FRAUD DETECTION IN INSURANCE CLAIMS USING MACHINE LEARNING

PROJECT REPORT

21AD1513-INNOVATION PRACTICES LAB

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In partial fulfillment of the requirements for the award of degree

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PANIMALAR ENGINEERING COLLEGE, CHENNAI-600123

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BONAFIDE CERTIFICATE

Certified that this project report titled "**FRAUD DETECTION IN INSURANCE CLAIMS USING MACHINE LEARNING**" is the bonafide work of **GAYATHRI KRISHNA (211422243074), HARINI C (211422243088), KEERTHANA V (211422243153)** who carried out the project work under my supervision.Certified further, that to the best of my knowledge the work reported here in does not form part of any other project reportor dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

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ABSTRACT

Abstract:

As the different countries around the world evolve into a more economical-based and stimulating their economy is the goal. The main purpose of most of these countries is to fight off money launderers and fraudsters for better economic growth. A popular fraud topic in this regard is insurance fraud since it costs the companies and the public billions. Applying data analysis and machine learning are great ways used to address many problems regarding any automated system. To address this problem, first extensive research should be made to check out what has been applied and what the most promising solution using machine learning and data analytics is out there. After learning, then applying and building upon the findings of the research we propose a model that can flag these suspicious fraudulent claims for the insurance companies to help them out in saving money and time and helping them become more efficient in reacting to these fraudulent claims.

Keywords: Machine learning, prediction analysis, supervised learning, fraudulent detection, data visualization, data analysis.

LISTOF FIGURES

LIST OF ABBREVIATIONS

ABBREVIATIONS	MEANING
AI	ARTIFICIAL INTELLIGENCE
API	APPLICATION PROGRAMMING INTERFACE
BI	BUSINESS INTELLIGENCE
CRM	CUSTOMER RELATIONSHIP MANAGEMENT
CSV	COMMA-SEPARATED VALUES
DNN	DEEP NEURAL NETWORK
IoT	INTERNET OF THINGS
KPI	KEY PERFORMANCE INDICATOR
ML	MACHINE LEARNING
NLP	NATURAL LANGUAGE PROCESSING
SVD	SINGULAR VALUE DECOMPOSITION
SLA	SERVICE LEVEL AGREEMENT
SQL	STRUCTURED QUERY LANGUAGE
TB	TELECOMMUNICATION BUSINESS
UAV	UNMANNED AERIAL VEHICLE
VPN	VIRTUAL PRIVATE NETWORK

XGBoost	EXTREME GRADIENT BOOSTING
QoS	QUALITY OF SERVICE
ROC	RECEIVER OPERATING CHARACTERISTICS
AUC	AREA UNDER THE CURVE
KNN	K-NEAREST NEIGHBORS

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND INFORMATION

As we live in a very materialistic world everyone is looking out to protect something they have or own in one way or another. Covid – 19 pandemic has proven difficult to many countries at the beginning of the vaccine revolution since every country is trying to protect their people. Many people were rushing to get the vaccine as insurance to protect themselves. That is the main point and idea behind insurance businesses. People are willing to pay money as a contingent against the unknown loss that they might face. In the U.S alone the insurance industry is valued at 1.28 trillion dollars and the U.S consumer market losses at least 80 billion to insurance fraud every year. That causes the insurance companies to increase the cost of their policies which puts them in a less competitive position against the competition. This in turn also increased the threshold of the minimal payment for a policy since they can afford to do so while everyone is raising prices.

This paper aims to suggest the most accurate and simplest way that can be used to fight fraudulent claims. The main problem with detecting fraudulent activities is the massive number of claims that run through the companies systems. This problem can also be used as an advantage if the officials were to take into account that they hold a big enough database if they combined the database of the claims. Which can be used in order to develop better models to flag the suspicious claims

1.2 STATE OF THE PROBLEM

The main purpose of this paper is to come up with a model to be used to find out if a certain insurance claim made is a fraud or not. The model will be designed after testing multiple algorithms to come up with the best model that can detect if a claim is fraudulent or not. This is aimed at the insurance companies as a pitch to come up with a more tailored model for their liking to their own systems. The model should be simple enough to calculate big datasets, yet complex enough to have a decent successful percentile

1.3 PROJECT DEFINITION AND GOALS

Research Question 1: what are some of the possible approaches to designing a model? Justification: many approaches can be taken, and many solutions can take place in designing a fraud detecting model. Each one of these solutions and models can be taken into account depending on the situation of the implementation of the model. Research Question 2: comparison of the different models and any used models used in a similar environment? Justification: To propose this solution to the desired customer or the end-user of this model a comparison must be available to justify why had this model has been picked over any other models Research Question 3: The impact of this model results in the real world application if it will be taken by an institution taking into account the effect of the different results of the model Justification: the main concern is how these results are translated into the real world. How will this affect the performance of a certain institution that will adopt this model as a solution in their operations.

1.4 METHODOLOGY

Overview:
For this project, a mixed research method will be used. The project will use some explanatory research methods along with experimental research methods and some qualitative and quantitative research methods to explain the findings and the result of the paper to explain the different results. First, we will identify what is important in running the data according to the business that might use the solutions or the model. In this case, it will most likely be an insurance company that will take into account the financial aspect of each claim as a priority and the personal details will take no account in designing the model itself. The paper will describe the data at hand and what are the different attributes and how is every attribute relevant to identify if this claim is fraud or not. What are the different types of data present at hand and is it possible to enhance and modify the existing data without tampering with the result of the end goal which is flagging out the suspicious claims. To do this it might be necessary to clean the data and remove some of the values or the attributes or even create new attributes and values by joining and using data integration methods to come up with new values

After that, we will run the data through different kinds of algorithms and models to try and find out the best model or algorithms for these kinds of data. From the previous research of a lot of the work that has been done on the subject. Decision trees, support vector machines, neural networks, and logistic regression are the top candidate algorithms. If it is possible, running the data through more than one model before coming up with the conclusion that this claim is fraud or not. Of course, this depends highly on the type of business and how much time they are willing to give the model to come up with a decision for a single claim. Finally evaluating the findings of each model and algorithms with a set of data that haven't been used in the training phase of the model to check how accurate is this model and find out if there is any overfitting or underfitting before the selection of the model or modifying it if it was possible to come up with a better and a more accurate model for the end-user or the customer.

This research is divided into following phases.


Phase 1: Dataset Exploration
• Dataset Overview
• Feature Exploration
Phase 2: Data Preprocessing
• Data Cleaning
• Data Transformation
Phase 3: Data Exploration
• Feature Visualisation
• Count Illustrations
Phase 4: Testing and Modeling
• Metric Overview
• Feature Importance
• Testing and Modeling Analysis
Phase 5: Results
• Insight Exploration
• Proposed Solution Validation

1.5 LIMITATIONS OF STUDY

One significant flaw in the study was the lack of computational resources to carry out machine learning algorithm's training, one repetition requires a significant amount of time and computational resources. This approach took longer to train the model since we do not have computational resources and a good platform to conduct training and testing analysis, which limited how thoroughly we would complete the research.

CHAPTER 2

LITERATURE REVIEW

● Fraud Detection System (FDS): A fraud detection system is a system that tries to identify suspicious activities while they go through the main system (Aisha Abdallah, 2016). Previously this process has been done manually and going through a sample of real fraud data to detect and identify these activities. The operation has been time-consuming and prone to human error, misinterpretation and overlooking of some of the details. Hence the evolution of fraud detection systems to automate the process and remove the human element from the operation level of the system, but a lot of the data mining methods were missing previously, and they are much more enhanced and effective nowadays to come up with better results and findings for an effective fraud detection system.

● Supervised learning methods for credit card fraud detection: Many financial institutions are looking to limit their losses in credit card fraudulent transactions. Since it's one of the most attractive research topics in the financial world many methods have been tried and tested in this domain from supervised learning to ensemble learning (Johannes Jurgovskya, 2018). Supervised learning has been found as the ideal way to detect fraud as it takes the datasets and uses its class attribute to find out and distinguish the two classes of the training data set (fraud, not fraud "genuine"). (E.W.T. Ngai, 2011) ran a systematic review of many journal articles and have found out that out of all the supervised methods running Decision trees, support vector machines, neural networks, and logistic regression have been found the widely used methods in coming up with a model for the fraud detection system.

● Experimental assessment of a similar data sets:
In an article by (Bart Baesens, 2021) the data set was divided into 30% and 70%, as in 70% of the data have been selected as a training set, and 30% of the data have been selected as the test set for a total of 31,763 records and 14 attributed. To experiment with their data set they have used many classification methods like logistic regression CART algorithms, decision tree, and many more algorithms. Many justifications have been given for each of these algorithms and why they have been taken into account. Logistic regression is very popular in establishing models for its speed and low cost of computation power, and that decision tree could give a better understanding of the decision process in understanding more about how the fraud was committed.

● Insight into credit card fraud types: Like any type and number of criminal activities, credit card fraud has more than one type. (Siddhartha Bhattacharyya, 2011) have described and broken down credit card fraud into two types: application and behavior fraud. Describing application fraud is the act of getting new cards from the issuing credit card companies without using their own personal information or using fake information to obtain and issue new cards. Behavior fraud can be broken into four subtypes: mail theft, counterfeited cards, stolen/lost cards, and 'cardholder not present fraud. In which the information of the real holder of the credit card has been stolen or obtained in an illegal way. While this information is used to run 'cardholder not present' types of transactions like through the internet and phone. Another issue in credit card fraud is the cruciality of time in detecting the fraud because the faster the fraud is detected the greater the avoidable loss.

● Classification of the existing financial fraud detection systems: (Jarrod West, 2016) have compared in his article many research papers about the fraud detection system and the different models that have been used in the detection of fraud and the accuracy of each model. Also previously in the same paper, a comprehensive discerption of each and every model has been conducted. Moreover, a comparison of the different types of fraud investigation types versus what type of methods have been used in the recent research and papers. For example, the most used method or algorithm for credit card fraud is the support vector machines, decision trees, hybrid methods, and artificial immune systems.

● Requirement of process mining to enhance the system: Process mining aims to analyze the process through the event logs. For this to take place and for process mining to work first every event needs to be connected to an activity for a particular case or instance. If possible, every event needs to be connected to a unique entity that generates these events. If the above criteria are met then process mining can be used for that process (Mieke Jans, 2011).

CHAPTER 3

PROJECT

DESCRIPTION

3.1. OVERVIEW:

Dataset discovery, data preprocessing, data exploration, testing and modeling, and outcomes are some of the stages that this study will go through. The chosen dataset will be created for usage in the project's various modeling and testing phases. The initial stage of the project will be the preprocessing phases of data cleaning and normalization, which involve dealing with redundant and missing data and making sure the data that is present in the dataset adheres to integrity. The data will be visualized using a variety of tools to produce a wide range of visuals that will help illustrate the relationships between the different features as part of a thorough analysis of the information. Our proposed solution will be validated using a range of techniques, including testing and modeling, incorporating model comparison and several estimations for a range of characteristics, such as accuracy, computational expense, and processing time. The dataset contains fellows-specific features.

3.2. DATA COLLECTION:

Data collection from synthetic datasets involves generating artificial data through various techniques, such as simulation models, generative algorithms (like GANs), or rule-based methods, to create datasets that mimic real-world scenarios. This approach is particularly useful when access to real-world data is limited,

, synthetic datasets can offer large volumes of diverse data, including rare or edge-case scenarios that might be difficult to capture in reality. However, it is crucial that the generated data is both realistic and representative of the problem domain to ensure its validity for use in machine learning, model validation, or other analytical tasks. Careful attention must also be given to ensuring data quality, consistency, and proper labeling, as these factors directly impact the effectiveness of the data in subsequent analysis or model development.

CHAPTER 4

PROJECT ANALYSIS

4.1. DATASET OVERVIEW:

The first important step is to collect and collect data. After formulating the business problem, it is important to understand the data sources. The data collected in this phase is raw data because it is collected maybe from different means and systems, so it is not organized as such in this phase. The set of data we collected from Kaggle is called binary data and ultimately classifies whether it is considered a scam or not. It has 15,420 insurance records and 33 functions. Features included in the following are:

'Month', 'WeekOfMonth', 'DayOfWeek', 'Make', 'AccidentArea', 'DayOfWeekClaimed', 'MonthClaimed', 'WeekOfMonthClaimed', 'Sex', 'MaritalStatus', 'Age', 'Fault', 'PolicyType', 'VehicleCategory', 'VehiclePrice', 'FraudFound_P', 'PolicyNumber', 'RepNumber', 'Deductible', 'DriverRating', 'Days_Policy_Accident', 'Days_Policy_Claim', 'PastNumberOfClaims', 'AgeOfVehicle', 'AgeOfPolicyHolder', 'PoliceReportFiled', 'WitnessPresent', 'AgentType', 'NumberOfSuppliments', 'AddressChange_Claim', 'NumberOfCars', 'Year', 'BasePolicy'.

4.2. DATA PREPROCESSING:

Data pre-processing in machine learning can be an important step that can make a difference in improving the quality of information to facilitate the extraction of meaningful knowledge from the information. Data preprocessing in machine learning refers to the method of preparing (cleaning and organizing) raw data to make it suitable for building and training machine learning models. In simple terms, machine learning data processing can be an information mining technique that transforms rough information into justifiable and lucid organization. After collecting the raw data, it is time to organize it so that it can be used for further processing.

4.3. DATA CLEANING:

It is important that the data set is free of defects that could prevent testing or, more seriously, lead to insufficient analysis. These deficiencies or problems caused by redundant records, missing values, or loss of dimension must be effectively resolved. So, in this step bad data will be removed, and missing data will be added. The information we currently have is a comprehensive general information from which we need to remove unnecessary information and perhaps add the missing information.

Month	0
WeekOfMonth	0
DayOfWeek	0
Make	0
AccidentArea	0
DayOfWeekClaimed	0
MonthClaimed	0
WeekOfMonthClaimed	0
Sex	0
MaritalStatus	0
Age	0
Fault	0
PolicyType	0
VehicleCategory	0
VehiclePrice	0
FraudFound_P	0
PolicyNumber	0
RepNumber	0
Deductible	0
DriverRating	0
Days_Policy_Accident	0
Days_Policy_Claim	0
PastNumberOfClaims	0
AgeOfVehicle	0
AgeOfPolicyHolder	0
PoliceReportFiled	0
WitnessPresent	0
AgentType	0
NumberOfSuppliments	0
AddressChange_Claim	0
NumberOfCars	0
Year	0
BasePolicy	0

Figure 2. Sum Of Null Values In The Dataset

4.4. EXPLORATORY DATA ANALYSIS:

The data contains a lot of information that needs to be discovered first in order to better understand and investigate the information and by visualizing the data we can get a better sense and information about the data.

4.5. DATA TRANSFORMATION:

In this phase data will be organized or managed so that it will be helpful to achieve the required goal.

WeekOfMonth	15420.000000	2.788586	1.287585	1.000000	2.000000	3.000000	4.000000	5.000000
WeekOfMonthClaimed	15420.000000	2.693969	1.259115	1.000000	2.000000	3.000000	4.000000	5.000000
Age	15420.000000	39.855707	13.492377	0.000000	31.000000	38.000000	48.000000	80.000000
FraudFound_P	15420.000000	0.059857	0.237230	0.000000	0.000000	0.000000	0.000000	1.000000
PolicyNumber	15420.000000	7710.500000	4451.514911	1.000000	3855.750000	7710.500000	11565.250000	15420.000000
RepNumber	15420.000000	8.483268	4.599948	1.000000	5.000000	8.000000	12.000000	16.000000
Deductible	15420.000000	407.704280	43.950998	300.000000	400.000000	400.000000	400.000000	700.000000
DriverRating	15420.000000	2.487808	1.119453	1.000000	1.000000	2.000000	3.000000	4.000000
Year	15420.000000	1994.866472	0.803313	1994.000000	1994.000000	1995.000000	1996.000000	1996.000000

Figure 4. Descriptive Statistics Summary Of The Dataset.

Figure 4 shows the entire summary of the descriptive statistics of the data set. We can clearly see that in the data set we have 15420 sets of data that the weekofmonth shows the week of the month when the accident occurred. The average number of weeks that occurred in a month is two and the maximum number of weeks in a month is five, similarly with the weekofmonth claimed contains weeks in the month that the claimed in field the mean of the weekofmonth is two and the max is 5. Age is the ages of individuals that make claims the average age of individual is 40 while the max age of 80. Column FraudoundP indicating whether the claim was fraudulent or not i.e. 1 or 0.

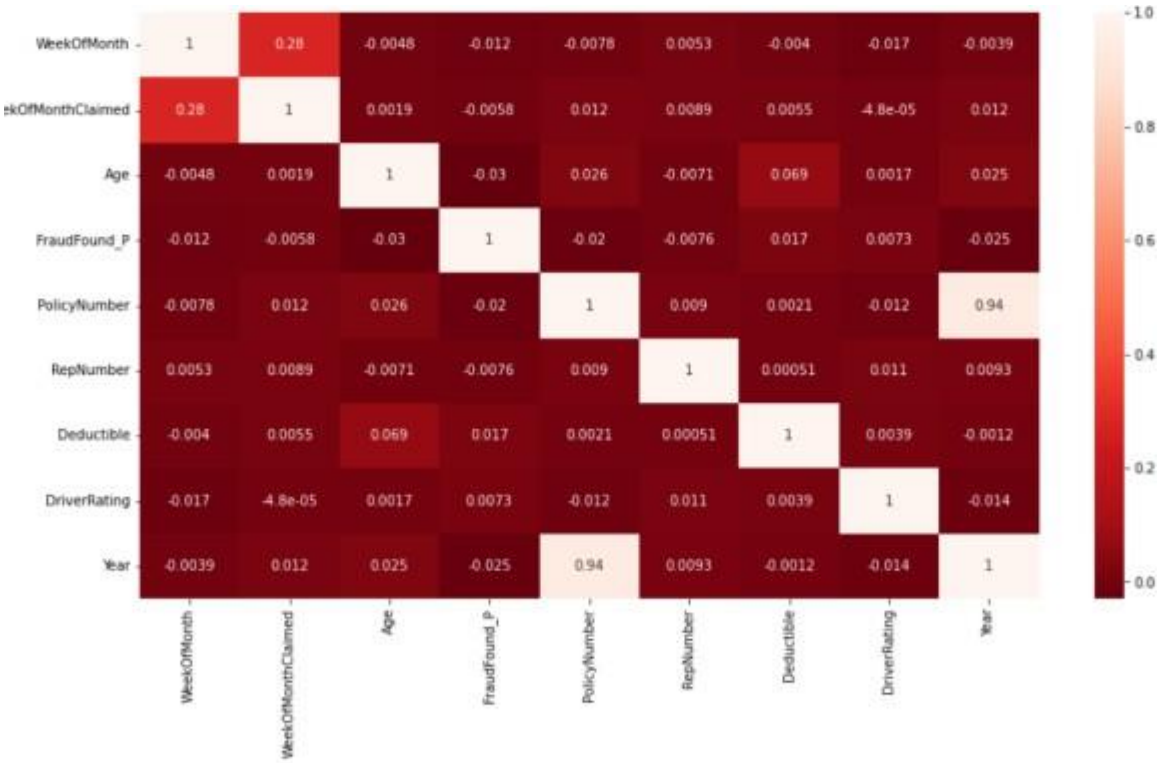

Figure 5. Relation Between Independent And Dependent Variables.

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We need to predict the output using supervised machine learning techniques. sometimes when we have small amount of data, we can easily work with it, but as the amount of data increases, it becomes difficult to find predictors or variables. In this situation, using all the data can often be detrimental, which affects not only the accuracy of the model, but also the computational resources when we use all the data. This is where the concept of correlation comes in as we explore the relationship between dependents and independents features, then select the features that are important for prediction. As shown in Figure 5, we can see the relationship between each feature and how they correlate with each other.

4.6. DATA EXPLORATION:

Using Pandas data frames, the required data is extracted from the initial loaded data. Data is completely examined and discovers information and at the end concludes it to generate the report. 36 The data is displayed using line graphs for the user to analyze using matplotlib and seaborn.For simpler comparison, all of the line graphs are displayed in one graph at the end. Prior to being combined into one large line graph for analysis and comparison with the same date, the data is first displayed on distinct graphs to demonstrate trends in the various dataset values obtained using data visualization

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	Month	WeekOfMonth	DayOfWeek	Make	AccidentArea	DayOfWeekClaimed	MonthClaimed	WeekOfMonthClaimed	Sex	MaritalStatus	Age	Fault
0	Dec	5	Wednesday	Honda	Urban	Tuesday	Jan	1	Female	Single	21	Policy Holder
1	Jan	3	Wednesday	Honda	Urban	Monday	Jan	4	Male	Single	34	Policy Holder
2	Oct	5	Friday	Honda	Urban	Thursday	Nov	2	Male	Married	47	Policy Holder
3	Jun	2	Saturday	Toyota	Rural	Friday	Jul	1	Male	Married	65	Third Party
4	Jan	5	Monday	Honda	Urban	Tuesday	Feb	2	Female	Single	27	Third Party
5	Oct	4	Friday	Honda	Urban	Wednesday	Nov	1	Male	Single	20	Third Party
6	Feb	1	Saturday	Honda	Urban	Monday	Feb	3	Male	Married	36	Third Party
7	Nov	1	Friday	Honda	Urban	Tuesday	Mar	4	Male	Single	0	Policy Holder
8	Dec	4	Saturday	Honda	Urban	Wednesday	Dec	5	Male	Single	30	Policy Holder
9	Apr	3	Tuesday	Ford	Urban	Wednesday	Apr	3	Male	Married	42	Policy Holder

Figure 6. Exploration Of Data To Check Categorical Data

In order to build a predictive model by using machine learning it is important to have all the input and output variables in numeric format not in categorical format as we know machines only understand numeric values, so we have to convert all the categorical variables into numeric to fit and access the model.

Reproducibility and comprehension of the data preparation procedure

15410	9	3	3	3	1	6	10	4	0	2	31	1
15411	9	4	5	6	0	7	10	5	1	1	42	1
15412	9	4	5	13	1	7	10	4	0	2	28	0
15413	9	4	4	9	1	2	10	4	1	1	40	0
15414	9	4	0	2	1	2	10	4	1	2	58	1
15415	9	4	0	17	1	6	10	5	1	1	35	0
15416	9	5	4	13	1	1	3	1	1	1	30	0
15417	9	5	4	17	0	1	3	1	1	2	24	0
15418	2	1	1	17	1	5	3	2	0	1	34	1
15419	2	2	6	17	1	5	3	3	1	2	21	0

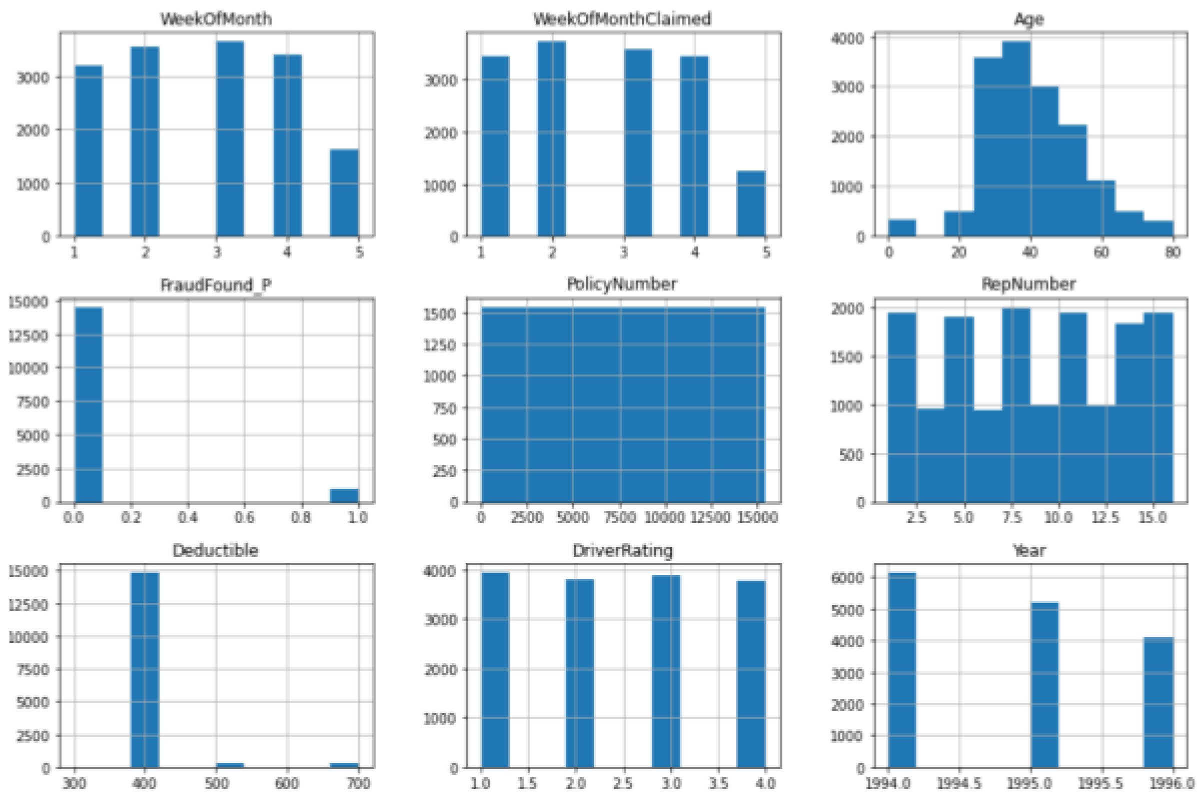


Figure 8. Visualization Of Categorical Columns

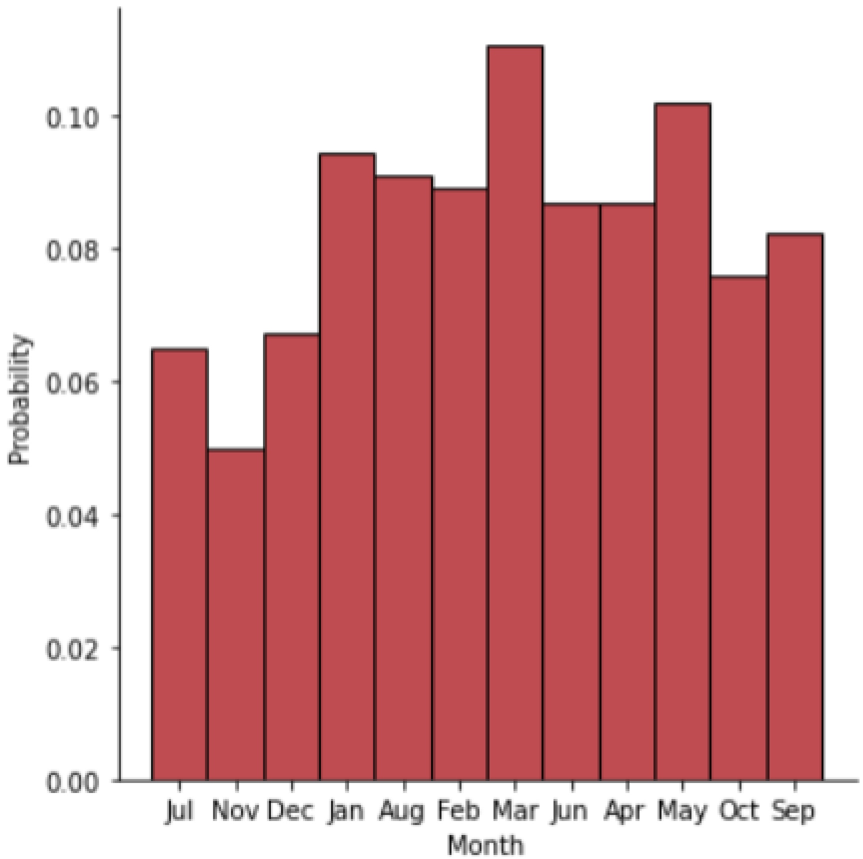


Figure 9. Fraudulent Cases Probability

we can clearly see that Amongst fraudulent cases months of march and may have higher probability.

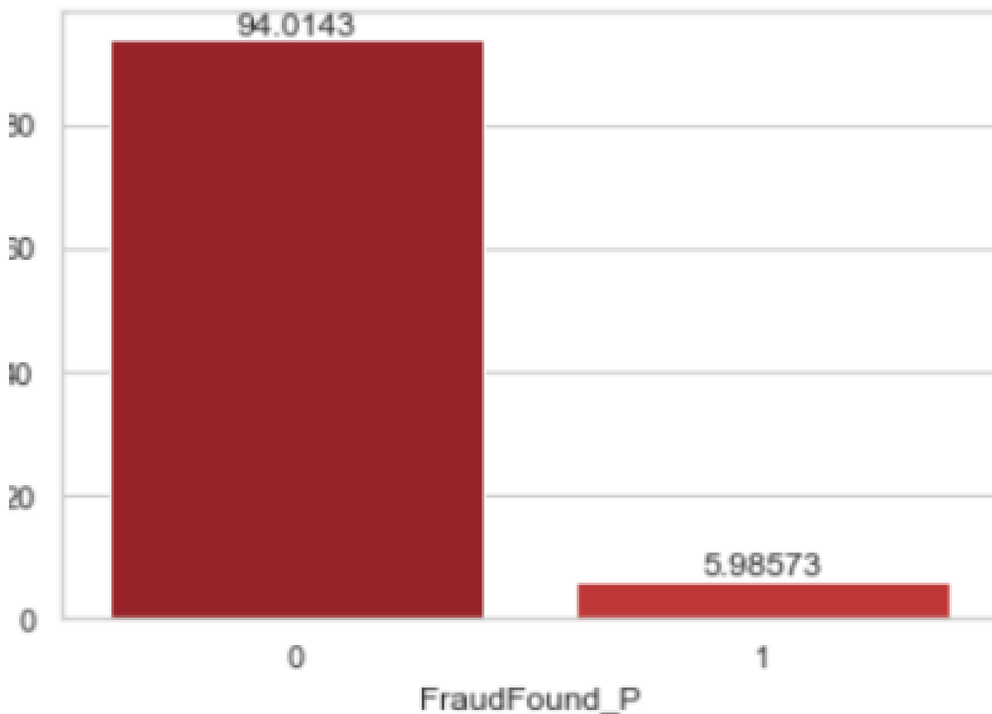


Figure 10. Distribution Of Fraudulent Claims.

Indicates whether the claim was fraudulent (1) or not (0) so we can clearly see that 94% are fair and only 6% are fraudulent claims.

Decision Trees: An interpretable model that divides data into branches for decision-making based on feature values.

Random Forests: An ensemble technique that reduces overfitting and increases accuracy by constructing many decision trees and combining their output.

SVMs, or support vector machines: a method of categorization that determines the hyperplane with the largest margin between classes.

Neural Networks: Specifically, deep learning models that use several layers of neurons to identify intricate patterns in big datasets.

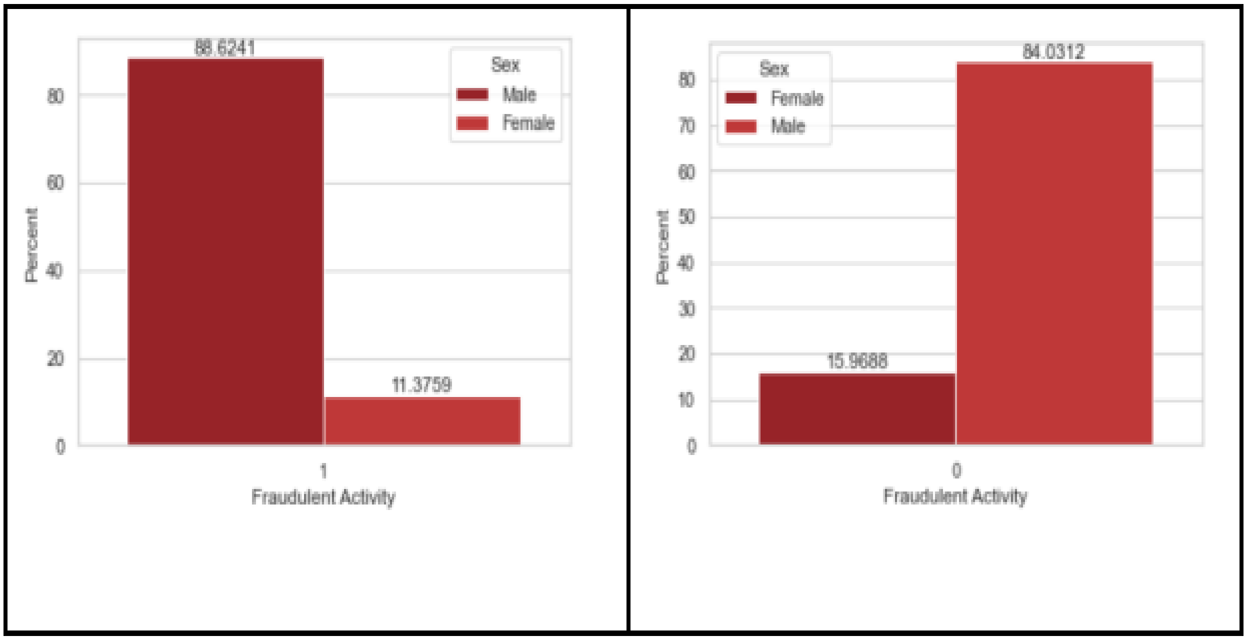


Figure 11. Gender Involved In Fraudulent Activity

The fraudulent claims according to gender, and it is clear that while men make up 84.03% of the total claims for legitimate transactions, they make up 88.62% of the fraudulent ones. Males are more prone than females to file false claims. entails making certain that categorical variables are encoded, features are scaled appropriately, and any missing values are taken care of.

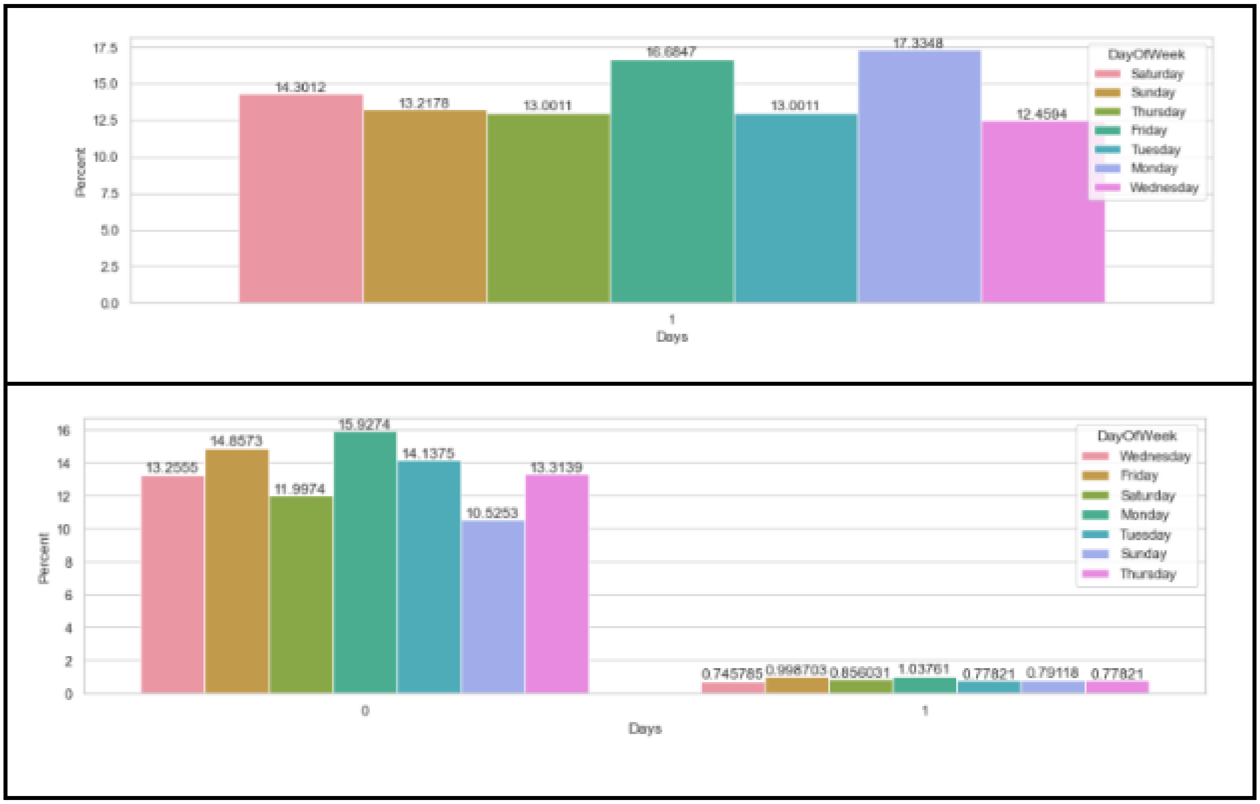


Figure 12. Fraudulent Activity On Days Of Week

The accompanying image reveals that Monday and Friday have the highest percentage of fraudulent actions. Similar to this, Monday and Friday also have the most claims.

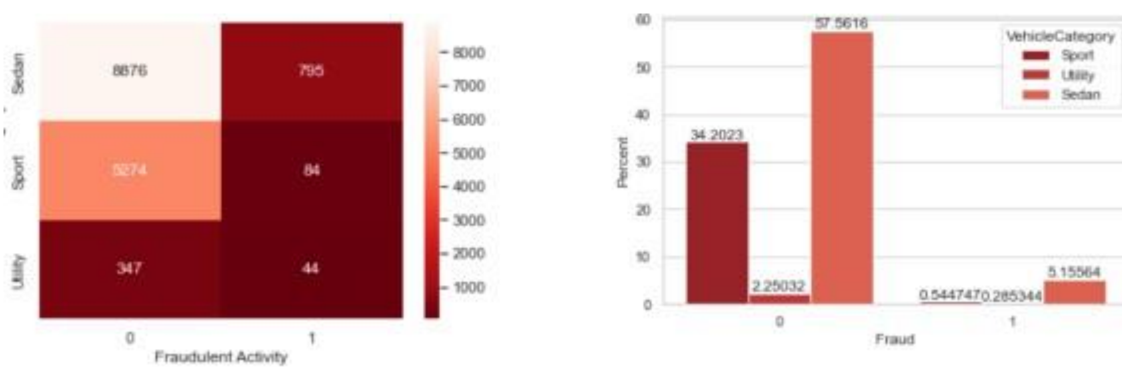


Figure 13. Car Categories With Respect To Fraudulent Claims.

Activation Functions: Select suitable activation functions for the output layer, The fact that sports cars are less likely to be used in fraud is one item that stands out. Sedans are the primary source of claims. They are also the most motivated, though. Sports cars are just 0.02% likely to be involved in false claims, whereas utility cars are generally 0.11% likely to have fraudulent claims. Utility vehicles have higher expectations of being involved in fraudulent operations, according to the correlation matrix above.

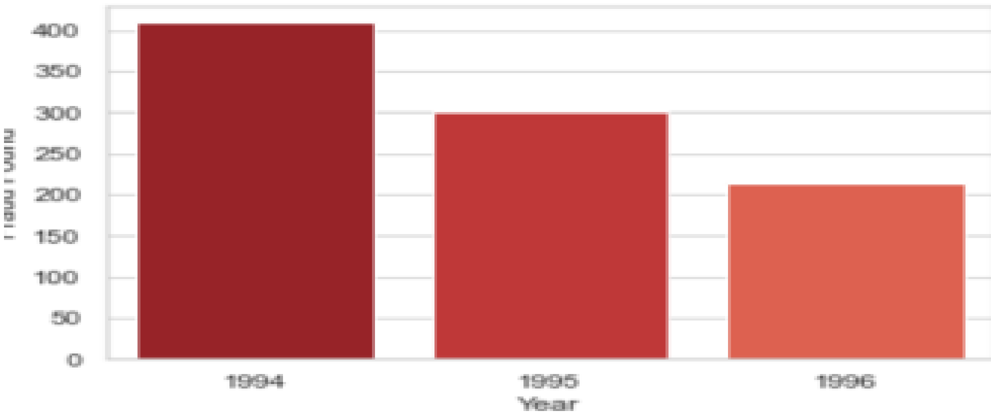


Figure 14. Year-Wise Fraudulent Claims

Inferred from the following graph is that the majority of fraud was committed in 1994. We can observe the qualities of the data and the type of correlation that exists between them. It is the quickest technique to determine whether the features match the output. However, when working on machine learning projects, we typically overlook the two components known as data and mathematics. We know that ML is a data-driven methodology, and our ML model will only deliver outcomes that are as excellent or as awful as the data we feed it.

Method of Training: Describe the training process, including optimization methods (like Adam and SGD), evaluation measures (like accuracy, precision)

4.7:BUILDING AND TRAINING MODEL

Once a pattern has been identified, a suitable model needs to be constructed. A model is created by studying, practicing, and then using it. The model will be put to use and produce fraud detection. We went through these 6 processes to create and train the model:

- Contextualize machine learning in your organization
- Explore the data and choose the type of algorithm
- Prepare and clean the dataset
- Split the prepared dataset and perform cross validation
- Perform machine learning optimization
- Deploy the model

The generic flow of machine learning data model is presented below: An integrated research approach will be applied for this project. To explain the findings and conclusions of the paper and the various results, the project will employ some explanatory research methods in addition to experimental research methods, some qualitative research methods, and some quantitative research methods.

We will start by determining what is crucial for managing the data in accordance with the business that may use the model or the solutions. In this situation, an insurance provider will probably prioritize the financial aspects of each claim while giving no consideration to personal information when developing the model.

The report will detail the available data, the many qualities, and how each attribute relates to determining whether or not this claim is fraudulent. What are the different forms of data that are available, and can the existing data be improved or changed without affecting the outcome of the end goal, which is identifying dubious claims? To do this, data cleaning is necessary. Some values or characteristics may need to be removed, or new values may need to be created by merging existing ones and using data integration techniques. Like how we presented all of the ideas we discovered from data analysis in the exploratory analysis. Once the data have been cleaned and thoroughly understood, following exploratory data analysis We also dealt with issues related to class inequality. Class imbalance issues dominate classification problems. It shows that the dependent or target class frequency is substantially out of balance,with one class happening far more frequently than the other. The target is therefore biased or skewed in our dataset. Because of our imbalanced target values, which are 94% fair and 6% fraudulent claims, we also have a problem with class imbalance. says that 94% of the claims are false, while only 6% are legitimate. Since this will affect the accuracy, we must first address the issue of the unbalanced class. To determine if the claim is false or not, we used a variety of supervised machine learning methods.

Random forest: In essence, Random Forest is used for both classification and regression issues. It is an ensemble classification method and a supervised machine learning classifier. The more trees there are, the more precise the outcome would be. The RF machine learning method is simple, easy to use, and capable of achieving outstanding outcomes in most cases without the need for hypertuning. Over-fitting is one of the decision tree algorithm's main problems. The decision tree appears to have remembered the data. Random Forest is utilized to prevent this and is an illustration of ensemble learning in action. The use of several repetitions of one or more algorithms is referred to as "ensemble learning." A "random forest" is a collection of decision trees.

Decision tree:

The decision tree approach is also included in the supervised learning category. Regression and classification problems can be solved with DT. However, it is used in this work to overcome categorization problems. DT breaks down the input into ever-smaller bits in attempt to solve the problem, which results in the prediction of a target value (diagnosis). A decision tree (DT) consists of decision nodes and leaf nodes, each of which is linked to a class label and traits that are shownon the interior node of the tree. Though DT is pretty simply many algorithms drive from its roots one of these algorithms is called XGBoost. Which is an incredibly quick machine learning technique that uses tree-based models to try to get the best accuracy possible by making the best use of available computing power, Extreme Gradient Boosting, often known as XGBoost, becomes the obvious option

Logistic regression:

It is a condensed version of "linear regression," a potent tool for visualizing data. The likelihood of an illness or other health concern as a result of a plausible cause is ascertained using logistic regression. The link between independent factors (X), also known as exposures or predictors, and a binary dependent (target) variable

(Y), also known as the outcome or response variable, is examined using both basic and multivariate logistic regressions. It is often applied to forecast changes in the dependent variable that will be binary or multiclass.

Several crucial procedures are usually included in the training steps: The dataset is first separated into sets for training and validation. The model architecture KNN:

K-Nearest Neighbor is one of the most straightforward machine learning algorithms, based on the supervised learning approach (KNN). The model is saved, and when a new data point is given, the model searches for similarities between the data points. K-nearest neighbors are identified by calculating the distance between each data point with respect to the new data point, and based on the similarity, it produces the output. This method is also referred to as lazy learning. This indicates that new data can be reliably and quickly categorized using the K-NN approach.

4.8 Classifier Score

The 80:20 test-train-split package in Python and its machine learning tools were used to compute classifier scores for several models to check against our suggested fraudulent detection once the unbalanced dataset was fixed:

unbalanced dataset was fixed.

Machine learning model	Train Accuracy	Test Accuracy
Logistic Regression	0.747790	0.754268
Random Forest	1.000000	0.997758
KNearest Neighbor	0.935590	0.897569
XGBoost	0.840224	0.840317

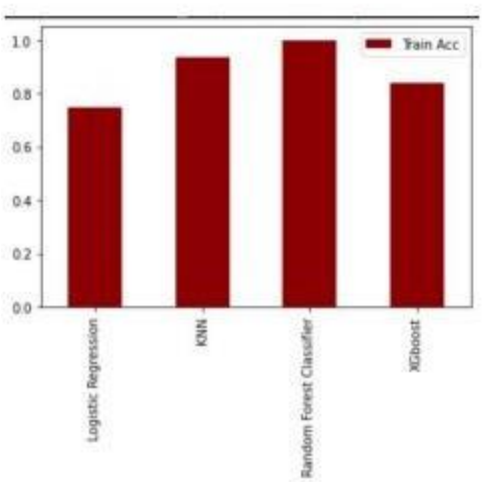
Table 1 Accuracy Comparison

	Train Acc
Logistic Regression	0.747790
KNN	0.935590
Random Forest Classifier	1.000000
XGboost	0.840224

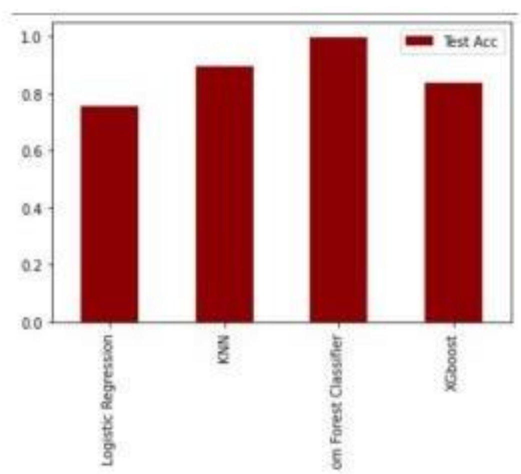
Train Accuracy Table

	Test Acc
Logistic Regression	0.754268
KNN	0.897569
Random Forest Classifier	0.997758
XGboost	0.840317

Test Accuracy Table



Train Accuracy Plot



Test Accuracy Plot

Figure 15. Train/Test-Sets Comparison

we can see in the above figure KNN , XGboost and Random Forest is working exponentially well on the dataset and achieving 93.5590% , 84.0224% and 100.0000% on train data respectively but on the other hand logistic regression is not working well here we implemented hyperparameter tuning as well in order to improve the model accuracy, but Accuracy of this model didn't much improved by tuning. So, we can say that Logistic Regression is not a reliable model for this dataset. But performance of other models is comparatively better than Logistic Regression Model.

Logistic regression is an effective approach for predicting the likelihood that a client will stop using a product or service in the context of your churn prediction project. Using a logistic function that yields values between 0 and 1, logistic 4.9 Classification Report: The categorization report includes a number of metrics that are crucial for assessing any model. Accuracy, precision, recall, and F1 are the included measures.Accuracy: it is the ratio of correct predictions against total observations.

● Precision: is the proportion of correctly made positive predictions to all positively observed data.

● Recall: The ratio of correctly predicted positive observations to all of the observations in a class, sometimes referred to as sensitivity.

● F1: is the average of the recall and precision scores.

The scikit-learn packages come within default parameters. The default parameters have resulted in undesired results, and so the tunning for the models have been done through tunning the hyperparameter. Accuracy of this model did not improve much in Logistic regression by hyperparameter tuning either. So, we can say that Logistic Regression is not a reliable model for this dataset. While other algorithms like KNN, XGboost and random forest work pretty well on the dataset and have given 96%, 89% and 100% respectively. We can say that these algorithms can be used to achieve accurate results with new and huge data. By fine tuning the model the accuracy of KNN has increased from 89% to 96%. XGBoost accuracy has increased from 84% to 89%. For the other two models the Logistic Regression did not improve after the fine tuning and the Random Forest was performing exceptionally well and most likely its overfitting on the default value of the model. After fine tuning the model to get a more realistic result it got 98.5% as its best result.

regression calculates the likelihood of churn by examining past customer data, including demographics, usage trends, and engagement levels. By using the log odds to express this relationship, the model lets you see how different attribute. Maximum

The other matrices of the models are shown in the following table:

Table 2: Classification report of Models.

Metrics	**Logistic Regression**	**KNN**	**Random Forest**	**XGBoost**
Tuned Accuracy	75.03%	96.28%	98.5 %	89.0%
Precision	0.78	0.97	0.98	0.89
Recall	0.75	0.96	0.98	0.89
F1	0.76	0.96	0.96	0.88

CHAPTER 5: CONCLUSION

5.1. Conclusion: As the different countries around the world evolve into a more economical-based one, stimulating their economy is the goal. To fight these fraudsters and money launderers was quite a complex task before the era of machine learning but thanks to machine learning and AI we are able to fight these kinds of attacks. The proposed solution can be used in insurance companies to find out if a certain insurance claim made is a fraud or not. The model was designed after testing multiple algorithms to come up with the best model that will detect if a claim is fraudulent or not. This is aimed at the insurance companies as a pitch to come up with a more tailored model for their liking to their own systems. The model should be simple enough to calculate big datasets, yet complex enough to have a decent successful percentile.

5.2. Recommendations:

The dataset which we used for building this insurance predictive model was taken from kaggle and it was the data between 1994 to 1996. It will be good for us if we collect the new dataset of the past 2 to 5 years To determine whether the suggested solution would perform well when compared to other datasets that might serve as imitations, testing random combinations or a predetermined set of parameters is advised or to test the model to a similar type of dataset. surroundings that are different from the environment created after data cleansing. Reducing the number of characteristics is advised to cut further computational costs. The study was done by the Machine learning supervised techniques, which are used to build insurance claims predictive models. We have used Random Forest, KNN, logistic regression and XGBoost, amongst all these four algorithms KNN and Random Forest performed exponentially well on the dataset.powerful way to categorize clients according to their propensity to leave. By recursively dividing the data into subsets according to the input feature values, the decision tree algorithm produces a structure resembling a tree, with each internal node denoting a feature decision, each branch denoting an outcome of that decision, and each leaf node denoting a final prediction . Until the tree meets a stopping criterion—such as a minimum number of samples per leaf or a maximum depth—this process keeps going. Decision trees' clear design makes it simple to understand how various customer attributes affect churn risk, giving businesses the ability to see crucial elements and put specific tactics into place to improve client retention and deal with certain problems that cause turnover.

5.3. Future Work: In order to compare the effectiveness of machine learning and deep learning methodologies, future research should focus on attempting to use an advanced or recently obtained dataset. Additionally, it is advised to utilize a different dataset in light of the fact that the one being used is unbalanced. Additional evaluation should be done to determine feature relevance across various datasets that may or may not have similar characteristics in order to develop a much more universal method to feature selection and focus. Because this research has been done by using all features in the future, we will do the feature selection to measure the variance between the total and selected features.

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