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CREDIT CARD FRAUD DETECTION USING MACHINE LEARNING AND DEEP LEARNING

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ABSTRACT

People can use credit cards for online transactions as it provides an efficient and easy-to-use facility. With the increase in usage of credit cards, the capacity of credit card misuse has also enhanced. Credit card frauds cause significant financial losses for both credit card holders and financial companies. In this research study, the main aim is to detect such frauds, including the accessibility of public data, high-class imbalance data, the changes in fraud nature, and high rates of false alarm. The relevant literature presents many machines learning based approaches for credit card detection, such as Extreme Learning Method, Decision Tree, Random Forest, Support Vector Machine, Logistic Regression and XG Boost. However, due to low accuracy, there is still a need to apply state of the art deep learning algorithms to reduce fraud losses. The main focus has been to apply the recent development of deep learning algorithms for this purpose. Comparative analysis of both machine learning and deep learning algorithms was performed to find efficient outcomes. The detailed empirical analysis is carried out using the European card benchmark dataset for fraud detection.
A machine learning algorithm was first applied to the dataset, which improved the accuracy of detection of the frauds to some extent. Later, three architectures based on a convolutional neural network are applied to improve fraud detection performance. Further addition of layers further increased the accuracy of detection. A comprehensive empirical analysis has been carried out by applying variations in the number of hidden layers, epochs and applying the latest models. The evaluation of research work shows the improved results achieved, such as accuracy, f1-score, precision and AUC Curves having optimized values of 99.9% ,85.71% 93%, and 98%, respectively. The proposed model outperforms the state-of-the-art machine learning and deep learning algorithms for credit card detection problems. In addition, we have performed experiments by balancing the data and applying deep learning algorithms to minimize the false negative rate. The proposed approaches can be implemented effectively for the real-world detection of credit card fraud.

Keywords-
Decision Tree, Random Forest, Support Vector Machine, Logistic Regression

I. Introduction

Credit card fraud (CCF) is a type of identity theft in which someone other than the owner makes an unlawful transaction using a credit card or account details. A credit card that has been stolen, lost, or counterfeited might result in The associate editor coordinating the review of this manuscript and approving it for publication was Liangxiu Han fraud. Card-not-present fraud or the use of your credit card number in e-commerce transactions has also become increasingly common as a result of the increase in online shopping. Increased fraud, such as CCF, has resulted from the expansion of e-banking and several online payment environments, resulting in annual losses of billions of dollars. In this era of digital payments, CCF detection has become one of the most important goals. As a business owner, it cannot be disputedthat the future is heading towards a cashless culture. As a result, typical payment methods will no longer be used in the future, and therefore they will not be helpful for expanding a business. Customers will not always visit the business with cash in their pockets. They are now placing a premium on debit and credit card payments. As a result, companies will need to

update their environment to ensure that they can take all types of payments. In the next years, this situation is expected to become much more severe.

1.1 Background

As a result, financial institutions should prioritize equipping themselves with an automated fraud detection system. The goal of supervised CCF detection is to create a machine learning (ML) model based on existing transactional credit card payment data. The model should distinguish between fraudulent and nonfraudulent transactions, and use this information to decide whether an incoming transaction is fraudulent or not. The issue involves a variety of fundamental problems, including the system's quick reaction time, cost sensitivity, and feature pre-processing. ML is a field of artificial intelligence that uses a computer to make predictions based on prior data trends [1] ML models have been used in many studies to solve numerous challenges. Deep learning (DL) algorithms applied applications in computer network, intrusion detection, banking, insurance, mobile cellular networks, health care fraud detection, medical and malware detection, detection for video surveillance, location tracking, Android malware detection, home 1.automation, and heart disease prediction. We explore the practical application of ML, particularly DL algorithms, to identify credit card thefts in the banking industry in this paper. For data categorisation challenges, the support vector machine (SVM) is a supervised ML technique. It is employed in a variety of domains, including image recognition [25], credit rating [5], and public safety [16]. SVM can tackle linear and nonlinear binary classification problems, and it finds a hyperplane that separates the input data in the support vector, which is superior to other classifiers. Neural networks were the first method used to identify credit card theft in the past [4]. As a result, (DL), a branch of ML, is currently focused on DL approaches.

1.2 Key Features of Credit Card

DEEP LEARNING APPROACHES:

DL algorithms are useful, including the convolutional neural network (CNN) algorithm, and more algorithms are deep belief networks (DBNs) and deep autoencoders; these are considered learning methods. They have numerous layers of processing data, illustration learning and classification of a pattern [7], [15]. The objective of deep-learning is to study artificial neural networks. The standard technique regards the size of neural networks, and it is considered the backpropagation model [8], [16]. The efficiency of the backpropagation algorithm decreases greatly, increasing the depth of the neural networks, which can cause problems, such as insufficient local goals and a dilution of errors. Deep designs should be considered to be an achievement. They can theoretically address the optimisation struggle in a profound manner within the training parameters [17], [18].

The training technique of the deep belief network is often considered the effective primary case of deep architecture training. Traditional ML algorithms, such as SVM, DT and LR, have been extensively proposed for CCF detection [3]. These traditional algorithms are not very well suited for large datasets. A CNN is a DL method; it can deeply relate to three dimensional data, such as image processing

This method is similar to the ANN; the CNN has the same structure hidden layer and a different number of channels in each layer in dimensionsional data, such as image processing. This method is similar to the ANN; the CNN has the same structure hidden layer and a different number of channels in each layer in addition to special convolution layers. The idea of moving filters through word convolution is linked to the data that can be used to capture the key information and automatically performs feature reduction. Thus, the CNN is widely used in image processing. The CNN does not require heavy data pre-processing for training.

II. Literature Survey

2.1 Introduction

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 Companies

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 Vector Machines (SVM). Those ML methods can either be applied independently or can be used collectively with the addition of ensemble or meta-learning techniques to develop classifiers (Zareapoor et al., 2012).

2.2 Literature Review

Zareapoor and his research team used multiple techniques to determine the best performing model in detecting fraudulent transactions, which was established using the accuracy of the model, the speed in detecting and the cost. The models used were Neural Network, Bayesian Network, SVM, KNN and more. The comparison table provided in the research paper showed that Bayesian Network was very fast in finding the transactions that are fraudulent, with high accuracy. The NN performed well as well as the detection was fast, with a medium accuracy. KNN's speed was good with a medium accuracy, and finally SVM scored one of the lower scores, as the speed was low, and the accuracy was medium. As for the cost All models built were expansive (Zareapoor et al., 2012). The model used by Alenzi and Aljehane to detect fraud in credit cards was Logistic Regression, their model scored 97.2% in accuracy, 97% sensitivity and 2.8% Error Rate. A comparison was performed between their model and two other classifier which are Voting Classifier and KNN. VC scored 90% in accuracy, 88% sensitivity and 10% error rate, as for KNN where k = 1:10, the accuracy of the model was 93%, the sensitivity 94% and 7% for the error rate.

2.3 Literature Review Conclusion

Throughout the search I found that there were many models created by other researchers which have proven that people have been trying to solve the credit card fraud problem. I found that Najdat Team used an approach that is established upon bidirectional long/short-term memory in building their model, other researchers have tried different data splitting ratios to generate different accuracies. The team of Sahin and Duman used different Support Vector Machine methods which are (SVM) Support Vector Machine with RBF, Polynomial, Sigmoid, and Linear Kernel. The lowest accuracy of the four models that will be studied in this research, is 54.86% for KNN and 36.40% for logistic Regression which were scored by Awoyemi and his team, as for Naïve Bayes the lowest accuracy was scored by Gupta and his team which is 80.4% and finally, SVM the lowest score was 94.65% and it was scored by Jain's team. To determine the best model out of the four models that will be studied through the research, the average of the best three accuracies of each model will be calculated, the average of the accuracy of KNN is 98.72%, the average of logistic regression is 98.11%, 98.85% for Naïve bayes and 96.16% for Support Vector Machine. So, for the best performing credit card fraud detecting model within the Literature review is the Logistic Regression model.

III. Proposed Work

We propose a Machine learning model to detect fraudulent credit card activities in online financial transactions. Analyzing fake transactions manually is impracticable due to vast amounts of data and its complexity. However, adequately given informative features, could make it is possible using Machine Learning. This hypothesis will be explored in the project. To classify fraudulent and legitimate credit card transaction by supervised learning Algorithm such as Randomforest. To help us to get awareness about the fraudulent and without loss of any financially.

3.1 Objectives:

1. **Develop a Comprehensive Dataset**:

- Utilize existing datasets (e.g., Kaggle Credit Card Fraud Detection Dataset) and collaborate with financial institutions to gather diverse and representative transaction data.
- Incorporate features such as transaction amount, merchant type, location, time, and customer behavior patterns.

2. **Preprocess and Engineer Features**:
o Handle class imbalance using techniques like SMOTE (Synthetic Minority Over-sampling Technique).
o Create additional features that capture temporal patterns, frequency of transactions, and user behavior
1. **Implement Machine Learning Algorithms**:
o Evaluate various traditional ML algorithms such as Logistic Regression, Decision Trees, Random Forests, and Support Vector Machines (SVM).
o Utilize ensemble methods to enhance detection capabilities and improve model robustness.
2. **Develop Deep Learning Models**:
o Design neural network architectures, including Feedforward Neural Networks, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), to capture complex transaction patterns.
o Experiment with Autoencoders for unsupervised anomaly detection, training models to recognize normal transaction behaviors.
3. **Real-time Detection System**:
o Implement a system architecture that allows for real-time transaction monitoring and fraud detection.
o Utilize streaming data processing frameworks (e.g., Apache Kafka) to ensure efficient handling of live transaction data.
4. **Model Evaluation and Optimization**:
o Use cross-validation and hyperparameter tuning to optimize model performance.
o Assess models using metrics such as accuracy, precision, recall, and F1 score, focusing particularly on reducing false positives.
5. **Interpretability and Explainability**:
o Integrate tools like SHAP and LIME to provide insights into model decisions, ensuring transparency in fraud detection.
o Develop visualizations to help stakeholders understand model behavior and risk factors associated with fraudulent transactions.

3.2 Methodology:

1. **Data Collection and Exploration**:
o Gather and merge transaction data from various sources, ensuring a diverse representation of legitimate and fraudulent transactions.
o Conduct exploratory data analysis (EDA) to understand patterns and distributions in the dataset.
2. **Data Preprocessing**:
o Normalize numerical features and encode categorical variables.
o Split the data into training, validation, and test sets while maintaining the distribution of fraud cases.
3. **Model Development**:
o Train and validate multiple ML models, comparing their performance based on evaluation metrics.
o Design and implement deep learning architectures, experimenting with various configurations and layers.
4. **System Implementation**
o Create a prototype for the fraud detection system that integrates both ML and DL models.
o Use cloud-based services to facilitate scalability and manage large volumes of transaction data.
5. **Monitoring and Adaptation**:
o Set up mechanisms for continuous monitoring of model performance in production.
o Establish a feedback loop to update models with new data, adapting to evolving fraud tactics.

3.3 Expected Outcomes

- **Improved Detection Rates**: A system that effectively detects fraudulent transactions with high precision and recall, minimizing the occurrence of false positives.

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- **Scalable Solution**: A robust architecture capable of handling large volumes of transactions in real-time.
- **Actionable Insights**: Comprehensive reporting and visualization tools that provide stakeholders with actionable insights into fraudulent behavior patterns.

IV. System Requirements

4.1 Data Preparation

The first figure bellow shows the structure of the dataset where all attributes are shown,
with their type, in addition to glimpse of the variables within each attribute, as shown at the end of the figure the Class type is integer which I needed to change to factor and identify the 0 as Not Fraud and the 1 as Fraud to ease the process of creating the model
and obtain visualizations.

```
'data.frame':   284807 obs. of  31 variables:
 $ Time  : num  0 0 1 1 2 2 4 7 7 9 ...
 $ V1    : num  -1.36 1.192 -1.358 -0.966 -1.158 ...
 $ V2    : num  -0.0728 0.2662 -1.3402 -0.1852 0.8777 ...
 $ V3    : num  2.536 0.166 1.773 1.793 1.549 ...
 $ V4    : num  1.378 0.448 0.38 -0.863 0.403 ...
 $ V5    : num  -0.3383 0.06 -0.5032 -0.0103 -0.4072 ...
 $ V6    : num  0.4624 -0.0824 1.8005 1.2472 0.0959 ...
 $ V7    : num  0.2396 -0.0788 0.7915 0.2376 0.5929 ...
 $ V8    : num  0.0987 0.0851 0.2477 0.3774 -0.2705 ...
 $ V9    : num  0.364 -0.255 -1.515 -1.387 0.818 ...
 $ V10   : num  0.0908 -0.167 0.2076 -0.055 0.7531 ...
 $ V11   : num  -0.552 1.613 0.625 -0.226 -0.823 ...
 $ V12   : num  -0.6178 1.0652 0.0661 0.1782 0.5382 ...
 $ V13   : num  -0.991 0.489 0.717 0.508 1.346 ...
 $ V14   : num  -0.311 -0.144 -0.166 -0.288 -1.12 ...
 $ V15   : num  1.468 0.636 2.346 -0.631 0.175 ...
 $ V16   : num  -0.47 0.464 -2.89 -1.06 -0.451 ...
 $ V17   : num  0.208 -0.115 1.11 -0.684 -0.237 ...
 $ V18   : num  0.0258 -0.1834 -0.1214 1.9658 -0.0382 ...
 $ V19   : num  0.404 -0.146 -2.262 -1.233 0.803 ...
 $ V20   : num  0.2514 -0.0691 0.525 -0.208 0.4085 ...
 $ V21   : num  -0.01831 -0.22578 0.248 -0.1083 -0.00943 ...
 $ V22   : num  0.27784 -0.63867 0.77168 0.00527 0.79828 ...
 $ V23   : num  -0.11 0.101 0.909 -0.19 -0.137 ...
 $ V24   : num  0.0669 -0.3398 -0.6893 -1.1756 0.1413 ...
 $ V25   : num  0.129 0.167 -0.328 0.647 -0.206 ...
 $ V26   : num  -0.189 0.126 -0.139 -0.222 0.502 ...
 $ V27   : num  0.13356 -0.00898 -0.05535 0.06272 0.21942 ...
 $ V28   : num  -0.0211 0.0147 -0.0598 0.0615 0.2152 ...
 $ Amount: num  149.62 2.69 378.66 123.5 69.99 ...
 $ Class : int  0 0 0 0 0 0 0 0 0 0 ...
```

Figure 1 - Dataset Structure

The second figure shows the distribution of the class, the red bar which contains 284,315 Variables represents the non-fraudulent transactions, and the blue bar with 492 variables represents the fraudulent transactions

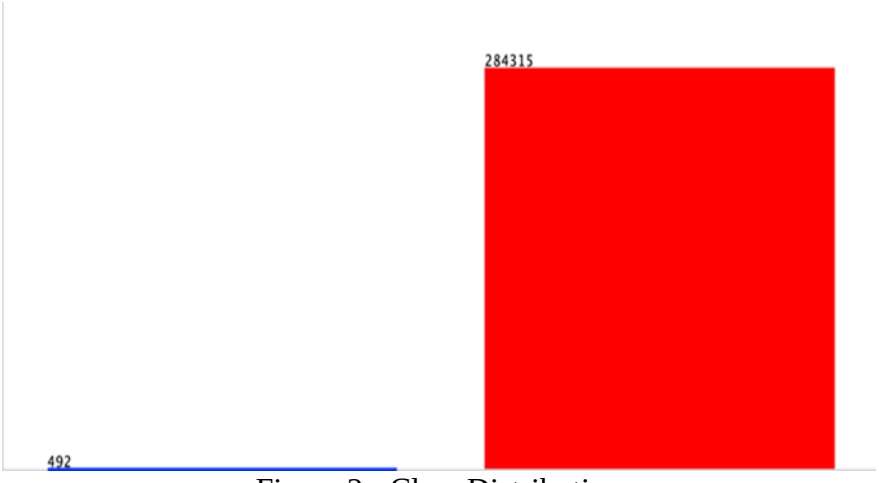

Figure 2 - Class Distribution

4.1.1 Correlation between attributes "Image from R"

The correlations between all the of the attributes within the dataset are presented in the figure below.

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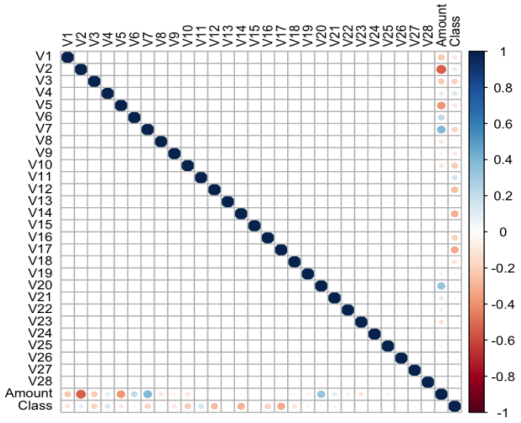

Figure 3 – Correlations

4.1.2 Attribute with the most fraud

Figure 4 below shows attribute 18 the attribute with the most credit card fraudulent transactions, the blue line represents the variable 1 which is the fraudulent transactions.

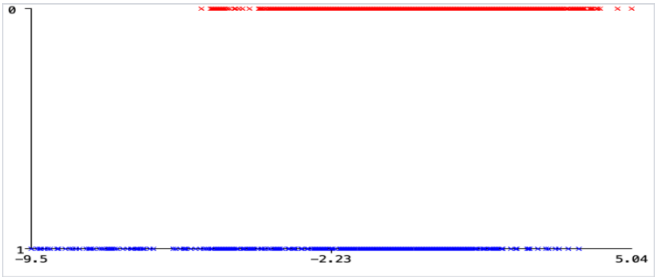

Figure 4 Transaction

4.1.3 Attribute with the less fraud

The figure below shows the variable that have the lowest number of fraudulent transactions, as mentioned earlier the blue line represents the fraudulent instances within the dataset.

4.2 Data Preprocessing

As there are no NAs nor duplicated variables, the preparation of the dataset was simple the first alteration that was made to be able to open the dataset on Weka program is changing the type of the class attribute from Numeric to Class and identify the class as {1,0} using the program Sublime Text. Another alteration was made on the type as well on the R program to be able to create the model and the visualization.

4.3 Data Modeling

After making sure that the data is ready to get modeled the four models were created using both Weka and R. the model SVM was created using Weka only, as for KNN, Logistic Regression and Naïve Bayes they were created using R and Weka.

4.3.1 KNN

The K-Nearest Neighbour algorithm (KNN) is a supervised ML technique that can be applied in both scenario instances, classification instances along with regression instances (Mahesh, 2020).To figure the best KNN model two Ks where used K=3 and K=7, both are presented with figures from both Weka and R.K = 3

During the making of the KNN model, I decided to create two models where K=3 and K=7.

Figure 5 shows the model created in R, the model scored an accuracy of 99.83% and managed to correctly identify 91,719 transactions and missed 155. As for the Weka program the model scored 99.94% for the accuracy and miss-classified 52 transactions. As there are different accuracies the average of the accuracies is 99.89%.

4.3.2 Naïve Bayes

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Naïve Bayes is a classification algorithm that consider the being of a certain trait within a class is unrelated to the being of any different feature, the main use of it is for clustering and classifications, depending on the conditional probability of happening (Mahesh, 2020).
The second model created by R is Naïve Bayes, figure 9 shows the performance of the model, it scored an accuracy of 97.77% and misclassified a total of 2,051 transactions, 33 fraudulent as nonfraudulent and 2018 nonfraudulent as fraudulent. There is a slight difference in the accuracy of the Naïve bayes model created within Weka as its 97.73% and the misclassification instances are 1,938.

```
Correctly Classified Instances       83504               97.7318 %
Incorrectly Classified Instances      1938                2.2682 %
Kappa statistic                          0.1292
Mean absolute error                      0.0227
Root mean squared error                  0.1491
Relative absolute error                626.539  %
Root relative squared error            330.6127 %
Total Number of Instances            85442

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.851    0.022    0.072      0.851    0.132      0.243    0.968     0.091     1
                 0.978    0.149    1.000      0.978    0.989      0.243    0.964     1.000     0
Weighted Avg.    0.977    0.149    0.998      0.977    0.987      0.243    0.964     0.998

=== Confusion Matrix ===

     a     b   <-- classified as
   148    26 |     a = 1
  1912 83356 |     b = 0
```

Figure 5 - Weka Naïve Bayes

4.3.3 Logistic Regression

Logistic Regression model is statical model where evaluations are formed of the connection among dependent qualitative variable (binary or binomial logistic regression) or variable with three values or higher (multinomial logistic regression) and one independent explanatory variable or higher whether qualitative or quantitative (Domínguez-Almendros et al., 2011). The last model created using both R and Weka is Logistic Regression, the model managed to score and accuracy of 99.92% in R (figure 11) with 70 misclassified instances, while it scored 99.91% in Weka with 77 misclassified instances as presented in figure 10.

```
  FALSE  TRUE
0 91693     9
1    61   111
[1] 99.92381
```

Figure 6 - Weka Logistic Regression

4.3.4 Support Vector Machine

Support Vector machine is a supervised ML technique with connected learning algorithms which inspect data used for both classification and regression analyses, it also performs linear classification, additionally to non-linear classification by creating margins between the classes, which are created in such a fashion that the space between the margin and the classes is maximum which minimizes the error of the classification (Mahesh, 2020).
Finally, the model Support Vector Machine as show in figure 12 managed to score 99.94% for the accuracy and misclassified 51 instances

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```
Correctly Classified Instances       85391               99.9403 %
Incorrectly Classified Instances        51                0.0597 %
Kappa statistic                          0.8388
Mean absolute error                      0.0006
Root mean squared error                  0.0244
Relative absolute error                 16.4433 %
Root relative squared error             54.1917 %
Total Number of Instances            85442

=== Detailed Accuracy By Class ===

               TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
               0.764    0.000    0.930      0.764    0.839      0.843    0.882     0.711     1
               1.000    0.236    1.000      1.000    1.000      0.843    0.882     1.000     0
Weighted Avg.  0.999    0.235    0.999      0.999    0.999      0.843    0.882     0.999

=== Confusion Matrix ===

     a     b   <-- classified as
   133    41 |     a = 1
    10 85258 |     b = 0
```

Figure 7 - Support Vector Machine

V. Conclusion

In conclusion, the main objective of this project was to find the most suited model in credit card fraud detection in terms of the machine learning techniques chosen for the project, and it was met by building the four models and finding the accuracies of them all, the best model in terms of accuracies is Support Vector Machine which scored 99.94% with only 51 misclassified instances. I believe that using the model will help in decreasing the am

ount of credit card fraud and increase the customers satisfaction as it will provide them with better experience in addition to feeling secure. 5.2 Recommendations There are many ways to improve the model, such as using it on different datasets with various sizes, different data types or by changing the data splitting ratio, in addition to viewing it from different algorithm perspective. An example can be merging telecom data to calculate the location of people to have better knowledge of the location of the card owner while his/her credit card is being used, this will ease the detection because if the card owner is in Dubai and a transaction of his card was made in Abu Dhabi it will easily be detected as fraud**.**

Key Findings

1. **The Evolving Nature of Fraud**: Fraudulent techniques continually evolve, with fraudsters employing increasingly sophisticated methods to bypass detection systems. Traditional rule-based systems, while useful, often fail to keep up with these changes. This necessitates a shift towards more adaptive and intelligent detection mechanisms.
2. **Machine Learning and Artificial Intelligence**: The integration of machine learning (ML) and artificial intelligence (AI) into fraud detection has proven to be transformative. These technologies enable the analysis of vast amounts of transaction data to identify patterns and anomalies indicative of fraud. By employing algorithms that learn from historical data, financial institutions can improve the accuracy of their detection systems significantly.

Real-Time Processing: Speed is critical in fraud detection. Real-time processing capabilities allow for immediate action to be taken upon identifying suspicious activity. This not only mitigates potential losses but also enhances customer trust and satisfaction. Systems that can analyze transactions as they occur are essential for effective fraud prevention.

3. **Behavioral Analysis**: Understanding customer behavior plays a crucial role in detecting fraud. By establishing a baseline of normal transaction patterns for individual users, detection systems can flag deviations that may indicate fraudulent activity. This approach minimizes false positives and improves the overall efficiency of fraud detection efforts.
4. **Data Privacy and Ethical Considerations**: As detection systems become more sophisticated, concerns around data privacy and ethical use of information arise. It is essential to balance the need for effective fraud detection with the protection of customer data. Regulatory frameworks and ethical guidelines should guide the implementation of these technologies to ensure they are used responsibly.

Challenges in Implementation

1. **Data Quality and Availability**: Effective fraud detection relies heavily on high-quality data. Incomplete or inaccurate transaction data can lead to false positives or negatives. Financial institutions

must invest in data management practices to ensure that their systems have access to reliable information.

2. **Integration with Legacy Systems**: Many financial institutions still rely on legacy systems that may not easily integrate with modern detection technologies. Overcoming these technological barriers is crucial for implementing effective fraud detection solutions.
3. **User Acceptance and Trust**: As technology evolves, users may have concerns regarding the surveillance and analysis of their transaction data. Financial institutions must foster transparency about how their data is used and how fraud detection technologies function to build trust with customers.
4. **Resource Allocation**: Developing and maintaining advanced fraud detection systems can be resource-intensive. Financial institutions must strategically allocate resources to ensure they can effectively combat fraud without compromising other areas of their operations.

Future Directions

1. **Enhanced Collaboration**: Collaboration between financial institutions, technology providers, and regulatory bodies will be key to advancing fraud detection efforts. Sharing insights, data, and best practices can enhance the collective ability to combat fraud.

Continued Research and Development: Ongoing research into new technologies, algorithms, and methodologies will be essential for staying ahead of fraudsters.

2. Investment in R&D can yield innovative solutions that further enhance detection capabilities.
3. **Holistic Approaches**: Moving towards a more holistic approach that combines multiple detection techniques (e.g., rule-based, ML, and behavioral analysis) will provide a more comprehensive defense against fraud.
4. **Consumer Education**: Educating consumers about potential fraud risks and the measures they can take to protect themselves will be vital. An informed customer base can serve as an additional layer of defense against fraud.

In conclusion, credit card fraud detection represents a dynamic and complex challenge that requires a multi-faceted approach. By leveraging advanced technologies, understanding consumer behavior, and fostering collaboration, financial institutions can significantly enhance their ability to detect and prevent fraud. While challenges remain, the ongoing evolution of detection methods promises a future where consumers can engage in electronic transactions with greater confidence and security.

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