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A Review on Fraud Detection Using Machine Learning and Deep Learning

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Abstract: ***Financial companies and cardholders both face large financial losses as a result of online fraud. This research study looks for such frauds using information from the general public, information on significant class problems, high false alarm rates, and changes in the manner of fraud. Various machine learning approaches, including the extreme learning method, support vector machine, random forest, XG boost (Extreme Gradient Boosting), decision tree, and logistic regression have been utilized to acquire credit card identity. However due to their low accuracy, fraud losses must be minimized using state-of-the-art deep learning algorithms. Utilizing different datasets for fraud detection, this analysis examines machine learning with deep learning methods. Since identifying credit card fraud is essential, our research makes use of both widely-used machine learning techniques and deep learning.. Many parameters, including specificity, recall, precision, accuracy, misclassification, and F1 score, are used to evaluate their efficiency. According to the results, deep learning and machine learning methods are useful for detecting fraud.***

Keywords: Training, Industries, Machine Learning Algorithms, Data Analysis, Costs, Deep Learning Algorithms

1. Introduction

Transactions and fraud detectors have traditionally played roles that are composite. Nowadays, the most common cause of financial losses is fraudulent transactions, which occur more frequently than in previous times due to mostly to the Internet. The economy experienced losses from transaction fraud totaling between $28 billion and $30 billion in 2019 and 2020 and over $32 billion in 2021..

It is predicted that worldwide transaction fraud will increase every year, reaching $34 billion by 2022 [1]. Consequently, to identify and analyze financial transactions, banks and other financial service providers could require an automated detection of fraud tool. Fraud detection systems are designed to follow incoming transaction patterns by analyzing huge numbers of transactional record, which can be utilized to identify or track incoming transactions[2]. Without the need for explicitly development, Artificial intelligence (AI) machine learning enables systems to automatically learn from experience and improve. Developing computer algorithms with the ability to collect data and utilize it for learning is the main goal of machine learning [3].

In order to find patterns in data and use the examples they provide to direct future decisions, instruction, direct experience, or the observations or facts which function as the foundation for learning are provided by observations.. Getting computers to learn on their own, without help or intervention from humans, and change their activities is the main goal [4].

Networks that are capable of learning unsupervised from unlabeled or unstructured data are used in the deep learning subset of machine learning in artificial intelligence. Using profile images, deep learning is a technology that generates face detection and uses them to differentiate between real and fake features [5]. It has been shown that machine learning is highly effective at classifying and identifying fraudulent transactions. Alternatively, to validate and train a fraud classifier, a large number of transaction reports could be used. Despite the fact that it has shown to be extremely successful at detecting fraudulent transactions, supervised learning, transactional fraud analysis tools will continue to improve. A small enhancement to the classifier can result in significant cost savings for the company.

As technological advances and worldwide communication have advanced, fraud has been significantly on increasing. Prevention and detection are the two basic strategies for avoiding fraud[6]. By adding an extra layer of defense, preventive measures ward against fraudsters attacks. When preventative measures have already failed, detection takes place. Detection, which helps in identifying and alerts participants to fraudulent transactions as soon as they appear. Online payment gateways have recently seen an increase in demand for card-not-present transactions [7] in credit card operations. Over $31 trillion was generated worldwide by online payment systems in 2015, up 7.3% from 2014, according to the Nilson Report published in October 2016. In 2015, there were $21 billion in worldwide losses resulting from credit card theft; by 2020, that amount could potentially increase to $31 billion. However fraudulent transactions have increased having a significant impact on the economy [8]. A number of categories exist for credit card fraud. Card-not-present (CNP) and Card-present (CP) frauds are the two categories of fraud that can be easily identified in a group of transactions. Fraud related to bankruptcy, theft/counterfeit, applications, and behavior can be further classified into those two categories [9]. This analysis is focused on the four fraud methods that fall within the previously described CNP fraud category, and they offer a real-time fraud detection technique. This generation's solution is machine learning, which can operate on large datasets more easily than human can be replaces such methodologies. The two primary classifications of machine

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learning approaches are supervised learning and unsupervised learning [10]. Either approach can be used for fraud detection and the dataset will choose when to submit applications. Prior classification of anomalies is necessary for supervised learning.

2. Literature Survey

K. Debnath and N. Kar, et.al [11] presented the email spam detection techniques utilizing deep learning and machine learning approaches to accurately differentiate spam emails from legitimate emails. Using Long Short-Term Memory (LSTM) and Bidirectional Encoder Representations from Transformers (BERT), deep learning methods to identify and categorize new emails as spam is developed using the Enron email dataset.

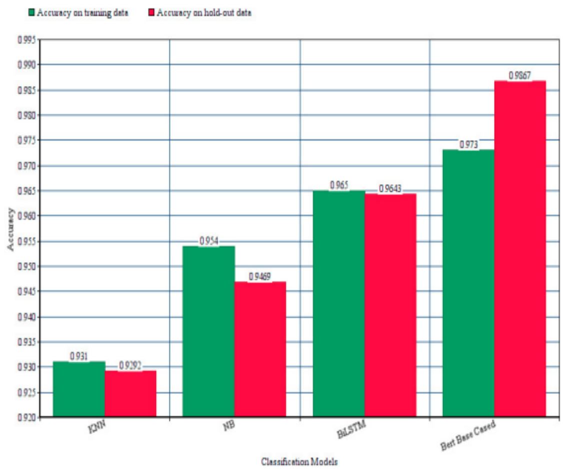

Figure 1: Accuracy Comparison Graph For Spam Detection Techniques

The email's text was analyzed, and data preprocessing was done using an Natural Language Processing (NLP) technique. The results in email spam detection are contrasted with those of earlier models. At 99.14% with BERT, 98.34% with Bidirectional Long Short-Term Memory (BiLSTM), and 97.15% with LSTM, the suggested deep learning method achieved the maximum accuracy. Every implementation makes use of Python.

Priyaradhikadevi T., Mathavan V., Vanakovarayan S., Praveena E., Prasanna S. and Madhan K., et.al [12] The detection framework was created using Quantum machine learning (QML) and Support Vector Machine (SVM) improved using quantum annealing solvers were then used to implement. To improve testQML's detection performance, twelve machine learning approaches have been applied, the results have been compared using two datasets is the QML application: Israeli bank loan applications are categorized as a time series while Israeli credit card transactions as a non-time series. Applying the quantum enhanced SVM to the bank loan dataset is provides better results than the other methods in terms of speed and accuracy. Comparable to others who utilize credit card transaction data from Israel, the detection accuracy is significant. Although there is no significant increase in accuracy, feature selection can significantly speed up the identification process for both types of data. These results show that time series data with significant imbalances can be used for QML applications, while standard machine learning approaches have been demonstrated useful for non-time series data. This work explains that to evaluate the trade-offs of speed, accuracy, and cost when selecting the best technique for different datasets.

Bharti Kudale, Swapnil Birajda, Abhishek Hattekar, Sameer Kulkarni, Sunil Gaikwad, et.al [13] Most credit card scams are simple and friendly targets. The risk of online fraud has increased, since the e-commerce and many other websites have developed online payment systems. In recent years, it is becoming increasingly challenging for banks to identify credit card fraud. A key element in identifying credit card fraud in transactions is Machine learning (ML). In order to analyze client transaction history identify behavioral patterns, developing and executing a fraud detection plan for streaming transaction data is the primary goal of the project. Support vector machine (SVM) classification is used in the proposed approach to identify frauds. This study conclusion explains the way to train and test a classifier using supervised techniques to find the best classifier that provides better results.

A. Maurya and A. Kumar, et.al [14] Due to the growth of e-commerce, most transactions are now completed online, which increases the possibility of being scammed. Consequently, this forces the financial institutions to constantly improve and upgrade their model. Credit card fraud has been identified by machine learning approaches; however, real-time data can present difficulties for machine learning.. Therefore, applying blockchain technology when combined with machine learning allows for increasing the model's accuracy and efficiency. The proposed approach uses machine learning algorithms to secure the fraudulent transaction and checks it using the Ethereum dataset. For the given dataset, XGBoost has achieved the greatest accuracy of 99.21% among all the classifiers.

Uddin, Mohammed & Azad, Salahuddin & Hossain, Rahat & Chugh, Ritesh. , et.al [15] recent times, there has been a significant risk of electronic transaction fraud, it can generate large financial losses and harm financial institutions reputations. To efficiently detect electronic transaction fraud, in the literature, several deep learning and machine learning models have been referenced. In order to improve a machine learning model's performance, feature selection is essential. The amount of time that was spent and the dataset could be modified to satisfy its evolving requirements, techniques for automatic feature engineering outperform methods for manual feature selection. To the best of knowledge there hasn't been a full investigation that advanced feature selection methods, like Deep Feature Synthesis (DFS), impact the effectiveness of deep learning-based electronic transaction fraud detection.

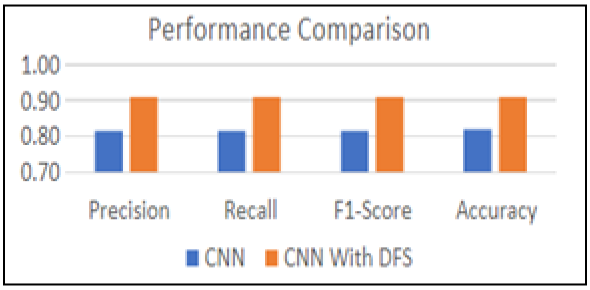

Figure 2: Performance Comparison Electronic Transaction Fraud

In this analysis, they utilize the DFS method to automatically extract features from the open-source, labelled credit card transaction dataset. Convolutional Neural Networks (CNNs), a baseline deep learning model, are fed the data in two different scenarios: one with DFS and the other without DFS. When the results from the two cases are compared, in comparison to standalone CNN, CNN with DFS performs significantly better in terms of memory, precision, F1 scores, and accuracy.

Ileberi, E., Sun, Y., Wang, Z., et.al [16] Credit card frauds are important and must be carefully selected when applying machine learning to the detection of credit card fraud. Using the Genetic algorithm (GA) for feature selection, this research suggests a Machine learning (ML) based credit card fraud detection engine. Random forest (RF), Decision tree (DT), Logistic regression (LR), Artificial neural network (ANN), and Naive bayes (NB) are the machine learning classifiers used by the proposed detection and the most effective features have been selected. Utilizing a dataset created from European cardholders, the suggested credit card fraud detection engine's performance is evaluated. The outcome showed that our proposed approach performs better than existing methods.

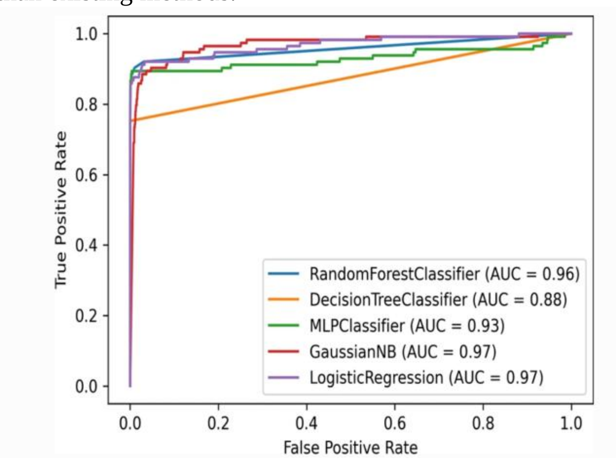

Figure 3: A Machine Learning Based Credit Card Fraud Detection Using the GA Algorithm For Feature Selection

Kewei X., Jiang Y., Peng B., and Lu T., et.al [17] Credit cards are being used for both online and offline transactions with increasing frequently. But increasing credit card fraud is occurring in combination with this increase. Accurate and effective fraud detection systems have become essential, due to Nilson Research predicts that this year's global loss from credit card theft will be $35 billion. In this research, they provide a deep learning approach to address this issue. To improve our model's performance, they used a number of methods, such as ensemble loss, mixed precision, memory compression, and feature engineering. The IEEE-CIS fraud dataset, which includes more than a million records, is used by Vesta Corporation for training and evaluating the model. Our approach performs better than traditional machine-learning-based techniques like Bayes and SVM, according to experiments.

V. Murthy, A. Bhanu Prasad, B. Varma and H. Shanmugasundaram, et.al [18] In this research, they examine the potential of deep neural networks in fraud detection using a dataset is made up of extensive public loan data from a financial organization called Lending Club. After this dataset was loaded, they handled the missing values and the pre-processing of the data. They created a CNN deep neural network to identify loan fraud on the Internet using this pre-processed data, and they used the XGBoost technique to extract significant features. To demonstrate the advantages of deep neural networks over widely used models, numerous experiments were carried out. This simple and efficient model may give light on that deep learning can be used to fight online loan fraud, which will be helpful to small and medium-sized financial corporations and financial engineers. M. Zamini and G. Montazer, et.al [19] Fraud detection has grown in importance for banks as a result of the growth in online payments and e-commerce. Financial transaction fraud carries a high risk of serious effects, including harm to the company's reputation among clients. Focusing on various fraud detection techniques together with innovative approaches is to address and prevent them becoming more and more essential. In this analysis, an unsupervised fraud detection method based on clustering and autoencoders has been introduced. 284807 transactions from European banks were used to evaluate an autoencoder using k-means clustering and three hidden layers. According to the results, this approach works better than others with an accuracy of 98.9% and a True Positive Rate of 81%.

Alkhatib K. I., Almahmoud M. H., Al-Aiad A. I., and Elayan O. N., et.al [20] Financial companies also mainly depend on new developments in technology to provide a range of services to their clients online. Credit cards, such as Visa and MasterCard, among the most widely used financial services. With these, consumers can make any type of financial transaction. But, criminals started working out to target consumers cards in order to commit fraud, which has created a significant problem for businesses as well as customers. Based on a dataset of consumers transactions from a well-known company named Vesta, this research offers a deep learning-based method for identifying credit card fraud. Effectively identifying transactions that were identified as fraudulent, the approach has an area under the Receiver Operating Characteristic curve (ROC) curve score of 99.1%.

Table 1: Review on Fraud Detection Using Machine Learning and Deep Learning

S. No	Author	Method used	Detection	Result (Accuracy)
1	K. Debnath and N. Kar [11]	LSTM and BERT	email spam detection models	99.14
2	Bharti Kudale, Swapnil Birajda, Abhishek Hattekar, Sameer Kulkarni, Sunil Gaikwad [13]	Support vector Machine (SVM) classification	online frauds	95.98
3	A. Maurya and A. Kumar [14]	Machine Learning	detect fraud in credit card transactions,	99.21
4	Uddin, Mohammed & Azad, Salahuddin & Hossain, Rahat & Chugh, Ritesh. [15]	Machine Learning	electronic transaction fraud	91
5	Ileberi, E., Sun, Y., Wang, Z.,[16]	Genetic Algorithm (GA)	credit card fraud detection	99.8
6	X. Kewei, B. Peng, Y. Jiang and T. Lu,[17]	deep-learning-based method	online and offline transactions.	95.8
7	M. Zamini and G. Montazer, [19]	unsupervised fraud detection	fraud detection methods	98.9
8	K. I. Alkhatib, A. I. Al-Aiad, M. H. Almahmoud and O. N. Elayan[20]	under-sampling method of deep learning approaches	attack customers' cards	99.1
9	Z. Zhang and S. Huang [21]	Convolutional Neural Network (CNN) and auto-encoder	detect fraud	93
10	K. J and A. Senthilselvi, [22]	Inception-ResNet-v2	detection model	96.57
11	A. M. Babu and A. Pratap [23]	convolutional neural network	Fraud detection	99.62

Z. Zhang and S. Huang, et.al [21] Identification of credit card fraud is becoming a major issue for financial organizations can be improved using deep learning algorithms. This study compares the effectiveness of two deep learning methods using two different data sets, Convolutional neural network (CNN) and auto-encoder, in the fraud detection task. This study uses a newly created dataset that contains all of the raw input variables as well as a preprocessed Principal Component Analysis (PCA) -based transaction dataset from the Université Libre de Bruxelles (ULB). They also preprocess the datasets using random under-sampling and the Synthetic minority oversampling techniques (SMOTE) to balance the datasets because imbalanced datasets can negatively impact the training quality. The results of the experiment demonstrate that the networks perform poorly (low performance) for the independent input dataset, they perform well (93% prediction accuracy) with the ULB dataset. The performance can be further enhanced by increasing the network's complexity. Additionally, in terms of increasing prediction accuracy, it is found that the under-sampling strategy performs better than the over-sampling strategy. The results indicate that more complicated systems are required to detect fraud when the criterion for fraud is stricter, while balancing the dataset before training will improve the results.

K. J and A. Senthilselvi, et.al [22] The Inception-ResNet-v2 technique was utilized on real-time data was methodically improved in this research work. The detection model presented in this analysis uses a convolutional neural network to operate from the start to the end. To address the training challenge of the deep network expand its reach, the greatest features of residual networks Inception convolution are combined in this model. In order to choose the optimum attributes and increase classification accuracy, the Hunter-Prey Optimization (HPO) model is also utilized. Each model uses a real-world dataset and stratified K-fold cross-validation to identify credit card theft from European cardholders. The proposed model is compared to modern models for evaluation. The results show that the suggested model is significantly more accurate than its predecessors (96.57%).

A. M. Babu and A. Pratap, et.al [23] A convolutional network and significantly skewed, imbalanced transactional data are suggested as tools for fraud detection. This dataset, which has significantly skewed data, is extracted for the purpose of detecting credit card fraud using the machine learning Kaggle dataset. The assessed features are 0 for the non-fraud class and 1 for the fraud class. In the banking industry, fraud detection analysis was an essential tool.

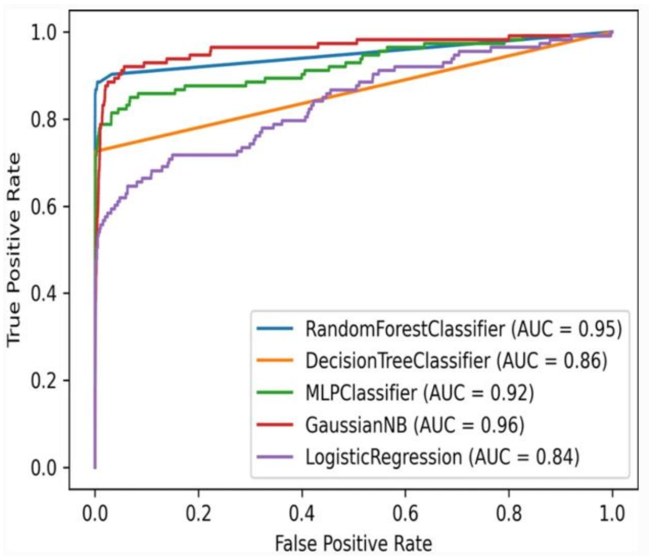

Figure 4: Graphical Representation of Fraud Detection Using Convolutional Network

These days, the artificial neural network is the least reliable method for identifying credit card fraud. There are a lot of false positives and misclassifications in the present fraud detection system. This work aims to create a model for credit card fraud detection that offers under these conditions with an extremely high level of accuracy by utilizing a combination of convolutional neural network layers. Predicting fraud within 300 epochs is the aim, and 99.62 percent performance can be achieved with the existing method.

Naby El A. A., Hemdan E. El-Din and Sayed A., El-Sayed et.al [24] According to Nielsen's estimate, It is estimated that worldwide credit card fraud losses will total around 28.65 billion in 2019 and approximately 32.96 billion by 2023. Thus, providers need to provide a reliable model for early fraud detection and prevention. In this research, they describe a deep learning-based effective strategy for identifying credit card fraudsters. As a result, they offer a model that uses Kaggle's credit card dataset to predict fraud or legitimate transactions. The OSCNN (Over sampling with convolution neural network) model is a suggested approach that utilizes CNN (Convolution neural network) with over-sampling preprocessing. The dataset had been submitted to the Multi-layer perceptron (MLP) algorithm. A comparison of the MLP-OSCNN outcomes, it was shown that, with 98% accuracy, the recommended model provided better results.

Mubalaike A. M. and Adali E., et.al [25] Deep learning (DL) models have been predicted to be very helpful in accurately identifying fraudulent transactions. An African mobile money service provider was provided a month's worth of real financial information which the dataset was extracted, and it included information on over six million transactions. The best machine learning methods, including Ensemble of decision trees (EDT) and deep learning algorithms are used to assess the preprocessed data, such as Restricted Boltzmann machines (RBM) classifiers and Stacked auto-encoders (SAE). Based on the ROC values, confusion matrix, accuracy, sensitivity, specificity, and precision of the result classifier models, their performance is evaluated. The optimal accuracy results are 90.53%, 80.52%, and 90.49%, according to this combination. The comparative results demonstrate the higher performance of the restricted Boltzmann machine over the other methods.

Yu X., Li X., Dong Y. and Zheng R., et.al [26] Using a credit card for online shopping or transactions is simple. However, credit card theft is every day worldwide and is challenging to detect manually. Billions of dollars were spent by a number of organizations, such as banks, information companies, and even the government, to develop an automated system for detecting fraud. They present a deep network for fraud detection technique in this research. To address the dataset's data skew issues, the log transform is utilized. To train the hard cases, the network is extended with the focal loss. According to the experiments, neural network model performs better than logistic regression and support vector machines, two other classical approaches.

G. Yedukondalu, K. Thrilokya, T. M. Reddy and K. S. Vasavi, et.al [27] Online fraud is also an increasing. Many methods exist for identifying these types of frauds, however they are inaccurate. This has to be improved. The XGBOOST and random forest algorithms are used in this study. To identify fraud, this study makes use of a large public loan dataset, like that from Lending Club. The first step is to fill in the missing data using a random forest. The XGBoost method is then used to select the most discriminating features. Financial engineers might benefit from an improved use of machine learning to identify fraudulent online loan applications, due to this effective approach.

3. Conclusion

Financial organizations are increasingly susceptible to fraud detection. Fraudsters frequently develop new techniques for their frauds. A robust classifier is able to adjust to the changing nature of fraud. A fraud detection system's primary goals are minimizing false-positive cases and accurately predicting fraud cases. ML techniques perform differently for every business case. One major issue that affects various machine learning techniques is the kind of input data. In order to detect Credit Card Fraud, the amount of features, the number of transactions, and the correlation between the features are the main factors determining the model's performance. Deep learning approaches are related to text processing the baseline model like CNNs their layers. These techniques perform better than traditional algorithms when used for credit card detection. Many sampling strategies are applied to improve the performance of the available examples, but they become much less effective when applied to the unseen data. With an increase in class imbalance came an increase in performance on unseen data. To improve the efficiency of the model that is suggested in this analysis, it is possible that more advanced deep learning techniques will be applied in this field of study in the future.

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