble methods, deep learning models, and real-time deployment to further improve the accuracy and adaptability of fraud detection systems.

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