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A Comparative Study of Using Various Machine Learning and Deep Learning-Based Fraud Detection Models For Universal Health Coverage Schemes

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***Abstract* — *Fraud detection is an important area of research in the healthcare systems due to its financial consequences arising mainly from investigation costs, revenue losses, and reputational risk. To mitigate this, most of the companies adopt Machine Learning and/or Deep Learning-based fraud detection models. Efficient fraud detection models improve the performance of healthcare systems. Key challenges in building an efficient fraud detection model include*

- *Data imbalance: skewed number of lesser fraudulent cases in comparison to the non-fraudulent cases,*
- *Selection of classification model: use of appropriate machine learning or deep learning models to identify fraud or non-fraud cases*

In this work, we have used three different data-imbalance techniques and six classification models to meet these challenges; we have also used six variants of neural network models. For this, we have used data from part of the world's largest universal health coverage scheme called Ayushman Bharat (PM-JAY India). There were a total of 26 models that were tested as part of this study. The performance of these models was measured using various metrics such as accuracy, sensitivity, specificity, and F1-score. It was identified that a neural network model trained on undersampled data performed better than other models in this study.
Code is available in the following link:
https://github.com/RohanYashraj/Healthcare-Fraud-Detection

Keywords — *Ayushman Bharat, PM-JAY India, Largest universal health coverage scheme, Machine learning, Deep learning, Data imbalance, Actuarial techniques, Data embedding, Classification models.*

I. INTRODUCTION

Healthcare fraud and abuse are some of the major concerns in various countries, costing billions of dollars in some cases [1]. According to the 2019 report of the National Health Care Anti-Fraud Association on healthcare fraud detection, the total losses in 2018 was USD 679.18 million, which is expected to reach USD 2.54 billion by 2024 (Health insurance fraud and its impact on the healthcare system). In India, according to the report of business today [2], around Rs. 45,000 crores were lost due to health insurance fraud in 2019.

Healthcare fraud can be broadly classified into three categories: provider fraud, customer fraud, and insurer fraud [3]. Provider healthcare fraud may be committed by individuals (e.g., physicians, doctors) or by organizations (e.g., hospitals). Sometimes provider fraud may also involve other service providers or individuals (e.g., patients). Customer fraud may be committed when the insured/ consumer knowingly misrepresents the facts to get additional benefits. They may work in union with healthcare providers (e.g., doctors, physicians). The focus of this paper is on customer-level fraud by observing the claim records as collected by the healthcare systems.

Traditional healthcare fraud detection models are heavily dependent on auditing and expert inspection [4]. These models are costly, inefficient, and time-consuming and require lots of human intervention [5]. Often thousands of records are handled by very few claims handlers who are expected to review all the claims. Under such circumstances, they only focus on some special characteristics of claims and pay very little attention to the relationships between the features.

This work is aimed to demonstrate how various machine learning and deep learning models can be used in healthcare systems for efficient fraud detection. We have applied various models on the part of the universal health coverage scheme, Ayushman Bharat (PM-JAY) (the world's largest health insurance scheme). This is aimed to identify the best model that can be used for identifying fraudulent claims. We have presented the performance of various models using standard performance metrics and presented the best performing among them.

The paper is organized as follows – we first provide a brief review of the literature in the area of healthcare fraud. Then we describe the two-phase.

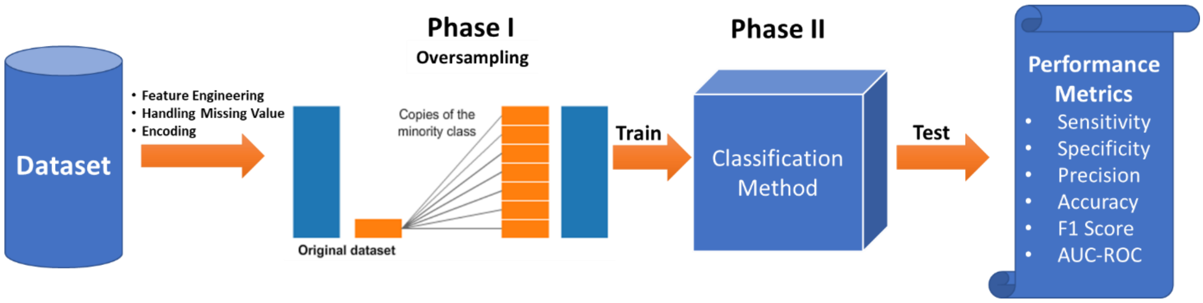

Figure 1 - Proposed method

Methodology adopted to arrive at the fraud detection model In the data section; we explain in detail the dataset used in this work and provide descriptive statistics of the data. Thereafter, we have the results section, which contains the results of the various implementation of the models in this study. Finally, we have the conclusion followed by the future work in this area.

II. RELATED WORK

Today, a growing number of healthcare insurers are using the latest machine learning and data mining tools to build fraud detection models [6]. An efficient fraud detection model can identify hidden patterns in the data which is otherwise not evident, and they only get better over time as they have more data to train on. Efforts are being made by various researchers in this domain. Rule-engines are used in various healthcare systems, which has a set of the pre-defined rule [7]–[10]. They are implemented to identify errors, incomplete data, duplicate claims, ineligible claims, suspicious claims, etc. These systems may not have the capability to model fraudulent behavior. More sophisticated fraud detection models are based on data mining and machine learning [6], [11]–[14]. A multidimensional data model was used by Thornton et al. for predicting healthcare fraud in Medicaid [15]. A process-mining framework proposed by Yang et al. is capable of identifying fraudulent cases that are not detected by manual rule-engine. Johnson et al. proposed a multi-stage methodology to detect fraud in health insurance claim records [16]. The proposed method is a five-stage methodology that is tested on real-world insurance data. There are instances when the fraud is identified post payment of the insurance claims. The outlier detection system proposed by Capelleveen et al. uses an unsupervised learning approach to identify outliers at a post-payment stage to detect a fraudulent pattern in the insurance claims [17]. Srinivasan et al. proposed two novel applications of big data analytics in healthcare to reduce the cost of operations by reducing fraud, errors, abuse, and waste [18]. Yongchang et al. proposed a combination of manifold learning and outlier detection to detect fraud in mobile healthcare services [19]. A scoring model developed by Shin et al. uses patterns based on profile information extracted from electronic insurance claims [20], [21]. These models are used to identify fraudulent billing patterns in healthcare claims. Bauder et al. have used an unsupervised approach to identify medical fraud [22], [23]. Fletcher et al. have proposed a very unique approach using Benford's Law distribution to detect fraud in the health insurance business [24]. Liou et al. have used diabetic outpatient service to detect hospital fraud and abuse using various data mining approach [1]. Rohan et. al. provided a framework for fraud detection in insurance [25]–[29]

In this work, we have used various machine learning and deep learning models to build an efficient fraud detection model for healthcare services.

III. METHODOLOGY

In this section, we will discuss the method adopted for building a fraud detection model. The schematic representation of our approach is shown in Figure 1. In phase I, we have handled the data imbalance using three over-sampling techniques – SMOTE, ADASYN, and TGANs, as shown in the works of Gupta et al. and Rai. et al. [28], [30]–[32]. Here, the minority samples are synthetically generated to balance the two classes in the dataset. In phase II, we have used various classification models such as Decision Tree (DT), Random Forest (RF), XGBoost, LightGBM, and Gradient Boosting Machine (GBM).

A. Phase I

In this phase, we have used Synthetic Minority Oversampling Technique (SMOTE), Adaptive synthetic sampling approach (ADASYN), and Tabular Generative Adversarial Networks (TGANs) to oversample fraudulent claims in the dataset.

SMOTE model is a class imbalance handling technique proposed by Chawla et al. [33]. This can be understood as new minority samples being synthesized between the two real samples in the dataset set.

ADASYN is similar to SMOTE, with the major difference being in consideration of density distribution of the minority samples. In SMOTE, uniform weight is given to all the samples.

TGANs is a neural network-based generative model which is trained to learn the distribution of the minority samples [28], [30], [31]. The model is said to be trained when the discriminator is no longer able to distinguish between real and synthetic datasets. The trained model is then used to generate minority samples.

B. Phase II

The classification of claims into fraud and non-fraud is done using five machine learning models – Decision trees, Random forests, Gradient Boosting Methods, and its two variants LightGBM, and XGBoost. Decision Tree (DT) learns from the data and fits an if-then-else decision rule into the dataset. The rules are then used for the classification of claims in fraud or non-fraud [34]. Random forest is an ensemble model which is constructed using multiple decision trees [35], [36]. This model is similar to decision trees with improved performance because of its ability to learn complex rules in the dataset. Gradient boosting is another machine learning model which is based on the ensemble of weak prediction models. There are various implementations of this in the literature [25], [37]. Variation of GBM called LightGBM and XGBoost is used in this work along with GBM. LightGBM is a gradient boosting framework that is fast and based on decision trees. XGBoost is different from GBM in the use of loss function.

Apart from these machine learning models, deep learning models are also used. In this study, six different variants of neural networks are used, and the results are analyzed

The combination of all the models explained as part of Phase I and II are implemented, and the results, along with the business interpretation of the best performing model, are shown in the results section.

IV. DATA AND DESCRIPTIVE STATISTICS

The dataset used for this work is from part of the world's largest group health insurance scheme (PM-JAY India)[27]. The data description and various data pre-processing performed on the data are presented here. There are a total of 3,82,587 claim records, and for each record, there are 98 features (after performing data-processing). The various data-preprocessing performed on this dataset is described in this section

A. Missing value analysis

The data used comprise of claim records of individuals. Figure 2 shows the heat map of the missing values in the dataset. The portion highlighted in yellow represents the missing value. The features which had a very high percentage of missing values were not considered for this study.

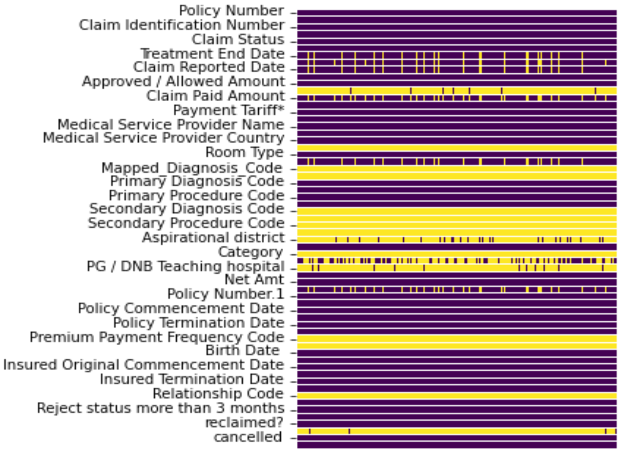

Figure 2 - Heatmap of the missing values in the dataset

The heat map of the dataset after removing features with a very high percentage of missing values is shown in Figure 3. Remaining features with few missing values were handled separately. Other missing values in the dataset were handled using statistical methods such as – mean value imputation, median value imputation, average value imputation, and random selection.

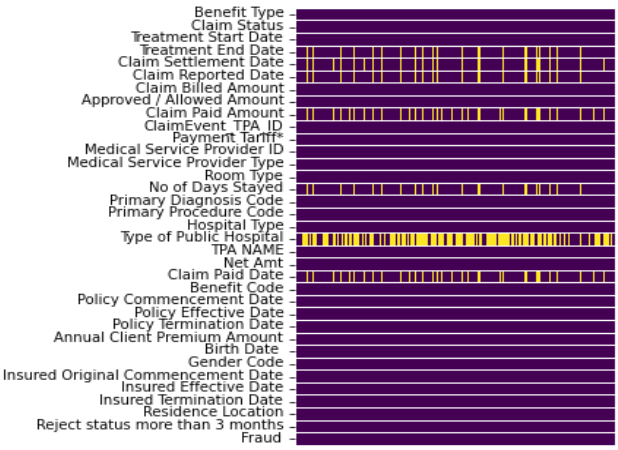

Figure 3 - Heatmap of the resulting dataset

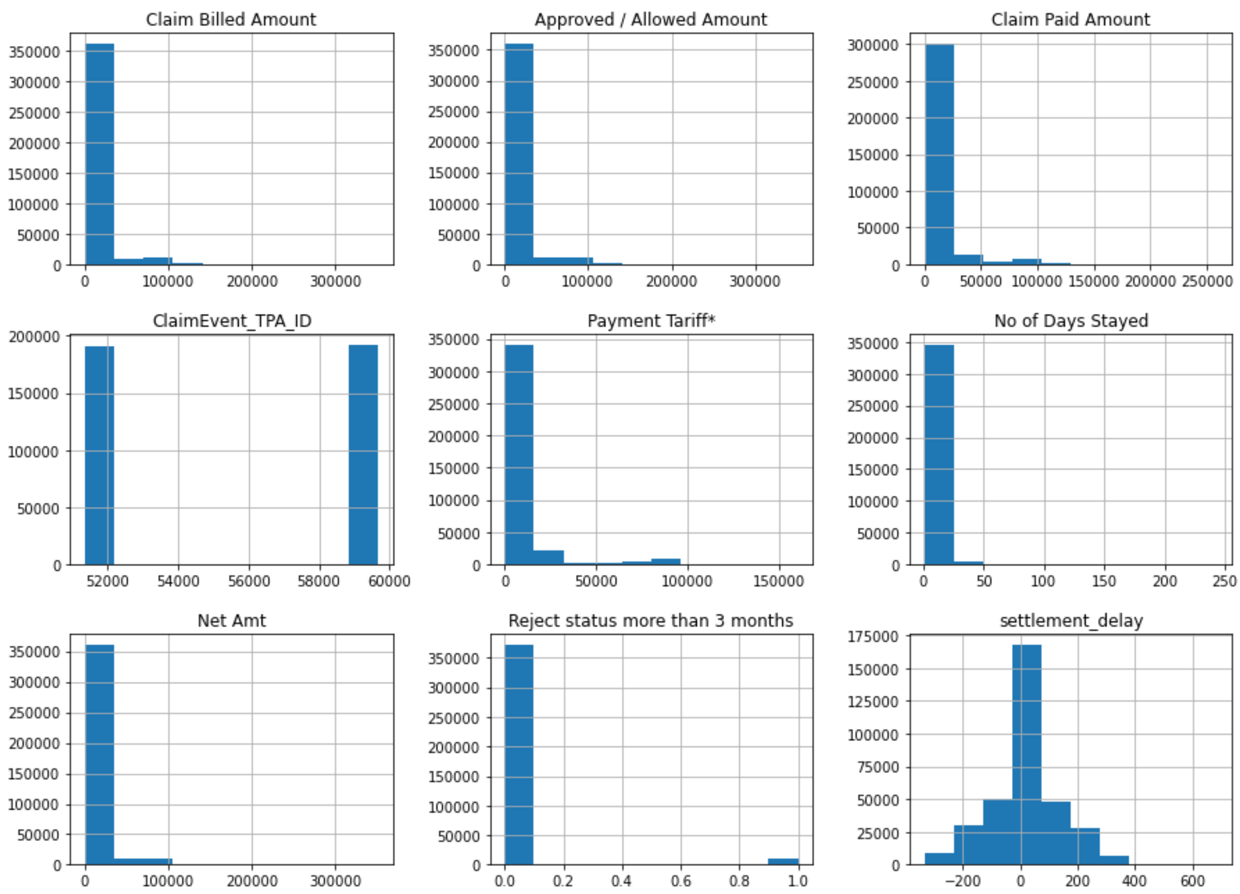

Figure 4 - Histogram of various field of the dataset

B. *Exploratory data analysis*

Figure 4 shows the histogram of the dataset for the various numerical fields in the dataset.

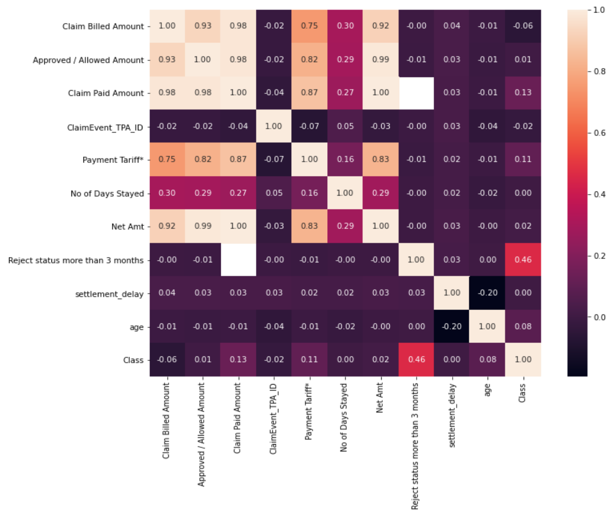

Figure 5 - Correlation graph of all the features in the dataset

Figure 5 shows the correlation between the variables in the dataset. Some features which were highly correlated with each other were removed, and only one of them was considered for the work. For example, 'Net Amt' is highly correlated with 'Claim billed amount,' 'Approved/ Allowed Amount,' 'Claim Paid Amount,' 'Payment Tariff,' in this situation on 'Net Amt' was considered, and others were removed. It can be observed that the class variable is correlated with 'Reject status more than 3 months with a correlation coefficient of 0.46.

C. *Feature engineering*

Using the date features in the dataset – 'Treatment Start Date,' 'Claim Reported Date,' 'Policy Commencement Date' and 'Policy Termination Date,' year month, week, day, any day of the week features were generated. 'Settlement delay' was calculated by taking the difference between 'Claim settlement date' and 'claim reported date.'

V. RESULTS

This section contains the results of various studies that were carried out. The dataset used was divided into train and test in the ratio of 75:25. The dataset is highly imbalanced in nature, with 12% of the claim as fraudulent, which is 46,400 claims out of 3,82,587. Figure 6 shows the histogram of fraud and not-fraud claims in the dataset.

TABLE 1 - PERFORMANCE METRICS OF FIVE MACHINE LEARNING MODELS USING BASELINE DATA AND OVERSAMPLED DATA

Models			AUC-ROC	Recall	Specificity	Precision	Accuracy	F1 Score
Decision Tree	Baseline	M1	**0.9566**	0.9248	0.9885	0.9174	0.9808	0.9211
	SMOTE	M2	0.9534	0.9208	0.9860	0.9006	0.9781	0.9106
	ADASYN	M3	0.9508	0.9155	0.9862	0.9016	0.9776	0.9085
	TGANs	M4	0.9548	0.9214	0.9883	0.9155	0.9801	0.9185
Random Forest	Baseline	M5	0.9462	0.8947	0.9977	0.9818	0.9852	0.9362
	SMOTE	M6	0.9493	0.9027	0.9959	0.9682	0.9846	0.9343
	ADASYN	M7	0.9500	0.9057	0.9942	0.9556	0.9834	0.9300
	TGANs	M8	0.9460	0.8942	0.9977	0.9820	0.9852	0.9361
XGBoost	Baseline	M9	0.9307	0.8615	0.9999	0.9989	0.9831	0.9252
	SMOTE	M10	0.9458	0.8970	0.9945	0.9572	0.9826	0.9262
	ADASYN	M11	0.9270	**0.9835**	0.8705	0.5119	0.8842	0.6733
	TGANs	M12	0.9111	0.8223	**1.0000**	**1.0000**	0.9784	0.9025
LightGBM	Baseline	M13	0.9486	0.8977	0.9994	0.9952	**0.9871**	**0.9440**
	SMOTE	M14	0.9499	0.9014	0.9988	0.9905	0.9869	0.9438
	ADASYN	M15	0.9523	0.9105	0.9940	0.9547	0.9839	0.9320
	TGANs	M16	0.9482	0.8970	0.9994	0.9950	0.9870	0.9435
GBM	Baseline	M17	0.9425	0.8852	0.9997	0.9975	0.9858	0.9380
	SMOTE	M18	0.9451	0.8958	0.9945	0.9576	0.9825	0.9257
	ADASYN	M19	0.9288	0.9779	0.8796	0.5288	0.8916	0.6864
	TGANs	M20	0.9282	0.8566	0.9992	0.9992	0.9224	0.9224

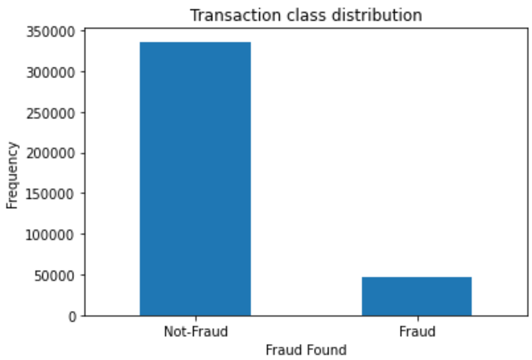

Figure 6 - Histogram of fraud and not-fraud claims in the baseline dataset

We have used five classification methods and implemented them on baseline data and balanced data. SMOTE, ADASYN, and TGANs were used to balance the dataset. Thus, for each of the five models, there are four different outputs. TABLE 1 contains the performance metrics for this study. There are a total of 20 different models, which are labeled from M1 to M20 for ease of reference. Five different metrics are used for comparing the models – AUC-ROC, Recall, Specificity, Precision, Accuracy, and F1-Score. For each of the five metrics, the highest scores are highlighted in bold. It can be observed that M1, M11, M12, and M13 are the models which have at least one of the metrics which is highest in comparison to others. However, it is essential to check the performance of the model, considering all the metrics. E.g., high specificity with very little recall and precision may be undesirable as this would indicate that the model has very high false positives. Also, it is essential to know the business requirements – in insurance business investigation; the cost is very high; thus, the insurers want very few false positives, which means a model with higher recall is desirable in comparison to others. With this idea in perspective, it can be observed that M14 and M15 are pretty balanced models with respect to all the performance metrics. M15 has the recall is 0.91 while having the sensitivity, precision, and accuracy of 0.9940, 0.9547, and 0.9839, respectively. M14 has a slightly lesser recall in comparison but has a much better precision with a value of 0.99. Thus, model M14 would be preferred here because this model can identify 90% of the fraudulent cases (recall) and is 99% correct in predicting fraudulent cases as fraudulent (precision). This indicates that the model has very few false-positive cases.

Though M14 is a pretty good model by itself, a recall of 0.90 also indicates that 10% of the fraudulent cases are not identified by the model at all. Thus, it was essential to find other models which had an improved recall while having better scores with respect to other metrics. For this, six deep learning-based models were implemented to identify a more efficient model.

TABLE 2 represents the architecture of the neural network model used in this study.

TABLE 2 - ARCHITECTURE OF THE BASELINE NEURAL NETWORK MODEL

Layer (type)	Output Shape	No. of parameters
dense_1 (Dense)	(None,49)	4,851
dense_2 (Dense)	(None,80)	4,000
dropout_1 (Dropout)	(None,80)	0
dense_3 (Dense)	(None,80)	6,480
dense_4 (Dense)	(None,49)	3,969
dense_5 (Dense)	(None,1)	50

TABLE 3 - PERFORMANCE OF THE MODEL USING VARIANTS OF NEURAL NETWORK MODELS

Models			AUC-ROC	Recall	Specificity	Precision	Accuracy	F1 Score
Neural Networks	Baseline	M21	0.9406	0.8826	0.9986	0.9885	**0.9845**	0.9325
	Weighted	M22	**0.9557**	0.9418	0.9644	0.7852	0.9617	0.8564
	Undersampled	M23	0.9525	0.9374	0.9676	0.9663	0.9526	**0.9516**
	SMOTE	M24	0.9496	0.9533	0.9459	0.7087	0.9468	0.8130
	ADASYN	M25	0.9389	**0.9822**	0.8955	0.5650	0.9061	0.7173
	TGANs	M26	0.9392	0.8795	**0.9989**	**0.9908**	**0.9844**	0.9318

There are six variants of the neural network model that is implemented here, and each of them is labeled from M21 to M26 for ease of reference (refer **TABLE 3**). M21 is the baseline model where the dataset used for training the model was the baseline dataset. M22, the dataset used, is adjusted to account for class imbalance by giving additional weight to the loss associated with errors made on fraudulent claims. The class fraud is assigned a weight of 4.12, and the class non-fraud is assigned a weight of 0.57. For M23, the dataset was undersampled to balance the fraudulent and non-fraudulent cases. M24, M25, and M26 used the oversampled dataset using SMOTE, ADASYN, and TGANs, respectively.

In **TABLE 3**, the highest scores for each of the performance metrics are highlighted in bold. M23 shows the performance of the model to be the best in comparison to all the other models. It has the highest F1-score of 0.95, as shown in **Figure 7**.

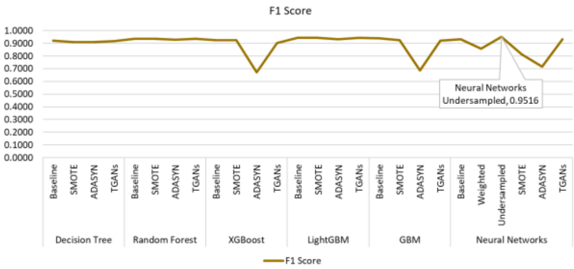

Figure 7 - F1-score of all the models

Also, the other metrics have a better score for this model. The recall is at 0.93; at the same time, there is a high value of precision of the model at 0.96. M26 has the highest scores in terms of specificity, precision, and accuracy but has a very low recall. **Figure 8** contains the AUC-ROC values of all 26 models. The top four models with the highest AUC-ROC values are highlighted, and M26 is one of them. Thus, keep all this into perspective, it can be concluded that M23 is the most efficient model.

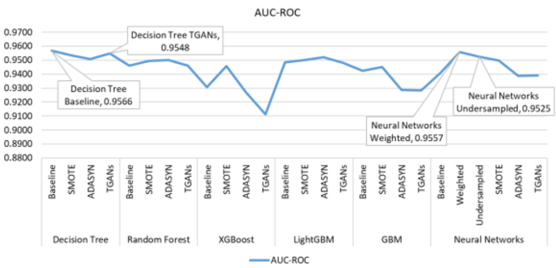

Figure 8 - AUC-ROC value of all the models

Figure 9 shows the plot of recall, precision, and accuracy of all the 26 models used in this study.

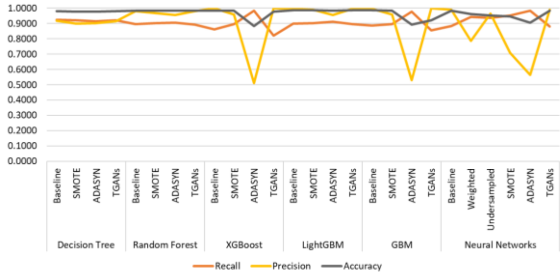

Figure 9 - Recall, precision, and accuracy of all the models

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we have performed a study of various machine learning and deep learning models for building a fraud detection model in the healthcare system. A total of 26 models were tested on the healthcare dataset of Ayushman Bharat (PM-JAY). SMOTE, ADASYN, and TGANs were used to handle the data imbalance in the dataset. It was observed that the neural networks, when trained on an undersampled dataset, performed better than other classification models. This model gave the highest value of F1-score of 0.95, which is the harmonic mean of precision and recall.

In the future, a similar study can be performed with other lines of business to find the best performing machine learning or deep learning models.

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