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Credit Card Fraud Detection in Data Mining using XGBoost Classifier

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Abstract*: In today's economy, credit card (CC) plays a major role. It is an inevitable part of a household, business & global business. While using CCs can offer huge advantages if used cautiously and safely, significant credit & financial damage can be incurred by fraudulent activity. Several methods to deal with the rising credit card fraud (CCF) have been suggested. Both such strategies, though, are meant to prevent CCFs; each of them has its own drawbacks, benefits, and functions. CCF has become a significant global concern because of the huge growth of e-commerce and the proliferation of payment online. Machine learning (ML) algo as a data mining technology (DM) was recently very involved in the detection of CCF. There are however several challenges, including the absence of publicly available data sets, high unbalanced size, and different confusing behavior. In this paper, we discuss the state of the art in credit card fraud detection (CCFD), dataset and assessment standards after analyzing issues with the CCFD. Dataset is publicly available in the CCFD data set used in experiments. Here, we compare two ML algos of performance: Logistic Regression (LR) and XGBoost in detecting CCF Transactions Real Life Data. XGBoosthas an inherent ability to handle missing values. When XGBoost encounters node at lost value, it tries to split left & right hands & learn all ways to the highest loss. This is when the test runs on the data. The experimental results show an effective use of the XGBoost classifier. Technique of performance is widely accepted metric based on exclusion: accuracy & recall. Also, the comparison between both approaches displayed based on the ROC curve.

Keywords* : credit card fraud detection, machine learning, class imbalance.

I. INTRODUCTION

With the latest technology and worldwide communications, fraud has increased significantly [1]. Fraud may be prevented by two methods: detection and prevention. Data prevention is where the protection layer is created to prevent outsiders from attacking them. It first attempts to prevent fraud. On the contrary, it helps to detect & alert people once AIDS fraud becomes permanent. So, if a container has already failed, the discovery comes to the scene. Thus, discovery needs always be made and no one may forecast after a breach will occur [2], [3].

CCF is a major problem & responsible principals have financial responsibility. Consequently, FD (fraud detection) strategies by safety modules that try to prevent fraud need to be improved. FD systems are designed to help resolve old transactions in the future. Sooner FD system works better.

In detecting fraud, no. of common cases is much higher than that of illegal cases. This leads to a situation called" imbalance data" wherever one class of files has more instances than another category of information. This leads us to a "class imbalance problem". Most standard methods are balanced delivery classes [3]. Understand Problem-solving data sets revealed many solutions over the years. Most general proposed answers fall into three broad collections: data layer, algo, & synthesis solutions. Class-imbalance is a negative result of reducing the preprocessing step as a re-sample to implement data-level solutions. The purpose of the algo level solution is to develop new algos or modify the learning bias of existing ones in the minority class. Assembly solutions can be used to add synchronous learning algo to preprocess data before a base stage classifier, or to add a cost-sensitive framework to the synchronization learning process [4]. In this paper, categories of ensemble methods are applied which is XG boost algo to balance the classes.

II. LITERATURE SURVEY

Iyad LahaneCherif [2019] The basic function of network control and monitoring operations is TC (Traffic Classification). Packet header fields (for example port no.s) or application layer decoding protocol techniques will depend on encrypted traffic flow and P2P(Peer-to-Peer). We solve problems with ML algo's flow-based TCs in this work. Our work is using a supervised approach known as XGBoost (Extreme Gradient Boosting) algo, something which TC presentation has never perceived. The evaluation results show that the actual flow is 99.5% accuracy with the data set. In addition, XGBoost is more accurate than other ML algos [5].D Varmedja et al [2019] This research shows no. of algos used to classify transactions as fraudulent or real. Because the data set is highly unequaled, SMOTE was used for excessive specimens. CCF was used in data set research. Furthermore, the facility was chosen and data set classified into 2 parts: test data & training data. Logistic regression, random forest, fabric foundation & multi-layer perceptron were used in the algos. Results show that anything can beused for high-precision detection of CCF.

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Other conditions can be observed using the proposed model. CCF refers to the loss of CC physical or sensitive CC information. Many algos can be used for learning machines [6]. GanglongDuan [2018]presents coupon personalized placement recommendations, which use XGBoostalgo to calculate whether users are using coupons for specified age of time. In this work, the grid search technique is applied to regulate parameters and the model is constantly optimized. THE final AUC value of the model was 0.8496, with instructions for individual coupons, increasing sales &collective profits. Experimental outcomes show that individual coupons based on XGBoostalgo contribute to best marketing [7].

Dilip Singh Sisodia [2017] reveals a large proportion of no. of online transactions done each day. CCFis an important part of these transactions. Financial losses also enlargedbyCCF transactions. Therefore, FD systems have become increasingly important for banks & financial institutions. Since there is no likelihood of fraud compared to usual transactions, we are dealing with class imbalance issues & we are re-designing methods in this paper to deal with this imbalance issue. Oversampling has been applied (SAFE SMOTE, SMOTE ENN, ROS, SMOTE TL). Using renamed data, we evaluate the performance of sensitivity, feature, G-fish and area under ROC with realistic cost-sensitive (C4.5, CSVM), and group classification (Adaboost & Bagging). We have seen SMOTE ENN identify fraud better than other disappointing techniques. TL has taken in combination with techniques to be considered, TL amongst undersampling techniques [8].

Xiang Zhang [2016]First we find that the context reduction is a question of class inequality when first and second classes belong to minority and majority classes. In analyzing spatial and temporal correlations inherent in video data, we propose an unbalanced context reduction compensation framework which includes two successive modules, unbalanced bilayer modeling and a Bayesian classification that is balanced by imbalances. For studying the bilayer model, related samples are added. In the second section, the solution to a class imbalance at some point is new cost functions. Cost functions are focused on unequaled measurements and are used by a Bayesian classification structure to shape previous periods. Experiments in public databases are carried out to demonstrate the feasibility of the proposed method [9].

The most effective of conventional algorithms have been Support Vector Machines (SVM), Gradient Boosting (GB), Decision Tree (DT), RF or LR. In paper[10] GB, a high reminder of more than 91% was made from paper, LR, RF, SVM and a combination of some classifications. Only after the dataset was balanced by undersampling data was high precision & reminder achieved.

European data were also used in paper[11] and models based on LR, RF & DT were comparable. RF was the highest among the three models, with 95.5 percent precision, followed by DT with 94.3% & LR with 90% precision.

Also, k-Nearest (KNN) neighbors and outliers can be effective in the detection of fraud, according to[12] and [13]. We also shown their effectiveness to increased false alarm rates & increase fraud detection rates. The KNN algorithm was also successful in paper experiments[14], in which the authors checked & compared it with further classical algorithms. A comparison was made in document [15] among profound learning techniques and classical algorithms, which is different from those mentioned so far. All the techniques tested were approximately 80 percent accurate.

Set the GB, RF, SVM, LR, KNN, NB, DT, XGBoost (XGB) & MLP classifiers (a mix of several machine learning graders) together with European datasets by the writers of the paper[16]. Bring them together, with the European data set. Due to the comprehensive preprocessing of data, all algorithms have been more than 90 percent accurate. With 95% precision and a 95% retrieval value, the stacking classification is the most successful.

A neural network on the European dataset has been checked in paper [17]. The experiment included the neural back spread network optimized for the algorithm of a whale. The neural network consisted of 2 layers of data, 20 hidden and 2 layers of output. Because of the optimization algorithm, excellent results have been obtained for 500 test samples: precision 96.40% and recall rate 97.83%.

Paper authors[18] have used neural networks to show improvement in the outcome of ensemble techniques.

Three datasets for comparing autoencoders and restricted Boltzmann machine algorithms were employed in Paper[19], concluding that algorithms such as MLP may be appropriate for detecting CCF. Many papers have been detected in deep neural networks for fraudulent transactions.

Such models, however, are computationally costly and are best done for wider datasets[20]. As we have seen from several papers, this approach may produce great results, but what if similar or even better results may be achieved with fewer resources. Our main aim is to demonstrate that various algorithms of machine learning can generate decent pre-processing results. Authors of most of the above-named papers utilized undersampling technology & it was just to use another method – techniques of over-sampling.

The 2015 edition of J. It's Esmaily and R. A hybrid artificial neural tree & DT has been proposed in Moradinezhad [21] in their paper. They used a two-stage approach in their model. In the 1st phase, Multilayer perceptron and Decision Tree classification results were utilized to create a new data set that was fed into the multilayer perceptron in the second phase to the final classification of the data.

In 2011, Siddhartha Bhattacharyya and four other[22] conducted a comprehensive comparative study on support vector machine and random forest along with logistical retrogression. This model is very accurate by providing very low detection rates. In 2011, Raghavendra Patidar and Lokesh Sharma[23] put in their paper the Artificial Neural Network and Genetic Algorithms hybrid. They concluded with experiments to show that Random Forest methodology is most accurate, followed by Logistic Regression and Support Vector Machines. They utilized neural nets to classify transactions & genetic algorithms so that solution is optimized & the system is not trained.

In 2015,[24] SuvasiniPanigrahi & Tanmay Kumar suggested, in their paper, use neural networks & fuzzy clustering for hybrid CCFD method. Two stages have been used. The first phase was used to create an algorithm for the clustering process, and the next step was to decide whether a transaction was fraudulent or not when a deal was believed it is fed into the neural network.

In their papers authors, Wen-Fang Yu & Na Wang [25] suggested the use of outliers dependent on distance amounts to identify credit card fraud. Furthermore, data mining is an area that is used primarily in monetary and internet matters. It detects objects separated from the principal system, i.e. transactions that are not genuine. We took customer's comportment attributes and measured comparison between observed value & pre-determined value based on the value of these attributes. AyushiAgrawal and others [26] Proposed transaction validation using the Model Hidden Markov, Behaviour bases and Genetic Algorithms, in which they utilized Model Hidden Markov to keep records of prior transactions, Behavior-based databases grouping strategies and eventually, the optimization Genetic Algorithm, i.e. the threshold measurement.

III. PROPOSED METHODOLOGY

A. Objective

The objective of this study was to investigate the performance of ML algos. The selection of algo is based on previous research work & adheres to the frequently used ML algo. We use the oversampling technique described later to correct an imbalance of the dataset. Section describes dataset & training-testing method, learning approaches & performance evaluation.

B. Problem Definition

In the previous research work, logistic regression was used which had some drawbacks. LR measurement is a relationship amongst the dependent variable (our label, what we should be) & one or more independent variables (our features) used to estimate underlying logistic function. Prediction is made so that these probabilities are then converted to binary values. It is a logistic function of function, also known as SF (Sigmoid Function). SF is an S-shaped curve that may proceed several no. of real values & map it to range amongst 0 & 1, but never satisfies those constraints. These values between 0 & 1 are then converted to 0 or 1 using a threshold classifier.One drawback of this is that the decision surface is the result of logistic regression with nonlinear problems.

C. Proposed Method

a) XGBoost Classifier

XGBoost has an inherent ability to handle missing values. When XGBoost encounters node at lost value, it tries to split left & right hands & learn all ways to the highest loss. This is when the test runs on the data. XGBoost namely Extreme Gradient Boosting (XGBoost) algo is supervised learning algo based on synthesis. It includes (written) an objective function consisting of a loss function (d) & regularization term (β):

$$\Omega(\theta) = \underbrace{\sum_{i=1}^{n} d(y_i, \hat{y}_i)}_{Loss} + \underbrace{\sum_{k=1}^{K} \beta(f_k)}_{regularization} , \quad (1)$$

Where yi is predictive value, n is a training set for no. of instances, K is no. of trees generated &fk is synthesis from a tree. The term Regularization is defined as:

$$\beta(f_t) = \gamma T + \frac{1}{2}\left[\alpha \sum_{j=1}^{T} | c_j | + \lambda \sum_{j=1}^{T} c_j^2\right] , \quad (2)$$

Where γ minimum split losses are minimized, is the weight of regularization period & weight c associated with each leaf.Let ft(xi) = cq(xi), in which q [1,T], in which T is no of leaves. A greedy method is to choose the most progressive partition. Annex A includes the detailed process of deriving the equation. Table III describes 10 important XGBoosts, default values of all parameters and ranges.

The most significant issue behind the success of the XGBoost is its scalability in every situation. System works ten times faster than machine & measures billions of instances of distributed or memory limited settings. XGBoost scalability is due to no. of key systems and algo.

b) Data Preparation

With all of the above guidelines in mind, we choose the SMOTE method to meet challenges. Sample Method samples may vary in number from the sample number of samples to sample minorities. The value utilized in experimental equations is 0.4 (most minority samples make up 40% of the class size). Samples of a minority group may vary.

c) Learning Approaches

There are dissimilar approaches to learning. The simplest but still static approach is a prediction model that simultaneously generates learning batch. The main drawback of such a model, once trained, is its ability to adapt to any change in input drift, which supports the drift concept. The periodic recycling method has the greatest resistance to non-standard entry products, but improvements after the last data are included in the classification model. In contrast to static, the incremental method is presented. Increasingly, learning is a non-environmental that comes as part of process data. Due to the deceptive behavior of unpredictability, patterns once used in the future may change later. For that area, the incremental approach uses a synthesis that includes all generated classifiers evaluated in the best data chain & classifiers.

D. Proposed Algorithm

Input: Publicly available in the CCFD data set.
Output: Precise credit card fraud detection.
Steps:

Step 1: Start the process
Step 2: Load the available CCFD dataset
Step 3: Normalize the number of feature
Step 4: Remove time feature

Step 5: Divide the dataset into two parts first one is in training & the other one is in testing
Step 6: Then apply SMOTE on the training dataset
Step 7: After this get oversampled transaction data
Step 8: On this oversampled transaction data apply XGBoost classifier to classify fraud activities
Step 9: Evaluate results by AUC curve, precision, recall, and ROC curve
Step 10: Stop.

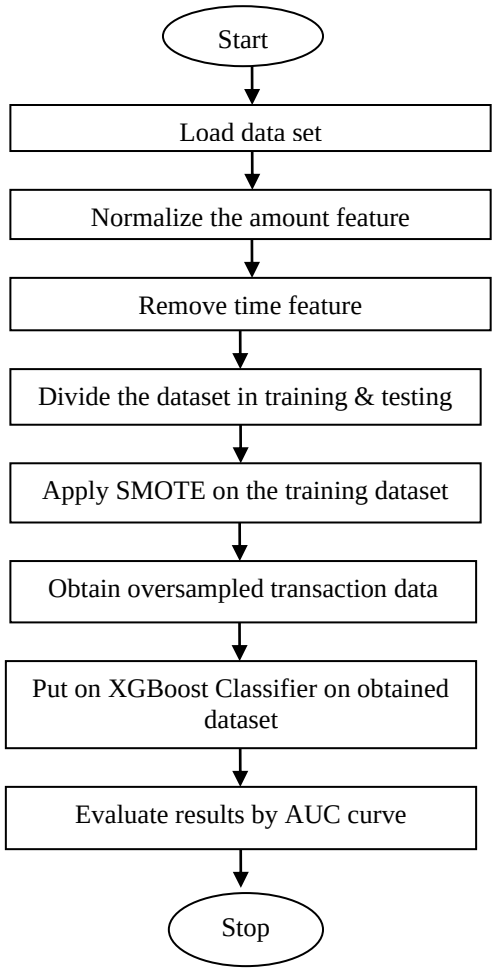

Fig. 1.Flow diagram of the working of the XGBoost Classifier

IV. EXPERIMENTAL RESULTS & DISCUSSIONS

All essential programming codes have been written in Python language & standard implementation of scikit learning has been utilized.

A. Dataset

Dataset is publicly available in the CCFD data set utilized in experiments. Dataset covers transactions made in European cardholders during the two days in September 2013. In 284807 transactions, there are 492 frauds. The data set is therefore extremely unequaled, with only 0.1727% of fraudulent transactions being accurate. The dataset expected 28 input numbers (named v1-v28), resulting from the change of provider of dataset & 2 other non-changed variables -time and amount.

B. Screenshot of Results

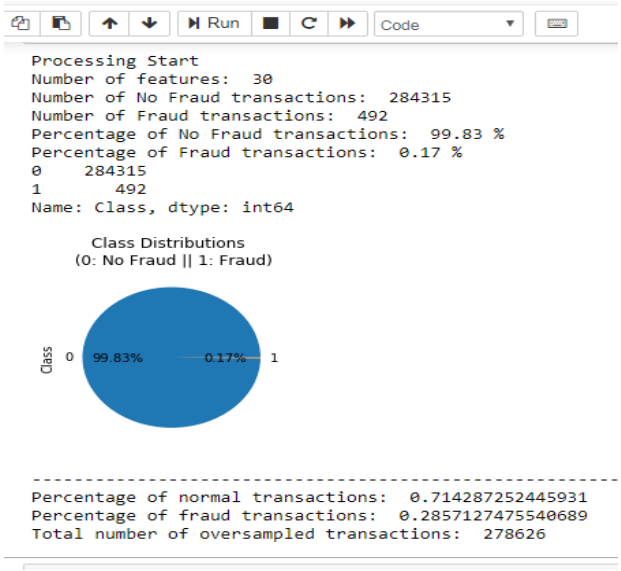

Fig. 2.Visualization of oversampled data set

To test learning processes and model efficiency, we use cross-validation. The data set is classified in a ratio of 70:30 in 2 elements, training, and tests.

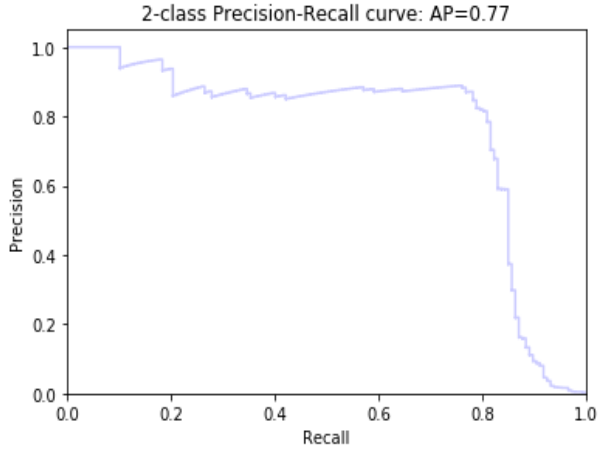

Fig. 3.Accuracy measures of static Logistic Regression

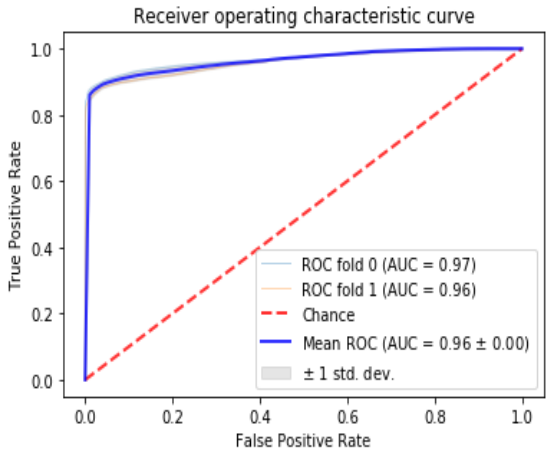

Fig. 4.Accuracy measures of incremental Logistic Regression

Figures 3 & 4 elaborate the accuracy measures of static & incremental logistic regression, respectively. The static logistic regression measures the accuracy in terms of recall & average precision.

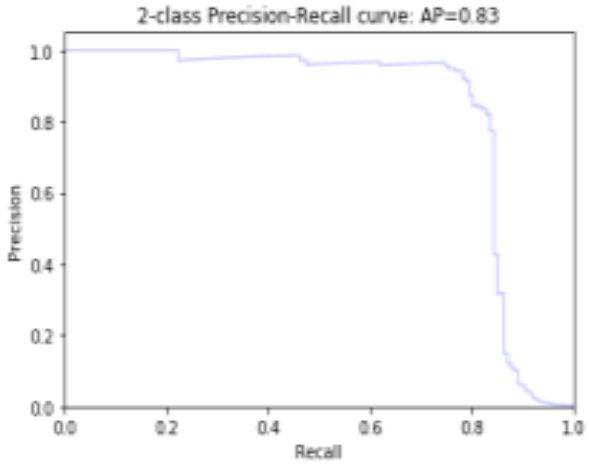

Fig. 5.Accuracy measures of static XGBoost

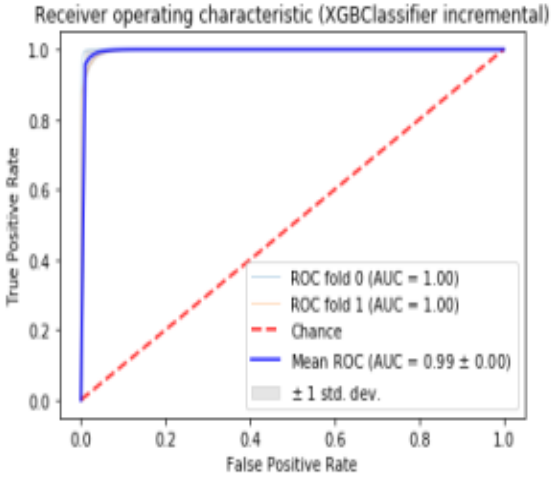

Fig. 6.Accuracy measures of incremental XGBoost

A figure 5 & 6 elaborates the accuracy measures of static & incremental XGBoost, respectively.

In experiments, we compared AKL algo on static & incremental learning. After using all data, all static approaches were trained & tested. For incremental learning, we divided data into two groups, which represent two days. We know that many data pieces are involved in real-life situations, but the limited data is available. Two different parts of manufacturing models have been trained and tested.

Models of H_i weighted synthesis defined as

$$E = \sum_{i=0}^{M} w_i h_i \quad (3)$$

Wherever M denotes the total no. of models (2 in our case). Weight of observed chunk wi is calculated accurately & then normalized to the 0–1 range.

C. Metrices

We estimate the area under the ROC curve (AUC) and average precision (AP) in two ways. In the ROC curve, Fallout (FPR) is considered another classification threshold plotted as recall (TPR). Transactions that have a probability of fraud equal to or higher than the threshold value are treated as fraudulent. The best classifier is points (0,1) that do not have false positive or false negative points. The AUC metric measures the optimum point in the close ROC curve of the individual classifier.

Table- I: Static Setup

Algos	Recall	Average Precision
Logistic Regression	58.47	0.77
XGBoost	73.83	0.83

Table- II: Incremental Setup

Algos	Recall
Logistic Regression	0.96
XGBoost	0.99

V. CONCLUSION

In this paper, we have explained major problems & the latest solutions in the field of CCFD. Our performance is measured & dignified using only publicly available datasets for CCFD two ML algos i.e, LR & XGBoost. The selected algos are related to the most commonly used ML algos in CCFD, & were selected from a scientific literature review. Experiments were conducted by two approaches: (i) static learning, (ii) incremental learning. To order to assess the output of something, the following steps are applied: ROC area (AUC) & the Average Precision (AP) area. It is evident from the findings described in the paper that XGBoost works well in both static and incremental installations. We produce realistic synthetic data that are working on our research project because abundant data sets are not publicly available. The results thus obtained show that the highest precision and accuracy of XGBoost is 83 percent for credit card fraud detection problems with machine learning data. the recall value is higher than the existing logistic regression method

which is 73.83 for the XGBoost classifier. Also, a ROC curve has increased up to 0.3 value.

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