FRAUD DETECTION

CREDIT CARD FRAUD DETECTION – PREDETIVE MODEL

Thanks to springboard mentor – DIPANJAN SARKAR, data science lead – google, author

PROBLEM STATEMENT

- Fraudulent transactions increased drastically in recent years

- As payment modes and platform increased, so did fraud landscape

- Thwarting fraud became a difficult task against sophisticated hacking tools and new techniques

- Customer satisfaction is compromised with manual anti-fraud controls

SOLUTION USING MACHINE LEARNING

SUPERVISED LEARNING ALGORITHMS CAN PREDICT CLASSIFLICATION PROBLEM EFFICIENTLY

DATA ANALYSIS & WRANGLING

- **DATA** https://www.kaggle.com/ealaxi/paysim1

  - Simulated mobile money transactions

  - 6362620 of records

  - 0.129 % transactions are fraud

  - oldbalanceDest and newblanceDest info is not available for the transaction to Merchants

  - Highly Imbalanced dataset

|	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	transactionHour
2	1	TRANSFER	181.0	C1305486145	181.0	0.0	C553264065	0.0	0.0	1	1
3	1	CASH_OUT	181.0	C840083671	181.0	0.0	C38997010	21182.0	0.0	1	1
251	1	TRANSFER	2806.0	C1420196421	2806.0	0.0	C972765878	0.0	0.0	1	1
252	1	CASH_OUT	2806.0	C2101527076	2806.0	0.0	C1007251739	26202.0	0.0	1	1
680	1	TRANSFER	20128.0	C137533655	20128.0	0.0	C1848415041	0.0	0.0	1	1
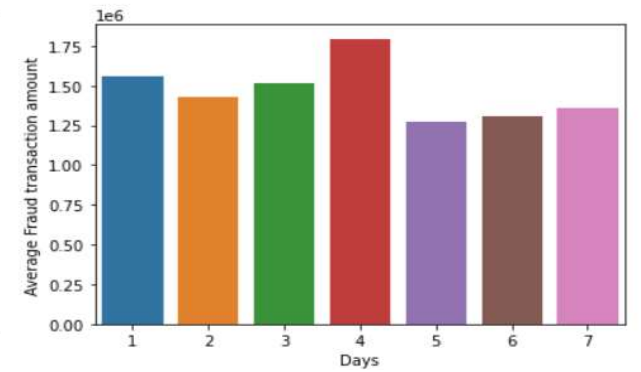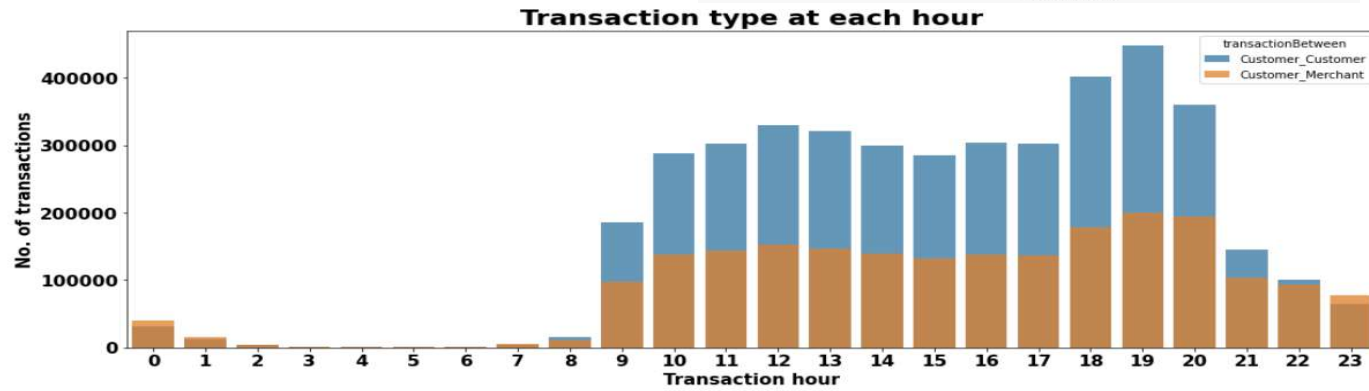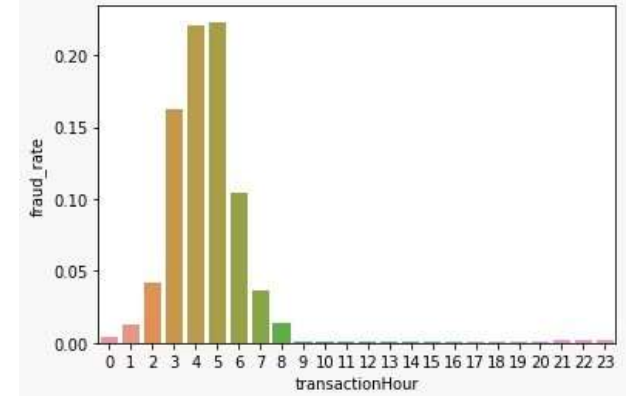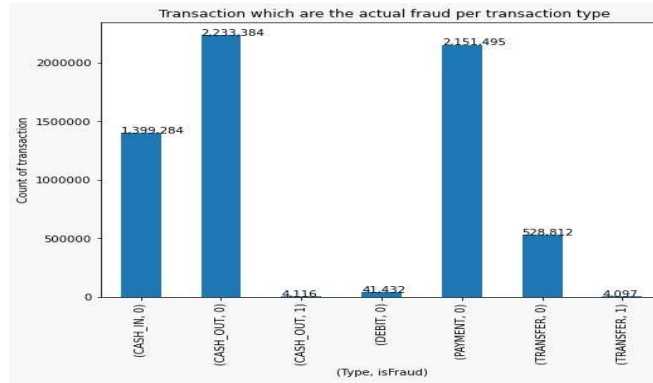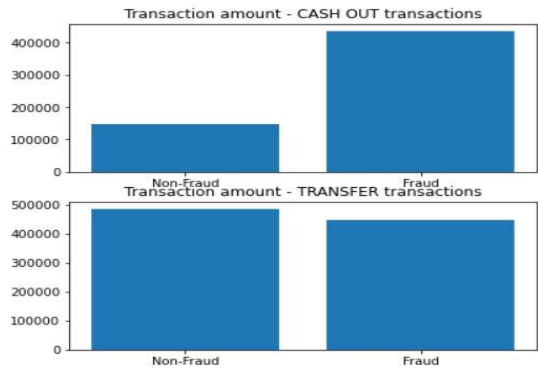
EXPLORATORY DATA ANALYSIS

EXPLORATORY DATA ANALYSIS SUMMARY

- 8213 fraud transactions:
  - 4116 in CASH_OUT
  - 4097 in TRANSFER
- The highest Fraud transaction is 10,000,000
- Most fraud transactions happened between 12:00am and 8:00am
- Transactions are stable during banking hours
- 16 System flagged fraud transaction in payment and cash-out
- Customer to Customer transactions are greater than Customer to Merchant transactions during banking hours
- Customer to Merchant transactions are more during off-peak hours
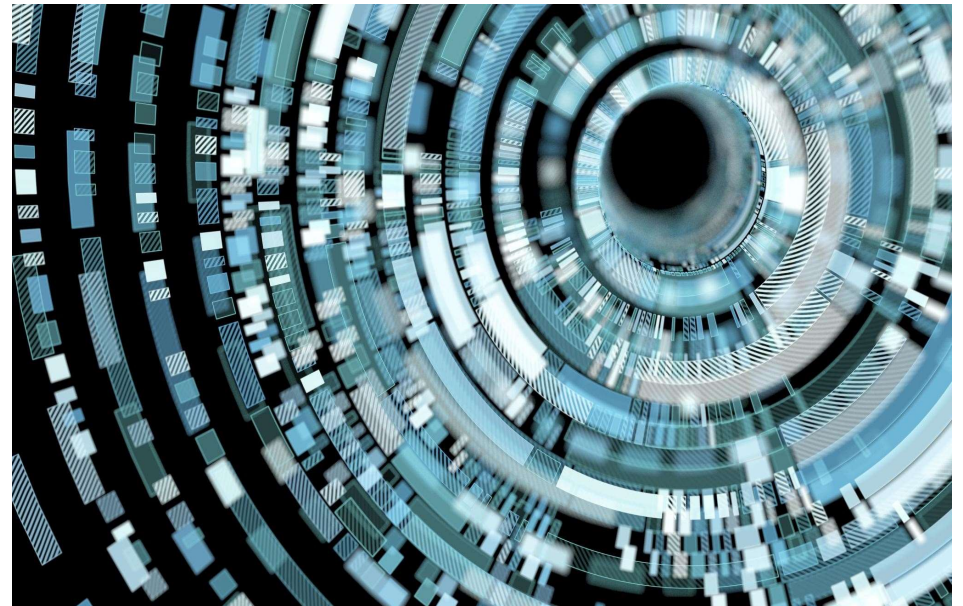
MODELING

- Supervised Learning

- Binary Classification

- Highly Imbalanced Data

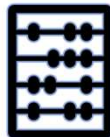- Tools : Python, SKlearn

MODELING…

Data Pre-Processing

Train and Test

Fit

Model Prediction
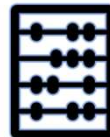
Compare
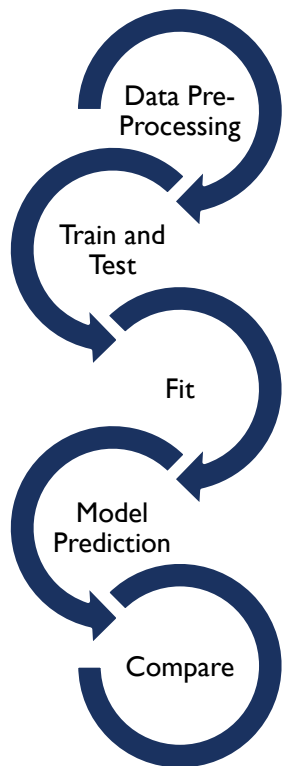
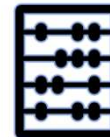| Feature Engineering | Derived Features | Split Data - 80/20 | Hyper Parameter Tuning |

Random Forest Classifier

XgBoost

Logistic Regression
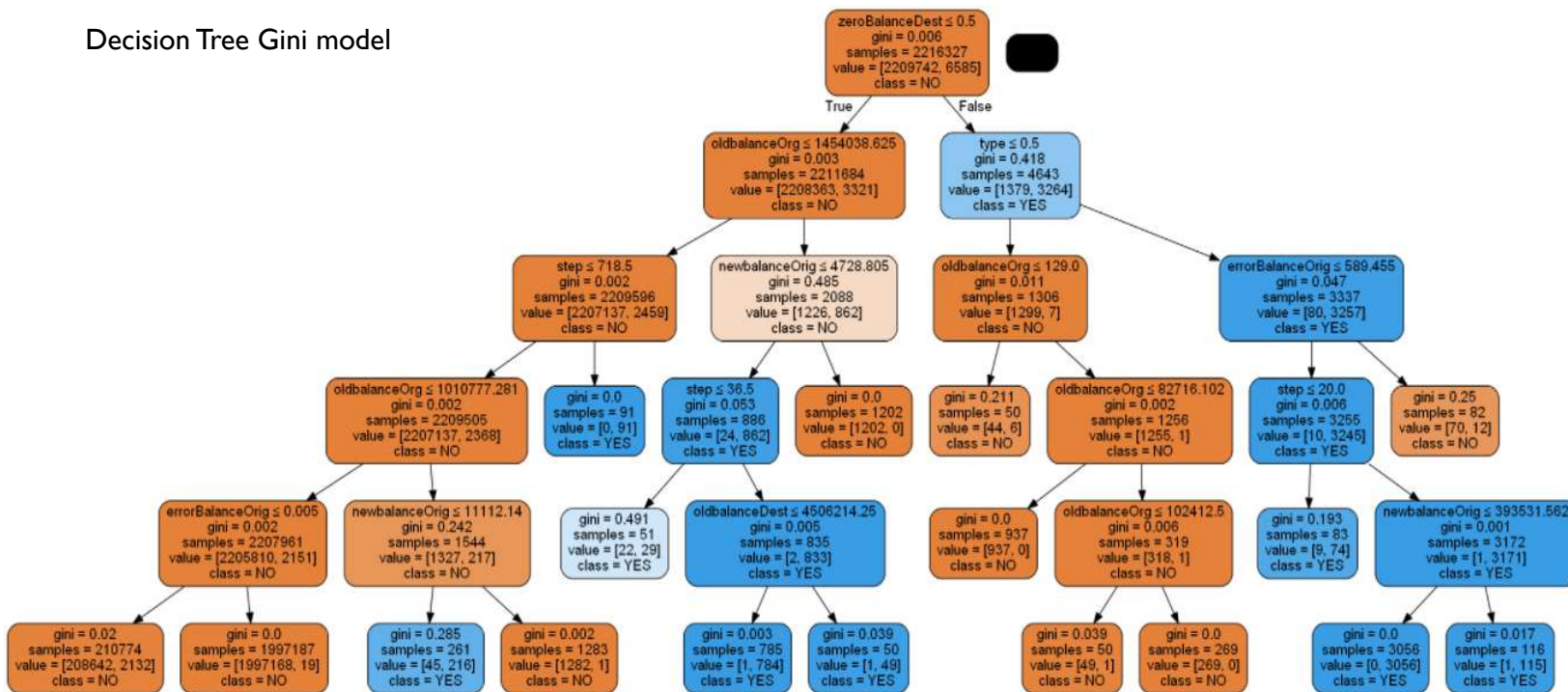
Decision Tree

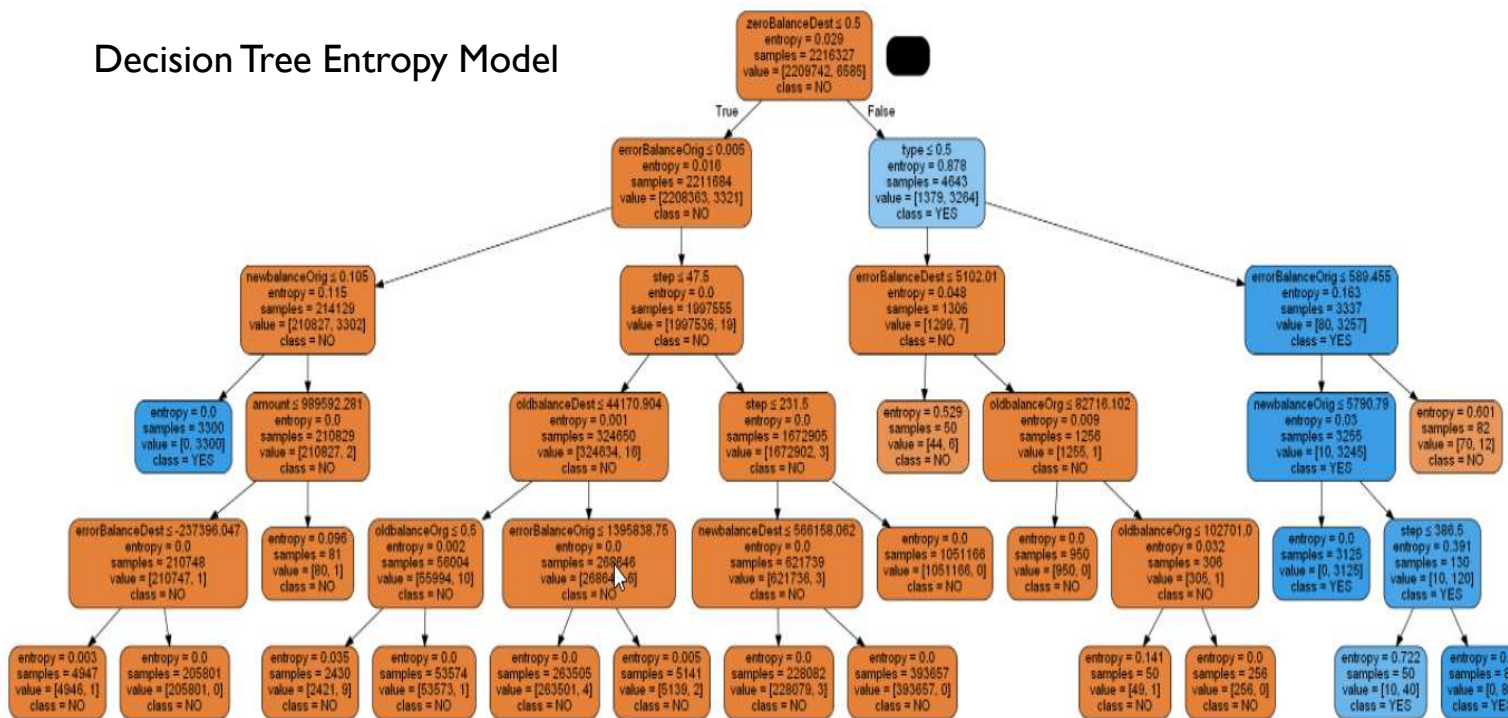Accuracy   Precision   F1-Score   Recall   AUC/ROC Bend

DECISION TREE MODELS

Decision Tree Gini model

- Root node split in this model started with zero balance destination

- Max-depth – 5, MIN sample leaf - 50, MIN sample split - 50

- Class – Yes=>Fraud, No=> Non-Fraud

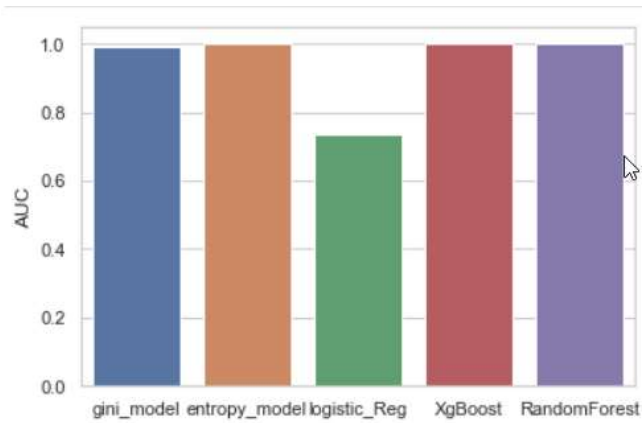- F1 score – 99.89%

- Precision score – 98.72%

DECISION TREE MODELS…
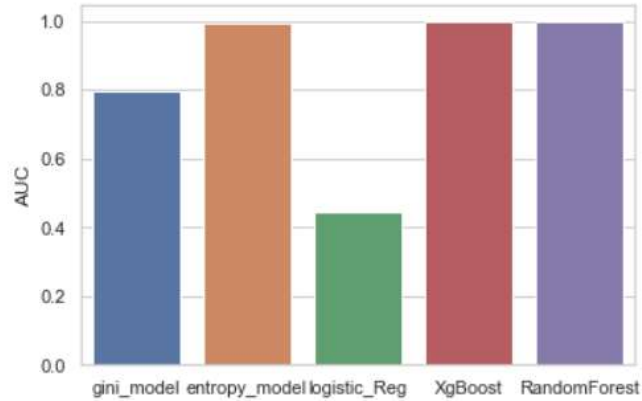
Decision Tree Entropy Model

- Root node split in this model started with zero balance destination

- Class – Yes=>Fraud, No=> Non-Fraud

- Max-depth – 5, MIN sample leaf - 50, MIN sample split - 50

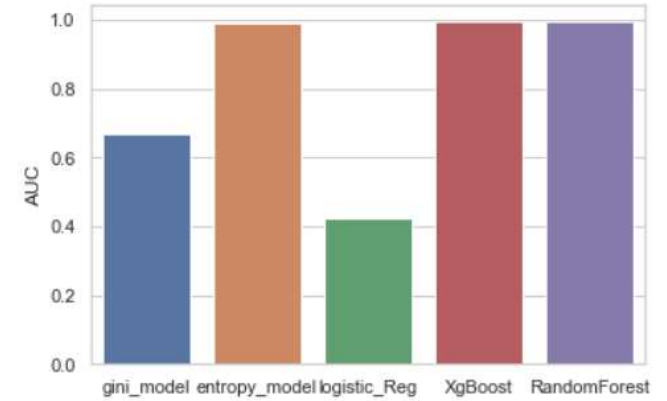- F1 score – 99.99%

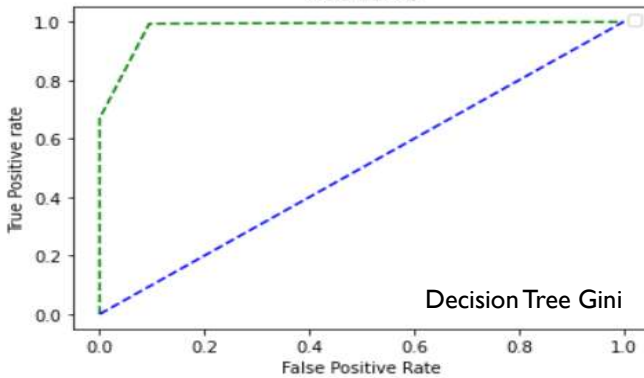- Precision score – 99.75%

SCORE COMPARISION
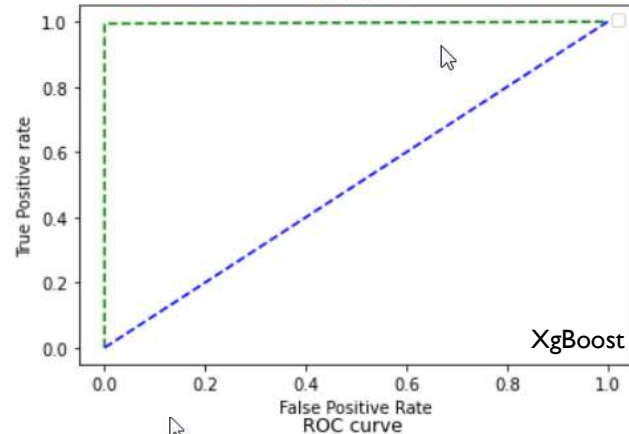

ROC-AUC Score
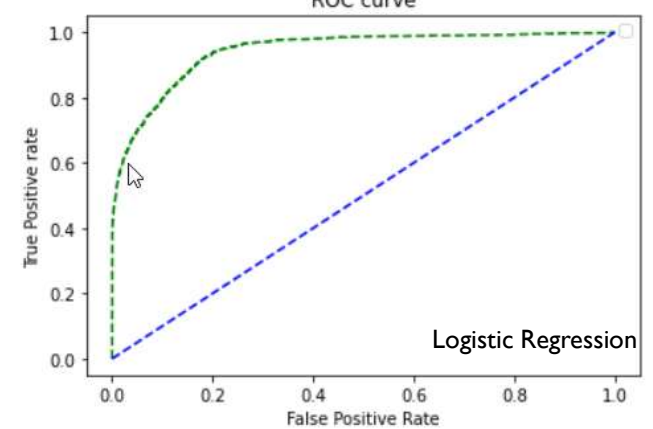

F-1 Score

Precision Score

ROC-AUC CURVE COMARISON
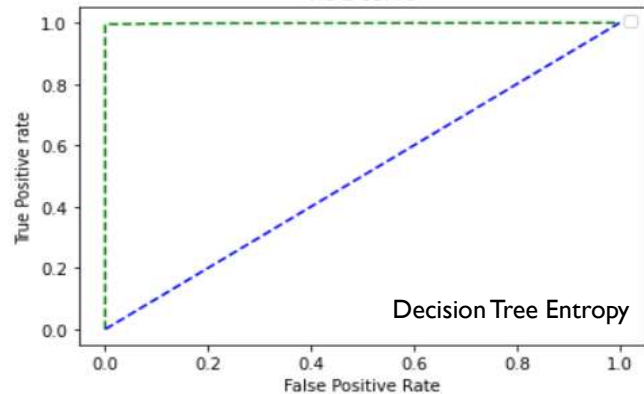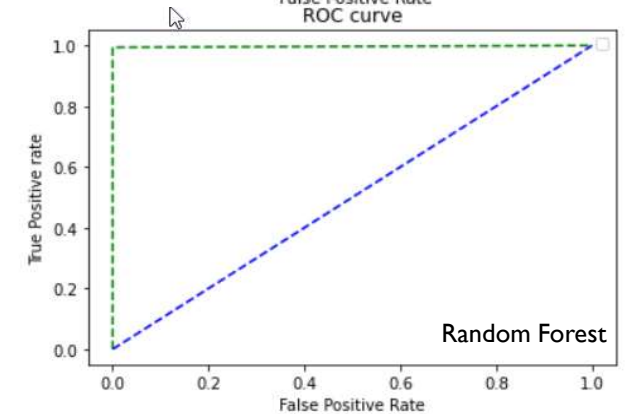

- Decision Tree Gini – 98.07%
- Decision Tree Entropy – 99.88%
- XgBoost – 99.83%
- Logistic Regression – 94.28%
- Random Forest – 99.69%

PRECISION/RECALL COMPARISON
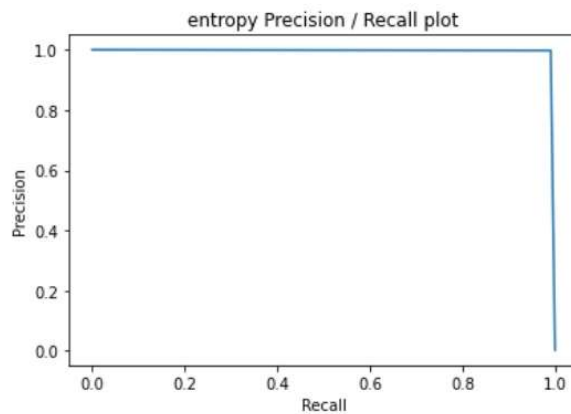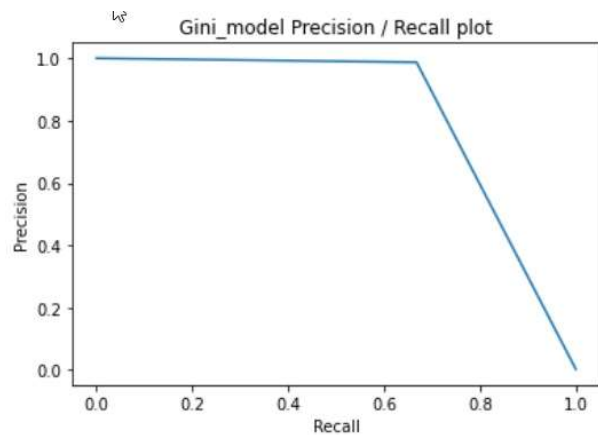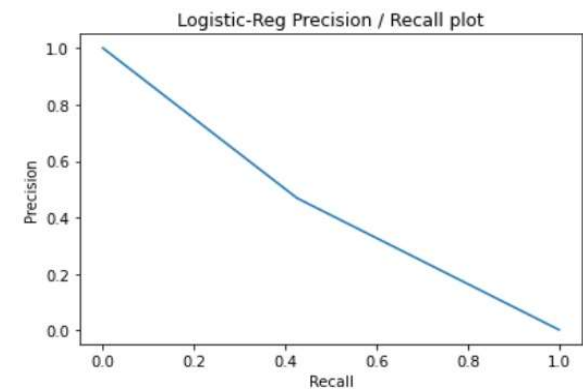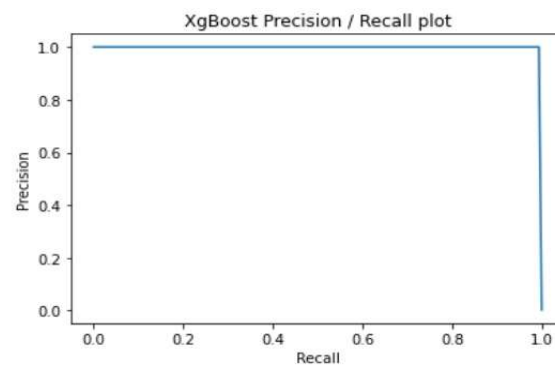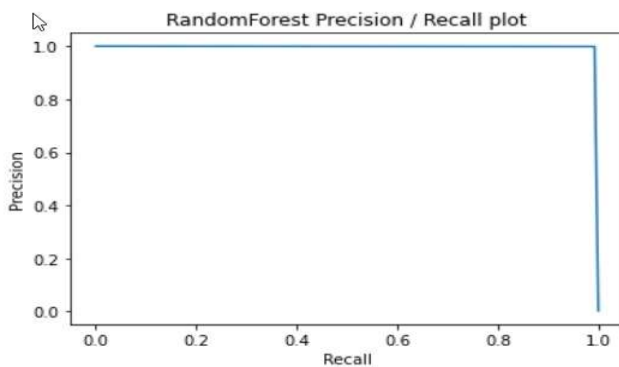

- Decision Tree Gini – 98.72%
- Decision Tree Entropy – 99.75%
- XgBoost – 100%
- Logistic Regression – 46.88%
- Random Forest – 99.87%

CONCLUSIONS

- XgBoot Classifier Model provided the best result

- Reduced type-1 error using Precision and F1- score

- Additional 5 features derived from the 11 features present in the initial data set

- Hyperparameter tuning techniques are performed to handle quantitative variables

- Logistic Regression used regularization tuning parameter 'C'

- Both Gini and Entropy model is performed in decision tree classification

Model Comparisons				
Model	Precision Score	F1-Score	Recall	ROC_AUC
Random Forest Classifier	99.87%	99.99	92.26%	99.69
XgBoost Classifier	100%	99.99%	99.38	99.83%
Logistic Regression	46.88%	99.68%	42.56%	94.28%
Decision Tree Gini Model	98.72%	99.89%	66.76%	98.07%
Decision Tree Entropy Model	99.75%	99.99%	99.07%	99.88%

THANK YOU

ARCHANA ROBIN