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A REVIEW ON: IDENTIFYING CREDIT CARD FRAUD USING A DEEP LEARNING APPROACH

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Abstract— Card companies lose billions of dollars annually due to fraudulent credit card transactions. A sophisticated fraud detection system with a cutting-edge fraud detection algorithm is believed to be necessary in order to reduce fraud losses. Our main accomplishment was creating a fraud detection system based on deep learning architecture. Perform a comparative analysis to evaluate the efficacy of the suggested framework using actual data from one of the biggest commercial banks. The results for the trial demonstrate the viability and effectiveness of the method we suggested for identifying credit card fraud. In terms of practice, While maintaining a respectable false positive rate, our suggested method can detect a higher percentage of fraudulent transactions than existing methods. The management value of our research is in the ability of credit card issuers to implement a recommended technique to quickly identify fraudulent transactions, safeguard client interests, and minimize fraud losses & regulatory costs.

Keywords— Deep learning,Deep Belief Networks,CNN,Credit Card Fraud Detection.

I. INTRODUCTION

Credit card theft refers to the unauthorized use of a credit or debit card. The objective could be to utilize services or make purchases, but it could also be to transfer money from one account to another so that a criminal can use it. To help financial institutions process card payments securely and cut down on card fraud, the Data Security Standards for the Payment Card Industry, a set of information security guidelines, were developed. (PKI DSS)[1][2]. Card fraud can be authorized, where a law-abiding customer uses their own credit card for a purchase via another account managed by a criminal, or it can be unauthorized, where the account owner refuses to allow the payment to continue as well as a third party completes the transaction. Online commerce has expanded significantly since its beginning. It is now an essential instrument used by the majority of businesses, government agencies, and non-profits to increase their efficiency in global trade[3][4]. How easy it is to complete credit card transactions is one of the crucial factors influencing whether credit cards are accepted. When discussing financial transactions, you should always be aware of the risk of financial fraud. Economic fraud is a deliberate offense in which the perpetrator preys on a victim for their financial or legal harm. In recent years, the use of credit cards has surpassed the use of cash[5]. The quantity of fraudulent credit card transactions has consequently significantly increased. How to spot credit card theft is shown in Figure 1.

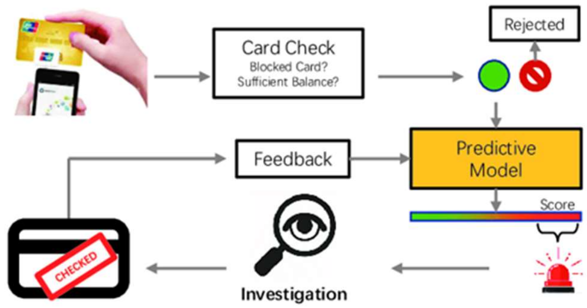

Fig. 1 Credit card fraud Detection

Computers can learn from their experiences on their own, without human input, thanks to deep learning, a subset of machine learning. Additionally, it uses a variety of mathematical models to predict outcomes in the future as precisely as possible. Because they are programmed to solve problems instead of just perform calculations, deep learning systems fundamentally differ from those used in traditional computation methods[6]. [7] Deep learning is the analysis of the raw data needed to train a model, where the model finds a range of patterns in the data and uses this understanding to predict outcomes that are not known. Deep learning has a wide range of applications[8]. Applications for it include the spam filter, facial recognition, fraud detection, autopilot, weather reporting, share market projections, and medical diagnostics. A model is developed from unlabeled data and learns a range of structures and patterns from this data. Applications for robotics, image recognition, and speech recognition typically employ it[9].

II. RELATED WORK

Salekshahrezaee 2023 et al. With the help of a dataset from a credit card theft ensemble classifier, this study examines these two preprocessing methods. LightGBM, XGBoost, CatBoost, Random Forest, and LightGBM. Comparing Convolutional Autoencoder (CAE) and Principal Component Analysis (PCA) techniques for feature extraction. evaluate the properties of data sampling using the tomek, synthetic minority oversampling, and random undersampling (RUS) strategies. Area The Receiver's Operating Characteristic Curve (AUC) and F1 value are used to assess classification performance. The data shows that the combination of the CAE approach with RUS technique offers the highest level of effectiveness for identifying credit card fraud[10].

Prabhakaran 2023 et al. The OCSODL-CCFD approach described in this study combines the deep learning model for CCFD with the novel op-positional cat swarm optimization-based feature selection system. The OCSODL-CCFD method's primary objective is to identify and categorise credit card fraud. The OCSODL-CCFD method makes use of a novel OCSO-based feature selection procedure to select the best subset of features. The chaotic krill herd algorithm (CKHA) as well as the bidirectional gated recurrent unit (BiGRU) architecture are extra classification methods for credit card thefts. The CKHA is used to tune the hyperparameters of a BiGRU model. Numerous simulation assessments were performed to highlight the outstanding outcomes of the OCSODL-CCFD model. Based on a number of assessment factors, the extensive comparison analysis showed that the findings produced by OCSODL-CCFD model was superior to those of the comparison models[11].

Mniai 2022 et al. This study seeks to create a hybrid approach for identifying credit card fraud. A hybrid technique combines Particle Swarm Optimization and Support Vector Data

Description (SVDD). (PSO). The efficiency-enhancing factors c &, which are randomly chosen, are also used to identify SVDD. To get the most precise values for such two parameters, the suggested model uses the rapid PSO approach. The performance using SVDD-PSO in comparison to a number of many other machine learning algorithms is shown through results of simulations on real datasets[12].

Bin Sulaiman 2022 et al. In this paper, a hybrid algorithm for detecting credit card fraud will be developed. This approach combines Particle Swarm Optimization and Support Vector Data Description (SVDD) (PSO). (PSO). The efficiency of SVDD, for instance, is determined by the random selection of a two variables c and. To determine the ideal pairing of these two factors for improving accuracy, the suggested model uses the PSO technique, which is renowned for its speed. Results from simulations on real-world datasets show how well SVDD-PSO performs in comparison to a few different machine learning algorithms[13].

Malik 2022 et al. In order to identify dishonesty using real-world data, this paper explores and recommends seven hybrid machine learning techniques. the hybrid models were created in two stages, the first of which involved the use of contemporary machine learning methods to identify credit card fraud. The only algorithm from the early phase was then used in the creation of the hybrid techniques. The hybrid technique Adaboost + LGBM performed the best overall, therefore that's why it's the best model, per the results. Future research ought to concentrate on analysing various credit card domain fusion and algorithm types[14].

Faraj 2022 et al. The main objective of this essay is to highlight the methods for supervised fraud detection that are regularly utilised. This study also intends to apply a few strategies to test their effectiveness on actual data and create an ensemble approach as a viable remedy. Logistic regression, decision trees, random forests, KNNs, & XGBoosts were some of the techniques utilised in this study to spot fraud. Contrary to appearances, In terms of precision, recall, and f1-score, XGBoost only fares better than arbitrary forests. It is therefore not the quickest option. Because they consistently outperform other methods, it is conceivable that KNN as well as logistic regression are better at identifying fraudulent deals. New data can be used with the present model instead of the more traditional methods[15].

Zhang 2022 et al. To precisely identify fraud behavior, the study uses kernel principal component modeling, isolation forest (IForest), kernel principal component modeling, and anomaly detection on unbalanced data. In order to identify outliers, two models are used: AdaBoost and a one-class support vector machine (OCSVM). This greatly improves the efficiency and precision of the detection procedure. Accordingly, the model received ratings of 98% F1, 96% Correctness, 100% Clarity, and 96% Retention. The evaluation reported in this research will give pertinent details about procedures for doing so, and the suggested model is anticipated to be helpful for identifying credit card fraud[16].

Plakandaras 2022 et al. The Just-Add-Data (JAD) system is used to quickly produce a prediction for credit card fraud detection. The JAD system automates the selection of machine-learning algorithms, the adjusting of the hyper-parameter characteristics, as well as the evaluation of performance to designed to detect fraudulent activity using a highly imbalance dataset. Prior to training the model, the user doesn't have to set any (hyper)parameters for the algorithms. At all management levels, applying the model and displaying, comprehending, and disseminating the results are all straightforward tasks. 32 of a 39 fraudulent transactions inside the test sample could be identified by the model chosen by JAD, and all of the missing transactions were tiny ones under 50 euros. All of the aforementioned methods have high forecasting capabilities, which are compatible with the corpus of current literature, as shown by the comparison with the other approaches on the same dataset[17].

Singh 2022 et al. The FFSVM support vector machine, which has two successive layers, and the firefly bio-inspired optimization algorithm have been combined to create a new method for detecting credit card fraud (financial fraud). In the first level, the subset of features were optimized using the firefly algorithm (FFA) or the CfsSubsetEval feature section technique, and in the second level, the training model for cases of credit card fraud was created using a support vector machine classifier. This study also compares the proposed strategy to the methods currently in use. The proposed method outperformed the existing methods, even with an accuracy of just 85.6% and 591 transactions accurately recognized. The proposed method has improved classification accuracy, decreased the cost of misclassification, and decreased the precision with which credit card transactions were classified. The evaluation findings reveal that the proposed FFSVM method performs better than currently used, non-optimized machine learning techniques[18].

Sasikala 2022 et al. utilizes a state-of-the-art sensing technique to evaluate the classification algorithm while taking the expenses of misclassification into account. To differentiate the hyperplane and keep robustness, grid search cross-validation as well as SVM hyperparameter optimization are used simultaneously. This has led to much greater success than in the past in identifying credit card theft[19].

III. CREDIT CARD DATA DESCRIPTION

A credit card transaction record includes the purchase information as well as the account status. Most transaction detail traits can be regarded as multilevel categorical variables that also include credit card transaction information. Here, the terms "transaction characteristics" and "transaction type" are used equally. The most common method for determining whether a transaction record is a purchase, cash withdrawal, or another type of transaction is to use the category of transaction field in the transaction record database. Any inherent characteristics of the related transaction behavior are included in a transaction's attributes[20][21]. A characteristic might indicate a classification based on a particular trait, such as the transaction's country of origin or the type of channel it took place through. It may also be divided into categories using criteria established by individuals. When a transaction's POS entry mode indicates that it was entered using a magnetic stripe, it has the characteristics of the magnetic stripe entry mode, for example. It is critical to look at their activity separately because transactions made using a magnetic stripe entry mechanism are more likely to have been fraudulent than those made using a chip and PIN. Another illustration is a transaction that happens between one and five in the early morning that could be classified as an abnormal time transaction as the transaction's abnormal time was a potential transaction feature[22][23].

IV. DEEP LEARNING

In the field of machine learning, deep learning has lately received a lot of attention. Hierarchical learning architectures, which use multiple levels of information processing to learn representations or recognize patterns, include convolutional networks, deep belief networks, as well as deep autoencoders as examples of deep learning techniques. Research upon artificial neural networks can be used to track the development of deep learning[24][25]. Typically, back-propagation is used to design the weights of neural networks. However, as neural networks become more complex, the efficacy of the back-propagation algorithm declines noticeably. This could be due to issues such as diluted errors and weak local optima[26]. The success of deep architectures should be attributed to the basic principle of unsupervised layer-by-layer greedy learning, which, through experimentation, removes the difficulty of optimizing the deep architecture training parameters[27]. The deep belief network training method is the first effective application of deep architecture training. Deep learning techniques can be used in the financial sector to improve prediction results in addition to the image and audio sectors[28]. Deep learning has a ton of promise for financial market forecasting, according to Fischer & Krauss, who used extended short-term memory networks to predict time series. Kraus and Feuerriegel analyzed the financial data using deep learning and transfer learning methods, then used the predictive outcomes to assist in making financial decisions. Deep learning has also been the subject of other innovative studies that aim to identify financial scams. Detecting deception with deep learning[29].

A. Deep Belief Networks

Layering numerous restricted Boltzmann machines could be used to create a deep belief network (DBN). (RBMs). A Gaussian-Bernoulli RBM is typically produced as the first layer for continuous value input data and a Bernoulli-Bernoulli RBM is typically produced as the first layer for binary input features. The concealed layer of a Bernoulli-Bernoulli RBM is used as the visible input layer to produce the second layer of an RBM after training the very first layer. The visible layer of one RBM serves as the hidden layer of the RBM within the layer above it, and more RBMs can be layered one on top of the other to form a DBN in a similar way. The key benefit of the layer-by-layer greedy training technique is that class name is not required. Figure 2 displays the Deep Belief Network's architectural layout.

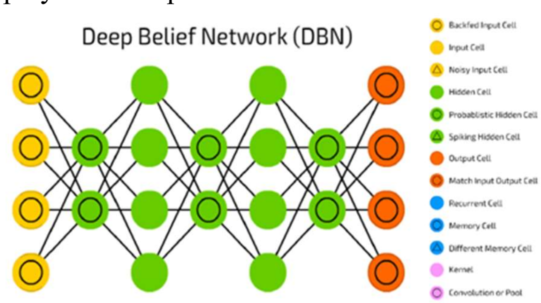

Fig.2 Deep Belief Network

B. Convolutional Neural Network

Convolutional layers, pooling layers, normalizing layers, and completely connected layers are among the convolutional neural network (CNN)'s hidden layers, which also include input, output, and several additional layers.[30][31] A few applications for the CNN model include recommendation systems, image identification, and natural language processing. It works well for picking up a lot of knowledge. Feature matrices utilizing derived one-dimensional features are produced via feature transformation in order for the CNN model to detect credit card fraud[32]. Figure 3 depicts the design of the CNN model.

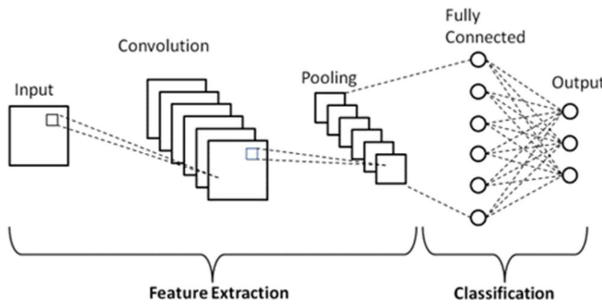

Fig.3 CNN Architecture

TABLE I. COMPARATIVE ANALYSIS OF DIFFERENT ALGORITHM

Paper, Year	Contribution	Advantages	Future Intentions
[33], 2020	ANN	Fraudsters take advantage of modern technical improvements by using websites, stolen or misplaced credit cards, and fake credit cards.	To reduce fraud and prevent future occurrences, it is possible to study past activities.
[34],2020	Supervised Learning	since it simply needs a tiny amount of training data.	may employ resampling techniques on the relevant datasets being used
[35], 2019	SMOTE	Storing, retrieving	Data includes some of the crucial components of the business's future operations
[36],2019	Neural Network,(SVM),LR,KNN	makes use of a sizable data collection with numerous dimensions. Benefits of Using Isolation Forests to Detect Anomalies	full-service bank solution
[37],2019	Supervised Random Forest algorithm	Quick results, reliable	It creates patterns, calculates numerical values, and orders values for the future.
[38],2018	complicated network classification method and hybrid data mining	Generic supervised methods work better at spotting unlawful transactions	Artificial intelligence and transaction costs

[39],2018	In a system for detecting fraud in the actual world, fraud detection relies on assumptions that are rarely true (FDS).	Better performance	The research of adaptive and potentially nonlinear aggregation techniques for classifiers trained using feedbacks with delayed supervised samples is a task for the future.
[40],2018	the majority-voting technique and AdaBoost	Quick result, better performance	Future work will expand on the strategies examined in this study to include online learning models. We'll also look into other online learning models.

V. CONCLUSION

Every year, fraudulent credit card purchases cost card companies billions of dollars. To minimize fraud losses, experts think a sophisticated fraud detection device with a state-of-the-art fraud detection algorithm is required. Building a deep learning-based fraud detection system is the main accomplishment of our effort. Do a comparative analysis to evaluate the efficacy of the suggested framework using actual data from one of the biggest commercial banks. The trial's outcomes prove the validity and efficiency of the technique we suggested for detecting credit card fraud. Practically speaking, our suggested strategy may distinguish a larger portion of fraudulent transactions from legitimate ones than the existing techniques while maintaining a respectable false positive rate. Our results have management ramifications because credit card issuers may employ the method they suggest to promptly spot fraudulent transactions, protect client interests, and reduce fraud losses and regulatory costs.

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