Scania APS Sensor Failure Prediction

1) Problem Statement

Data: Sensor Data

Problem Statement:

- The system in focus is the Air Pressure System (APS) which generates pressurized air that are utilized in various functions in a truck, such as braking and gear changes. The datasets positive class corresponds to component failure for a specific component of the APS system. The negative class corresponds to trucks with failures for components not related to the APS system.

- The problem is to reduce the cost due to unnecessary repais. So it is required to minimize the false predictions.

True Class	Positive	Negative
Predicted class		
Positive	-	cost_1
Negative	cost_2	-

cost_1 = 10

cost_2 = 500

- The total cost of a prediction model the sum of `Cost_1` multiplied by the number of Instances with type 1 failure and `Cost_2` with the number of instances with type 2 failure, resulting in a `Total_cost`. In this case `Cost_1` refers to the cost that an unnessecary check needs to be done by an mechanic at an workshop, while `Cost_2` refer to the cost of missing a faulty truck, which may cause a breakdown.
- `Total_cost = Cost_1 * No_Instances + Cost_2 * No_Instances.`

- From the above problem statement we could observe that, we have to reduce false positives and false negatives. More importantly we have to **reduce false negatives, since cost incurred due to false negative is 50 times higher than the false positives.**

Challenges and other objectives

- Need to handle many null values in almost all columns
- No low-latency requirement
- Interpretability is not important
- Misclassification leads to unncessary repair cost

In [41]:
```
### Import required libraries
```

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from statistics import mean

import warnings
warnings.filterwarnings('ignore')

from sklearn.pipeline import Pipeline
from sklearn.utils import resample

from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, AdaBoos
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC

from sklearn.metrics import accuracy_score, precision_score, recall_score,f1_score, clas

from sklearn import metrics
from sklearn.model_selection import train_test_split, RepeatedStratifiedKFold, cross_val
from sklearn.preprocessing import OneHotEncoder, LabelEncoder, PowerTransformer, MinMaxS
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer, KNNImputer

from xgboost import XGBClassifier
from catboost import CatBoostClassifier
```

Read Data

In [42]:
```
df = pd.read_csv('aps_failure_training_set.csv', na_values = 'na')
```

In [43]:
```
# check top 5 rows
df.head()
```

Out[43]:

	class	aa_000	ab_000	ac_000	ad_000	ae_000	af_000	ag_000	ag_001	ag_002	...	ee_002	ee_003
0	pos	153204	0.0	182.0	NaN	0.0	0.0	0.0	0.0	0.0	...	129862.0	26872.0
1	pos	453236	NaN	2926.0	NaN	0.0	0.0	0.0	0.0	222.0	...	7908038.0	3026002.0
2	pos	72504	NaN	1594.0	1052.0	0.0	0.0	0.0	244.0	178226.0	...	1432098.0	372252.0
3	pos	762958	NaN	NaN	NaN	NaN	NaN	776.0	281128.0	2186308.0	...	NaN	NaN
4	pos	695994	NaN	NaN	NaN	NaN	NaN	0.0	0.0	0.0	...	1397742.0	495544.0

5 rows × 171 columns

In [44]:
```
# check number of rows and columns
df.shape
```

Out[44]:
```
(36188, 171)
```

In [45]:
```
# check unique values of target variable
df['class'].value_counts()
```

Out[45]:
```
class
neg    35188
pos     1000
Name: count, dtype: int64
```

In [46]:

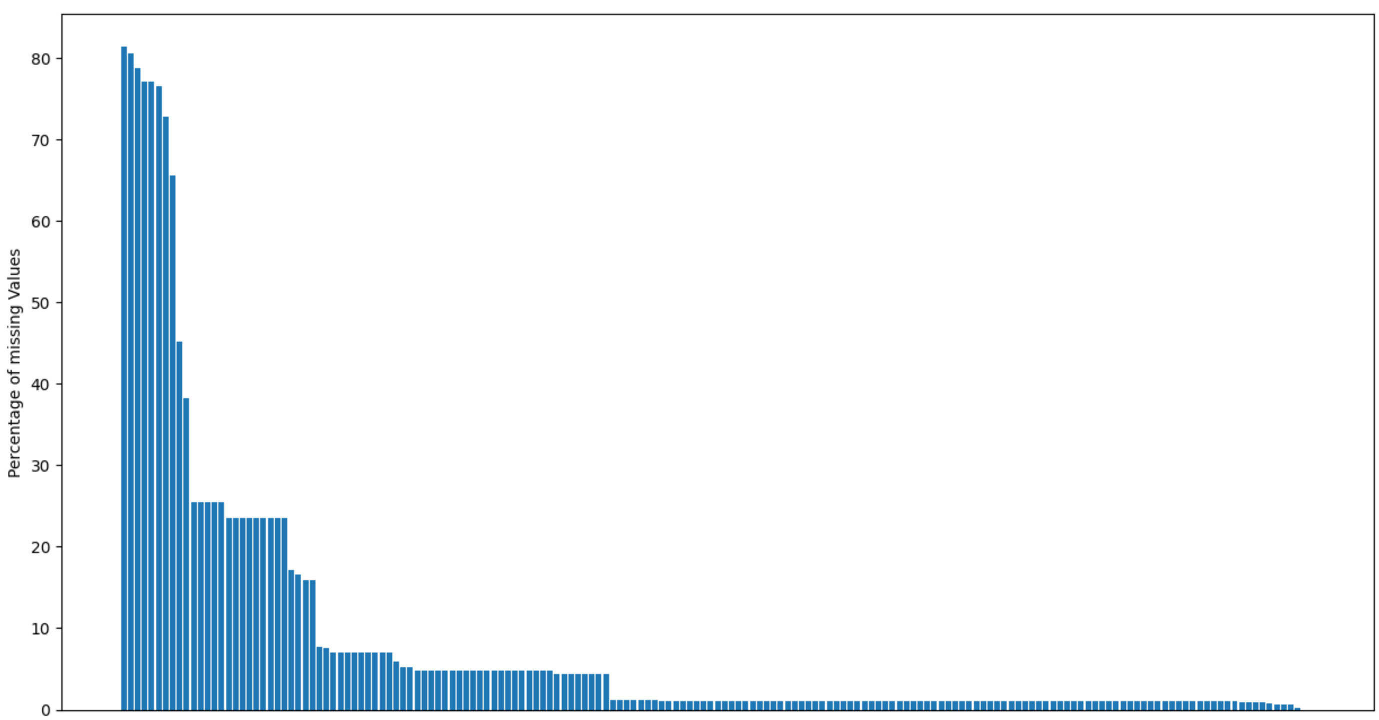
```
# define numerical and categorical features
numerical_features = [feature for feature in df.columns if df[feature].dtype != 'O']
categorical_features = [feature for feature in df.columns if df[feature].dtype == 'O']

# print features
print(' we have {} numerical features: {}'.format(len(numerical_features),numerical_feat
print(' we have {} categorical features: {}'.format(len(categorical_features),categorica
```

```
 we have 170 numerical features: ['aa_000', 'ab_000', 'ac_000', 'ad_000', 'ae_000', 'af_
000', 'ag_000', 'ag_001', 'ag_002', 'ag_003', 'ag_004', 'ag_005', 'ag_006', 'ag_007', 'a
g_008', 'ag_009', 'ah_000', 'ai_000', 'aj_000', 'ak_000', 'al_000', 'am_0', 'an_000', 'a
o_000', 'ap_000', 'aq_000', 'ar_000', 'as_000', 'at_000', 'au_000', 'av_000', 'ax_000',
'ay_000', 'ay_001', 'ay_002', 'ay_003', 'ay_004', 'ay_005', 'ay_006', 'ay_007', 'ay_00
8', 'ay_009', 'az_000', 'az_001', 'az_002', 'az_003', 'az_004', 'az_005', 'az_006', 'az_
007', 'az_008', 'az_009', 'ba_000', 'ba_001', 'ba_002', 'ba_003', 'ba_004', 'ba_005', 'b
a_006', 'ba_007', 'ba_008', 'ba_009', 'bb_000', 'bc_000', 'bd_000', 'be_000', 'bf_000',
'bg_000', 'bh_000', 'bi_000', 'bj_000', 'bk_000', 'bl_000', 'bm_000', 'bn_000', 'bo_00
0', 'bp_000', 'bq_000', 'br_000', 'bs_000', 'bt_000', 'bu_000', 'bv_000', 'bx_000', 'by_
000', 'bz_000', 'ca_000', 'cb_000', 'cc_000', 'cd_000', 'ce_000', 'cf_000', 'cg_000', 'c
h_000', 'ci_000', 'cj_000', 'ck_000', 'cl_000', 'cm_000', 'cn_000', 'cn_001', 'cn_002',
'cn_003', 'cn_004', 'cn_005', 'cn_006', 'cn_007', 'cn_008', 'cn_009', 'co_000', 'cp_00
0', 'cq_000', 'cr_000', 'cs_000', 'cs_001', 'cs_002', 'cs_003', 'cs_004', 'cs_005', 'cs_
006', 'cs_007', 'cs_008', 'cs_009', 'ct_000', 'cu_000', 'cv_000', 'cx_000', 'cy_000', 'c
z_000', 'da_000', 'db_000', 'dc_000', 'dd_000', 'de_000', 'df_000', 'dg_000', 'dh_000',
'di_000', 'dj_000', 'dk_000', 'dl_000', 'dm_000', 'dn_000', 'do_000', 'dp_000', 'dq_00
0', 'dr_000', 'ds_000', 'dt_000', 'du_000', 'dv_000', 'dx_000', 'dy_000', 'dz_000', 'ea_
000', 'eb_000', 'ec_00', 'ed_000', 'ee_000', 'ee_001', 'ee_002', 'ee_003', 'ee_004', 'ee
_005', 'ee_006', 'ee_007', 'ee_008', 'ee_009', 'ef_000', 'eg_000']
 we have 1 categorical features: ['class']
```

Checking missing values

In [47]:

```
fig, ax = plt.subplots(figsize=(15,8))
missing = df.isna().sum().div(df.shape[0]).mul(100).to_frame().sort_values(by=0, ascendi
ax.bar(missing.index, missing.values.T[0])
plt.xticks([])
plt.ylabel('Percentage of missing Values')
plt.show()
```



- Dropping columns which has more than 70% missing values

In [48]:
```
dropcols = missing[missing[0]>70]
dropcols
```

Out[48]:

	0
br_000	81.410965
bq_000	80.501824
bp_000	78.794075
ab_000	77.086327
cr_000	77.086327
bo_000	76.533658
bn_000	72.761689

In [49]:
```
df.drop(list(dropcols.index), axis=1, inplace=True)
```

In [50]:
```
# check shape of dataset after dropping columns
df.shape
```

Out[50]:
```
(36188, 164)
```

check total percentage of missing values of full dataset after dropping columns with more than 70% of missing values

In [51]:
```
missing_values_count = df.isnull().sum()
total_missing = missing_values_count.sum()
total_cells = np.product(df.shape)

print(f'Percentage of total missing cells in the data {(total_missing/total_cells)*100}'
```

```
Percentage of total missing cells in the data 5.37059852747306
```

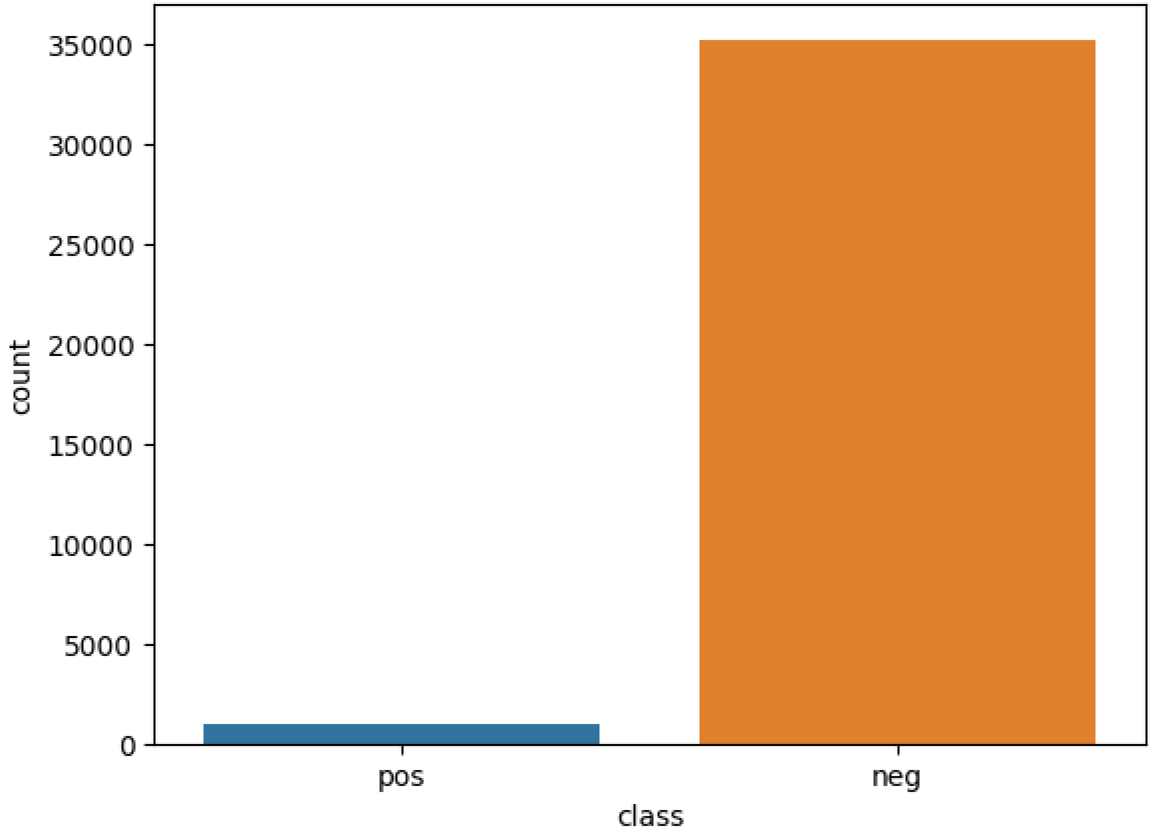
Visualization of Unique values in Target variable

In [52]:
```
df['class'].value_counts()
```

Out[52]:
```
class
neg    35188
pos     1000
Name: count, dtype: int64
```

In [53]:
```
sns.countplot(df,x='class')
```

Out[53]:
```
<Axes: xlabel='class', ylabel='count'>
```



Report

- target classes are highly imbalanced
- class imbalance is a scenario that arises when we have unequal distribution of class in a dataset i.e no. of datapoints in the negative class (mojority class) very large compared to that of the positive class(minority class)
- if imbalanced data is not treated beforehand, then this will degrade the performance of the classifier model
- hence, we should handle imbalanced data with certain methods

How to handle imbalanced data?

- Resampling data is one of the most common way to deal with imbalanced data. There are two types of resampling - Undersampling ad Oversampling
- In most cases, oversampling is preffered over undersampling techniques. In undersampling we tend to remove instances from data that may be carrying some important information
- SMOTE (Synthetic Minority Oversampling Technique): It is oversampling technique where synthetic samples are generated for minority class
- Hybridization techniques invlove combining both oversampling and undersampling techniques. This is done to optimize performance of the classifier models for samples created as part of these techniques.
- It only duplicates the data and it wont add new information.

Create functions for model training and evaluation

In [54]:
```
def evaluate_clf(true, predicted):
    '''
    This function takes the true and predicted values
    Returns: Accuracy, F1 Score, Precision, Recall, Roc-Auc-Score
    '''
```

```
    acc = accuracy_score(true, predicted) # calculate accuracy
    f1 = f1_score(true, predicted) # calculate f1
    precision = precision_score(true, predicted) # calculate precision
    recall = recall_score(true,predicted) # calculate recall
    roc_auc = roc_auc_score(true, predicted) # calculate roc_auc_score
    return acc, f1, precision, recall, roc_auc
```

In [55]:
```
# Create cost of the model as per data description
def total_cost(y_true,y_pred):
    '''
    This function takes y_true and y_predicted values and prints total cost due to miscl
    '''
    tn,fp,fn,tn =  confusion_matrix(y_true, y_pred).ravel()
    cost = 10 * fp + 500 * fn
    return cost
```

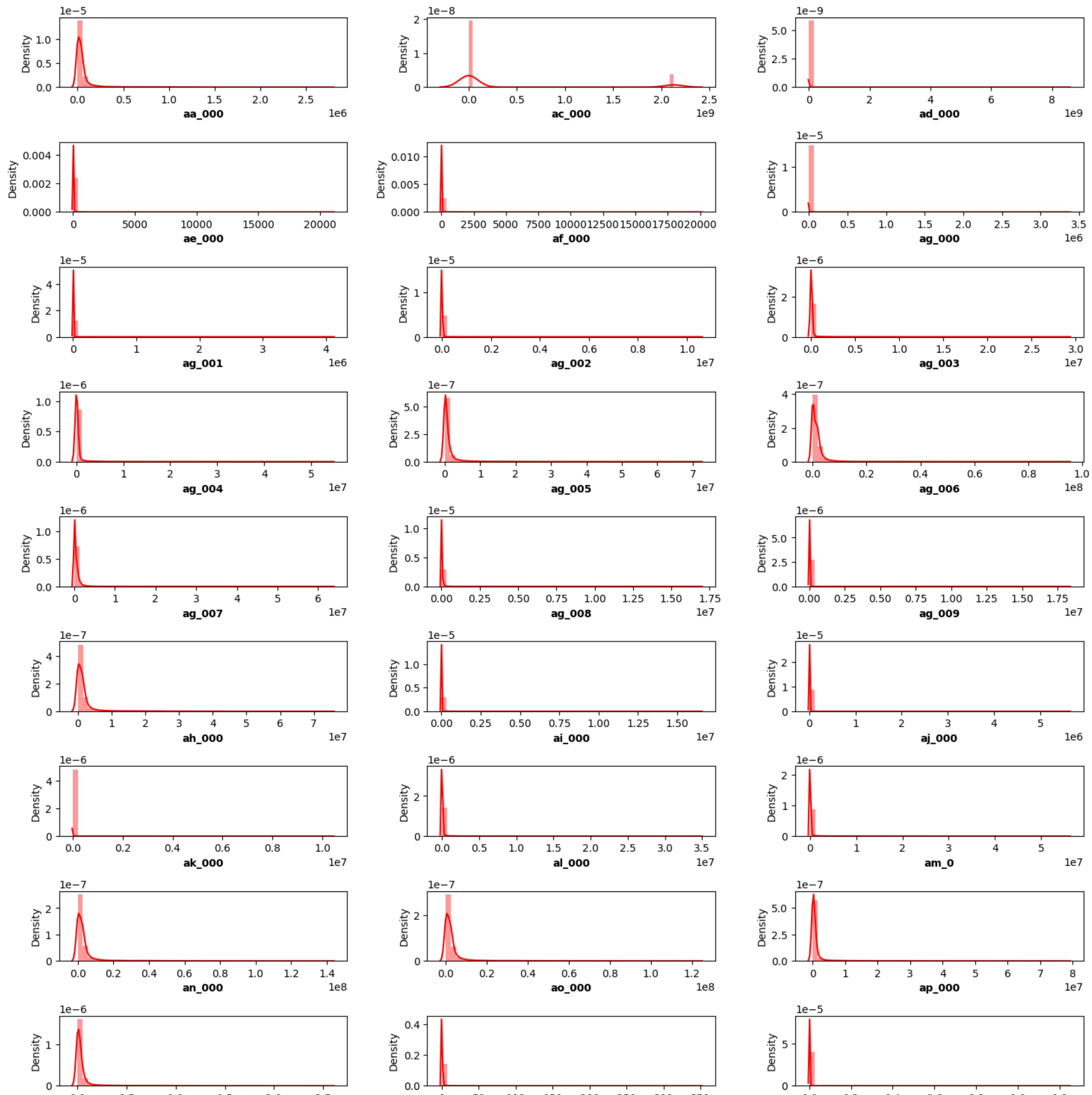
In [81]:
```
# create function to evaluate model and return a report
def evaluate_models(X,y, models):
    '''
    This function takes in X and y and models dictionary as input
    It splits data into training and testing sets
    Iterates through given model dictionary and evaluates metrics
    Returns: Dataframe which contains report of all models metrics with cost
    '''
    # split data into training and testing
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=4

    cost_list = []
    models_list = []
    accuracy_list = []

    for i in range(len(list(models))):
        model = list(models.values())[i]
        model.fit(X_train, y_train) # train model

        # make predictions
        y_train_pred = model.predict(X_train)
        y_test_pred = model.predict(X_test)

        # training set performance
        model_train_accuracy, model_train_f1, model_train_precision, \
        model_train_recall, model_train_rocauc_score = evaluate_clf(y_train, y_train_pre
        train_cost = total_cost(y_train, y_train_pred)

        # test set performance
        model_test_accuracy, model_test_f1, model_test_precision, \
        model_test_recall, model_test_rocauc_score = evaluate_clf(y_test, y_test_pred)
        test_cost = total_cost(y_test, y_test_pred)

        print(list(models.keys())[i])
        models_list.append(list(models.keys())[i])

        print('Model Performance for Training set')
        print("- Accuracy: {:.4f}".format(model_train_accuracy))
        print("- F1 Score: {:.4f}".format(model_train_f1))
        print("- Precision: {:.4f}".format(model_train_precision))
        print("- Recall: {:.4f}".format(model_train_recall))
        print("- ROC AUC Score: {:.4f}".format(model_train_rocauc_score))
        print('- Cost: {}'.format(train_cost))

        print("----------------------------------")

        print('Model Performance for Testing set')
        print("- Accuracy: {:.4f}".format(model_test_accuracy))
        accuracy_list.append(model_test_accuracy)
```

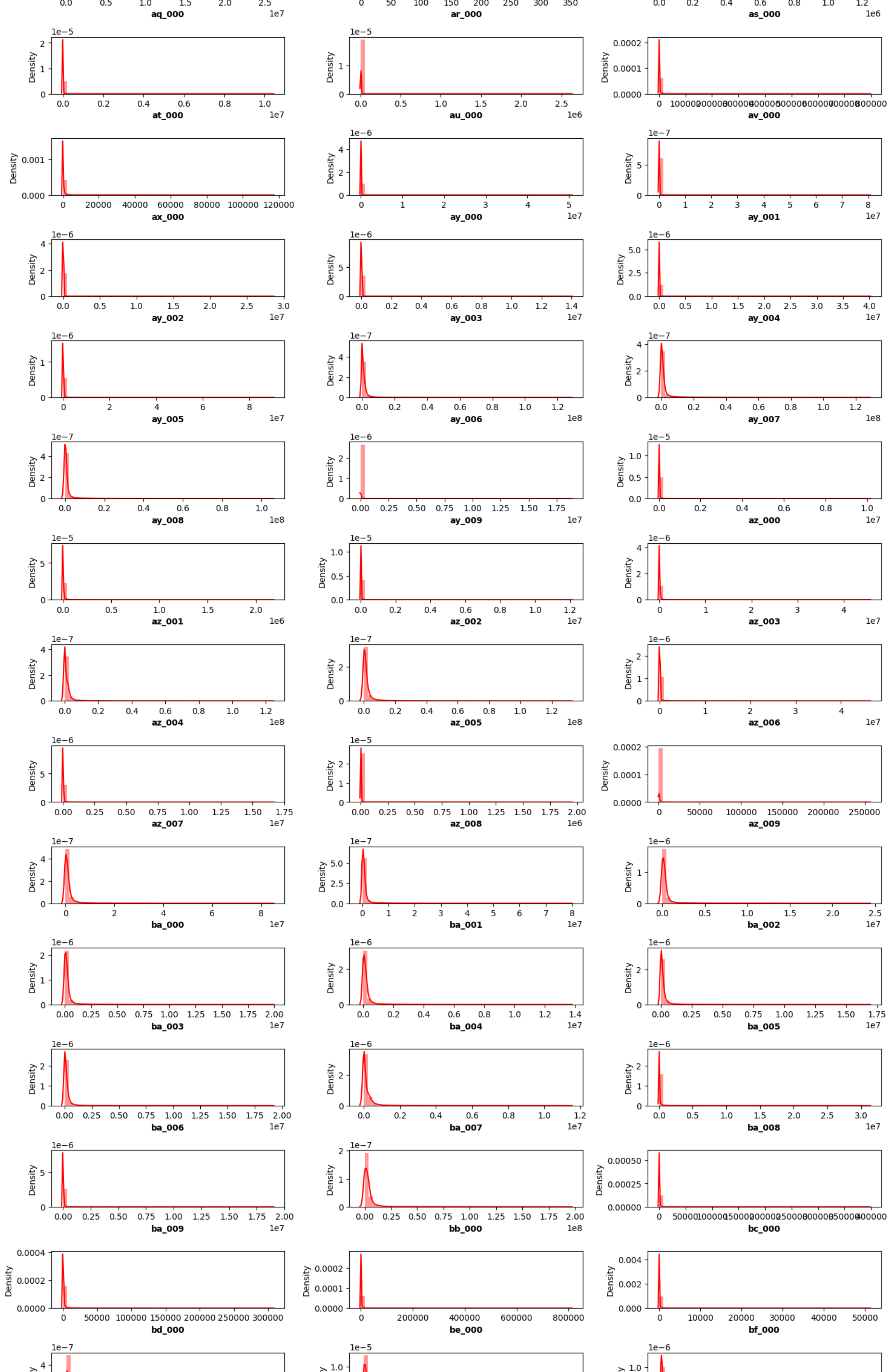
```
        print("- F1 Score: {:.4f}".format(model_test_f1))
        print("- Precision: {:.4f}".format(model_test_precision))
        print("- Recall: {:.4f}".format(model_test_recall))
        print("- ROC AUC Score: {:.4f}".format(model_test_rocauc_score))
        print('- Cost: {}'.format(test_cost))
        cost_list.append(test_cost)
        print('='*35)
        print('\n')

    report = pd.DataFrame(list(zip(models_list, cost_list, accuracy_list)), columns=['Mo
    return report
```

Plot distribution of all independent numeric features

In [62]:

```
numeric_features = [feature for feature in df.columns if df[feature].dtype != 'O']
plt.figure(figsize=(15,100))
for i, col in enumerate(numeric_features):
    plt.subplot(60, 3, i+1)
    sns.distplot(x=df[col], color='red')
    plt.xlabel(col, weight='bold')
    plt.tight_layout()
```




aq_000
ar_000
as_000
at_000
au_000
av_000
ax_000
ay_000
ay_001
ay_002
ay_003
ay_004
ay_005
ay_006
ay_007
ay_008
ay_009
az_000
az_001
az_002
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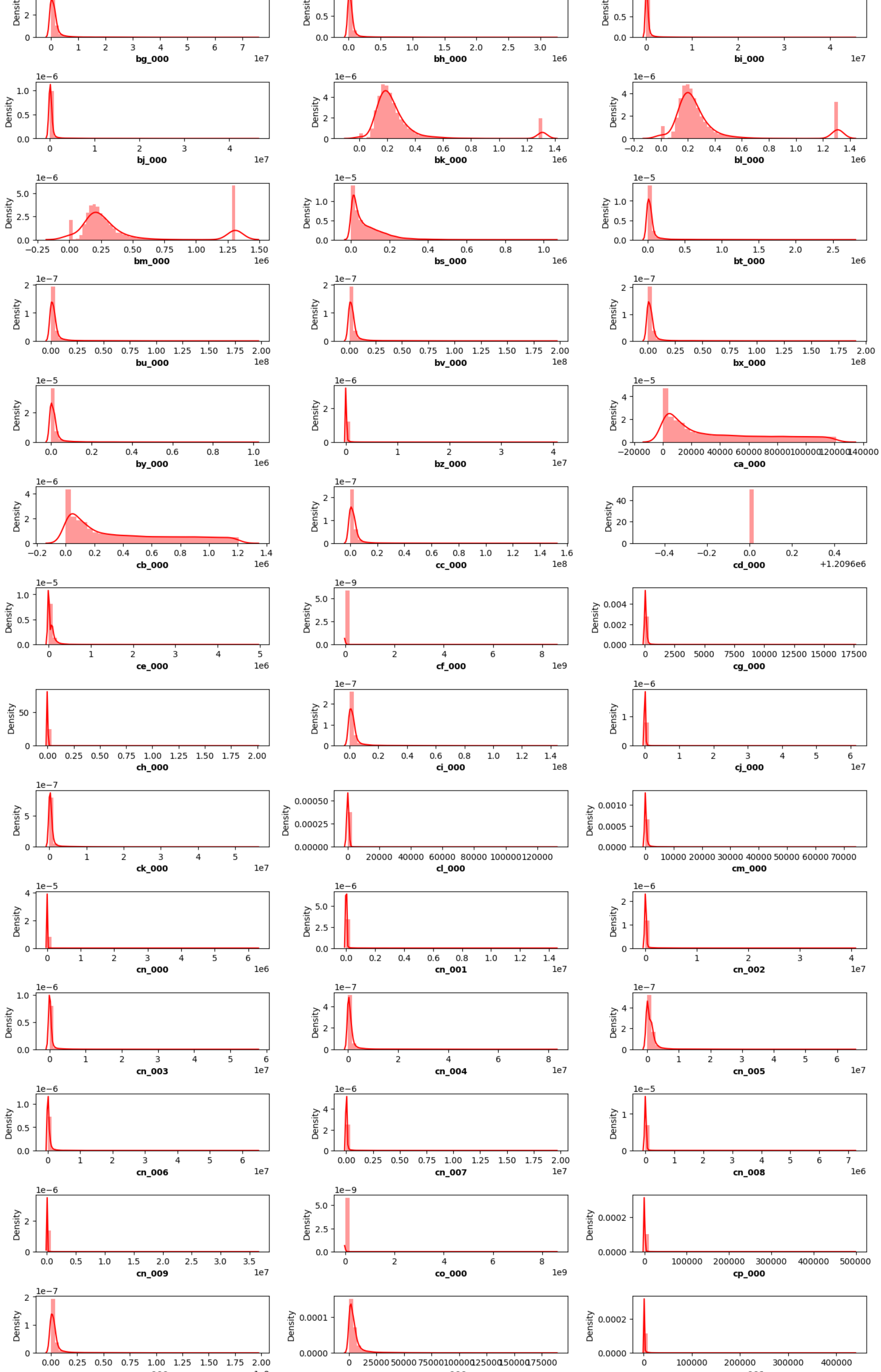
az_005
az_006
az_007
az_008
az_009
ba_000
ba_001
ba_002
ba_003
ba_004
ba_005
ba_006
ba_007
ba_008
ba_009
bb_000
bc_000
bd_000
be_000
bf_000
Density


bg_000
bh_000
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bs_000
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bx_000
by_000
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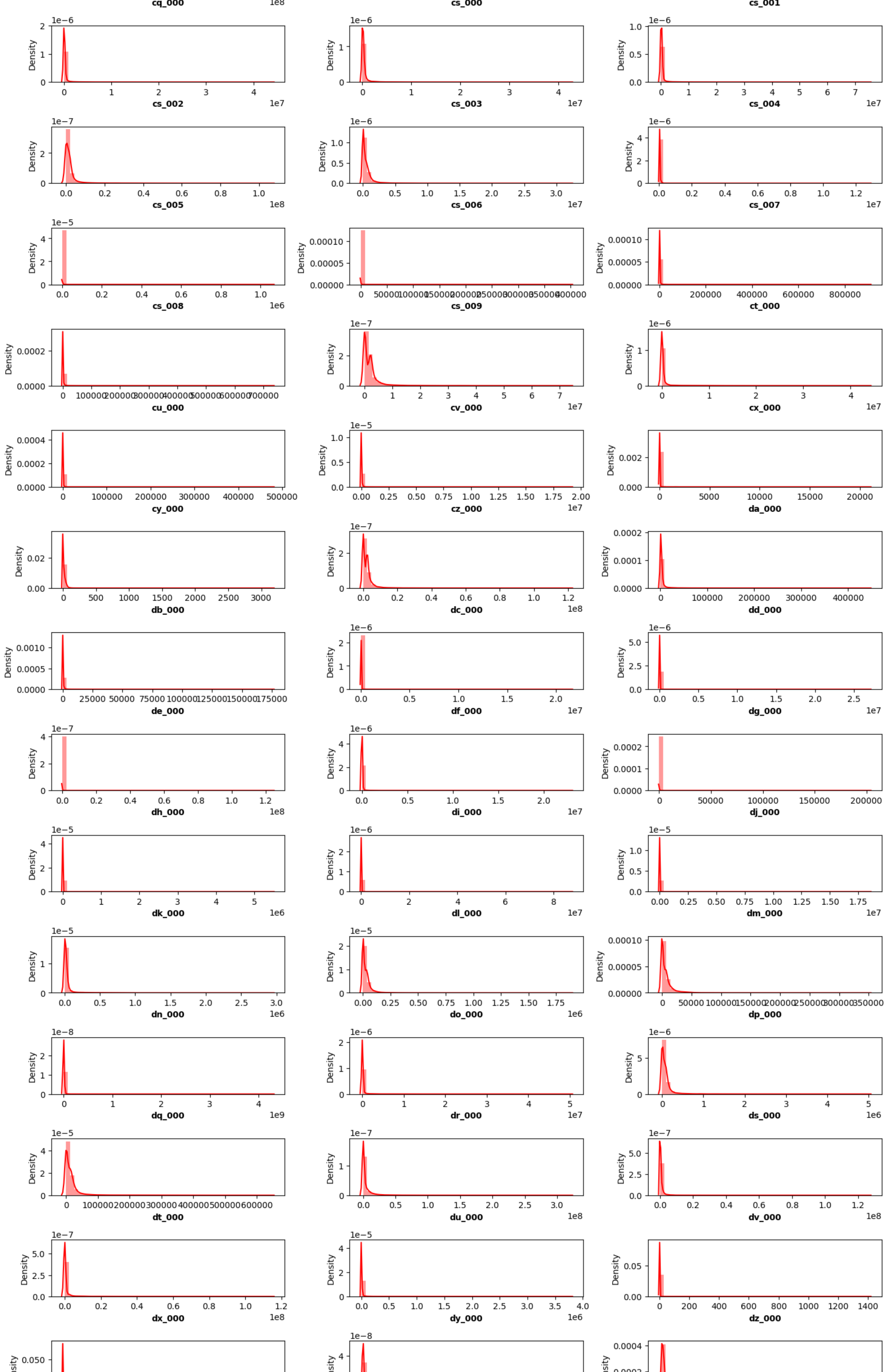
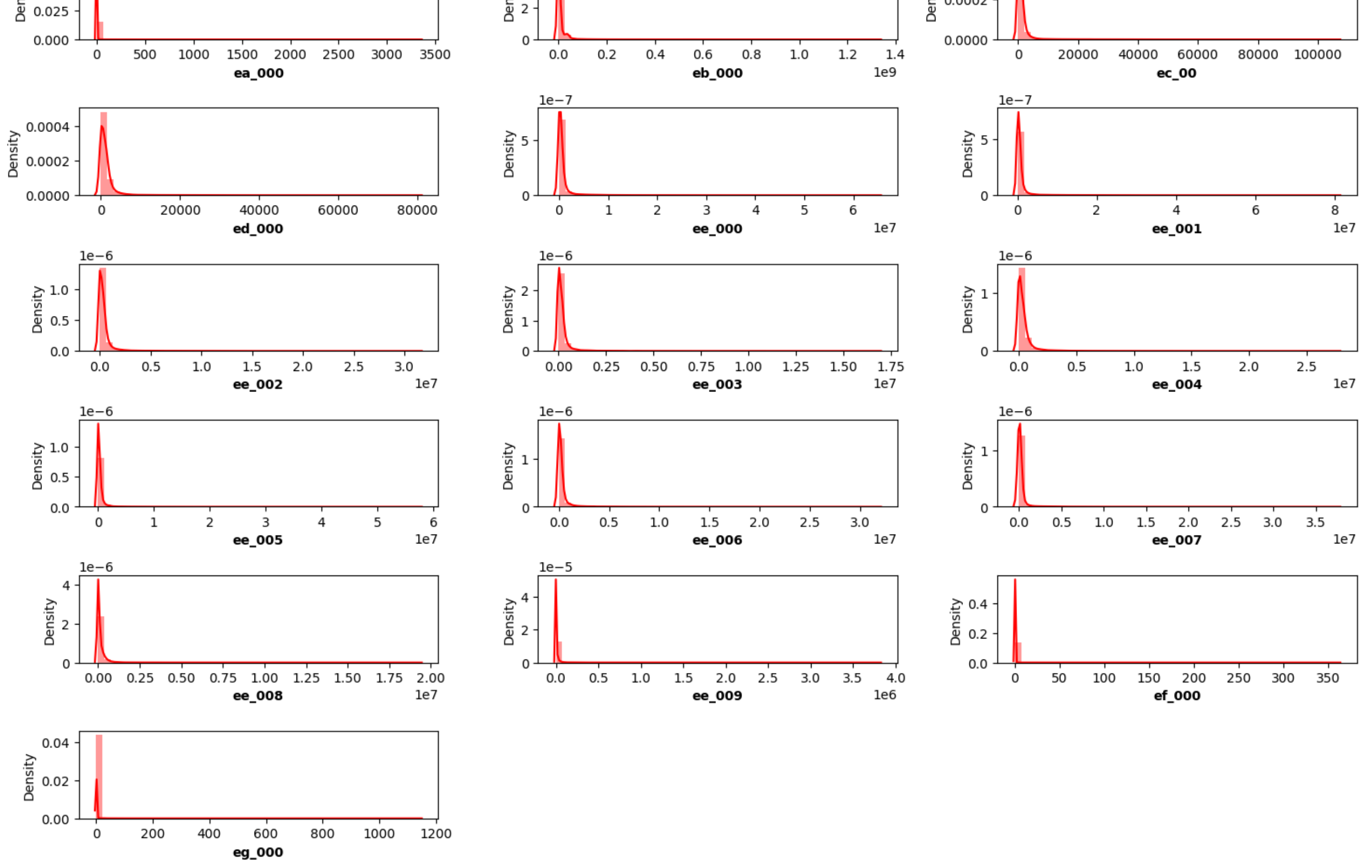
ca_000
cb_000
cc_000
cd_000
ce_000
cf_000
cg_000
ch_000
ci_000
cj_000
ck_000
cl_000
cm_000
cn_000
cn_001
cn_002
cn_003
cn_004
cn_005
cn_006
cn_007
cn_008
cn_009
co_000
cp_000
Density


cq_000
cs_000
cs_001
cs_002
cs_003
cs_004
cs_005
cs_006
cs_007
cs_008
cs_009
ct_000
cu_000
cv_000
cx_000
cy_000
cz_000
da_000
db_000
dc_000
dd_000
de_000
df_000
dg_000
dh_000
di_000
dj_000
dk_000
dl_000
dm_000
dn_000
do_000
dp_000
dq_000
dr_000
ds_000
dt_000
du_000
dv_000
dx_000
dy_000
dz_000
Density



- most of the features are not normally distributed
- transformation of data is not of prime importance since it is a classification problem
- interpreting each and every column is not necessary as this is sensor data

Evaluate model on different experiments

In [63]:
```
# Spliting Independent feature X and Target feature y
X = df.drop('class', axis=1)
y = df['class']
```

Manually Encoding target variable

In [65]:
```
y = y.replace({'pos':1,'neg':0})
```

Experiment 1: KNN Imputer for null values

Why RobustScaler and not StandardScaler?

- Scaling the data using RobustScaler
- Since most of the independent variables are not normally distributed we cannot use standard scaler

Why RobustScaler and MinMaxScaler? *

- because most features has outliers. so MinMax will scale data according to Max values which is outlier.
- This scaler removes the median and scales the data according to the quantile range (defauls to IQR: Interquartile range)
- IQR is range between 1 st Quartile and 3 rd Quartile

In [67]:
```
# Fit with Robust Scaler for KNN best K selection experiment
```

```
robustscaler = RobustScaler()
X1 = robustscaler.fit_transform(X)
```

Why KNN Imputer?

- KNN Imputer by scikit learn is widely used method to impute missing values. It is widely being observed as a replacement for traditional imputation techniques.
- KNN Imputer helps to impute missing values present in the observations by finding the nearest neighbors with Euclidean distance matrix.
- Here we iterates through different K values and get accuracy and choose best K values

Finding optimal n_neighbor value for KNN imputer

In [69]:

```
results = []
# define imputer
imputer = KNNImputer(n_neighbors=5, weights='uniform', metric='nan_euclidean')

strategies = [str(i) for i in [1,3,5,7,9]]
for s in strategies:
    pipeline = Pipeline(steps=[('i', KNNImputer(n_neighbors=int(s))),('m', LogisticRegre
    scores = cross_val_score(pipeline, X1, y, scoring='accuracy', cv=2, n_jobs=-1)
    results.append(scores)
    print(f'n_neighbors = {s} | accuracy = {mean(scores)})')
```

```
n_neighbors = 1 | accuracy = 0.7500552669393169)
n_neighbors = 3 | accuracy = 0.7146291588371836)
n_neighbors = 5 | accuracy = 0.7186636454073173)
n_neighbors = 7 | accuracy = 0.7118381784016801)
n_neighbors = 9 | accuracy = 0.7211782911462363)
```

- We can observe n_neighbors = 1 able to produce highest accuracy

In [73]:

```
#### Pipeline for KNN Imputer
```

In [74]:

```
num_features = X.select_dtypes(exclude='object').columns

# fit KNN Imputer with selected K value
knn_pipeline = Pipeline(steps=[
    ('imputer', KNNImputer(n_neighbors=1)),
    ('RobustScaler', RobustScaler())
])
```

In [75]:

```
X_knn = knn_pipeline.fit_transform(X)
```

Handling Imbalanced Data

Smote Tomek is one of such hybrid technique that aims to clean overlapping data points for each classes distributed in sample space.

- This method combines the SMOTE ability to generate synthetic data for minority class and Tomek Links ability to remove data that are identified as Tomek links from majority class.

- To add new data of minority class

1. Choose random data from minority class
2. Calculate distance between random data and its k nearest neighbors

3. Multiply difference with random number between 0 and 1, then add result to minority class as synthetic sample
4. Repeat step number 2-3 until desired proportion of minority class is met

- To remove the tomek links of majority class

1. Choose random data from majority class
2. If random data's nearest neighbor is the data from minority class (i.e create Tomek Link) then remove the Tomek link

- This method instead of adding duplicate data it synthesises the new data based on already available classes. Hence we choose this as our imputer method for this problem.

In [77]:
```
from imblearn.combine import SMOTETomek

# Resampling minority class. strategy can be changed as required.
smt = SMOTETomek(random_state = 42, sampling_strategy='minority', n_jobs = -1)

# Fit the model to generate data
X_res, y_res = smt.fit_resample(X_knn, y)
```

In [78]:
```
### Initialize Default Models in Dictionary

# Dictionary which contains models for experiment
models = {
    'Random Forest': RandomForestClassifier(),
    'Gradient Boosting': GradientBoostingClassifier(),
    'AdaBoosting': AdaBoostClassifier(),
    'Logistic Regression': LogisticRegression(),
    'Decision Tree Classifier': DecisionTreeClassifier(),
    'Support Vector Classifier': SVC(),
    'K- Neighbors Classifier': KNeighborsClassifier(),
    'XGBoost Classifier': XGBClassifier(),
    'Catboost Classifier': CatBoostClassifier(verbose=False)
}
```

Fit KNN Imputed Data for models in dictionary

In [82]:
```
report_knn = evaluate_models(X_res, y_res, models)
```

```
Random Forest
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 0
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9916
- F1 Score: 0.9917
- Precision: 0.9875
- Recall: 0.9959
- ROC AUC Score: 0.9916
- Cost: 15390
===================================


Gradient Boosting
Model Performance for Training set
```

```
- Accuracy: 0.9838
- F1 Score: 0.9838
- Precision: 0.9814
- Recall: 0.9862
- ROC AUC Score: 0.9838
- Cost: 198730
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9819
- F1 Score: 0.9821
- Precision: 0.9790
- Recall: 0.9851
- ROC AUC Score: 0.9819
- Cost: 53990
===================================


AdaBoosting
Model Performance for Training set
- Accuracy: 0.9750
- F1 Score: 0.9749
- Precision: 0.9756
- Recall: 0.9743
- ROC AUC Score: 0.9750
- Cost: 367320
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9761
- F1 Score: 0.9763
- Precision: 0.9748
- Recall: 0.9779
- ROC AUC Score: 0.9761
- Cost: 79790
===================================


Logistic Regression
Model Performance for Training set
- Accuracy: 0.5863
- F1 Score: 0.6903
- Precision: 0.5510
- Recall: 0.9239
- ROC AUC Score: 0.5869
- Cost: 1276340
----------------------------------
Model Performance for Testing set
- Accuracy: 0.5888
- F1 Score: 0.6935
- Precision: 0.5553
- Recall: 0.9235
- ROC AUC Score: 0.5862
- Cost: 322780
===================================


Decision Tree Classifier
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 0
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9857
```

```
- F1 Score: 0.9858
- Precision: 0.9824
- Recall: 0.9892
- ROC AUC Score: 0.9856
- Cost: 39250
===================================


Support Vector Classifier
Model Performance for Training set
- Accuracy: 0.7536
- F1 Score: 0.6811
- Precision: 0.9617
- Recall: 0.5272
- ROC AUC Score: 0.7532
- Cost: 6624880
----------------------------------
Model Performance for Testing set
- Accuracy: 0.7552
- F1 Score: 0.6873
- Precision: 0.9642
- Recall: 0.5340
- ROC AUC Score: 0.7569
- Cost: 1648400
===================================


K- Neighbors Classifier
Model Performance for Training set
- Accuracy: 0.9796
- F1 Score: 0.9798
- Precision: 0.9689
- Recall: 0.9910
- ROC AUC Score: 0.9797
- Cost: 134410
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9729
- F1 Score: 0.9735
- Precision: 0.9606
- Recall: 0.9867
- ROC AUC Score: 0.9728
- Cost: 49860
===================================


XGBoost Classifier
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 0
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9964
- F1 Score: 0.9964
- Precision: 0.9939
- Recall: 0.9989
- ROC AUC Score: 0.9963
- Cost: 4430
===================================


Catboost Classifier
```

```
Model Performance for Training set
- Accuracy: 0.9995
- F1 Score: 0.9995
- Precision: 0.9995
- Recall: 0.9995
- ROC AUC Score: 0.9995
- Cost: 6650
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9953
- F1 Score: 0.9953
- Precision: 0.9925
- Recall: 0.9982
- ROC AUC Score: 0.9953
- Cost: 7030
===================================
```

Report for KNN Imputed Data

In [83]:
```
report_knn
```

Out[83]:

	Model Name	Cost	Accuracy
7	XGBoost Classifier	4430	0.996364
8	Catboost Classifier	7030	0.995295
0	Random Forest	15390	0.991588
4	Decision Tree Classifier	39250	0.985672
6	K- Neighbors Classifier	49860	0.972911
1	Gradient Boosting	53990	0.981893
2	AdaBoosting	79790	0.976119
3	Logistic Regression	322780	0.588751
5	Support Vector Classifier	1648400	0.755204

- for the experiment 1: KNN Imputer has XGBoost classifier as the best model

Experiment 2: Simple Imputer with Strategy Median

- SimpleImputer is a class in sklearn.impute module that can be used to replace missing value in dataset using variety of input strategies
- Here we use SimpleImputer can also be used to impute multiple columns at once by passing in a list of column names. Simple Imputer will then replace missing values in all of the specified columns

In [84]:
```
num_features = X.select_dtypes(exclude="object").columns

# Fit simple imputer with strategy median
median_pipeline = Pipeline(steps = [
    ('imputer', SimpleImputer(strategy="median")),
    ('Robust Scaler', RobustScaler())
])
```

In [85]:
```
# Fit X with median_pipeline
```

```python
X_median = median_pipeline.fit_transform(X)
```

In [86]:
```python
# Resampling minority class. strategy can be changed as required
smt = SMOTETomek(random_state =42, sampling_strategy="minority")

# Fit model to generate data
X_res, y_res = smt.fit_resample(X_median, y)
```

In [87]:
```python
# Training models
report_median = evaluate_models(X_res, y_res, models)
```

```
Random Forest
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 0
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9917
- F1 Score: 0.9918
- Precision: 0.9868
- Recall: 0.9967
- ROC AUC Score: 0.9916
- Cost: 12440
===================================


Gradient Boosting
Model Performance for Training set
- Accuracy: 0.9840
- F1 Score: 0.9840
- Precision: 0.9813
- Recall: 0.9867
- ROC AUC Score: 0.9840
- Cost: 190760
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9809
- F1 Score: 0.9812
- Precision: 0.9755
- Recall: 0.9868
- ROC AUC Score: 0.9808
- Cost: 48250
===================================


AdaBoosting
Model Performance for Training set
- Accuracy: 0.9749
- F1 Score: 0.9749
- Precision: 0.9740
- Recall: 0.9757
- ROC AUC Score: 0.9749
- Cost: 346790
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9727
- F1 Score: 0.9731
- Precision: 0.9702
- Recall: 0.9760
- ROC AUC Score: 0.9727
- Cost: 87120
```

```
====================================


Logistic Regression
Model Performance for Training set
- Accuracy: 0.6323
- F1 Score: 0.7167
- Precision: 0.5821
- Recall: 0.9324
- ROC AUC Score: 0.6330
- Cost: 1133260
----------------------------------
Model Performance for Testing set
- Accuracy: 0.6287
- F1 Score: 0.7165
- Precision: 0.5827
- Recall: 0.9300
- ROC AUC Score: 0.6260
- Cost: 294600
====================================


Decision Tree Classifier
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 0
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9861
- F1 Score: 0.9863
- Precision: 0.9807
- Recall: 0.9919
- ROC AUC Score: 0.9860
- Cost: 29880
====================================


Support Vector Classifier
Model Performance for Training set
- Accuracy: 0.7613
- F1 Score: 0.6936
- Precision: 0.9645
- Recall: 0.5416
- ROC AUC Score: 0.7609
- Cost: 6417580
----------------------------------
Model Performance for Testing set
- Accuracy: 0.7585
- F1 Score: 0.6931
- Precision: 0.9649
- Recall: 0.5408
- ROC AUC Score: 0.7604
- Cost: 1624890
====================================


K- Neighbors Classifier
Model Performance for Training set
- Accuracy: 0.9789
- F1 Score: 0.9791
- Precision: 0.9683
- Recall: 0.9902
```

```
- ROC AUC Score: 0.9789
- Cost: 146570
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9718
- F1 Score: 0.9724
- Precision: 0.9596
- Recall: 0.9854
- ROC AUC Score: 0.9716
- Cost: 54430
===================================


XGBoost Classifier
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 500
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9951
- F1 Score: 0.9951
- Precision: 0.9920
- Recall: 0.9983
- ROC AUC Score: 0.9950
- Cost: 6570
===================================


Catboost Classifier
Model Performance for Training set
- Accuracy: 0.9996
- F1 Score: 0.9996
- Precision: 0.9997
- Recall: 0.9996
- ROC AUC Score: 0.9996
- Cost: 5590
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9935
- F1 Score: 0.9936
- Precision: 0.9889
- Recall: 0.9983
- ROC AUC Score: 0.9935
- Cost: 6790
===================================
```

In [123…

```
report_median
```

Out[123]:

	Model Name	Cost	Accuracy
7	XGBoost Classifier	6570	0.995078
8	Catboost Classifier	6790	0.993508
0	Random Forest	12440	0.991654
4	Decision Tree Classifier	29880	0.986089
1	Gradient Boosting	48250	0.980882
6	K- Neighbors Classifier	54430	0.971751

2	AdaBoosting	87120	0.972749
3	Logistic Regression	294600	0.628692
5	Support Vector Classifier	1624890	0.758453

Experiment 3: MICE for imputing Null Values

- MICE stands for Multivariate Imputation By Chained Equations algorithm
- This techcnique by which we can efoortlessly impute missing values in dataset by looking at data from other columns and try to estimate best prediction for each missing value -ImputationKernel creates kernel dataset. This dataset can perform MICE on itself and impute new data from models obtained during MICE

In [93]:

```
import miceforest as mf
X_mice = X.copy()
kernel = mf.ImputationKernel(X_mice, save_all_iterations = True, random_state = 42)
kernel.mice(3)
```

In [94]:

```
X_mice = kernel.complete_data()
```

In [95]:

```
X_mice
```

Out[95]:

	aa_000	ac_000	ad_000	ae_000	af_000	ag_000	ag_001	ag_002	ag_003	ag_004	...	
0	153204	1.820000e+02	242.0	0.0	0.0	0.0	0.0	0.0	11804.0	684444.0	...	
1	453236	2.926000e+03	20416.0	0.0	0.0	0.0	0.0	222.0	323436.0	2999280.0	...	7
2	72504	1.594000e+03	1052.0	0.0	0.0	0.0	244.0	178226.0	1249396.0	3813464.0	...	1
3	762958	1.420000e+02	1992.0	2.0	70.0	776.0	281128.0	2186308.0	8123016.0	18022646.0	...	3
4	695994	4.760000e+02	444.0	0.0	0.0	0.0	0.0	0.0	55620.0	1190014.0	...	1
...	...	...	...	...	...	...	...	...	...	...	...	
36183	153002	6.640000e+02	186.0	0.0	0.0	0.0	0.0	0.0	2564.0	59100.0	...	
36184	2286	2.130707e+09	224.0	0.0	0.0	0.0	0.0	0.0	0.0	104.0	...	
36185	112	2.130706e+09	18.0	0.0	0.0	0.0	0.0	0.0	0.0	28.0	...	
36186	80292	2.130706e+09	494.0	0.0	0.0	0.0	0.0	0.0	0.0	330.0	...	
36187	40222	6.980000e+02	628.0	0.0	0.0	0.0	0.0	0.0	0.0	1226.0	...	

36188 rows × 163 columns

In [99]:

```
# fit robust scaler
mice_pipeline = Pipeline(steps =[
    ('RobustScaler',RobustScaler())
])
```

In [100…

```
# Fit with mice imputer
X_mice = mice_pipeline.fit_transform(X_mice)
```

In [101…

```
# Resampling minority class. strategy can be changed as required.
smt = SMOTETomek(sampling_strategy = 'minority',random_state=42, n_jobs=-1)
```

```
# fit model to generate data
X_res, y_res = smt.fit_resample(X_mice, y)
```

In [102…

```
# Traingin the models
report_mice = evaluate_models(X_res, y_res, models)
```

```
Random Forest
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 0
--------------------------------
Model Performance for Testing set
- Accuracy: 0.9917
- F1 Score: 0.9917
- Precision: 0.9885
- Recall: 0.9950
- ROC AUC Score: 0.9917
- Cost: 18310
===================================


Gradient Boosting
Model Performance for Training set
- Accuracy: 0.9838
- F1 Score: 0.9839
- Precision: 0.9805
- Recall: 0.9873
- ROC AUC Score: 0.9838
- Cost: 183500
--------------------------------
Model Performance for Testing set
- Accuracy: 0.9816
- F1 Score: 0.9816
- Precision: 0.9783
- Recall: 0.9850
- ROC AUC Score: 0.9816
- Cost: 54030
===================================


AdaBoosting
Model Performance for Training set
- Accuracy: 0.9758
- F1 Score: 0.9759
- Precision: 0.9742
- Recall: 0.9775
- ROC AUC Score: 0.9758
- Cost: 322760
--------------------------------
Model Performance for Testing set
- Accuracy: 0.9765
- F1 Score: 0.9764
- Precision: 0.9767
- Recall: 0.9761
- ROC AUC Score: 0.9765
- Cost: 85130
===================================


Logistic Regression
Model Performance for Training set
```

```
- Accuracy: 0.6119
- F1 Score: 0.7132
- Precision: 0.5658
- Recall: 0.9646
- ROC AUC Score: 0.6116
- Cost: 704290
----------------------------------
Model Performance for Testing set
- Accuracy: 0.6109
- F1 Score: 0.7124
- Precision: 0.5640
- Recall: 0.9670
- ROC AUC Score: 0.6120
- Cost: 167760
===================================


Decision Tree Classifier
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 0
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9858
- F1 Score: 0.9858
- Precision: 0.9817
- Recall: 0.9900
- ROC AUC Score: 0.9858
- Cost: 36290
===================================


Support Vector Classifier
Model Performance for Training set
- Accuracy: 0.7670
- F1 Score: 0.7058
- Precision: 0.9584
- Recall: 0.5586
- ROC AUC Score: 0.7671
- Cost: 6201810
----------------------------------
Model Performance for Testing set
- Accuracy: 0.7643
- F1 Score: 0.6991
- Precision: 0.9614
- Recall: 0.5492
- ROC AUC Score: 0.7637
- Cost: 1577040
===================================


K- Neighbors Classifier
Model Performance for Training set
- Accuracy: 0.9789
- F1 Score: 0.9792
- Precision: 0.9670
- Recall: 0.9916
- ROC AUC Score: 0.9789
- Cost: 127490
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9710
```

```
- F1 Score: 0.9714
- Precision: 0.9562
- Recall: 0.9871
- ROC AUC Score: 0.9711
- Cost: 48160
===================================


XGBoost Classifier
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 0
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9957
- F1 Score: 0.9956
- Precision: 0.9930
- Recall: 0.9983
- ROC AUC Score: 0.9957
- Cost: 6490
===================================


Catboost Classifier
Model Performance for Training set
- Accuracy: 0.9996
- F1 Score: 0.9996
- Precision: 0.9996
- Recall: 0.9997
- ROC AUC Score: 0.9996
- Cost: 4610
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9946
- F1 Score: 0.9946
- Precision: 0.9913
- Recall: 0.9979
- ROC AUC Score: 0.9946
- Cost: 8110
===================================
```

Report for MICE Imputer algorithm

In [103…

```
report_mice
```

Out[103]:

	Model Name	Cost	Accuracy
7	XGBoost Classifier	6490	0.995650
8	Catboost Classifier	8110	0.994581
0	Random Forest	18310	0.991728
4	Decision Tree Classifier	36290	0.985810
6	K- Neighbors Classifier	48160	0.971050
1	Gradient Boosting	54030	0.981603
2	AdaBoosting	85130	0.976469

3	Logistic Regression	167760	0.610881
5	Support Vector Classifier	1577040	0.764333

- for experiment 3: Mice Imputerhas XGBoost classifier as best model

Experiment 4: Simple Imputer with strategy Constant

- Another strategy which can be used is replacing missing values with fixed constant value
- to do this , specify "constant" for strategy and specify fill value using fill_value parameter

In [104…

```
# Create pipeline with simple imputer with strategy constant and fill_value = 0
constant_pipeline = Pipeline(steps =[
    ('Imputer', SimpleImputer(strategy = 'constant',fill_value=0)),
    ('RobustScaler',RobustScaler())
])
```

In [105…

```
X_const = constant_pipeline.fit_transform(X)
```

In [106…

```
# Resample minority class. strategy can be changed as required
smt = SMOTETomek(sampling_strategy='minority', random_state=42, n_jobs=-1)
X_res, y_res = smt.fit_resample(X_const,y)
```

In [107…

```
# Training the models
report_const = evaluate_models(X_res, y_res, models)
```

```
Random Forest
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 0
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9929
- F1 Score: 0.9930
- Precision: 0.9896
- Recall: 0.9964
- ROC AUC Score: 0.9929
- Cost: 13240
===================================


Gradient Boosting
Model Performance for Training set
- Accuracy: 0.9829
- F1 Score: 0.9829
- Precision: 0.9798
- Recall: 0.9861
- ROC AUC Score: 0.9829
- Cost: 200690
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9806
- F1 Score: 0.9807
- Precision: 0.9773
- Recall: 0.9842
- ROC AUC Score: 0.9806
- Cost: 57110
```

```
==================================


AdaBoosting
Model Performance for Training set
- Accuracy: 0.9735
- F1 Score: 0.9735
- Precision: 0.9731
- Recall: 0.9739
- ROC AUC Score: 0.9735
- Cost: 374050
--------------------------------
Model Performance for Testing set
- Accuracy: 0.9734
- F1 Score: 0.9735
- Precision: 0.9745
- Recall: 0.9724
- ROC AUC Score: 0.9734
- Cost: 98790
==================================


Logistic Regression
Model Performance for Training set
- Accuracy: 0.6687
- F1 Score: 0.7469
- Precision: 0.6040
- Recall: 0.9783
- ROC AUC Score: 0.6689
- Cost: 483330
--------------------------------
Model Performance for Testing set
- Accuracy: 0.6687
- F1 Score: 0.7479
- Precision: 0.6047
- Recall: 0.9800
- ROC AUC Score: 0.6678
- Cost: 115560
==================================


Decision Tree Classifier
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 0
--------------------------------
Model Performance for Testing set
- Accuracy: 0.9884
- F1 Score: 0.9885
- Precision: 0.9833
- Recall: 0.9937
- ROC AUC Score: 0.9884
- Cost: 23190
==================================


Support Vector Classifier
Model Performance for Training set
- Accuracy: 0.7608
- F1 Score: 0.6936
- Precision: 0.9635
- Recall: 0.5418
```

```
- ROC AUC Score: 0.7607
- Cost: 6427750
----------------------------------
Model Performance for Testing set
- Accuracy: 0.7617
- F1 Score: 0.6956
- Precision: 0.9678
- Recall: 0.5429
- ROC AUC Score: 0.7624
- Cost: 1608770
===================================


K- Neighbors Classifier
Model Performance for Training set
- Accuracy: 0.9803
- F1 Score: 0.9805
- Precision: 0.9682
- Recall: 0.9932
- ROC AUC Score: 0.9803
- Cost: 105130
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9750
- F1 Score: 0.9754
- Precision: 0.9626
- Recall: 0.9885
- ROC AUC Score: 0.9749
- Cost: 43200
===================================


XGBoost Classifier
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 500
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9969
- F1 Score: 0.9969
- Precision: 0.9945
- Recall: 0.9993
- ROC AUC Score: 0.9969
- Cost: 2890
===================================


Catboost Classifier
Model Performance for Training set
- Accuracy: 0.9992
- F1 Score: 0.9992
- Precision: 0.9992
- Recall: 0.9992
- ROC AUC Score: 0.9992
- Cost: 11720
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9963
- F1 Score: 0.9963
- Precision: 0.9936
- Recall: 0.9990
- ROC AUC Score: 0.9963
```

```
- Cost: 3950
==================================
```

Report for Simple Imputer with Constant Strategy

In [108…
```
report_const
```

Out[108]:

	Model Name	Cost	Accuracy
7	XGBoost Classifier	2890	0.996863
8	Catboost Classifier	3950	0.996293
0	Random Forest	13240	0.992942
4	Decision Tree Classifier	23190	0.988379
6	K- Neighbors Classifier	43200	0.974975
1	Gradient Boosting	57110	0.980607
2	AdaBoosting	98790	0.973407
3	Logistic Regression	115560	0.668687
5	Support Vector Classifier	1608770	0.761728

- for experiment 4: Simple Imputer with constant startegy has XGBoost classifier as best model

Experiment 5: Simple imputer with Strategy Mean

- replacing missing values with mean
- here, we replace the missing values with mean of column

In [109…
```
# create pipeline with Simple Imputer with strategy mean
mean_pipeline = Pipeline(steps = [
    ('Imputer', SimpleImputer(strategy='mean')),
    ('RobustScaler', RobustScaler())
])
```

In [110…
```
X_mean = mean_pipeline.fit_transform(X)
```

In [111…
```
# Resampling minority class. strategy can be changes as required
smt = SMOTETomek(sampling_strategy='minority', random_state=42, n_jobs=-1)

# fit model to generate data
X_res, y_res = smt.fit_resample(X_mean, y)
```

In [112…
```
# Training models
report_mean = evaluate_models(X_res, y_res, models)
```

```
Random Forest
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 0
----------------------------------
```

```
Model Performance for Testing set
- Accuracy: 0.9939
- F1 Score: 0.9938
- Precision: 0.9900
- Recall: 0.9977
- ROC AUC Score: 0.9939
- Cost: 8700
===================================


Gradient Boosting
Model Performance for Training set
- Accuracy: 0.9856
- F1 Score: 0.9857
- Precision: 0.9828
- Recall: 0.9886
- ROC AUC Score: 0.9856
- Cost: 164880
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9865
- F1 Score: 0.9863
- Precision: 0.9835
- Recall: 0.9892
- ROC AUC Score: 0.9865
- Cost: 38650
===================================


AdaBoosting
Model Performance for Training set
- Accuracy: 0.9760
- F1 Score: 0.9761
- Precision: 0.9765
- Recall: 0.9757
- ROC AUC Score: 0.9760
- Cost: 349100
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9767
- F1 Score: 0.9764
- Precision: 0.9786
- Recall: 0.9742
- ROC AUC Score: 0.9767
- Cost: 90980
===================================


Logistic Regression
Model Performance for Training set
- Accuracy: 0.6661
- F1 Score: 0.7338
- Precision: 0.6114
- Recall: 0.9175
- ROC AUC Score: 0.6654
- Cost: 1324650
----------------------------------
Model Performance for Testing set
- Accuracy: 0.6652
- F1 Score: 0.7317
- Precision: 0.6057
- Recall: 0.9238
- ROC AUC Score: 0.6682
- Cost: 305690
===================================
```

```
Decision Tree Classifier
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 0
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9860
- F1 Score: 0.9858
- Precision: 0.9829
- Recall: 0.9887
- ROC AUC Score: 0.9860
- Cost: 40190
===================================


Support Vector Classifier
Model Performance for Training set
- Accuracy: 0.8474
- F1 Score: 0.8273
- Precision: 0.9566
- Recall: 0.7288
- ROC AUC Score: 0.8478
- Cost: 3825310
----------------------------------
Model Performance for Testing set
- Accuracy: 0.8513
- F1 Score: 0.8295
- Precision: 0.9568
- Recall: 0.7321
- ROC AUC Score: 0.8499
- Cost: 930790
===================================


K- Neighbors Classifier
Model Performance for Training set
- Accuracy: 0.9816
- F1 Score: 0.9819
- Precision: 0.9711
- Recall: 0.9929
- ROC AUC Score: 0.9816
- Cost: 107820
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9743
- F1 Score: 0.9743
- Precision: 0.9611
- Recall: 0.9879
- ROC AUC Score: 0.9744
- Cost: 44770
===================================


XGBoost Classifier
Model Performance for Training set
- Accuracy: 1.0000
- F1 Score: 1.0000
- Precision: 1.0000
- Recall: 1.0000
- ROC AUC Score: 1.0000
- Cost: 500
```

```
--------------------------------
Model Performance for Testing set
- Accuracy: 0.9971
- F1 Score: 0.9970
- Precision: 0.9948
- Recall: 0.9993
- ROC AUC Score: 0.9971
- Cost: 2860
===================================


Catboost Classifier
Model Performance for Training set
- Accuracy: 0.9994
- F1 Score: 0.9994
- Precision: 0.9995
- Recall: 0.9993
- ROC AUC Score: 0.9994
- Cost: 9650
--------------------------------
Model Performance for Testing set
- Accuracy: 0.9960
- F1 Score: 0.9960
- Precision: 0.9935
- Recall: 0.9984
- ROC AUC Score: 0.9960
- Cost: 5950
===================================
```

Report for Simple Imputer with strategy mean

In [113…

```
report_mean
```

Out[113]:

	Model Name	Cost	Accuracy
7	XGBoost Classifier	2860	0.997078
8	Catboost Classifier	5950	0.996009
0	Random Forest	8700	0.993870
1	Gradient Boosting	38650	0.986458
4	Decision Tree Classifier	40190	0.985959
6	K- Neighbors Classifier	44770	0.974269
2	AdaBoosting	90980	0.976693
3	Logistic Regression	305690	0.665217
5	Support Vector Classifier	930790	0.851319

- for experiment 5: Simple Imputer with Strategy Mean xgboost classifier performs best

Experiment 6: Principle Component Analysis with imputing median

- Principal Component Analysis is a technique for feature extraction - so it combines our input variables in a specific way, then we can drop least important variables while still retaning most valuable parts of all variables

- As dataset has 164 columns, we can try PCA and check out metrics Cost

In [114…
```
pca_pipeline = Pipeline(steps=[
    ('Imputer', SimpleImputer(strategy='constant', fill_value=0)),
    ('RobustScaler', RobustScaler())
])
```

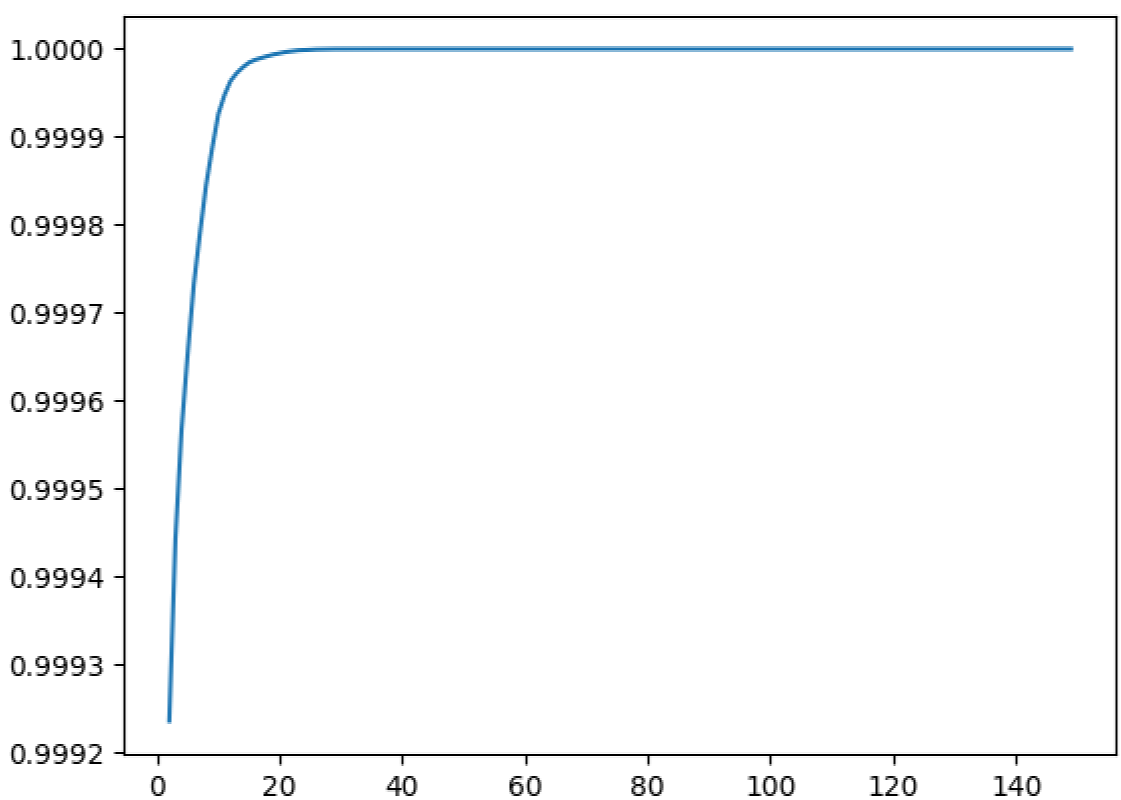
In [115…
```
X_pca = pca_pipeline.fit_transform(X)
```

In [116…
```
# Applying PCA
from sklearn.decomposition import PCA
var_ratio = {}
for n in range(2,150):
    pc = PCA(n_components=n)
    df_pca = pc.fit(X_pca)
    var_ratio[n] = sum(df_pca.explained_variance_ratio_)
```

Variance plot

In [117…
```
pd.Series(var_ratio).plot()
```

Out[117]:
```
<Axes: >
```



Kneed algorithm to find elbow point

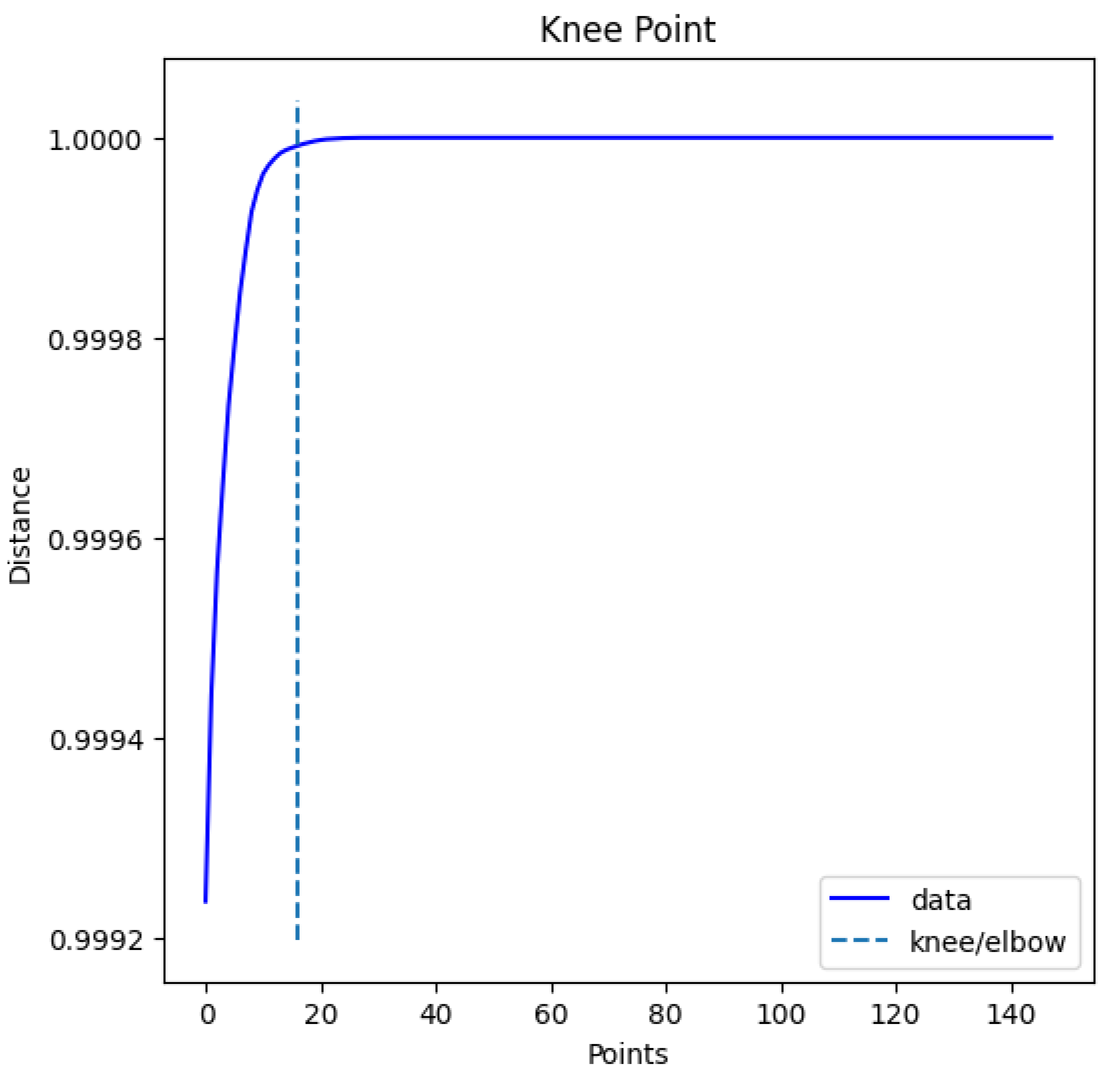
In [118…
```
from kneed import KneeLocator

i = np.arange(len(var_ratio))
variance_ratio = list(var_ratio.values())
components = list(var_ratio.keys())
knee = KneeLocator(i, variance_ratio, S=1, curve='concave', interp_method='polynomial')

fig = plt.figure(figsize=(5,5))
knee.plot_knee()
```

```
plt.xlabel("Points")
plt.ylabel('Distance')
plt.show()
k = components[knee.knee]
print('Knee Locator k =',k)
```

```
<Figure size 500x500 with 0 Axes>
```




```
Knee Locator k = 18
```

In [119…

```
# Reducing the dimensions of data
pca_final = PCA(n_components=18, random_state=42).fit(X_res)
reduced = pca_final.fit_transform(X_pca)
```

In [120…

```
# Resampling the minority class. strategy can be changed as required
smt = SMOTETomek(random_state=42, sampling_strategy='minority', n_jobs=-1)

# Fit model to generate data
X_res, y_res = smt.fit_resample(reduced, y)
```

In [121…

```
# Training models
report_pca = evaluate_models(X_res, y_res, models)
```

```
Random Forest
Model Performance for Training set
- Accuracy: 0.9986
- F1 Score: 0.9986
- Precision: 1.0000
- Recall: 0.9972
- ROC AUC Score: 0.9986
- Cost: 38510
----------------------------------
```

```
Model Performance for Testing set
- Accuracy: 0.9819
- F1 Score: 0.9821
- Precision: 0.9742
- Recall: 0.9902
- ROC AUC Score: 0.9819
- Cost: 36340
===================================


Gradient Boosting
Model Performance for Training set
- Accuracy: 0.9421
- F1 Score: 0.9419
- Precision: 0.9440
- Recall: 0.9398
- ROC AUC Score: 0.9421
- Cost: 856570
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9372
- F1 Score: 0.9373
- Precision: 0.9385
- Recall: 0.9361
- ROC AUC Score: 0.9372
- Cost: 228300
===================================


AdaBoosting
Model Performance for Training set
- Accuracy: 0.9209
- F1 Score: 0.9206
- Precision: 0.9233
- Recall: 0.9179
- ROC AUC Score: 0.9209
- Cost: 1168790
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9179
- F1 Score: 0.9178
- Precision: 0.9219
- Recall: 0.9137
- ROC AUC Score: 0.9179
- Cost: 307930
===================================


Logistic Regression
Model Performance for Training set
- Accuracy: 0.8749
- F1 Score: 0.8647
- Precision: 0.9406
- Recall: 0.8002
- ROC AUC Score: 0.8749
- Cost: 2805120
----------------------------------
Model Performance for Testing set
- Accuracy: 0.8726
- F1 Score: 0.8627
- Precision: 0.9386
- Recall: 0.7982
- ROC AUC Score: 0.8728
- Cost: 711160
===================================
```

```
Decision Tree Classifier
Model Performance for Training set
- Accuracy: 0.9986
- F1 Score: 0.9986
- Precision: 1.0000
- Recall: 0.9972
- ROC AUC Score: 0.9986
- Cost: 38500
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9745
- F1 Score: 0.9748
- Precision: 0.9695
- Recall: 0.9800
- ROC AUC Score: 0.9745
- Cost: 72160
===================================


Support Vector Classifier
Model Performance for Training set
- Accuracy: 0.7624
- F1 Score: 0.6959
- Precision: 0.9648
- Recall: 0.5442
- ROC AUC Score: 0.7622
- Cost: 6373050
----------------------------------
Model Performance for Testing set
- Accuracy: 0.7591
- F1 Score: 0.6926
- Precision: 0.9620
- Recall: 0.5411
- ROC AUC Score: 0.7598
- Cost: 1610500
===================================


K- Neighbors Classifier
Model Performance for Training set
- Accuracy: 0.9725
- F1 Score: 0.9727
- Precision: 0.9645
- Recall: 0.9810
- ROC AUC Score: 0.9725
- Cost: 275080
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9609
- F1 Score: 0.9616
- Precision: 0.9477
- Recall: 0.9759
- ROC AUC Score: 0.9608
- Cost: 88280
===================================


XGBoost Classifier
Model Performance for Training set
- Accuracy: 0.9907
- F1 Score: 0.9907
- Precision: 0.9915
- Recall: 0.9899
- ROC AUC Score: 0.9907
- Cost: 143870
```

```
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9775
- F1 Score: 0.9777
- Precision: 0.9721
- Recall: 0.9835
- ROC AUC Score: 0.9775
- Cost: 59980
===================================


Catboost Classifier
Model Performance for Training set
- Accuracy: 0.9824
- F1 Score: 0.9824
- Precision: 0.9814
- Recall: 0.9833
- ROC AUC Score: 0.9824
- Cost: 238210
----------------------------------
Model Performance for Testing set
- Accuracy: 0.9722
- F1 Score: 0.9724
- Precision: 0.9671
- Recall: 0.9778
- ROC AUC Score: 0.9722
- Cost: 80330
===================================
```

Report for PCA and mean imputed data

In [122…

```
report_pca
```

Out[122]:

	Model Name	Cost	Accuracy
0	Random Forest	36340	0.981904
7	XGBoost Classifier	59980	0.977541
4	Decision Tree Classifier	72160	0.974537
8	Catboost Classifier	80330	0.972177
6	K- Neighbors Classifier	88280	0.960875
1	Gradient Boosting	228300	0.937200
2	AdaBoosting	307930	0.917889
3	Logistic Regression	711160	0.872613
5	Support Vector Classifier	1610500	0.759102

Final Model

In [126…

```
from prettytable import PrettyTable

pt = PrettyTable()
pt.field_names = ['Model','Imputation_method', 'Total_cost']
pt.add_row(['XGBClassifier','Simple Imputer - Mean','2860'])
pt.add_row(['XGBClassifier','Simple Imputer-Constant','2890'])
pt.add_row(['XGBClassifier','KNN-Imputer','4430'])
pt.add_row(['XGBClassifier','Mice','6490'])
```

```
pt.add_row(['XGBClassifier','Median','6570'])
pt.add_row(['Random Forest','PCA','36340'])
print(pt)
```

```
+---------------+-------------------------+------------+
|     Model     |    Imputation_method    | Total_cost |
+---------------+-------------------------+------------+
| XGBClassifier |  Simple Imputer - Mean  |    2860    |
| XGBClassifier | Simple Imputer-Constant |    2890    |
| XGBClassifier |       KNN-Imputer       |    4430    |
| XGBClassifier |           Mice          |    6490    |
| XGBClassifier |          Median         |    6570    |
| Random Forest |           PCA           |   36340    |
+---------------+-------------------------+------------+
```

- from final report we can see than XGBClassifier with Simple Imputer with strategy mean has performed best with cost of 2860

Fitting final model and get reports

In [127…
```
final_model = XGBClassifier()

# Resampling minority class. strategy can be changed as required
smt = SMOTETomek(random_state = 42, sampling_strategy='minority',n_jobs=-1)

# Fit model to generate data
X_res, y_res = smt.fit_resample(X_mean, y)
```

In [128…
```
X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size=0.2, random_

final_model = final_model.fit(X_train, y_train)
y_pred = final_model.predict(X_test)
```

In [129…
```
print('Final XGBoost Classifier Accuracy Score (Train): ', final_model.score(X_train,y_t
print('Final XGBoost Classifier Accuracy Score (Test): ', accuracy_score(y_pred, y_test)
```

```
Final XGBoost Classifier Accuracy Score (Train):  0.9999821810406272
Final XGBoost Classifier Accuracy Score (Test):  0.9970776906628653
```

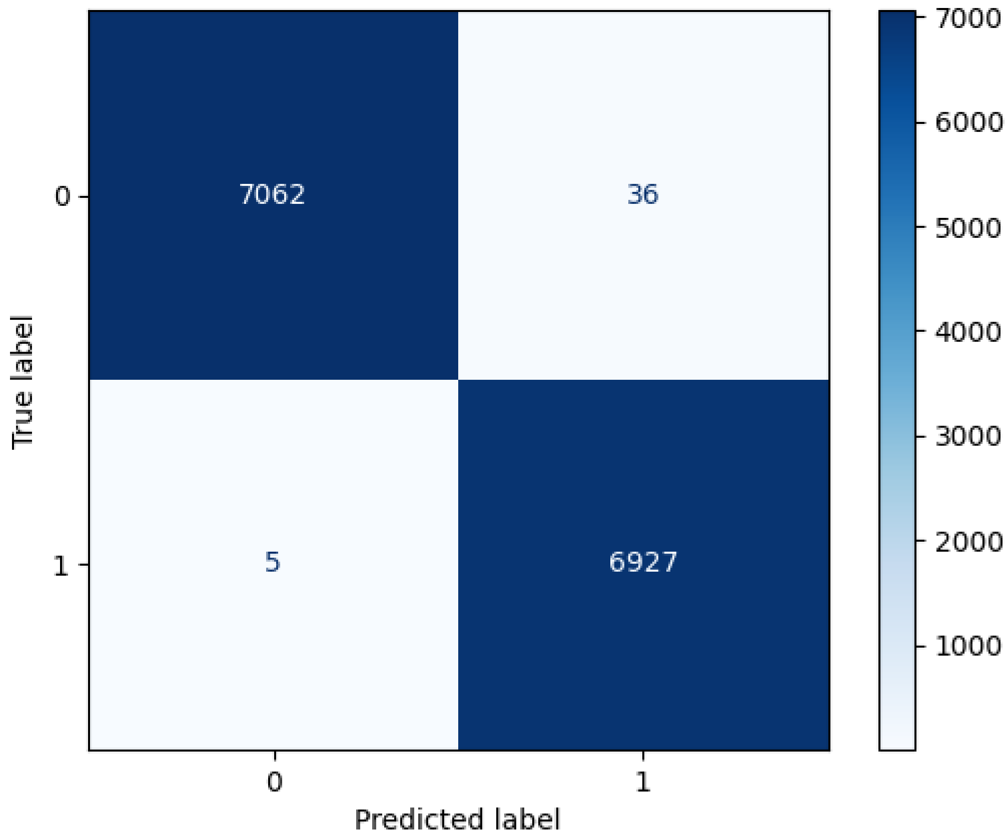
In [130…
```
print('Final XGBoost Classifier Cost Metric(Test) :', total_cost(y_test, y_pred))
```

```
Final XGBoost Classifier Cost Metric(Test) : 2860
```

In [140…
```
# from sklearn.metrics import plot_confusion_matrix

# plot confusion matrix
ConfusionMatrixDisplay.from_estimator(final_model, X_test, y_test,cmap='Blues', values_f
```

Out[140]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x20d97047fd0>
```



The best model is XGBoost Classifier with 99.7% accuracy and cost of 2860

In [ ]: