PROBLEM STATEMENT

You are a Data scientist at the Forest bank, and the bank has been facing a number of fraudulent transactions. Fradulent transaction are those which are not done by the user itself but by a hacker or by a card thief or by doing a fishing attack. The bank has a huge dataset of it's credit card users and the bank has also done the job of marking these transactions as fraudulent or not. You being banks' Data science expert have been given the task to first analyse this data and generate insights and then predict if a transaction on a credit card is going to be fraud or not.

IMPORT LIBRARIES

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
import warnings
warnings.filterwarnings("ignore")
```

UNDERSTAND DATASET

```
train_data= pd.read_csv("fraudTrain.csv")
test_data=pd.read_csv("fraudTest.csv")
```

Data Dictionary

- **transdatetrans_time:** The date and time of the transaction.
- **cc_num:** credit card number.
- **merchant:** Merchant who was getting paid.
- **category:** In what area does that merchant deal.
- **amt:** Amount of money in American Dollars.

- **first:** first name of the card holder.
- **last:** last name of the card holder.
- **gender:** Gender of the cardholder.Just male and female!
- **street:** Street of card holder residence
- **city:** city of card holder residence
- **state:** state of card holder residence
- **zip:** ZIP code of card holder residence
- **lat:** latitude of card holder
- **long:** longitude of card holder
- **city_pop:** Population of the city
- **job:** trade of the card holder
- **dob:** Date of birth of the card holder
- **trans_num:** Transaction ID
- **unix_time:** Unix time which is the time calculated since 1970 to today.
- **merch_lat:** latitude of the merchant
- **merch_long:** longitude of the merchant
- **is_fraud:** Whether the transaction is fraud(1) or not(0)

```
train_data.head()

   Unnamed: 0 trans_date_trans_time            cc_num  \
0           0   2019-01-01 00:00:18  2703186189652095
1           1   2019-01-01 00:00:44      630423337322
2           2   2019-01-01 00:00:51    38859492057661
3           3   2019-01-01 00:01:16  3534093764340240
4           4   2019-01-01 00:03:06   375534208663984

                             merchant       category     amt
first  \
0          fraud_Rippin, Kub and Mann       misc_net    4.97
Jennifer
1     fraud_Heller, Gutmann and Zieme    grocery_pos  107.23
Stephanie
2                fraud_Lind-Buckridge  entertainment  220.11
Edward
3  fraud_Kutch, Hermiston and Farrell  gas_transport   45.00
```

```
Jeremy
4                 fraud_Keeling-Crist       misc_pos   41.96
Tyler

      last gender                        street  ...      lat
long  \
0    Banks      F                561 Perry Cove  ...  36.0788  -
81.1781
1     Gill      F  43039 Riley Greens Suite 393  ...  48.8878 -
118.2105
2  Sanchez      M      594 White Dale Suite 530  ...  42.1808 -
112.2620
3    White      M   9443 Cynthia Court Apt. 038  ...  46.2306 -
112.1138
4   Garcia      M              408 Bradley Rest  ...  38.4207  -
79.4629

   city_pop                                job         dob  \
0      3495           Psychologist, counselling  1988-03-09
1       149  Special educational needs teacher  1978-06-21
2      4154         Nature conservation officer  1962-01-19
3      1939                    Patent attorney  1967-01-12
4        99     Dance movement psychotherapist  1986-03-28

                          trans_num   unix_time  merch_lat  merch_long
\
0  0b242abb623afc578575680df30655b9  1325376018  36.011293  -82.048315

1  1f76529f8574734946361c461b024d99  1325376044  49.159047 -118.186462

2  a1a22d70485983eac12b5b88dad1cf95  1325376051  43.150704 -112.154481

3  6b849c168bdad6f867558c3793159a81  1325376076  47.034331 -112.561071

4  a41d7549acf90789359a9aa5346dcb46  1325376186  38.674999  -78.632459


   is_fraud
0         0
1         0
2         0
3         0
4         0

[5 rows x 23 columns]

test_data.head()

   Unnamed: 0 trans_date_trans_time            cc_num  \
0           0   2020-06-21 12:14:25  2291163933867244
1           1   2020-06-21 12:14:33  3573030041201292
```

```
2           2   2020-06-21 12:14:53  3598215285024754
3           3   2020-06-21 12:15:15  3591919803438423
4           4   2020-06-21 12:15:17  3526826139003047

                                merchant        category    amt   first
\
0                   fraud_Kirlin and Sons   personal_care   2.86    Jeff

1                    fraud_Sporer-Keebler   personal_care  29.84  Joanne

2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28  Ashley

3                       fraud_Haley Group        misc_pos  60.05   Brian

4                   fraud_Johnston-Casper          travel   3.19  Nathan


       last gender                       street  ...      lat
long  \
0   Elliott      M            351 Darlene Green  ...  33.9659  -
80.9355
1  Williams      F             3638 Marsh Union  ...  40.3207 -
110.4360
2     Lopez      F         9333 Valentine Point  ...  40.6729  -
73.5365
3  Williams      M  32941 Krystal Mill Apt. 552  ...  28.5697  -
80.8191
4    Massey      M     5783 Evan Roads Apt. 465  ...  44.2529  -
85.0170

   city_pop                       job         dob  \
0    333497       Mechanical engineer  1968-03-19
1       302  Sales professional, IT  1990-01-17
2     34496       Librarian, public  1970-10-21
3     54767            Set designer  1987-07-25
4      1126      Furniture designer  1955-07-06

                          trans_num   unix_time  merch_lat  merch_long
\
0  2da90c7d74bd46a0caf3777415b3ebd3  1371816865  33.986391  -81.200714

1  324cc204407e99f51b0d6ca0055005e7  1371816873  39.450498 -109.960431

2  c81755dbbbea9d5c77f094348a7579be  1371816893  40.495810  -74.196111

3  2159175b9efe66dc301f149d3d5abf8c  1371816915  28.812398  -80.883061

4  57ff021bd3f328f8738bb535c302a31b  1371816917  44.959148  -85.884734


   is_fraud
```

```
0         0
1         0
2         0
3         0
4         0

[5 rows x 23 columns]
```

```
train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296675 entries, 0 to 1296674
Data columns (total 23 columns):
 #   Column                 Non-Null Count    Dtype
---  ------                 --------------    -----
 0   Unnamed: 0             1296675 non-null  int64
 1   trans_date_trans_time  1296675 non-null  object
 2   cc_num                 1296675 non-null  int64
 3   merchant               1296675 non-null  object
 4   category               1296675 non-null  object
 5   amt                    1296675 non-null  float64
 6   first                  1296675 non-null  object
 7   last                   1296675 non-null  object
 8   gender                 1296675 non-null  object
 9   street                 1296675 non-null  object
 10  city                   1296675 non-null  object
 11  state                  1296675 non-null  object
 12  zip                    1296675 non-null  int64
 13  lat                    1296675 non-null  float64
 14  long                   1296675 non-null  float64
 15  city_pop               1296675 non-null  int64
 16  job                    1296675 non-null  object
 17  dob                    1296675 non-null  object
 18  trans_num              1296675 non-null  object
 19  unix_time              1296675 non-null  int64
 20  merch_lat              1296675 non-null  float64
 21  merch_long             1296675 non-null  float64
 22  is_fraud               1296675 non-null  int64
dtypes: float64(5), int64(6), object(12)
memory usage: 227.5+ MB
```

```
train_data.columns
```

```
Index(['Unnamed: 0', 'trans_date_trans_time', 'cc_num', 'merchant',
'category',
       'amt', 'first', 'last', 'gender', 'street', 'city', 'state',
'zip',
       'lat', 'long', 'city_pop', 'job', 'dob', 'trans_num',
'unix_time',
```

```
       'merch_lat', 'merch_long', 'is_fraud'],
      dtype='object')
```

Data Cleaning

Data cleaning by removing all unimportant columns that cotnains personal information and missing values

```
columns_to_drop = ["Unnamed: 0","trans_date_trans_time","cc_num","first","last",'street','zip','lat','long','dob','trans_num','unix_time','merch_lat','merch_long']
train_data = train_data.drop(columns=columns_to_drop)
#'category','gender','job','merchant','amt',
'city','city_pop','state','is_fraud
#columns_to_drop =["Unamed: 0
","trans_date_trans_time","cc_num","first","last",'street','zip','lat','long','dob','trans_num','unix_time','merch_lat','merch_long']
#columns_to_drop = ['trans_date_trans_time',"cc_num","first","last"]

columns_to_drop = ["Unnamed: 0","trans_date_trans_time","cc_num","first","last",'street','zip','lat','long','dob','trans_num','unix_time','merch_lat','merch_long']
test_data = test_data.drop(columns=columns_to_drop)

train_data.head()

                             merchant       category     amt gender  \
0          fraud_Rippin, Kub and Mann       misc_net    4.97      F
1     fraud_Heller, Gutmann and Zieme    grocery_pos  107.23      F
2                fraud_Lind-Buckridge  entertainment  220.11      M
3  fraud_Kutch, Hermiston and Farrell  gas_transport   45.00      M
4                 fraud_Keeling-Crist       misc_pos   41.96      M

             city state  city_pop                                job
is_fraud
0  Moravian Falls    NC      3495          Psychologist, counselling
0
1          Orient    WA       149  Special educational needs teacher
0
2      Malad City    ID      4154        Nature conservation officer
0
3         Boulder    MT      1939                    Patent attorney
0
4        Doe Hill    VA        99      Dance movement psychotherapist
0

test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 555719 entries, 0 to 555718
Data columns (total 9 columns):
 #   Column    Non-Null Count   Dtype
---  ------    --------------   -----
 0   merchant  555719 non-null  object
 1   category  555719 non-null  object
 2   amt       555719 non-null  float64
 3   gender    555719 non-null  object
 4   city      555719 non-null  object
 5   state     555719 non-null  object
 6   city_pop  555719 non-null  int64
 7   job       555719 non-null  object
 8   is_fraud  555719 non-null  int64
dtypes: float64(1), int64(2), object(6)
memory usage: 38.2+ MB
```

```
train_data.shape
```

```
(1296675, 9)
```

There are overall total 1296675 rows and 9 columns in train dataset

```
test_data.shape
```

```
(555719, 9)
```

There are overall total 555719 rows and 9 columns in train dataset.

```
train_data.isna().sum()
```

```
merchant    0
category    0
amt         0
gender      0
city        0
state       0
city_pop    0
job         0
is_fraud    0
dtype: int64
```

```
test_data.isna().sum()
```

```
merchant    0
category    0
amt         0
gender      0
city        0
state       0
```

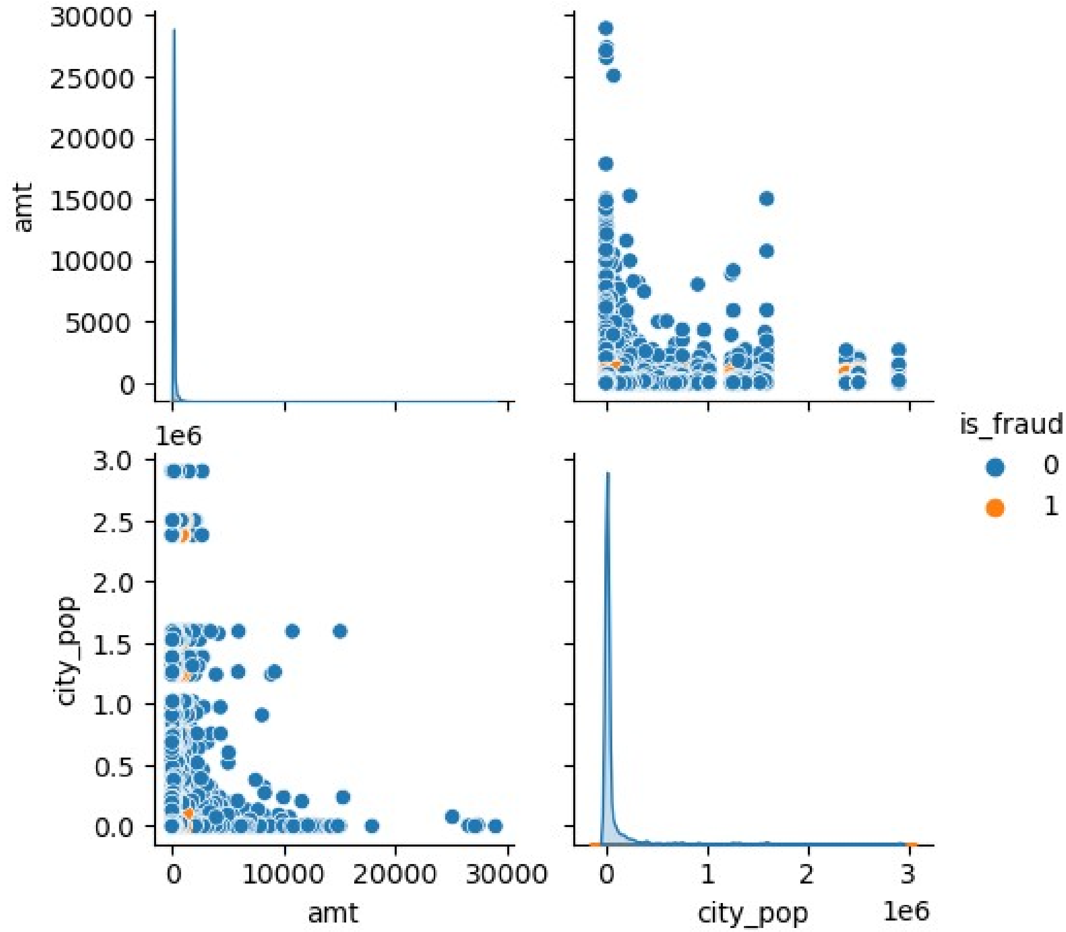
```
city_pop    0
job         0
is_fraud    0
dtype: int64
```

There are no null values present in dataset. Hence, there is no need to perform missing value treatment.

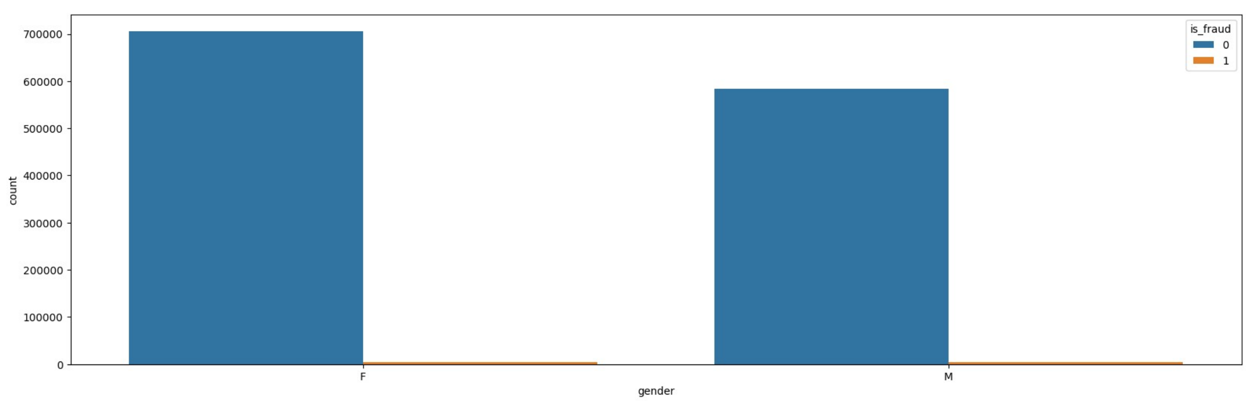
```
train_data.columns

Index(['merchant', 'category', 'amt', 'gender', 'city', 'state',
'city_pop',
       'job', 'is_fraud'],
      dtype='object')
```

EXPLORATORY DATA ANALYSIS

```
plt.figure(figsize=(15,2))
sns.pairplot(train_data[['category', 'gender', 'job', 'merchant',
'amt', 'city', 'city_pop', 'state', 'is_fraud']], hue='is_fraud')
plt.show()

<Figure size 1500x200 with 0 Axes>
```

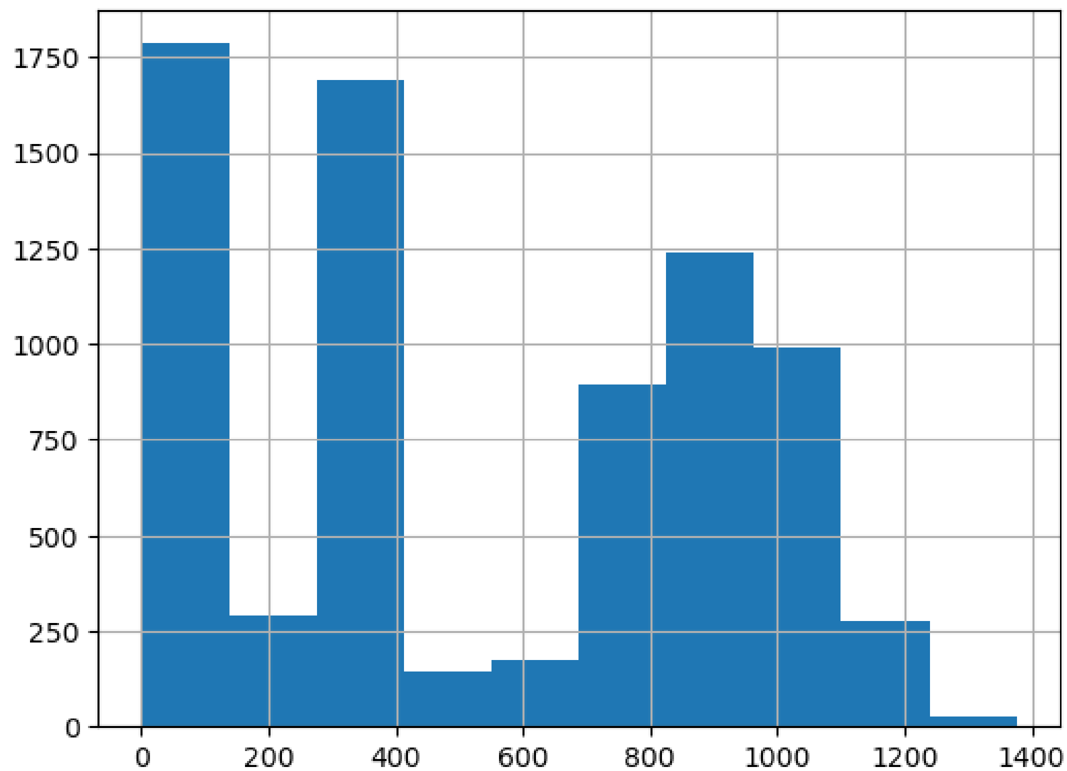



```
plt.figure(figsize=(20,6))
sns.countplot(data=train_data, x = 'gender',hue='is_fraud')
plt.show()
```




```
train_data[train_data.is_fraud==1]['amt'].hist()
```

```
<Axes: >
```



As can be seen in the histogram, around 1750+ fraudulent transactions were in the bucket 0-100 dollars and least on the 1200-1400 dollars bucket

ENCODING

```
numerical = []
categorical = []
for i in train_data.columns:
    if train_data[i].dtype == 'int64' or train_data[i].dtype ==
'float64':
        numerical.append(i)
    else:
        categorical.append(i)


numerical_test = []
categorical_test = []
for i in test_data.columns:
    if test_data[i].dtype == 'int64' or test_data[i].dtype ==
'float64':
        numerical_test.append(i)
    else:
        categorical_test.append(i)
```

```
binary_cols = []
for col in train_data.select_dtypes(include=['int', 'float']).columns:
    unique_values = train_data[col].unique()
    if np.in1d(unique_values, [0, 1]).all():
        binary_cols.append(col)


numerical = [i for i in numerical if i not in binary_cols]

binary_cols_test = []
for col in train_data.select_dtypes(include=['int', 'float']).columns:
    unique_values = train_data[col].unique()
    if np.in1d(unique_values, [0, 1]).all():
        binary_cols_test.append(col)

numerical_test = [i for i in numerical if i not in binary_cols]

for i in categorical:
        train_data[i] = train_data[i].astype('category')
        train_data[i] = train_data[i].cat.codes

for i in categorical_test:
        test_data[i] = test_data[i].astype('category')
        test_data[i] = test_data[i].cat.codes
```

FEATURE SCALING

```
from sklearn.preprocessing import StandardScaler
sc_x = StandardScaler()
train_data[numerical] = sc_x.fit_transform(train_data[numerical])


sc_x = StandardScaler()
test_data[numerical] = sc_x.fit_transform(test_data[numerical_test])

test_data.head()
```

	merchant	category	amt	gender	city	state	city_pop	job	is_fraud
0	319	10	-0.424463	1	157	39	0.816521	275	0
1	591	10	-0.252337	0	16	43	-0.292685	392	0
2	611	5	-0.179353	0	61	33	-0.178853	259	0
3	222	9	-0.059605	1	764	8	-0.111371	407	0
4	292	13	-0.422358	1	247	21	-0.289942	196	0

```
train_data.head()
```

```
   merchant  category       amt  gender  city  state  city_pop  job
is_fraud
0       514         8 -0.407826       0   526     27 -0.282589  370
0
1       241         4  0.230039       0   612     47 -0.293670  428
0
2       390         0  0.934149       1   468     13 -0.280406  307
0
3       360         2 -0.158132       1    84     26 -0.287742  328
0
4       297         9 -0.177094       1   216     45 -0.293835  116
0
```

CLASSIFICATIONS MODEL TO PREDICT FRAUDLENT OR NOT

```
x_train = train_data.drop('is_fraud', axis=1)
y_train = train_data['is_fraud']

x_test = test_data.drop('is_fraud', axis=1)
y_test = test_data['is_fraud']
```

MODEL 1: LOGISTIC REGRESSION

```
logistic_reg = LogisticRegression()
logistic_reg.fit(x_train, y_train)
y_pred_logistic = logistic_reg.predict(x_test)
accuracy_logistic = accuracy_score(y_test, y_pred_logistic)
print(f"Logistic Regression Accuracy: {accuracy_logistic:}")
```

```
Logistic Regression Accuracy: 0.9955139198047934
```

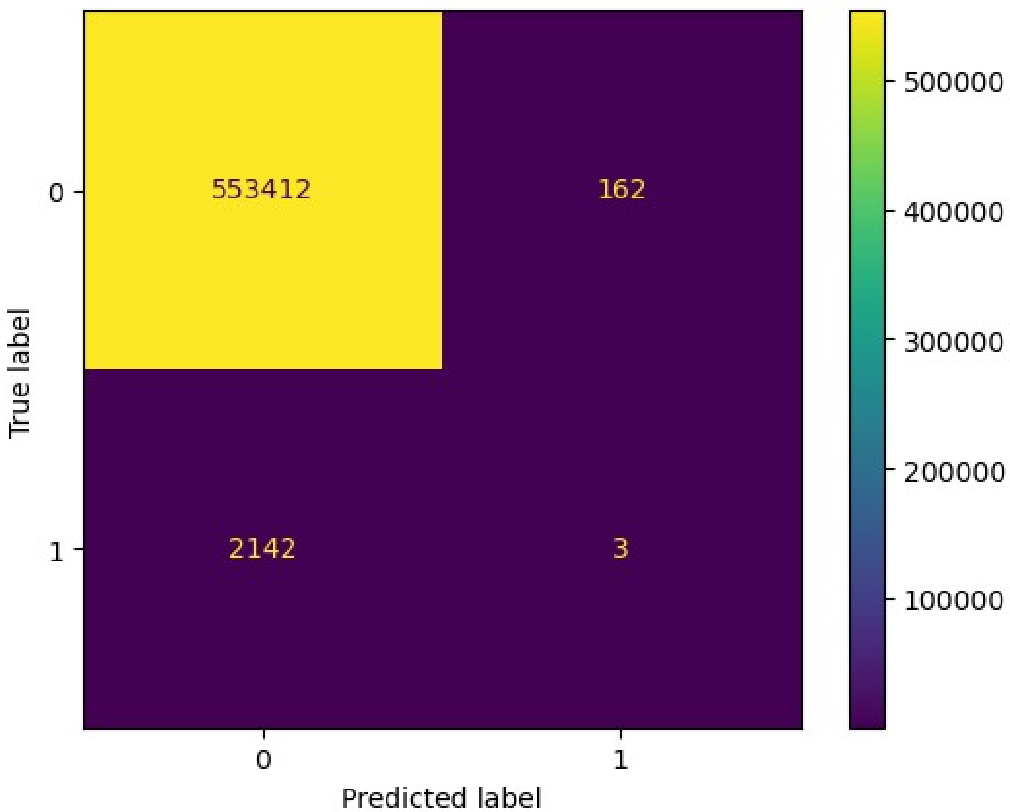
MODEL 2:KNN

```
knn = KNeighborsClassifier()
knn.fit(x_train, y_train)
y_pred_knn = knn.predict(x_test)
accuracy_knn = accuracy_score(y_test, y_pred_knn)
print(f"K-Nearest Neighbors Accuracy: {accuracy_knn:}")
```

```
K-Nearest Neighbors Accuracy: 0.9958540197473903
```

```python
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm= confusion_matrix(y_test, y_pred_knn)

cm_disp= ConfusionMatrixDisplay(confusion_matrix=cm)

cm_disp.plot()
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x1ef890fac10>
```




```python
from sklearn.metrics import classification_report, accuracy_score,
log_loss

target_names= ["Negative(0)","Positive(1)"]
# Classification Report
print(classification_report(y_test,knn.predict(x_test),target_names=ta
rget_names))
```

```
              precision    recall  f1-score   support

 Negative(0)       1.00      1.00      1.00    553574
 Positive(1)       0.02      0.00      0.00      2145

    accuracy                           1.00    555719
   macro avg       0.51      0.50      0.50    555719
```

```
weighted avg       0.99      1.00      0.99    555719
```

```
accuracy_score(y_test, y_pred_knn)
```

```
0.9958540197473903
```

MODEL 3: DECISION TREE

```
decision_tree = DecisionTreeClassifier()
decision_tree.fit(x_train, y_train)
y_pred_tree = decision_tree.predict(x_test)
accuracy_tree = accuracy_score(y_test, y_pred_tree)
print(f"Decision Tree Accuracy: {accuracy_tree:}")
```

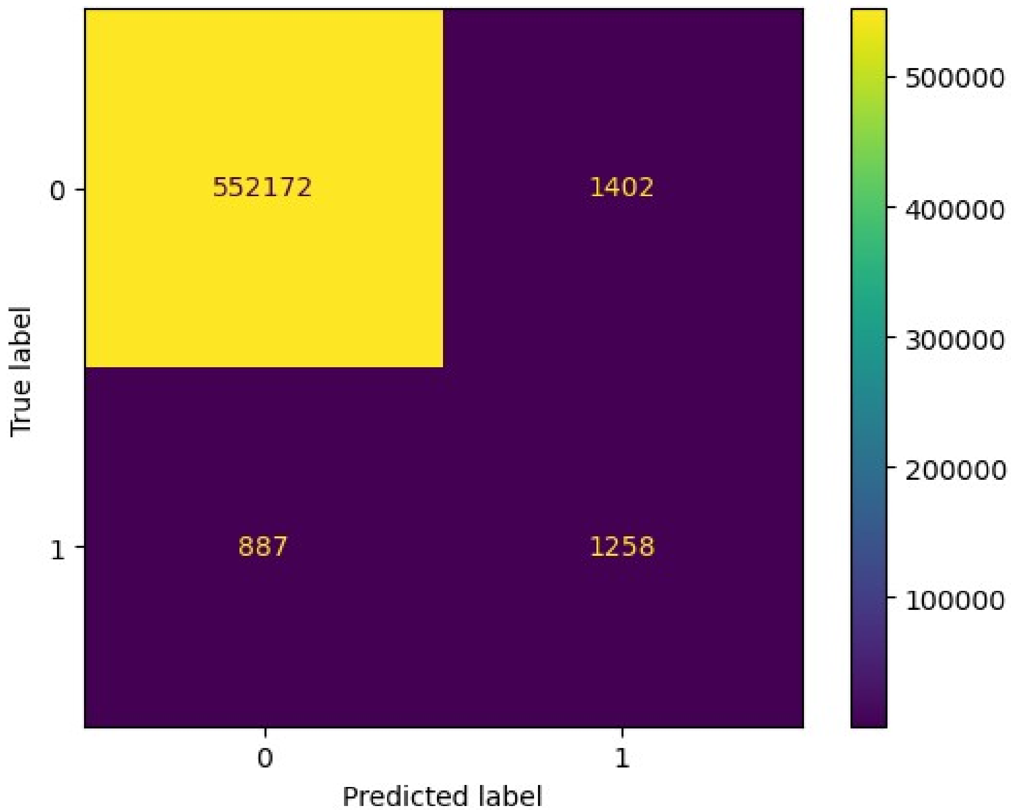
```
Decision Tree Accuracy: 0.9958810118063266
```

```
cm_dt= confusion_matrix(y_test, y_pred_tree)
```

```
cm_disp= ConfusionMatrixDisplay(confusion_matrix=cm_dt)
```

```
cm_disp.plot()
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x1ef88fa64d0>
```




```
target_names= ["Negative(0)","Positive(1)"]
# Classification Report
print(classification_report(y_test,decision_tree.predict(x_test),targe
t_names=target_names))
```

```
              precision    recall  f1-score   support

 Negative(0)       1.00      1.00      1.00    553574
 Positive(1)       0.47      0.59      0.52      2145

    accuracy                           1.00    555719
   macro avg       0.74      0.79      0.76    555719
weighted avg       1.00      1.00      1.00    555719
```

```
accuracy_score(y_test, y_pred_tree)
```

```
0.9958810118063266
```

MODEL 4: RANDOM FOREST

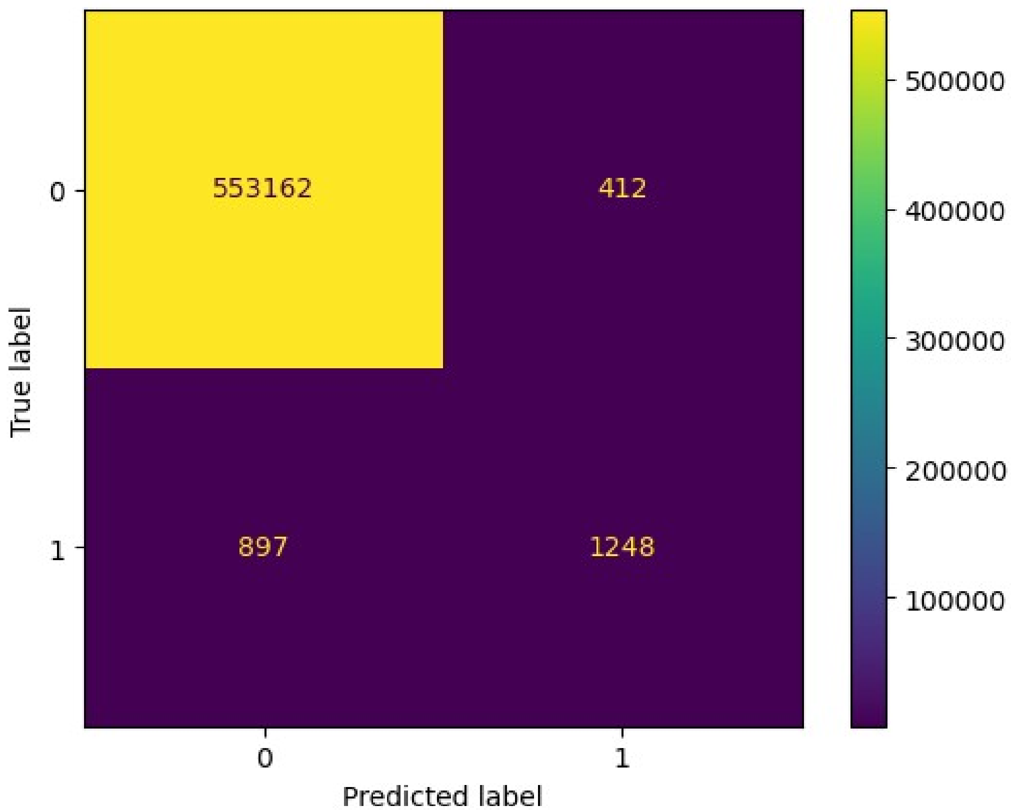
```
random_forest = RandomForestClassifier()
random_forest.fit(x_train, y_train)
```

```python
y_pred_forest = random_forest.predict(x_test)
accuracy_forest = accuracy_score(y_test, y_pred_forest)
print(f"Random Forest Accuracy: {accuracy_forest:}")
```

```
Random Forest Accuracy: 0.9976444929901623
```

```python
cm_rf= confusion_matrix(y_test, y_pred_forest)

cm_disp= ConfusionMatrixDisplay(confusion_matrix=cm_rf)

cm_disp.plot()
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1ef891fb9d0>
```



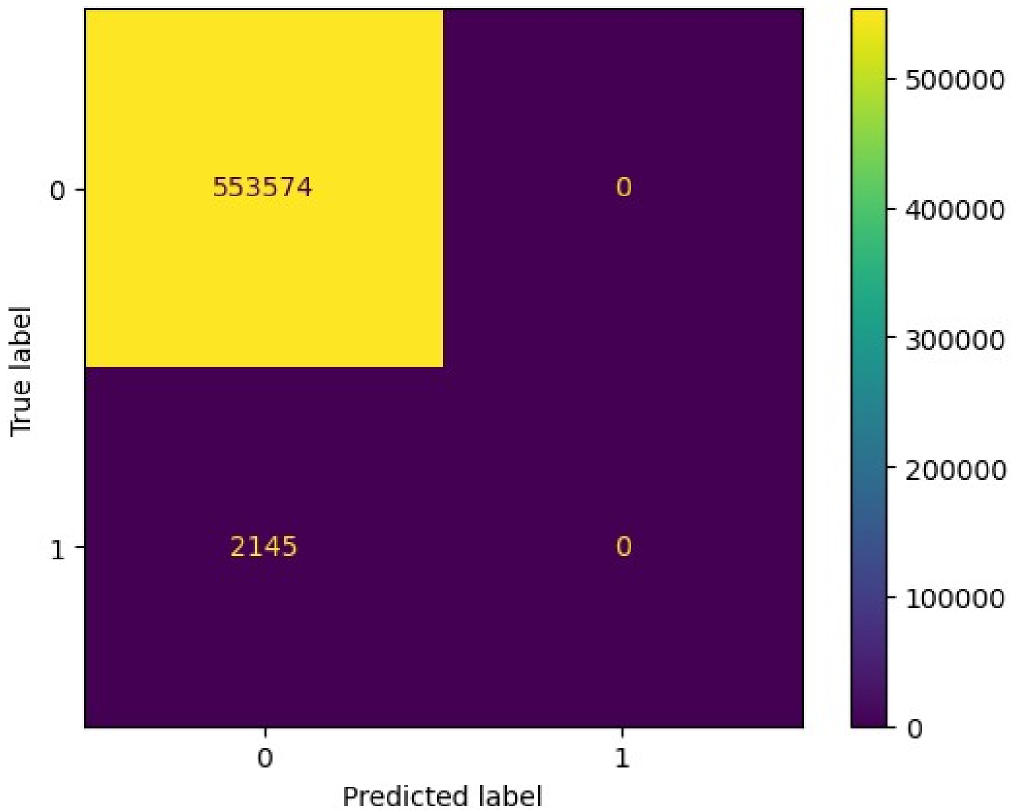

```python
target_names= ["Negative(0)","Positive(1)"]
# Classification Report
print(classification_report(y_test,random_forest.predict(x_test),target_names=target_names))
```

```
              precision    recall  f1-score   support

 Negative(0)       1.00      1.00      1.00    553574
 Positive(1)       0.75      0.58      0.66      2145
```

```
    accuracy                           1.00    555719
   macro avg       0.88      0.79      0.83    555719
weighted avg       1.00      1.00      1.00    555719


accuracy_score(y_test, y_pred_forest)

0.9976444929901623
```

MODEL 5: SVM

```
svm = SVC()
svm.fit(x_train, y_train)
y_pred_svm = svm.predict(x_test)
accuracy_svm = accuracy_score(y_test, y_pred_svm)
print(f"SVM Accuracy: {accuracy_svm:}")

SVM Accuracy: 0.9961401355721147

cm_svm= confusion_matrix(y_test, y_pred_svm)

cm_disp= ConfusionMatrixDisplay(confusion_matrix=cm_svm)

cm_disp.plot()

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x1ef9a77c810>
```




```
target_names= ["Negative(0)","Positive(1)"]
# Classification Report
print(classification_report(y_test,svm.predict(x_test),target_names=ta
rget_names))
```

```
              precision    recall  f1-score   support

 Negative(0)       1.00      1.00      1.00    553574
 Positive(1)       0.00      0.00      0.00      2145

    accuracy                           1.00    555719
   macro avg       0.50      0.50      0.50    555719
weighted avg       0.99      1.00      0.99    555719
```

```
accuracy_score(y_test, y_pred_svm)
```

```
0.9961401355721147
```

All the 5 Models are giving excellent results with more than 99% of accuracy and hence there is no need of tuning any parameter.