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Fraudulent Financial Transactions Detection Using Machine Learning

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***Abstract**: It is crucial to actively detect the risks of transactions in a financial company to improve customer experience and minimize financial loss. In this study, we compare different machine learning algorithms to effectively and efficiently predict the legitimacy of financial transactions. The algorithms used in this study were: MLP Repressor, Random Forest Classifier, Complement NB, MLP Classifier, Gaussian NB, Bernoulli NB, LGBM Classifier, Ada Boost Classifier, K Neighbors Classifier, Logistic Regression, Bagging Classifier, Decision Tree Classifier and Deep Learning. The dataset was collected from Kaggle depository. It consists of 6362620 rows and 10 columns. The best classifier with unbalanced dataset was the Random Forest Classifier. The Accuracy 99.97%, precession 99.96%, Recall 99.97% and the F1-score 99.96%. However, the best classifier with balanced dataset was the Bagging Classifier. The Accuracy 99.96%, precession 99.95%, Recall 99.98% and the F1-score 99.96%.*

Keywords: Financial Transactions, Deep learning, Machine Learning

1. Introduction

For a long time, fraudulent transaction and detectors have a composite role. Fraudulent transactions are happening more frequently than ever before, principally in today's era of Internet, and it is the cause of foremost financial losses. Transaction fraud cost the economy around $28 billion in 2019, around $30 billion in 2020, and more than $32 billion in the year 2021. The rate of global transaction fraud is expected to rise year after year, reaching $34 billion in 2022. As a result, banks and financial service providers may need an automatic fraud detection instrument to recognize and screen financial transactions. Fraud detection systems are intended to differentiate strange action patterns from a massive number of transactional records and then use those patterns to detect or track incoming transactions [2].

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves [1-10].

The process of learning begins with observations or data, such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that we provide [11-20]. The primary aim is to allow the computers learn automatically without human intervention or assistance an adjust actions accordingly [21-30].

Deep learning is a subset of machine learning in artificial intelligence that has networks capable of learning unsupervised from data that is unstructured or unlabeled[31-40]. Deep learning is a technique used to generate face detection and recognize it for real or fake by using profile images and determine the differences between them [41-50].

Machine learning has revealed to be very rewarding at detecting and classification of fraud transactions [51-60]. In another way, a great number of transaction reports may be used to train and validate fraud classifier] 61-70]. In spite of the fact that supervised learning has been tremendously successful in detecting fraudulent transactions, the progression of transactional fraud analysis technologies will never end [71-76]. A Small enhancement in the classifier will save a company a noteworthy amount of money.

2. Literature Survey

Numerous studies have discussed the fraudulent transactions. The study in [77] stated that the fast evolution of technology all around the world was more often used cards as compared to cash in their day to day life. The MasterCard became the highly useable equipment for Internet shopping. This up surged in use causes a considerable damage and fraud cases also. It was very much necessary to stop the fraud transactions because it impacted on financial conditions over time the anomaly detection was having some important application to detect the fraud detection. This paper is mainly focused on checking if the transaction was legal or fraud. They presented models like Bidirectional Long short-term memory and Bidirectional Gated recurrent unit. They also apply deep learning and Machine Learning algorithms. But their model shows much better results than the machine learning classifiers which was 91.37% score.

The authors in [78] mainly focused on the solution that tackles the imbalance problem of classification they explore the solution for fraud detection using machine learning algorithms. They also find the summarized results and weakness that they get using credit card fraud labeled dataset. They give us the conclusion that the imbalanced classification is ineffective when the data are highly imbalanced. In this paper, the authors found that the existing methods were costlier and show many false alarms.

In the study [79] DT, LR, and RF algorithms were operated to measure the operation for credit card fraud identification. On behalf of a rather unbalanced dataset oversampling was required. After oversampling, 60% legal and 40% unlawful transactions are found. R language was used for the implementation of these algorithms. Accuracy of LR is 90.0%, RF 95.5%, and DT 94.3%. Sensitivity, error rates, and specificity are also measured. RF algorithm performs nicely amongst them.

In the study [80] an automatic classification and guide classification were used in fraud identification as properly as one of a kind ML algorithm is compared to pick out the frauds. RF, SVM, and LR were used. They find out about targets to advance a threat scoring model. All the algorithms were tested and RF was performed properly and accomplished with the best possible accuracy. And this algorithm was effortless to practice and works precisely on a massive dataset. The result confirmed that sort of algorithm performs very properly in the real-world.

In the study [81] some ML algorithms were proposed to test the performance of fairly unbalanced data. SVM, RF, DT, and LR are operated to take a look at the potential. These algorithms were examined on pre-processed and uncooked data. The accuracy of these algorithms was SVM 97.5%, RF 98.6%. DT 95.5% and LR 97.7% respectively. The RF performs very well on a large quantity of information however it suffers from speed. If records are more pre-processed then SVM can work properly amongst them.

In the study [82] SVM was used to identify transactions as valid or fraudulent. The SVM analyzed the past transaction habits of the cardholder. When a new transaction happens, by marking it as an unlawful transaction, it deviates from its previous behavior. On SVM, the highest fraud detection score was 91%.

The study in [83] suggested a deep network method for fraud detection. To manipulate the data skew troubles that occur in the dataset, the log transformation was used. For the training of difficult examples, the focal reduction is utilized to the network. The effects showed that the different classical models such as SVM and LR are outperformed by using the neural network model.

In the study [84] a hybrid strategy was proposed for identifying credit card frauds by operating the DT and Rough Set method that can be used in detection. The total work has utilized the usage of the software's WEKA and MATLAB. After the 10-time execution of the proposed and existing method, the proposed technique performed well with 84.25%.

In the study [85] an algorithm Lightgbm was proposed for detecting frauds. After that, a comparison was made with other methods like Logistic Regression, SVM, and Xgboost. The accuracy of Lightgbm was 98% as opposed to Logistic Regression 92.60%, SVM 95.20%, and Xgboost 97.10% but Lightgbm performed very properly when is compared to others.

In the study [86] REDBSCAN algorithm was used to decrease the number of samples and it helped to remain the form of data. The comparison made with the SVM technique and AUC of SVDD was 97.75% and SVM 94.60%. When SVDD was applied except REDBSCAN, it took 194 seconds and when utilized with REDBSCAN, it took 1.69 seconds which was much faster. REDCSCAN algorithm provided faster and preferred results.

3. Methodology

The researchers are attempting to develop fraud detection technologies that uses machine learning and deep learning techniques to determine whether the online transactions are real or fake based on the transaction databases. However, the detection of online transaction fraud is getting more and more difficult as illegal payments becomes closer to legitimate ones.

3.1 Dataset

We collected the dataset called "fraudulent transaction" from Kaggle Depository for fraud transaction detection. The dataset consists of 6362620 records with 10 features. The mean value of all transactions is 144972 USD while the largest transaction recorded in this data set amounts to 1991430 USD. However, as you might be guessing right now based on the mean and maximum, the distribution of the monetary value of all transactions is heavily right-skewed. The vast majority of transactions are relatively small and only a tiny fraction of transactions comes even close to the maximum.

The features of the fraudulent transaction dataset are shown in Table 1.

Table1: shows the features in the dataset

Features	Description
step	Maps a unit of time in the real world. In this case 1 step is 1 hour of time. Total steps 744 (30 days simulation).
type	CASH-IN, CASH-OUT, DEBIT, PAYMENT and TRANSFER
amount	Amount of the transaction in local currency.
nameOrig	customer who started the transaction
oldbalanceOrg	initial balance before the transaction
newbalanceOrig	new balance after the transaction
nameDest	customer who is the recipient of the transaction
oldbalanceDest	Initial balance recipient before the transaction. Note that there is not information for customers that start with M (Merchants).
newbalanceDest	New balance recipient after the transaction. Note that there is not information for customers that start with M (Merchants).
isFraud	This is the transactions made by the fraudulent agents inside the simulation. In this specific dataset the fraudulent behavior of the agents aims to profit by taking control or customers accounts and try to empty the funds by transferring to another account and then cashing out of the system.
isFlaggedFraud	The business model aims to control massive transfers from one account to another and flags illegal attempts. An illegal attempt in this dataset is an attempt to transfer more than 200.000 in a single transaction.

3.2 Dataset Analysis

Model efficiency is measured using product performance metrics such as accuracy, recall, precision and F1-Score.

The target feature is isFraud which is a binary feature with 0 (not fraud) and 1 (is fraud). There are 6084104 non-fraudulent transactions (99.870%) and 6485 fraudulent transactions (0.129%).

As expected, most transactions are non-fraudulent. The following visualization underlines this significant contrast (see Figure 1).

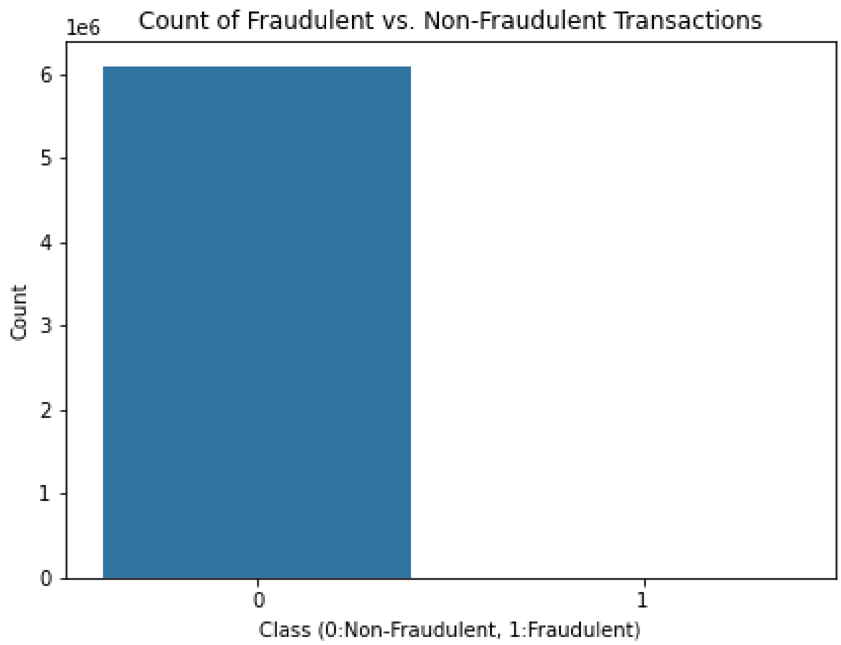

Figure 1: shows the distribution of isFraud.

Finally, it would be interesting to know if there are any significant correlations between our predictors, especially with regards to our class variable (isFraud). One of the most visually appealing ways to determine that is by using a heatmap.

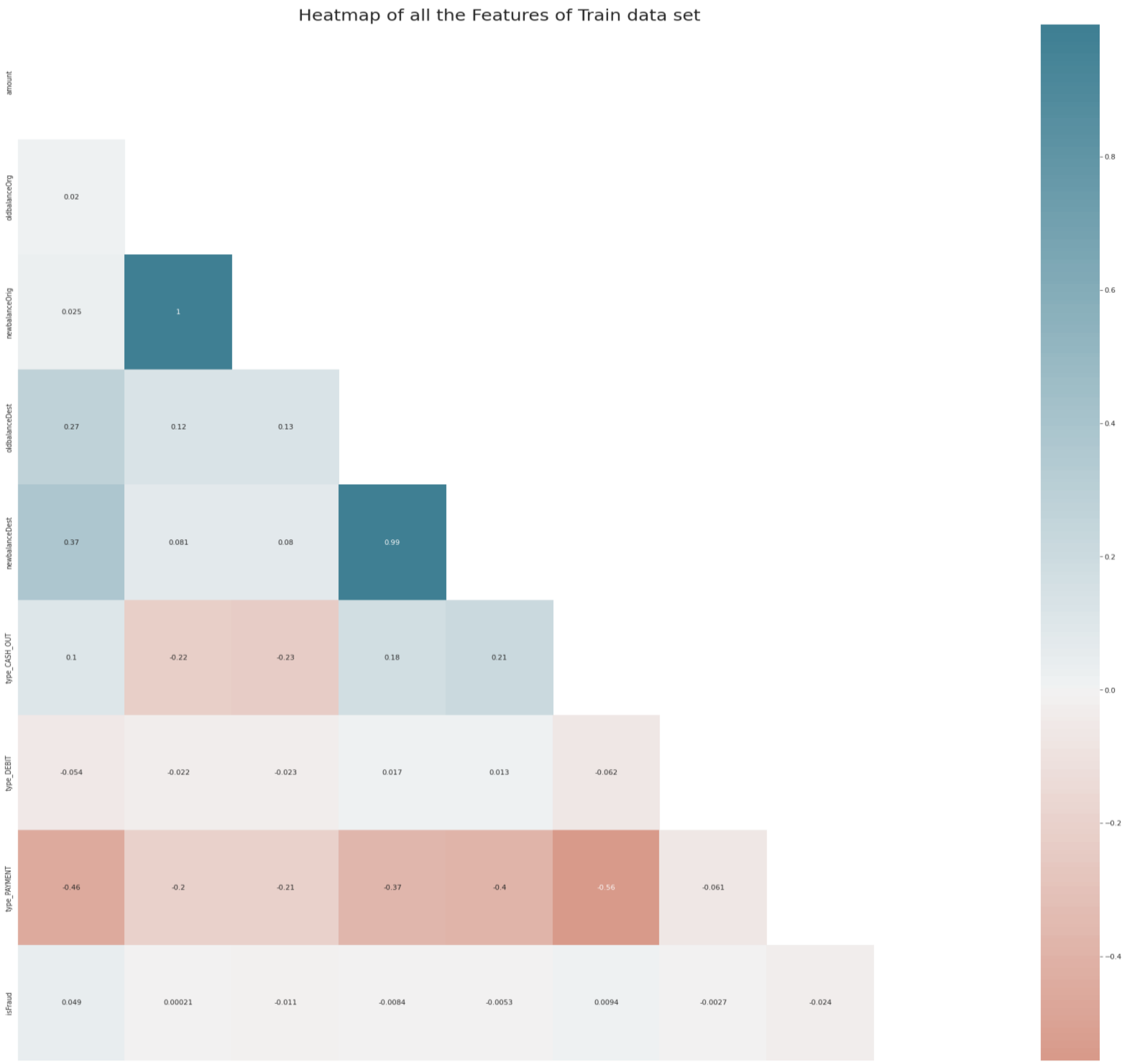

Figure 2: shows the heatmap of all features of the training dataset

As can be seen in Figure 2, some of our predictors do seem to be correlated with the isFraud variable. Nonetheless, there seem to be relatively significant correlations for such variables. This can probably be attributed to the factor: huge class imbalance might distort the importance of certain correlations with regards to our class variable.

Furthermore we have checked the negative correlation and positive correlation with class isFraud as can be seen in Figure 3 and Figure 4.

It turned out that the features with positive correlation are amount, oldbalanceOrg, type_CASH_OUT,

And the negative correlation are: newbalanceOrig, newbalanceDest, oldbalanceDest, type_PAYMENT, and type_DEBIT.

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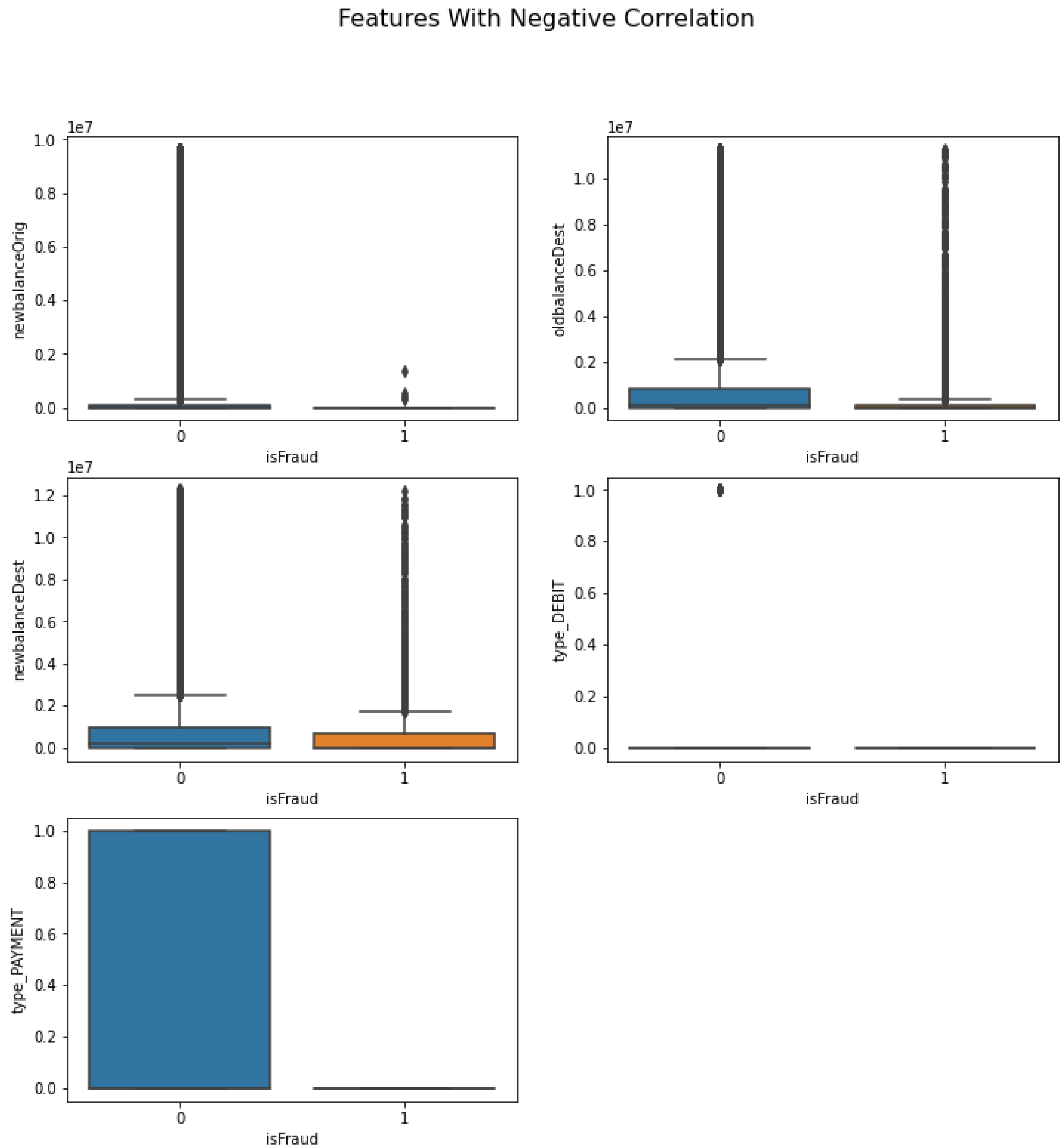

Figure 3: shows the features with negative correlation with isFraud

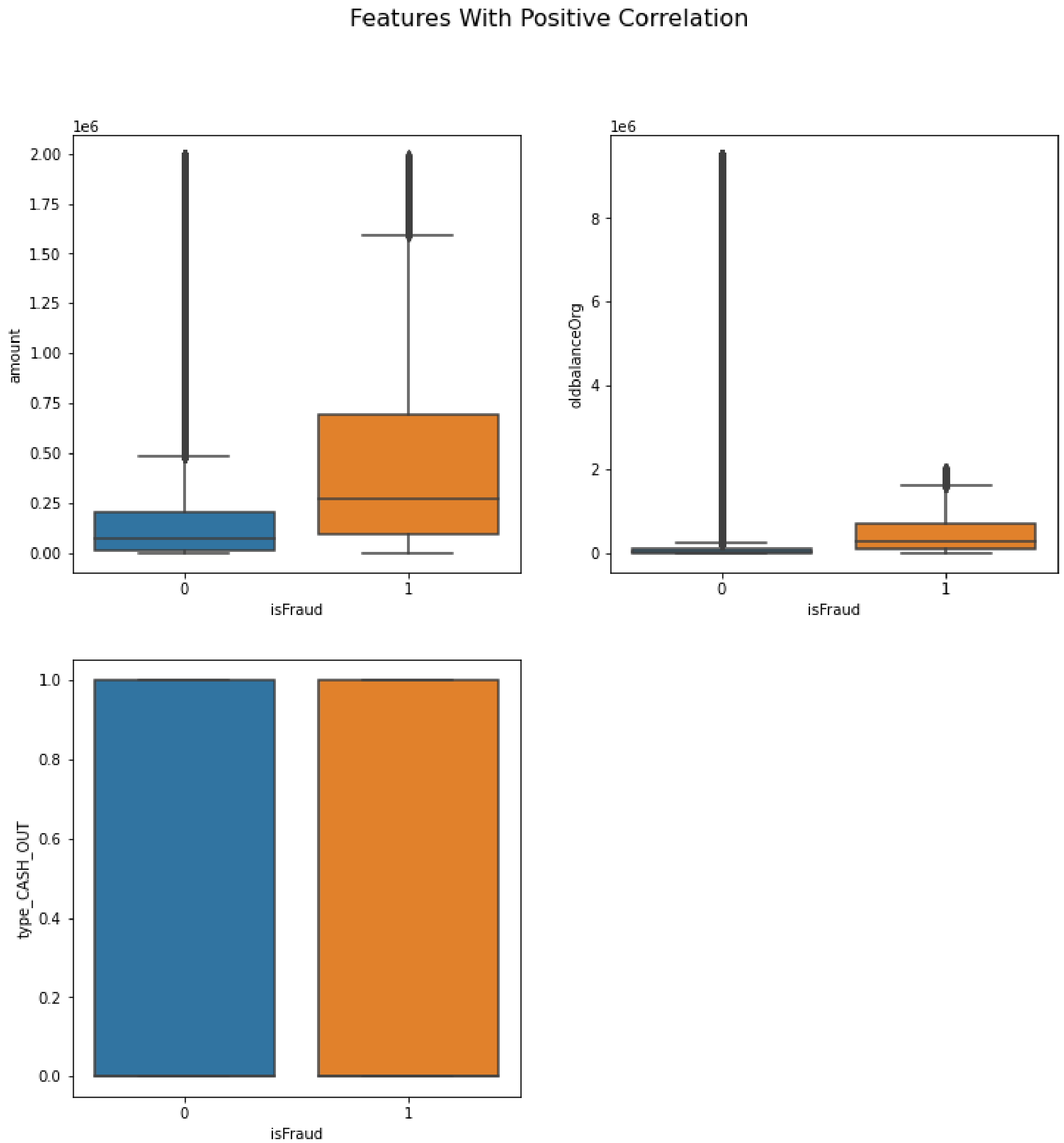

Figure 4: shows the features with positive correlation with isFraud

3.3 First Experiment:

We have used the dataset as is (unbalanced). We have split the dataset into three datasets: training, validating and testing. The ratio of the splitting was (60 x 20 x 20). We have trained and tested each model and recorded the results (accuracy, Precision, Recall, F1-score and time required for the training process in seconds) as can be seen in Table 2.

Table2: shows the result of the 12 models without SMOTE (unbalanced dataset)

Model Name	**Accuracy**	**Precision**	**Recall**	**F1_score**	**Time in Sec**
Decision Tree Classifier	99.97%	88.22%	84.44%	86.29%	35
MLP Regressor	99.94%	99.94%	99.94%	99.93%	859
Random Forest Classifier	99.97%	99.96%	99.97%	99.96%	1098
Complement NB	54.05%	0.24%	99.62%	0.47%	5

MLP Classifier	99.95%	96.34%	55.41%	70.36%	766
Gaussian NB	58.93%	0.26%	99.62%	0.53%	6
Bernoulli NB	99.89%	100.00%	0.15%	0.30%	5
LGBM Classifier	99.92%	64.80%	55.64%	59.87%	34
Ada Boost Classifier	99.93%	90.67%	41.65%	57.08%	435
K. Neighbors Classifier	99.96%	91.03%	67.14%	77.28%	914
Logistic Regression	99.91%	94.50%	14.21%	24.71%	34
Bagging Classifier	99.97%	93.78%	81.58%	87.25%	251
Deep Learning	99.956%	98.898%	60.752%	75.268%	280

This dataset is severely imbalanced (most of the transactions are non-fraud). So the algorithms are much more likely to classify new observations to the majority class and high accuracy won't tell us anything. To address the problem of imbalanced dataset we can use undersampling and oversampling data approach techniques. Oversampling increases the number of minority class members in the training set. The advantage of oversampling is that no information from the original training set is lost unlike in undersampling, as all observations from the minority and majority classes are kept. On the other hand, it is prone to overfitting. There is a type of oversampling called SMOTE (Synthetic Minority Oversampling Technique), which we are going to use to make our dataset balanced. It creates synthetic points from the minority class.

Also we shouldn't use accuracy score as a metric with imbalanced datasets (will be usually high and misleading), instead we should use f1-score, precision/recall score and confusion matrix

- **Recall of fraud cases (sensitivity)** summarizes true positive rate (True positive/True positive + False Negative) - how many cases we got correct out of all the positive ones
- **Recall of non-fraud (specificity)** summarizes true negative rate (True negative/True negative + False positive) - how many cases we got correct out of all the negative ones
- **Precision of fraud cases** (True positive/True positive + False positive) summarizes the accuracy of fraud cases detected - out of all predicted as fraud, how many are correct
- **Precision of non-fraud cases** (True negative/True negative + False negative) summarizes the accuracy of non-fraud cases detected - out of all predicted as non-fraud, how many are correct
- **F1-score** is the harmonic mean of recall and precision.

3.4 Second Experiment:

We have balanced the dataset using SMOTE technique. The class feature (isFraud) now is balanced (50% for fraud transaction and 50% for non-fraud transaction) as in Figure 5. Then we have split the dataset for three datasets: training, validating and testing as in the first experiment. The ratio of splitting was (60 x 20 x 20). We have trained and tested each model and recorded the results (accuracy, Precision, Recall, F1-score and time required for the training process in seconds) as can be seen in Table 3.

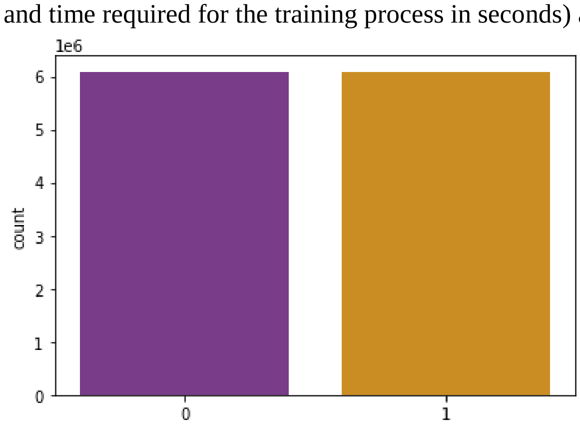

Figure 5: class feature (isFraud) is balanced

Table3: shows the result of the 12 models with SMOTE (balanced dataset)

Model Name	**Accuracy**	**Precision**	**Recall**	**F1_score**	**Time in Sec**
Decision Tree Classifier	99.958%	99.945%	99.971%	99.958%	**67**
MLP Regressor	99.389%	99.390%	99.389%	99.389%	1244
Random Forest Classifier	99.950%	99.950%	99.950%	99.950%	1550
Complement NB	78.753%	70.222%	99.799%	82.438%	10
MLP Classifier	99.420%	99.269%	99.574%	99.421%	1798
Gaussian NB	78.331%	69.820%	99.756%	82.145%	11
Bernoulli NB	90.442%	84.089%	99.746%	91.251%	11
LGBM Classifier	99.710%	99.588%	99.833%	99.710%	89
AdaBoost Classifier	97.556%	95.853%	99.411%	97.599%	623
K Neighbors Classifier	99.681%	99.421%	99.943%	99.681%	1624
Logistic Regression	96.694%	94.452%	99.213%	96.774%	109
Bagging Classifier	99.962%	99.946%	99.978%	99.962%	414
Deep Learning	99.183%	99.305%	99.058%	99.183%	560

As can be seen from table 2 and table 3 the followings:

- In the unbalanced dataset, the Recall and F1-Score is very low for most models.
- The only two models with unbalanced dataset and have very high Recall and F1-Score are: MLP Regressor and Random Forest Classifier only.
- In the balanced dataset, the Recall and F1-Score is very high for all models.
- The top two highest models are Bagging Classifier and Decision Tree Classifier.
- Some models can give high recall and F1-Score regardless of the dataset balanced or unbalanced.

After finishing the training of the 13 models we determined the best features in the dataset by Plotting Feature Importance using Bagging Classifier because it is the best classifier as in Figure 5.

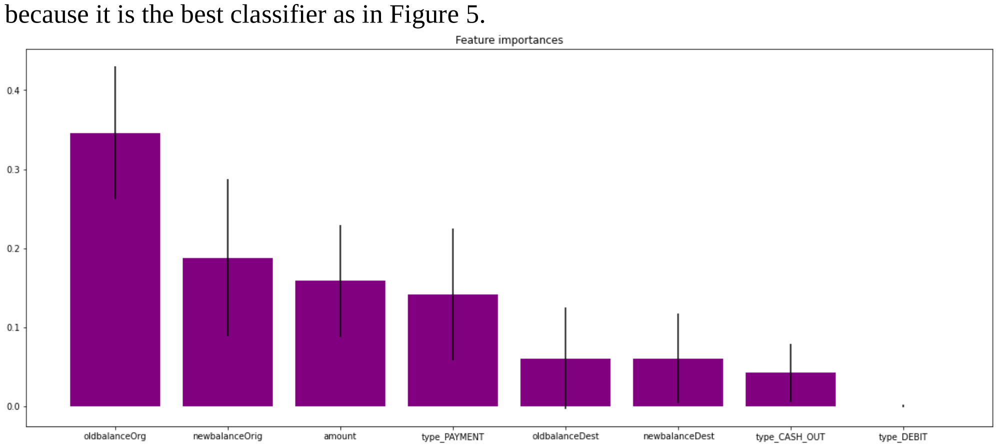

Figure 6: Feature Importance

4. Conclusions

Good prediction results can be achieved with imbalanced datasets as well as with balanced ones. Bagging Classifier, Decision Tree Classifier and Random Forest Classifier gave us the best results being able to detect more than 99.50% fraud transactions and at the same time not classifying some of non-fraud transactions as fraud. There is no perfect model and there will always be a trade-off between precision and recall. It is up to the company and its objectives to decide which approach is the best in each particular situation.

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