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"AUTO INSURANCE FRAUD DETECTION"

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INTRODUCTION

- An improper activity committed by individuals in order to gain benefit.
- There are various types of frauds viz. Health care, Agricultural frauds but we are focusing on Auto Insurance Fraud Detection.

What is Auto Insurance and Eraud Detection

 The insurance industry is concerned with the detection of fraudulent behavior with insurance company due to vehicles. The number of automobile claims involving some kind of suspicious circumstance is high and has become a subject of major interest for companies. By building a classification model auto insurance fraud can be detected.

Need of Auto insurance and fraud detection

- India is one of the biggest market for insurance industries all over the world, yet it is not free from risks.
- Indian Insurance Industry looses around \$6 billion every year to this insurance frauds.
- Hence there is an urgent need to develop a capability which can help companies identify whether the given insurance claim is fraud or genuine with high degree of accuracy and with less amount of time.
- This will also help in maintaining the customers satisfaction and also the trust towards the insurance company.

OBJECTIVE

- To minimize number of fraud claim cases.
- To build a classification methodology to determine whether a customer is placing a fraudulent insurance claim or not.
- To provide quickness & high accuracy for claiming process.
- To reduce the amount of financial loss of company due to such illegals frauds.

Methodolog

y

- We use machine learning & their algorithm using python.
- The data used for this study is secondary data. It is extracted and compiled from Kaggle website
- The data is then preprocessed and after training, the data is modeled using Xgboost classifier and we predict given claim is fraud

Importing Libraries Libraries In this step we import all necessary libraries required in

our project

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Load the Dataset

- Pataset After importing all our required libraries then we load the Dataset.
 - The Dataset we used in this project is a publicly available dataset taken from Kaggle

```
data = pd.read_csv("insuranceFraud.csv")
```

Basic Operation on Dataset.

Here we perform some basic operation on our dataset to check whether our dataset working

```
data.head()

data.info()
```

data.describe()

data.isnull().sum()

Checking the Nullalues

Val data.isna().sum()

months_as_customer	0
age	0
policy_csl	0
policy_deductable	0
policy_annual_premium	0
umbrella_limit	0
insured_sex	0
insured_education_level	0
insured_occupation	0
insured_relationship	0
capital-gains	0
capital-loss	0
incident_type	0
collision_type	178
incident_severity	0
authorities_contacted	0
incident_hour_of_the_day	0
number_of_vehicles_involved	0
property_damage	360
bodily_injuries	0
witnesses	0
police_report_available	343
total_claim_amount	0
injury_claim	0
property_claim	0
vehicle_claim	0
fraud_reported	0

Cleaning missing values using categorical imputer

```
from sklearn_pandas import CategoricalImputer
imputer = CategoricalImputer()
```

```
data['collision_type']=imputer.fit_transform(data['collision_type'])
data['property_damage']=imputer.fit_transform(data['property_damage'])
data['police_report_available']=imputer.fit_transform(data['police_report_available'])
```

Extracting categorical data data

cat_data = data.select_dtypes("object").copy()

cat_data.head()

insured_sex	insured_education_level	insured_occupation	insured_relationship	incident_type	collision_type
MALE	MD	craft-repair	husband	Single Vehicle Collision	Side Collision
MALE	MD	machine-op-inspct	other-relative	Vehicle Theft	Rear Collision
FEMALE	PhD	sales	own-child	Multi-vehicle Collision	Rear Collision
FEMALE	PhD	armed-forces	unmarried	Single Vehicle Collision	Front Collision
MALE	Associate	sales	unmarried	Vehicle Theft	Rear Collision

Encoding

In this step we perform label encoding on categorical variables in the dataset

```
cat_data["policy_csl"] = cat_data["policy_csl"].map({ '100/300':1,"250/500":2, '500/1000':3})
cat_data["insured_sex"] = cat_data["insured_sex"].map({ "FEMALE": 0 ,"MALE": 1})
cat_data["insured_education_level"] = cat_data["insured_education_level"].map({'JD' : 1, 'High School' : 2, cat_data["incident_severity"] = cat_data["incident_severity"].map({"Trivial Damage":1 , "Minor Damage":2 , cat_data["property_damage"] = cat_data["property_damage"].map({"NO": 0 , "YES": 1})
cat_data["police_report_available"] = cat_data["police_report_available"].map({"NO": 0 , "YES": 1})
cat_data["fraud_reported"] = cat_data["fraud_reported"].map({"N": 0 , "Y": 1})
```

Catagorical Data after Encoding Encoding

policy_csl	insured_sex	insured_education_level	incident_severity	property_damage	police_report_available	fraud_reported
2	1	6	3	1	1	1
2	1	6	2	0	0	1
1	0	7	2	0	0	0
2	0	7	3	0	0	1
3	1	5	2	0	0	0

Combining categorical & merical numerical data

final_data =pd.concat([num_data,cat_data],axis=1)

final_data.head()

	months_as_customer	age	policy_deductable	umbrella_limit	capital- gains	capital- loss	incident_hour_of_the_day	number_of_vehicles_involved
0	328	48	1000	0	53300	0	5	1
1	228	42	2000	5000000	0	0	8	1
2	134	29	2000	5000000	35100	0	7	3
3	256	41	2000	6000000	48900	-62400	5	1
4	228	44	1000	6000000	66000	-46000	20	1

Separating Feature column and Target Column

```
#removing target column from feature column
x=final_data.drop("fraud_reported",axis= 1)
```

```
#making feature column
y=final_data["fraud_reported"]
```



Here we plot heatmap showing relation between the variables

months_as_customer	1	0.92	0.027	0.015	0.0064	0.02	0.071	0.015	-0.01	0.058	0.062	0.065	0.035	0.061
age ·	0.92	1	0.029	0.018	-0.0071	0.0074	0.087	0.022	-0.016	0.052	0.07	0.076	0.061	0.063
policy_deductable	0.027	0.029	1	0.011	0.035	-0.024	0.061	0.051	-0.023	0.067	0.023	0.039	0.065	0.0053
umbrella_limit	0.015	0.018	0.011	1	-0.047	-0.024	-0.023	-0.021	0.023	-0.0067	-0.04	-0.045	-0.024	-0.039
capital-gains	0.0064	-0.0071	0.035	-0.047	1	-0.047	-0.016	0.062	0.056	-0.018	0.016	0.026	-0.00078	0.016
capital-loss	0.02	0.0074	-0.024	-0.024	-0.047	1	-0.025	-0.015	-0.024	-0.041	-0.036	-0.046	-0.023	-0.033
dent_hour_of_the_day	0.071	0.087	0.061	-0.023	-0.016	-0.025	1	0.12	-0.035	0.0065	0.22	0.17	0.18	0.22
_of_vehicles_involved	0.015	0.022	0.051	-0.021	0.062	-0.015	0.12	1	0.014	-0.015	0.27	0.22	0.22	0.27
bodily_injuries	-0.01	-0.016	-0.023	0.023	0.056	-0.024	-0.035	0.014	1	-0.0056	0.047	0.047	0.04	0.043
witnesses	0.058	0.052	0.067	-0.0067	-0.018	-0.041	0.0065	-0.015	-0.0056	1	-0.011	-0.025	0.053	-0.023
total_claim_amount	0.062	0.07	0.023	-0.04	0.016	-0.036	0.22	0.27	0.047	-0.011	1	0.81	0.81	0.98
injury_claim	0.065	0.076	0.039	-0.045	0.026	-0.046	0.17	0.22	0.047	-0.025	0.81	1	0.56	0.72
property_claim	0.035	0.061	0.065	-0.024	-0.00078	-0.023	0.18	0.22	0.04	0.053	0.81	0.56	1	
vehicle_claim	0.061	0.063	0.0053	-0.039	0.016	-0.033	0.22	0.27	0.043	-0.023	0.98	0.72	0.73	1
	months_as_customer -	- age	policy_deductable -	umbrella_limit -	capital-gains -	capital-loss -	cident_hour_of_the_day -	er_of_vehicles_involved -	bodily_injuries -	witnesses -	total_claim_amount -	injury_claim -	property_claim -	vehicle_claim -

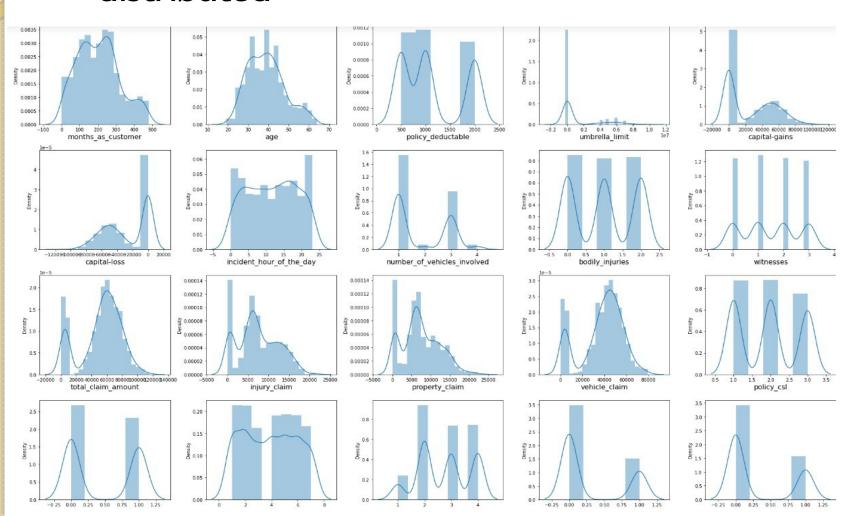
Removing highly correlated columns columns

•Here we remove age column and Total claim amount column

```
x.drop(columns=["age","total_claim_amount"],inplace = True)
```

Normalization

Here our data is normally distributed



Standardisati

Standardisation makes all variable to a common scale

from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()

Training & testing of del

Here we split our dataset in train and test set. 75% of our dataset is for training purpose and 25 % is for testing.

```
from sklearn.model_selection import train_test_split
train_x,test_x,train_y,test_y = train_test_split(x,y,test_size=0.35)
```

Using Xgboost algorithm

algorithm
Here we use X gboost algorithm and train the model by 75% of the dataset

```
from xgboost import XGBClassifier
```

```
xgb=XGBClassifier()
```

```
y_pred = xgb.fit(train_x, train_y).predict(test_x)
```

Output

Here we test the model by 25 % of the dataset. Where 0 represent fraud not happen and 1 represents

```
y_pred
```

Conclusion

 Here we check all suitable algorithms for better accuracy and found that Xgboost has highest accuracy among all of them having 75% accuracy so we used xgboost algorithm for further predictions

```
ac2=accuracy_score(test_y,y_pred)
ac2
```

0.748

Futurescope

Sinchis Project, we learned how machine learning can be applied to decide which claims are genuine and which claims are fraudulent. In future it saves time and money for dealing with fraudulent claims

Research paper

Tisurvey of Insurance Fraud Detection Using Data Mining Techniques H.Lookman Sithic, T.Balasubramanian

 2] Use of optimized Fuzzy C-Means clustering and supervised classifiers for

automobile insurance fraud detection [Sharmila Subudhi, Suvasini Panigrahi]

- 3] Application of Clustering Methods to Health Insurance Fraud Detection Yi Peng1
 - , Gang Kou1, *, Alan Sabatka2 , Zhengxin Chen1 , Deepak Khazanchi1 ,Yong Shi1
- 4] CLAIMS AUDITING IN AUTOMOBILE INSURANCE: FRAUD DETECTION AND DETERRENCE OBJECTIVES Sharon Tennyson Pau Salsas-Forn
- 5] Big Data and Specific Analysis Methods for Insurance Fraud Detection Ana- Ramona BOLOGA, Razvan BOLOGA, Alexandra FLOREA
- 6] Analytics for Insurance Fraud Detection: An Empirical Study Carol Anne Hargreaves*, Vidyut Singhania* (Business Analytics) Institute of Systems Science, National University of Singapore, Singapore

THANK YOU!