Loading the required libraries

In [1]:
```
import pandas as pd
import numpy as np
from sklearn import preprocessing
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.impute import SimpleImputer
from sklearn import metrics
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from tabulate import tabulate
import warnings
warnings.filterwarnings("ignore")
```

Loading the datasets

In [2]:
```
X_train_df = pd.read_csv(r"D:\Monsoon Credittech\DS Test\DS Test\Training\X_tr
ain.csv")
X_train_df.head()
```

Out[2]:

	Unique_ID	C1	C2	C3	C4	C5	C6	C7	C8	N1	...	N26	N27	N28	N29
0	Candidate_5926	1	0	11	31	0	False	0	True	23.75	...	NaN	NaN	NaN	NaN
1	Candidate_48134	1	4	2	66	2	False	1	True	11.05	...	NaN	NaN	NaN	NaN
2	Candidate_51717	1	0	19	2	0	False	0	True	29.00	...	NaN	NaN	NaN	NaN
3	Candidate_26401	1	1	16	47	1	False	4	True	17.99	...	NaN	NaN	NaN	NaN
4	Candidate_34872	1	1	13	1	1	True	6	True	27.50	...	NaN	NaN	NaN	NaN

5 rows × 44 columns

In [3]:
```
Y_train_df = pd.read_csv(r"D:\Monsoon Credittech\DS Test\DS Test\Training\y_tr
ain.csv")
Y_train_df.head()
```

Out[3]:

	Unique_ID	Dependent_Variable
0	Candidate_5926	1
1	Candidate_48134	0
2	Candidate_51717	1
3	Candidate_26401	0
4	Candidate_34872	0

In [4]:
```
X_test_df = pd.read_csv(r"D:\Monsoon Credittech\DS Test\DS Test\Test\X_test.cs
v")
X_test_df.head(2)
```

Out[4]:

	Unique_ID	C1	C2	C3	C4	C5	C6	C7	C8	N1	...	N26	N27	N28	N29	I
0	Candidate_1602	1	0	0	23	0	True	0	True	18.00	...	NaN	NaN	NaN	NaN	N
1	Candidate_29650	1	0	2	4	2	True	2	True	16.75	...	NaN	NaN	NaN	NaN	N

2 rows × 44 columns

Removing Unique_ID feature from the training and test dataset

In [5]:
```
Y_train = Y_train_df.drop(['Unique_ID'], axis=1)
X_train = X_train_df.drop(['Unique_ID'], axis=1)
X_test = X_test_df.drop(['Unique_ID'], axis=1)
print(Y_train.shape)
print(X_train.shape)
print(X_test.shape)
```

```
(33050, 1)
(33050, 43)
(11017, 43)
```

Data Preprocessing

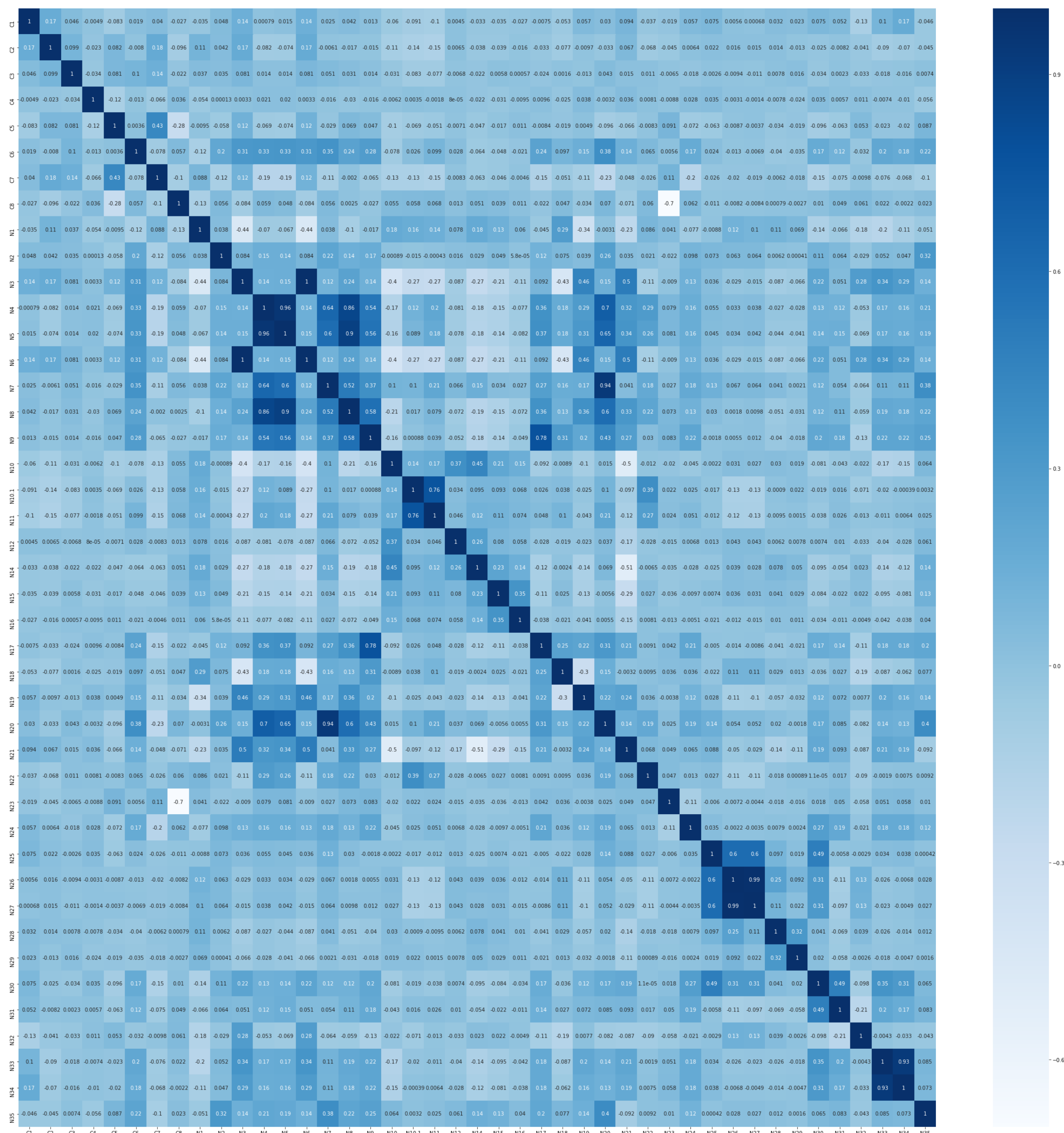
Converting boolean values (True and Flase) of columns "C6" and "C8" to 1 and 0 respectively

In [6]:
```
X_train["C6"] = X_train["C6"].apply(lambda x:1 if x==True else 0)
X_train["C8"] = X_train["C8"].apply(lambda x:1 if x==True else 0)
```

In [7]:
```
X_test["C6"] = X_test["C6"].apply(lambda x:1 if x==True else 0)
X_test["C8"] = X_test["C8"].apply(lambda x:1 if x==True else 0)
```

Checking the correlation between features

In [8]:
```
plt.figure(figsize = (40,40))
sb.heatmap(X_train.corr(), cmap="Blues", annot=True)
plt.show()
```



In [9]:
```
corr_matrix = X_train.corr().abs()
```

In [10]:
```
# Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.b
ool))
```

Finding features having correlation greather than 90%

In [11]:
```
to_drop = [column for column in upper.columns if any(upper[column] > 0.90)]
```

In [12]:
```
to_drop
```

Out[12]:
```
['N5', 'N6', 'N20', 'N27', 'N34']
```

Dropping features in the training dataset having correlation of greater than 0.9

In [13]:
```
X_train.drop(to_drop, axis=1, inplace=True)
X_train.shape
```

Out[13]:
```
(33050, 38)
```

Dropping the same columns(columns that have been droppped from the train dataset having correlation of greater than 0.9) from the test dataset as well

In [14]:
```
X_test.drop(to_drop, axis=1, inplace=True)
X_test.shape
```

Out[14]:
```
(11017, 38)
```

Handling missing values

In [15]:
```
print("Columns having null data in the train dataset:\n",X_train.columns[X_tra
in.isnull().any()].tolist())
```

```
Columns having null data in the train dataset:
 ['N2', 'N3', 'N4', 'N7', 'N10', 'N10.1', 'N11', 'N12', 'N14', 'N15', 'N16',
'N17', 'N18', 'N19', 'N21', 'N22', 'N23', 'N25', 'N26', 'N28', 'N29', 'N30',
'N31', 'N32', 'N35']
```

In [16]:
```
print("Percentage of null data in the columns:")
print(((X_train[X_train.columns[X_train.isnull().any()]].isnull().sum())*100)/
X_train.shape[0])
```

```
Percentage of null data in the columns:
N2       13.954614
N3        1.104387
N4       13.936460
N7        1.291982
N10       1.291982
N10.1     1.291982
N11       2.166415
N12      13.960666
N14       1.839637
N15       1.291982
N16      13.936460
N17      13.936460
N18      13.936460
N19      13.830560
N21      13.830560
N22      13.830560
N23       7.521936
N25      81.025719
N26      81.025719
N28      81.025719
N29      81.025719
N30      81.025719
N31      81.025719
N32      81.180030
N35       1.291982
dtype: float64
```

Finding columns having more than 80 percent of null values

In [17]:
```
columns_with_null_gt_80 = X_train.columns[X_train.isna().sum()/len(X_train) >
0.8]
columns_with_null_gt_80
```

Out[17]:
```
Index(['N25', 'N26', 'N28', 'N29', 'N30', 'N31', 'N32'], dtype='object')
```

Dropping columns having more than 80 percent of null values

Dropping the columns having more than 80 percent of null data as the performance of the models after removing these columns is relatively same to the performance of models trained on the dataset wherein the null values in these columns are filled with their mean values.

Since we have no information about the column and its importance; we drop these columns as 80 percent is relatively high and also since there is no drop in performance.

In [18]:
```
X_train.dropna(thresh=X_train.shape[0]*0.8,how='all',axis=1, inplace=True)
X_train.head()
```

Out[18]:

	C1	C2	C3	C4	C5	C6	C7	C8	N1	N2	...	N16	N17	N18	N19	N21	N2
0	1	0	11	31	0	0	0	1	23.75	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN
1	1	4	2	66	2	0	1	1	11.05	22.0	...	0.0	1944.0	0.06	25856.0	0.88	1.0
2	1	0	19	2	0	0	0	1	29.00	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN
3	1	1	16	47	1	0	4	1	17.99	1.0	...	0.0	8244.0	0.89	1006.0	1.00	0.0
4	1	1	13	1	1	1	6	1	27.50	206.0	...	0.0	57532.0	0.97	3398.0	0.96	0.0

5 rows × 31 columns

In [19]:
```
X_train.shape
```

Out[19]: (33050, 31)

Dropping the same columns(columns that have been droppped from the train dataset having more than 80 percent of null values) from the test dataset as well

In [20]:
```
X_test.drop(columns_with_null_gt_80, axis=1, inplace=True)
X_test.head()
```

Out[20]:

	C1	C2	C3	C4	C5	C6	C7	C8	N1	N2	...	N16	N17	N18	N19	N21	N2
0	1	0	0	23	0	1	0	1	18.00	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN
1	1	0	2	4	2	1	2	1	16.75	107.0	...	0.0	59435.0	0.83	12165.0	0.94	2.0
2	1	2	3	38	1	0	4	1	29.99	45.0	...	0.0	1996.0	0.79	504.0	0.70	2.0
3	1	1	28	20	2	0	2	1	17.70	20.0	...	0.0	9281.0	0.84	1428.0	0.77	0.0
4	1	1	15	1	3	0	5	0	28.00	2.0	...	0.0	13902.0	0.64	6324.0	0.92	2.0

5 rows × 31 columns

In [21]:
```
print("Columns having null data in the train dataset:\n",X_train.columns[X_tra
in.isnull().any()].tolist())
```

```
Columns having null data in the train dataset:
 ['N2', 'N3', 'N4', 'N7', 'N10', 'N10.1', 'N11', 'N12', 'N14', 'N15', 'N16',
'N17', 'N18', 'N19', 'N21', 'N22', 'N23', 'N35']
```

Filling null values

After trying various methods like dropping rows with null values; filling null values with mean, median, mode; and using interpolation, it was found that by filling null values with their mean there is an improvement in the performance. So, we fill the null values with mean.

If the class labels of the test dataset would have been available we could have tried filling the null values with mean of the data in the column having the same class label.

In [22]:
```
imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
```

In [23]:
```
X_train = pd.DataFrame(imputer.fit_transform(X_train), columns = X_train.columns)
```

In [24]:
```
print("Columns having null data in the train dataset:\n",X_train.columns[X_train.isnull().any()].tolist())
```

```
Columns having null data in the train dataset:
 []
```

Filling null values in the test dataset with their mean

In [25]:
```
X_test = pd.DataFrame(imputer.fit_transform(X_test), columns = X_test.columns)
```

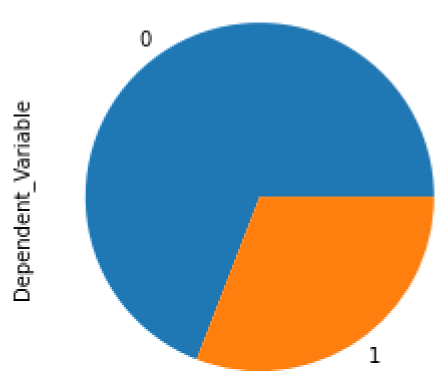
In [26]:
```
print("Columns having null data in the test dataset:\n",X_test.columns[X_test.isnull().any()].tolist())
```

```
Columns having null data in the test dataset:
 []
```

Checking the distribution of the class labels

In [27]:
```
Y_train['Dependent_Variable'].value_counts().plot.pie(figsize=(6,4))
```

Out[27]: `<AxesSubplot:ylabel='Dependent_Variable'>`



We can see that the training data is highly imbalanced

Using SMOTE (Synthetic Minority Oversampling Technique) to balance the class distribution by randomly increasing minority class examples by replicating them

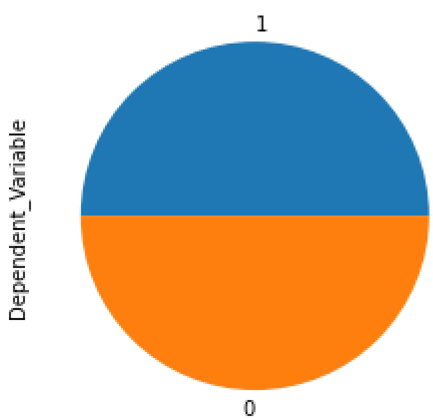
In [28]:
```
smote = SMOTE(sampling_strategy='minority')
X_train, Y_train = smote.fit_resample(X_train, Y_train)
```

In [29]:
```
print(X_train.shape)
print(Y_train.shape)
```

```
(45688, 31)
(45688, 1)
```

In [30]:
```
Y_train['Dependent_Variable'].value_counts().plot.pie(figsize=(6,4))
```

Out[30]: <AxesSubplot:ylabel='Dependent_Variable'>



In [31]:
```
X_train.head(2)
```

Out[31]:

	C1	C2	C3	C4	C5	C6	C7	C8	N1	N2	...	N16	N17	
0	1.0	0.0	11.0	31.0	0.0	0.0	0.0	1.0	23.75	81.34271	...	0.023203	15820.726797	0.528
1	1.0	4.0	2.0	66.0	2.0	0.0	1.0	1.0	11.05	22.00000	...	0.000000	1944.000000	0.060

2 rows × 31 columns

In [32]:
```
Y_train.head(2)
```

Out[32]:

	Dependent_Variable
0	1
1	0

In [33]:
```
X_test.head(2)
```

Out[33]:

	C1	C2	C3	C4	C5	C6	C7	C8	N1	N2	...	N16	N17	
0	1.0	0.0	0.0	23.0	0.0	1.0	0.0	1.0	18.00	81.279492	...	0.024032	15937.365096	0.53
1	1.0	0.0	2.0	4.0	2.0	1.0	2.0	1.0	16.75	107.000000	...	0.000000	59435.000000	0.83

2 rows × 31 columns

Preprocessing the numerical values

After trying both normalizing the numerical values and standardizing the numerical values, it was found that standardizing works better. So, we standardize the numerical values in the training and test dataset

In [34]:
```
scaler = preprocessing.StandardScaler()
```

In [35]:
```
X_train = pd.DataFrame(scaler.fit_transform(X_train), columns = X_train.column
s)
X_train.head()
```

Out[35]:

	C1	C2	C3	C4	C5	C6	C7	C8	
0	-0.302789	-0.719094	-0.158062	1.156846	-1.319561	-0.961579	-1.452604	0.30378	0.
1	-0.302789	0.512251	-0.946089	3.541748	0.216968	-0.961579	-0.986711	0.30378	-1
2	-0.302789	-0.719094	0.542405	-0.819216	-1.319561	-0.961579	-1.452604	0.30378	1.
3	-0.302789	-0.411258	0.279730	2.247087	-0.551297	-0.961579	0.410968	0.30378	-0
4	-0.302789	-0.411258	0.017055	-0.887356	-0.551297	1.120599	1.342754	0.30378	0.

5 rows × 31 columns

In [36]:
```
X_test = pd.DataFrame(scaler.transform(X_test), columns = X_test.columns)
X_test.head()
```

Out[36]:

	C1	C2	C3	C4	C5	C6	C7	C8
0	-0.302789	-0.719094	-1.121206	0.611726	-1.319561	1.120599	-1.452604	0.303780
1	-0.302789	-0.719094	-0.946089	-0.682936	0.216968	1.120599	-0.520818	0.303780
2	-0.302789	-0.103421	-0.858530	1.633827	-0.551297	-0.961579	0.410968	0.303780
3	-0.302789	-0.411258	1.330432	0.407305	0.216968	-0.961579	-0.520818	0.303780
4	-0.302789	-0.411258	0.192171	-0.887356	0.985232	-0.961579	0.876861	-3.567258

5 rows × 31 columns

Implementing Machine Learning Models

Logisitic Regression

In [37]:
```
parameters = {"C":[10**-x for x in range(-3,3)]}

model = LogisticRegression(penalty='l2', random_state=0)
clf_log = GridSearchCV(model, parameters, cv=10, scoring='roc_auc', n_jobs=-1)
clf_log.fit(X_train,Y_train.values.ravel())

print("Best estimator=", clf_log.best_estimator_)
print("Best score =", clf_log.best_score_)
```

```
Best estimator= LogisticRegression(C=100, random_state=0)
Best score = 0.7502915727859788
```

In [38]:
```
model_log = LogisticRegression(C= clf_log.best_params_['C'], penalty='l2', ran
dom_state=0)
model_log.fit(X_train, Y_train.values.ravel())

Y_pred_log = model_log.predict_proba(X_test)
```

Decision Trees

In [39]:
```
model_DT = DecisionTreeClassifier(random_state=0)
parameters={'criterion': ['gini','entropy','log_loss'] ,'min_samples_split':[4
,8,10,12], 'max_features':['sqrt','log2','None']}
clf_DT = GridSearchCV(model_DT, parameters, cv=10, scoring='roc_auc', n_jobs=-
1)
clf_DT.fit(X_train, Y_train.values.ravel())

print("Best estimator=", clf_DT.best_estimator_)
print("Best score=", clf_DT.best_score_)
```

```
Best estimator= DecisionTreeClassifier(criterion='entropy', max_features='sqr
t',
                       min_samples_split=12, random_state=0)
Best score= 0.7673087437186636
```

In [40]:
```
model_DT = RandomForestClassifier(criterion = clf_DT.best_params_['criterion']
                                  , min_samples_split= clf_DT.best_params_['mi
n_samples_split']
                                  , max_features = clf_DT.best_params_['max_fe
atures']
                                  , random_state=0)
model_DT.fit(X_train, Y_train.values.ravel())

Y_pred_DT = model_DT.predict_proba(X_test)
```

Random Forest

In [43]:
```
model_RF = RandomForestClassifier(random_state=0)
parameters={'criterion': ['gini','entropy','log_loss']
            , 'min_samples_split':[4,8,10,12]
            , 'n_estimators':[350, 400, 500]
            , 'max_features':['sqrt','log2','None']}
clf_RF = GridSearchCV(model_RF, parameters, cv=10, scoring='roc_auc', n_jobs=-
1)
clf_RF.fit(X_train, Y_train.values.ravel())

print("Best estimator=", clf_RF.best_estimator_)
print("Best score=", clf_RF.best_score_)
```

```
Best estimator= RandomForestClassifier(criterion='entropy', max_features='sqr
t',
                       min_samples_split=4, n_estimators=500, random_state=0)
Best score= 0.9025488993051087
```

In [44]:
```
model_RF = RandomForestClassifier(criterion = clf_RF.best_params_['criterion']
                                  , min_samples_split= clf_RF.best_params_['mi
n_samples_split']
                                  , max_features = clf_RF.best_params_['max_fe
atures']
                                  , n_estimators= clf_RF.best_params_['n_estim
ators']
                                 , random_state=0)
model_RF.fit(X_train, Y_train.values.ravel())

Y_pred_RF = model_RF.predict_proba(X_test)
```

Gradient Boosting Decision Trees

In [46]:
```
model_GBDT = GradientBoostingClassifier(random_state=0)
parameters = {'learning_rate':[0.1, 0.2, 0.3, 0.4]
              , 'min_samples_split':[4,8,10,12]
              , 'n_estimators':[200, 300, 400, 500]
              , 'max_features':['sqrt','log2','None']}
clf_GBDT = GridSearchCV(model_GBDT, parameters, cv=10, scoring='roc_auc', n_jo
bs=-1)
clf_GBDT.fit(X_train, Y_train.values.ravel())

print("Best estimator=", clf_GBDT.best_estimator_)
print("Best score=", clf_GBDT.best_score_)
```

```
Best estimator= GradientBoostingClassifier(learning_rate=0.2, max_features='s
qrt',
                           min_samples_split=10, n_estimators=500,
                           random_state=0)
Best score= 0.8931136232903331
```

In [47]:
```
model_GBDT = GradientBoostingClassifier(learning_rate= clf_GBDT.best_params_[
'learning_rate']
                                        , min_samples_split= clf_GBDT.best_par
ams_['min_samples_split']
                                        , n_estimators= clf_GBDT.best_params_[
'n_estimators']
                                        , max_features= clf_GBDT.best_params_[
'max_features']

                                       )
model_GBDT.fit(X_train, Y_train.values.ravel())

Y_pred_GBDT = model_GBDT.predict_proba(X_test)
```

Summary

In [66]:
```
# assigning data
table_data = [("Logistic Regression", clf_log.best_score_)
              ,("Decision Trees", clf_DT.best_score_)
              ,("Random Forest", clf_RF.best_score_)
              ,("Gradient Boosting Decision Trees", clf_GBDT.best_score_)
             ]

# creating header
table_head = ["Model", "Mean cross-validated roc-auc score calculated using Gr
idSearcCV"]

# displaying the table
print(tabulate(table_data, headers=table_head, tablefmt="grid"))
```

```
+---------------------------------+-----------------------------------------
-------------------------+
| Model                           |   Mean cross-validated roc-auc score cal
culated using GridSearcCV |
+=================================+=========================================
=========================+
| Logistic Regression             |
0.750292 |
+---------------------------------+-----------------------------------------
-------------------------+
| Decision Trees                  |
0.767309 |
+---------------------------------+-----------------------------------------
-------------------------+
| Random Forest                   |
0.902549 |
+---------------------------------+-----------------------------------------
-------------------------+
| Gradient Boosting Decision Trees |
0.893114 |
+---------------------------------+-----------------------------------------
-------------------------+
```

As we can see that the mean cross-validated roc-auc score using Random Forest is the highest, we will use Random Forest model to predict the class labels of the test dataset

Predicting Dependent_Variable using RandomForest model

In [71]:
```
Class_1_Probability_RF = pd.DataFrame(Y_pred_RF, columns=model_DT.classes_)[1]
.to_numpy()
Class_1_Probability_RF
```

Out[71]:
```
array([0.5236    , 0.3793    , 0.34496667, ..., 0.42028571, 0.3007    ,
       0.22995   ])
```

In [72]:
```
result_df = pd.DataFrame(X_test_df['Unique_ID'].copy())
```

In [73]:
```
result_df['Class_1_Probability'] = Class_1_Probability_RF
result_df.head()
```

Out[73]:

	Unique_ID	Class_1_Probability
0	Candidate_1602	0.523600
1	Candidate_29650	0.379300
2	Candidate_31061	0.344967
3	Candidate_5768	0.203617
4	Candidate_27059	0.535033

Dataframe to csv

In [77]:
```
result_df.to_csv(r"D:\Monsoon Credittech\DS Test\DS Test\Test\final_prediction
s.csv", index = False)
```