In [3]:

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

from imblearn.over_sampling import SMOTE
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
```

In [4]:

```
beneficiary = pd.read_csv("/content/sample_data/Beneficiarydata.csv")
in_patient = pd.read_csv("/content/sample_data/Inpatientdata.csv")
out_patient = pd.read_csv("/content/sample_data/Outpatientdata.csv")
provider = pd.read_csv("/content/sample_data/Provider.csv")
```

In [4]:

Checking for null values in all the tables

In [5]:

```
tables = {
    "Beneficiary": beneficiary,
    "In_patient": in_patient,
    "Out_patient": out_patient,
    "Provider": provider
}

# Loop through each dataframe and check for null values
for name, df in tables.items():
    print(f"\nNull values in {name} table:")
    print(df.isnull().sum())
```

```
Null values in Beneficiary table:
BeneID                                 0
DOB                                    0
DOD                                63394
Gender                                 0
Race                                   0
RenalDiseaseIndicator                  0
State                                  0
County                                 0
NoOfMonths_PartACov                    0
NoOfMonths_PartBCov                    0
ChronicCond_Alzheimer                  0
ChronicCond_Heartfailure               0
ChronicCond_KidneyDisease              0
ChronicCond_Cancer                     0
ChronicCond_ObstrPulmonary             0
ChronicCond_Depression                 0
ChronicCond_Diabetes                   0
ChronicCond_IschemicHeart              0
ChronicCond_Osteoporasis               0
ChronicCond_rheumatoidarthritis        0
ChronicCond_stroke                     0
IPAnnualReimbursementAmt               0
IPAnnualDeductibleAmt                  0
OPAnnualReimbursementAmt               0
OPAnnualDeductibleAmt                  0
dtype: int64

Null values in In_patient table:
BeneID                       0
ClaimID                      0
ClaimStartDt                 0
ClaimEndDt                   0
Provider                     0
InscClaimAmtReimbursed       0
AttendingPhysician          31
OperatingPhysician        3962
OtherPhysician            8538
AdmissionDt                  0
ClmAdmitDiagnosisCode        0
DeductibleAmtPaid          196
DischargeDt                  0
DiagnosisGroupCode           0
ClmDiagnosisCode_1           0
ClmDiagnosisCode_2          54
ClmDiagnosisCode_3         169
ClmDiagnosisCode_4         404
ClmDiagnosisCode_5         719
ClmDiagnosisCode_6        1197
ClmDiagnosisCode_7        1736
ClmDiagnosisCode_8        2360
ClmDiagnosisCode_9        3238
ClmDiagnosisCode_10       8664
ClmProcedureCode_1        4118
ClmProcedureCode_2        8297
ClmProcedureCode_3        9328
ClmProcedureCode_4        9522
ClmProcedureCode_5        9549
ClmProcedureCode_6        9551
dtype: int64
```

```
Null values in Out_patient table:
BeneID                         0
ClaimID                        0
ClaimStartDt                   0
ClaimEndDt                     0
Provider                       0
InscClaimAmtReimbursed         0
AttendingPhysician           316
OperatingPhysician        104237
OtherPhysician             78222
ClmDiagnosisCode_1          2578
ClmDiagnosisCode_2         47731
ClmDiagnosisCode_3         76575
ClmDiagnosisCode_4         95371
ClmDiagnosisCode_5        107875
ClmDiagnosisCode_6        114035
ClmDiagnosisCode_7        117871
ClmDiagnosisCode_8        120310
ClmDiagnosisCode_9        122278
ClmDiagnosisCode_10       125578
ClmProcedureCode_1        125807
ClmProcedureCode_2        125832
ClmProcedureCode_3        125839
ClmProcedureCode_4        125841
ClmProcedureCode_5        125841
ClmProcedureCode_6        125841
DeductibleAmtPaid              0
ClmAdmitDiagnosisCode     100036
dtype: int64

Null values in Provider table:
Provider    0
dtype: int64
```

In [6]:
```
# Here we can there are no null values in primary key cols of the table
```

In [7]:
```
# These are the required features to be included.


# Target Variable: Flag claims as fraudulent or non-fraudulent (based on provide


# Features to include:
# Claim amount (InscClaimAmtReimbursed)
# Provider ID
# Number of physicians involved
# Chronic conditions
# Claim type (inpatient / outpatient)
```

In [8]:
```
# In order to have these features we need a summary table where we can only have
```

In [9]:
```
# Adding a claim type column to both the in_patient and out_patient table
in_patient["ClaimType"] = "Inpatient"
out_patient["ClaimType"] = "Outpatient"
```

In [10]:
```
# Adding a physician count column to both the in_patient and out_patient table
def count_physicians(row):
  return sum([ pd.notna(row.get("AttendingPhysician")),
                pd.notna(row.get("OperatingPhysician")),
                pd.notna(row.get("OtherPhysician"))
            ])

in_patient["NumPhysicians"] = in_patient.apply(count_physicians, axis=1)
out_patient["NumPhysicians"] = out_patient.apply(count_physicians, axis=1)
```

In [11]:

```
# Selecting the relevant columns
in_patient_sel = in_patient[["BeneID", "ClaimID", "InscClaimAmtReimbursed", "Prc
out_patient_sel = out_patient[["BeneID", "ClaimID", "InscClaimAmtReimbursed", "P
```

In [12]:

```
# Combine inpatient and outpatient
claims = pd.concat([in_patient_sel, out_patient_sel], ignore_index=True)
```

In [13]:

```
# Here we now have a combined claims table from both in_patient and out_patient
claims.head()
```

Out[13]:

	BeneID	ClaimID	InscClaimAmtReimbursed	Provider	NumPhysicians	ClaimTy
0	BENE11014	CLM67387	9000	PRV57070	2	Inpatie
1	BENE11017	CLM31237	14000	PRV54750	2	Inpatie
2	BENE11026	CLM78930	2000	PRV53758	1	Inpatie
3	BENE11031	CLM56810	16000	PRV55825	2	Inpatie
4	BENE11085	CLM34625	19000	PRV52338	1	Inpatie

In [14]:

```
# Now we will merge the claims table with beneficiary

# Here we will create the chronic condition col.

chronic_cols = [ "ChronicCond_Alzheimer",
                 "ChronicCond_Heartfailure",
                 "ChronicCond_KidneyDisease",
                 "ChronicCond_Cancer",
                 "ChronicCond_ObstrPulmonary",
                 "ChronicCond_Depression",
                 "ChronicCond_Diabetes",
                 "ChronicCond_IschemicHeart",
                 "ChronicCond_Osteoporasis",
                 "ChronicCond_rheumatoidarthritis",
                 "ChronicCond_stroke"  ]

# This is our final summary table after pulling data from all the tables

df = claims.merge(beneficiary[["BeneID", "Gender", "Race"] + chronic_cols], on =
df.head()
```

Out[14]:

	BeneID	ClaimID	InscClaimAmtReimbursed	Provider	NumPhysicians	ClaimTy
0	BENE11014	CLM67387	9000	PRV57070	2	Inpatie
1	BENE11017	CLM31237	14000	PRV54750	2	Inpatie
2	BENE11026	CLM78930	2000	PRV53758	1	Inpatie
3	BENE11031	CLM56810	16000	PRV55825	2	Inpatie
4	BENE11085	CLM34625	19000	PRV52338	1	Inpatie

In [15]:

```
# Now we need to create a col that flags claims
# It wil tell us if the claims are approved or not

df["ClaimApproved"] = df["InscClaimAmtReimbursed"].apply(lambda x: 1 if x > 0 el
```

In [16]:

```
df["ClaimApproved"].value_counts()
```

Out[16]:

	count
ClaimApproved	
1	130469
0	4923

dtype: int64

In [17]:

```
# Here we can see the distribution of Approved (x = 1) and not (x = 0) claims
```

In [18]:

```
df.head()
```

Out[18]:

	BeneID	ClaimID	InscClaimAmtReimbursed	Provider	NumPhysicians	ClaimTy
0	BENE11014	CLM67387	9000	PRV57070	2	Inpatie
1	BENE11017	CLM31237	14000	PRV54750	2	Inpatie
2	BENE11026	CLM78930	2000	PRV53758	1	Inpatie
3	BENE11031	CLM56810	16000	PRV55825	2	Inpatie
4	BENE11085	CLM34625	19000	PRV52338	1	Inpatie

In [19]:

```
# Now we need to do some EDA on this dataset
```

In [20]:

```
df["Gender"].value_counts()
```

Out[20]:

Gender	count
2	78017
1	57375

dtype: int64

In [21]:

```
# Here in the Gender col (1 = Male and 2 = Female)
```

EDA

Univariarte Analysis

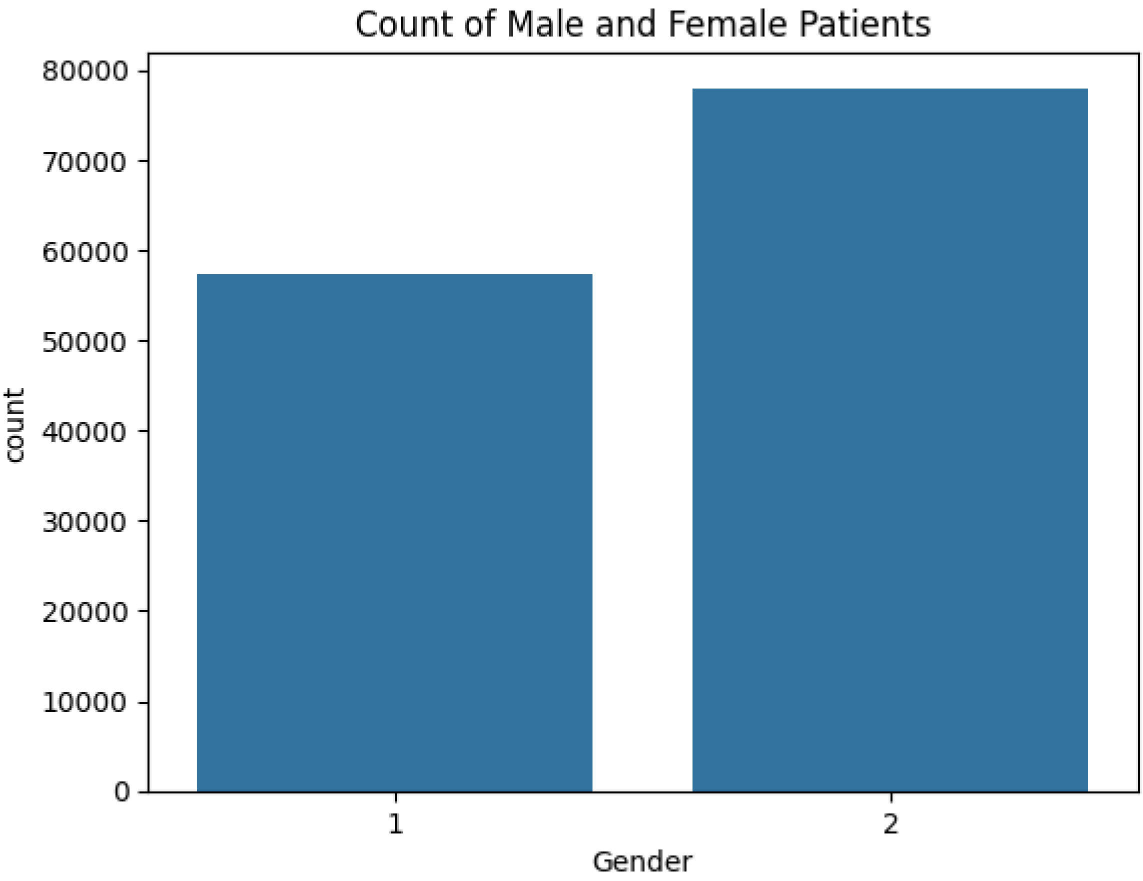
In [22]:

```
Male = len(df[df["Gender"] == 1])
Female = len(df[df["Gender"] == 2])

print("Percentage of Male patient is {:.2f}%".format(Male/len(df.Gender)*100))
print("Percentage of Female patient is {:.2f}%".format(Female/len(df.Gender)*100
```

```
Percentage of Male patient is 42.38%
Percentage of Female patient is 57.62%
```

In [23]:

```
sns.countplot(x = "Gender", data = df)
plt.title("Count of Male and Female Patients")
plt.show()
```



In [24]:
```
# In the above graph we can see there are more "Female" patients than male.
```

In [25]:
```
df["ClaimApproved"].value_counts()
```

Out[25]:

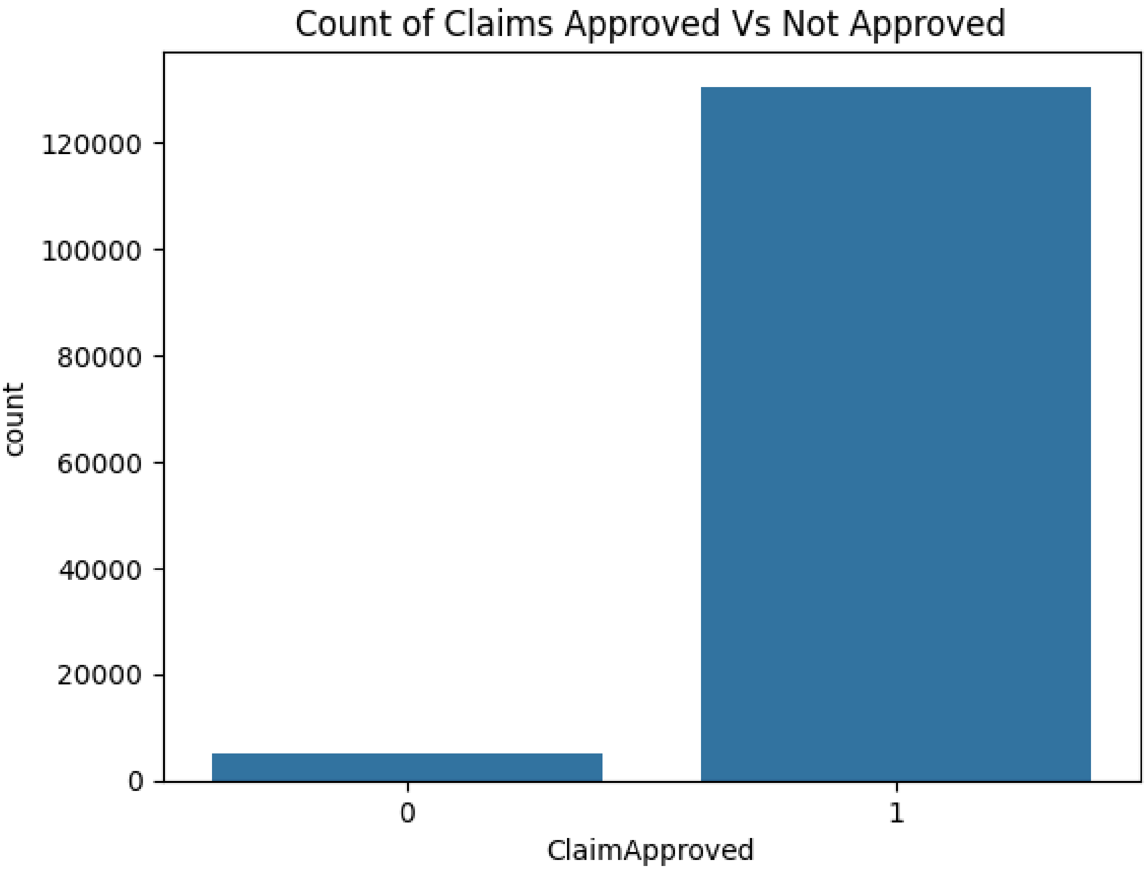
ClaimApproved	count
1	130469
0	4923

dtype: int64

In [26]:
```
claims_approved = len(df[df["ClaimApproved"] == 1])
claims_not_approved = len(df[df["ClaimApproved"] == 2])

print("Percentage of claims approved is {:.2f}%".format(Male/len(df.Gender)*100)
print("Percentage of claims not approved is {:.2f}%".format(Female/len(df.Gender
```

```
Percentage of claims approved is 42.38%
Percentage of claims not approved is 57.62%
```

In [27]:
```
sns.countplot(x = "ClaimApproved", data = df)
plt.title("Count of Claims Approved Vs Not Approved")
plt.show()
```



In [27]:

```
```

In [28]:

```
df["Race"].value_counts()
```

Out[28]:

Race	count
1	115067
2	13496
3	4118
5	2711

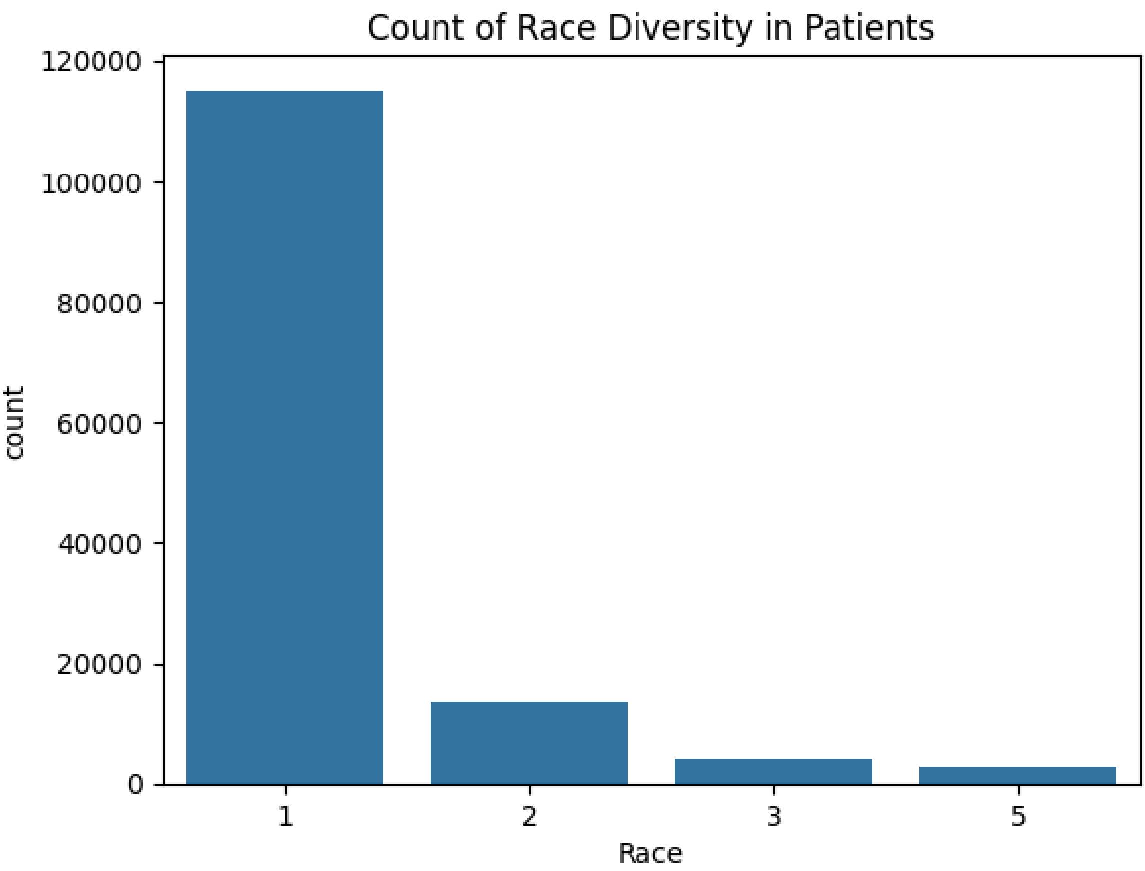
dtype: int64

In [29]:

```
# Percentage of different races r1, r2, r3, r4

r1 = len(df[df["Race"] == 1])
r2 = len(df[df["Race"] == 2])
r3 = len(df[df["Race"] == 3])
r4 = len(df[df["Race"] == 4])

print("Percentage of r1 patient is {:.2f}%".format(r1/len(df.Race)*100))
print("Percentage of r2 patient is {:.2f}%".format(r2/len(df.Race)*100))
print("Percentage of r3 patient is {:.2f}%".format(r3/len(df.Race)*100))
print("Percentage of r4 patient is {:.2f}%".format(r4/len(df.Race)*100))
```

```
Percentage of r1 patient is 84.99%
Percentage of r2 patient is 9.97%
Percentage of r3 patient is 3.04%
Percentage of r4 patient is 0.00%
```

In [30]:
```
sns.countplot(x = "Race", data = df)
plt.title("Count of Race Diversity in Patients")
plt.show()
```



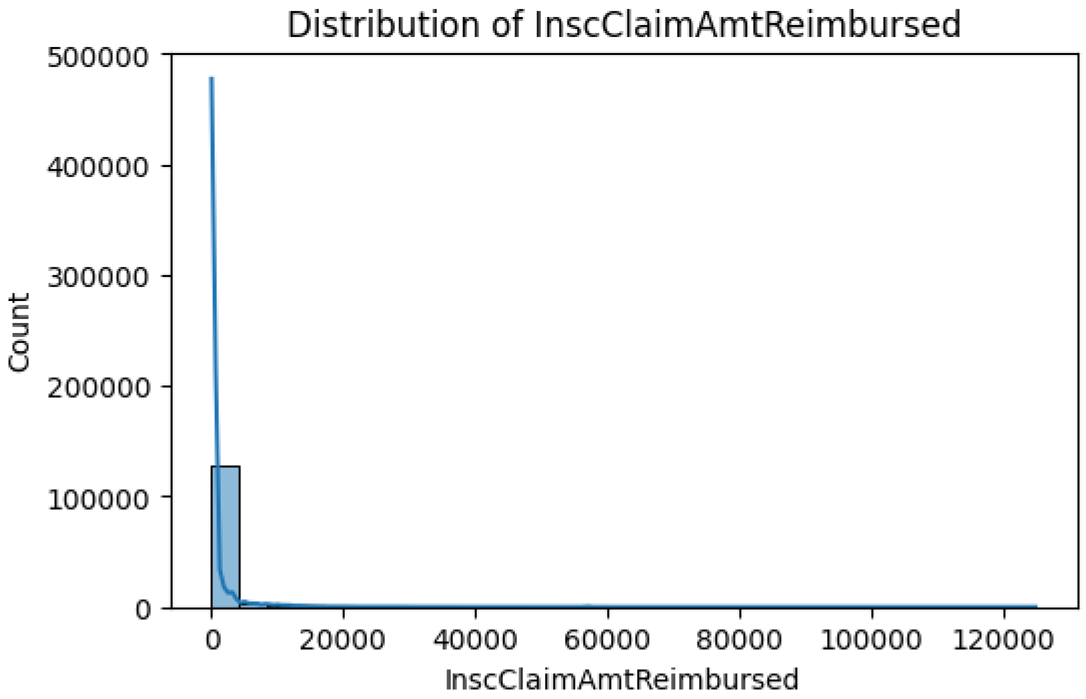
In [31]:
```
df.describe()
```

Out[31]:

	InscClaimAmtReimbursed	NumPhysicians	Gender	Race	Chronic
count	135392.000000	135392.000000	135392.000000	135392.000000	
mean	981.307906	1.557478	1.576231	1.240605	
std	3788.177532	0.636914	0.494157	0.695578	
min	0.000000	0.000000	1.000000	1.000000	
25%	40.000000	1.000000	1.000000	1.000000	
50%	80.000000	1.000000	2.000000	1.000000	
75%	300.000000	2.000000	2.000000	1.000000	
max	125000.000000	3.000000	2.000000	5.000000	

In [32]:
```
plt.figure(figsize=(15, 10))
cols = ['InscClaimAmtReimbursed']
```

```
for i in range(len(cols)):
    plt.subplot(3, 3, i + 1)  # 3 rows × 3 cols grid
    sns.histplot(df[cols[i]], kde = True, bins = 30)
    plt.title(f'Distribution of {cols[i]}')

plt.tight_layout()
plt.show()
```

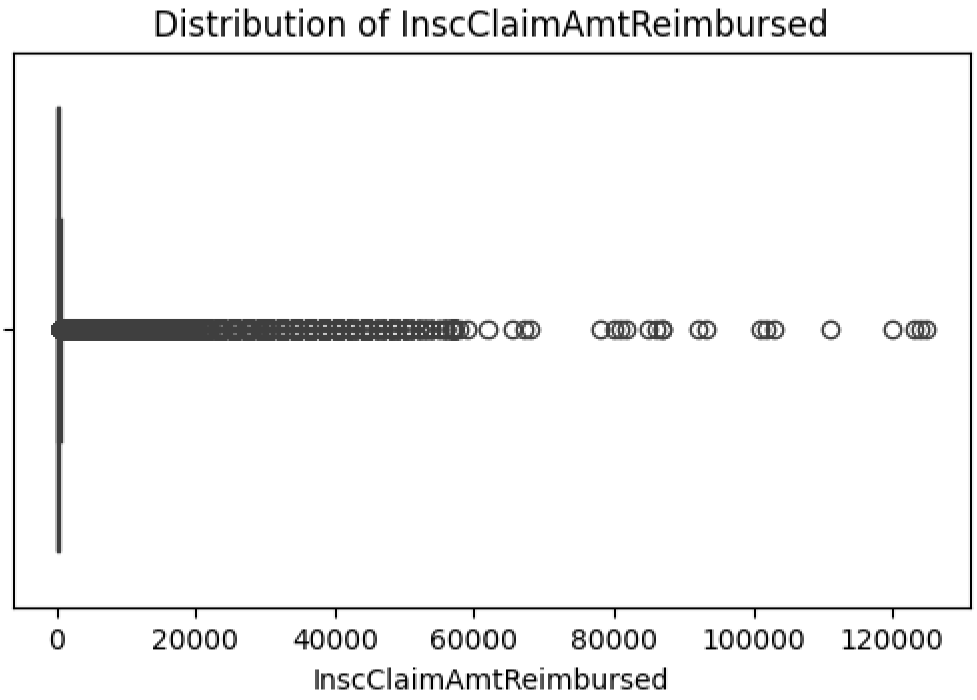


In [32]:

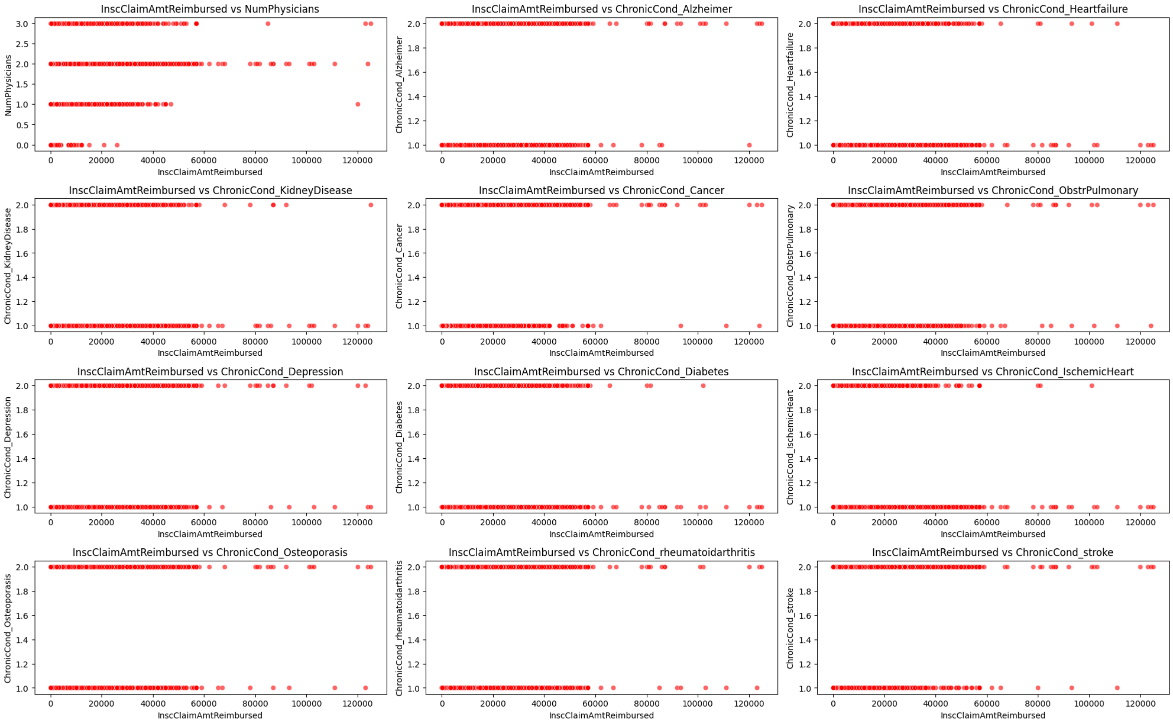
```

```

In [33]:

```
plt.figure(figsize=(15, 10))
cols = ['InscClaimAmtReimbursed']

for i in range(len(cols)):
    plt.subplot(3, 3, i + 1)  # 3 rows × 3 cols grid
    sns.boxplot(x = df[cols[i]])
    plt.title(f'Distribution of {cols[i]}')

plt.tight_layout()
plt.show()
```



In [34]:
```
plt.figure(figsize=(20, 15))
cols = [
        'NumPhysicians',
        'ChronicCond_Alzheimer',
        'ChronicCond_Heartfailure',
        'ChronicCond_KidneyDisease',
        'ChronicCond_Cancer',
        'ChronicCond_ObstrPulmonary',
        'ChronicCond_Depression',
        'ChronicCond_Diabetes',
        'ChronicCond_IschemicHeart',
        'ChronicCond_Osteoporasis',
        'ChronicCond_rheumatoidarthritis',
        'ChronicCond_stroke'
        ]

for i in range(len(cols)):
    plt.subplot(5, 3, i + 1)  # 3 rows × 3 cols grid
    sns.scatterplot(data = df, x = 'InscClaimAmtReimbursed', y = cols[i], color
    plt.title(f'InscClaimAmtReimbursed vs {cols[i]}')

plt.tight_layout()
plt.show()
```



InscClaimAmtReimbursed vs NumPhysicians

InscClaimAmtReimbursed vs ChronicCond_Alzheimer

InscClaimAmtReimbursed vs ChronicCond_Heartfailure

InscClaimAmtReimbursed vs ChronicCond_KidneyDisease

InscClaimAmtReimbursed vs ChronicCond_Cancer

InscClaimAmtReimbursed vs ChronicCond_ObstrPulmonary

InscClaimAmtReimbursed vs ChronicCond_Depression

InscClaimAmtReimbursed vs ChronicCond_Diabetes

InscClaimAmtReimbursed vs ChronicCond_IschemicHeart

InscClaimAmtReimbursed vs ChronicCond_Osteoporasis

InscClaimAmtReimbursed vs ChronicCond_rheumatoidarthritis

InscClaimAmtReimbursed vs ChronicCond_stroke

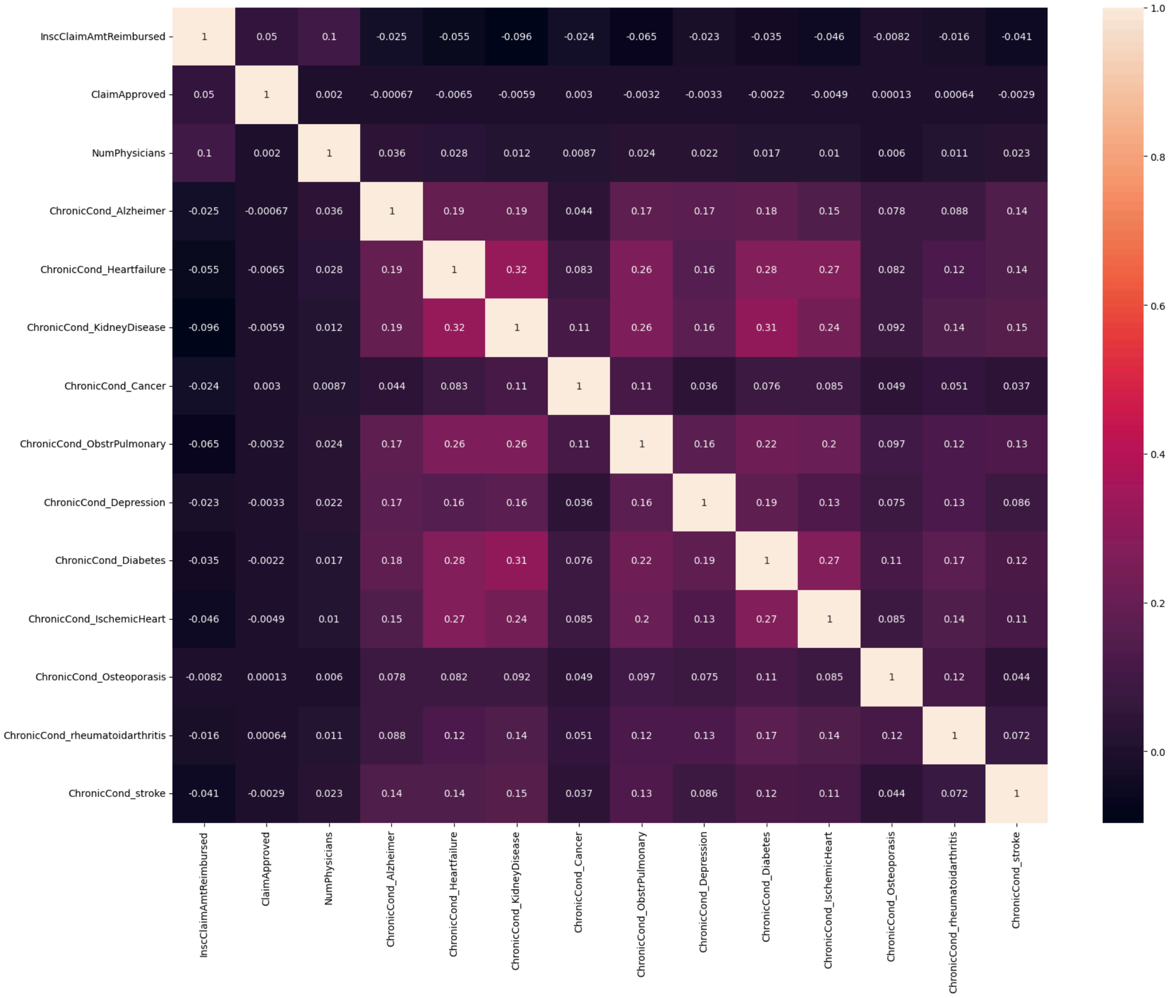
In [34]:

```
```

Multivariate Analysis

In [35]:

```
# Correlation Table - Heat Map
plt.figure(figsize=(20, 15))

cols = ['InscClaimAmtReimbursed',
        'ClaimApproved',
        'NumPhysicians',
        'ChronicCond_Alzheimer',
        'ChronicCond_Heartfailure',
        'ChronicCond_KidneyDisease',
        'ChronicCond_Cancer',
        'ChronicCond_ObstrPulmonary',
        'ChronicCond_Depression',
        'ChronicCond_Diabetes',
        'ChronicCond_IschemicHeart',
        'ChronicCond_Osteoporasis',
        'ChronicCond_rheumatoidarthritis',
        'ChronicCond_stroke']

sns.heatmap(data = df[cols].corr(), annot = True, cmap = 'rocket')
plt.show()
```



In [35]:

Data Preprocessing

In [36]:
```
model_data = df.copy()
```

In [37]:
```
# Removing unnesecary cols
model_data.columns
```

Out[37]:
```
Index(['BeneID', 'ClaimID', 'InscClaimAmtReimbursed', 'Provider',
       'NumPhysicians', 'ClaimType', 'Gender', 'Race', 'ChronicCond_Alzheimer',
       'ChronicCond_Heartfailure', 'ChronicCond_KidneyDisease',
       'ChronicCond_Cancer', 'ChronicCond_ObstrPulmonary',
       'ChronicCond_Depression', 'ChronicCond_Diabetes',
       'ChronicCond_IschemicHeart', 'ChronicCond_Osteoporasis',
       'ChronicCond_rheumatoidarthritis', 'ChronicCond_stroke',
       'ClaimApproved'],
      dtype='object')
```

In [38]:
```
model_data = model_data.drop(["BeneID", "ClaimID"], axis=1)
```

In [39]:
```
model_data.columns
```

```
Out[39]: Index(['InscClaimAmtReimbursed', 'Provider', 'NumPhysicians', 'ClaimType',
               'Gender', 'Race', 'ChronicCond_Alzheimer', 'ChronicCond_Heartfailure',
               'ChronicCond_KidneyDisease', 'ChronicCond_Cancer',
               'ChronicCond_ObstrPulmonary', 'ChronicCond_Depression',
               'ChronicCond_Diabetes', 'ChronicCond_IschemicHeart',
               'ChronicCond_Osteoporasis', 'ChronicCond_rheumatoidarthritis',
               'ChronicCond_stroke', 'ClaimApproved'],
              dtype='object')
```

```
In [40]: # Removing Null Values
         model_data.isnull().sum()
```

Out[40]:

	0
InscClaimAmtReimbursed	0
Provider	0
NumPhysicians	0
ClaimType	0
Gender	0
Race	0
ChronicCond_Alzheimer	0
ChronicCond_Heartfailure	0
ChronicCond_KidneyDisease	0
ChronicCond_Cancer	0
ChronicCond_ObstrPulmonary	0
ChronicCond_Depression	0
ChronicCond_Diabetes	0
ChronicCond_IschemicHeart	0
ChronicCond_Osteoporasis	0
ChronicCond_rheumatoidarthritis	0
ChronicCond_stroke	0
ClaimApproved	0

dtype: int64

```
In [41]: model_data.columns
```

```
Out[41]: Index(['InscClaimAmtReimbursed', 'Provider', 'NumPhysicians', 'ClaimType',
               'Gender', 'Race', 'ChronicCond_Alzheimer', 'ChronicCond_Heartfailure',
               'ChronicCond_KidneyDisease', 'ChronicCond_Cancer',
               'ChronicCond_ObstrPulmonary', 'ChronicCond_Depression',
               'ChronicCond_Diabetes', 'ChronicCond_IschemicHeart',
               'ChronicCond_Osteoporasis', 'ChronicCond_rheumatoidarthritis',
               'ChronicCond_stroke', 'ClaimApproved'],
              dtype='object')
```

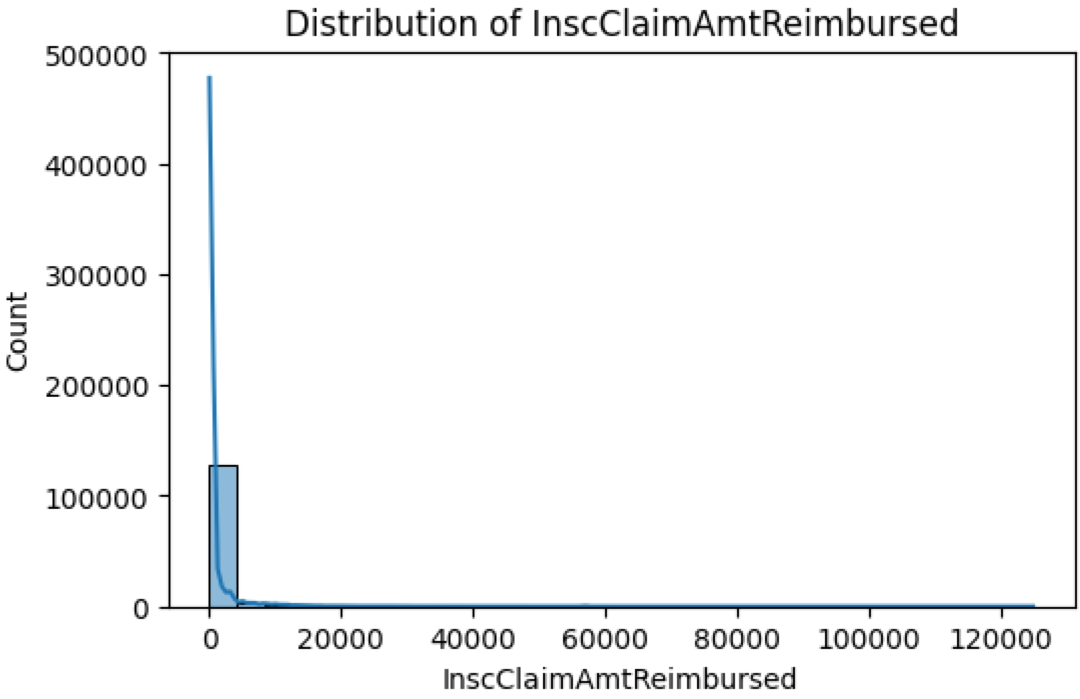
Data Transformation

In [42]:

```
model_data["InscClaimAmtReimbursed"] = np.log1p(model_data["InscClaimAmtReimburs
```

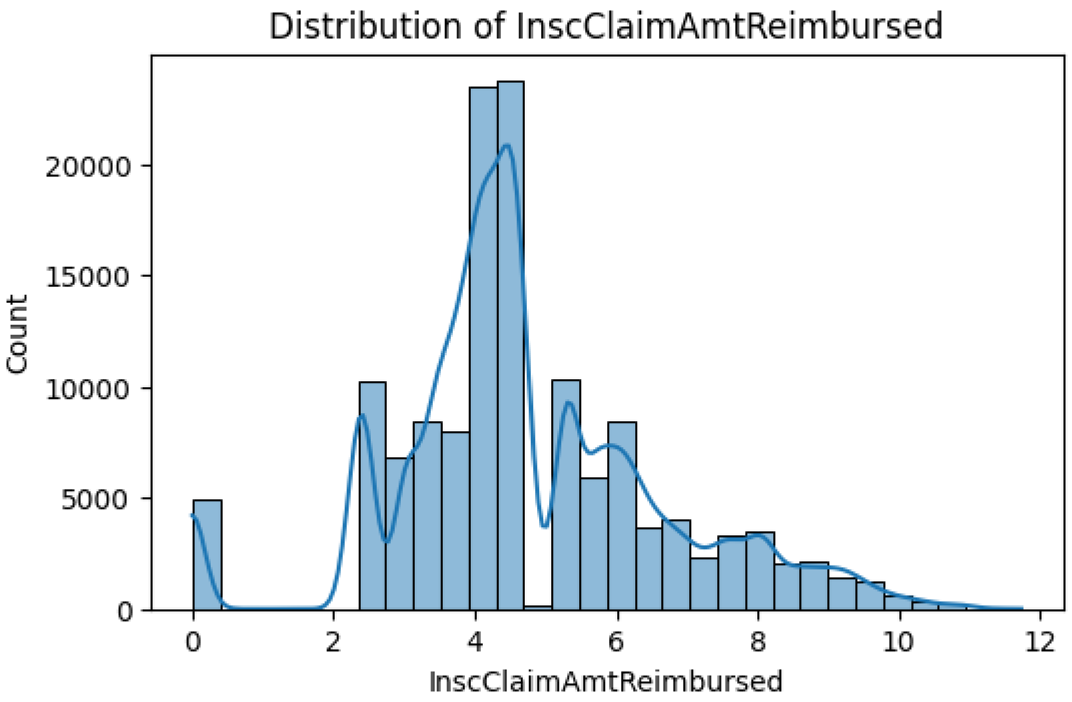
In [43]:

```
plt.figure(figsize=(15, 10))
cols = ['InscClaimAmtReimbursed']

for i in range(len(cols)):
    plt.subplot(3, 3, i + 1)  # 3 rows × 3 cols grid
    sns.histplot(df[cols[i]], kde = True, bins = 30)
    plt.title(f'Distribution of {cols[i]}')

plt.tight_layout()
plt.show()
```



In [44]:

```
plt.figure(figsize=(15, 10))
cols = ['InscClaimAmtReimbursed']

for i in range(len(cols)):
    plt.subplot(3, 3, i + 1)  # 3 rows × 3 cols grid
    sns.histplot(model_data[cols[i]], kde = True, bins = 30)
    plt.title(f'Distribution of {cols[i]}')

plt.tight_layout()
plt.show()
```



In [45]:
```
# We can see that earlier the data did not had a normal distribution now it foll
```

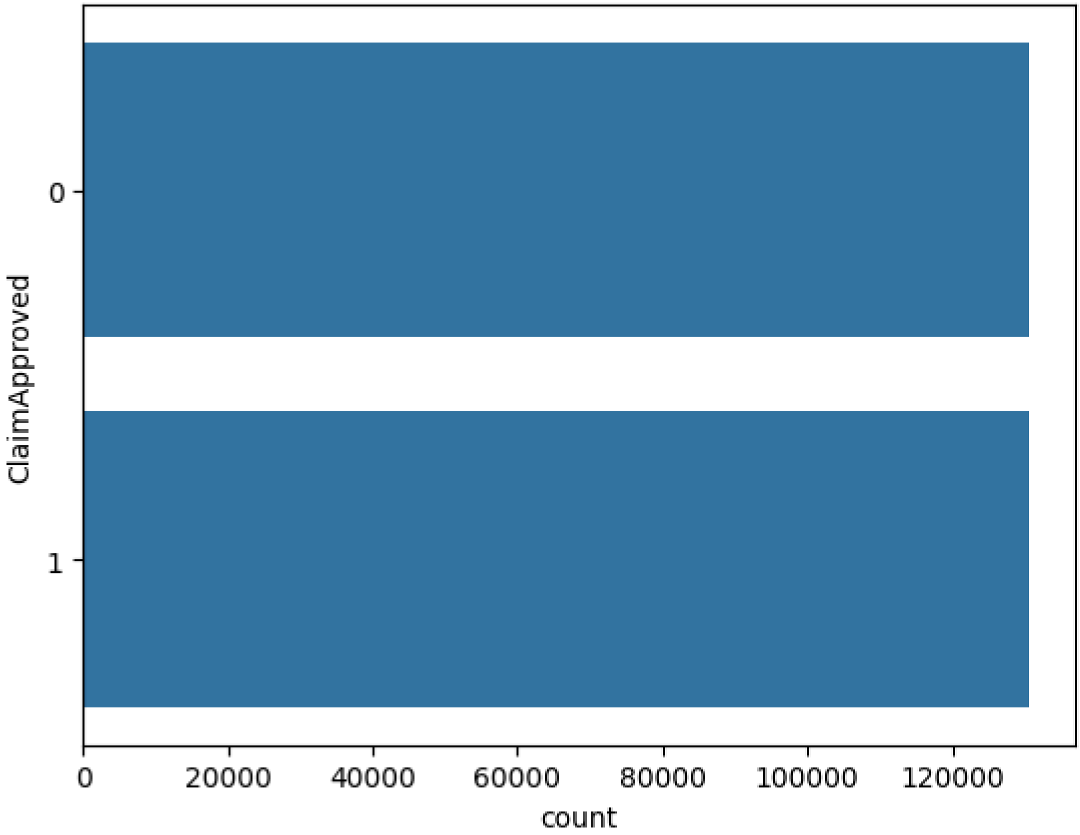
In [48]:
```
model_data = pd.get_dummies(model_data, dtype = int)
```

In [49]:
```
# Feature separation - x and y (Target variable and independent variable)
x = model_data.drop(["ClaimApproved"], axis =1)
y = model_data["ClaimApproved"]
```

In [51]:
```
x,y = SMOTE().fit_resample(x,y)
```

In [52]:
```
sns.countplot(y = y, data = model_data)
```

Out[52]:
```
<Axes: xlabel='count', ylabel='ClaimApproved'>
```



```
In [50]: x = MinMaxScaler().fit_transform(x)
         x
```

```
Out[50]: array([[0.77582066, 0.66666667, 1.        , ..., 0.        , 1.        ,
                 0.        ],
                [0.81346467, 0.66666667, 1.        , ..., 0.        , 1.        ,
                 0.        ],
                [0.64769533, 0.33333333, 0.        , ..., 0.        , 1.        ,
                 0.        ],
                ...,
                [0.29260094, 0.33333333, 1.        , ..., 0.        , 0.        ,
                 1.        ],
                [0.29260094, 0.66666667, 0.        , ..., 0.        , 0.        ,
                 1.        ],
                [0.66670029, 0.33333333, 0.        , ..., 0.        , 0.        ,
                 1.        ]])
```

```
In [53]: #Train test split

         x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.2, random_sta
```

```
In [54]: #Modelling:

         #Logistic regression

         classifier = LogisticRegression(solver = 'saga', max_iter = 500, random_state= 1

         classifier.fit(x_train, y_train)

         y_pred = classifier.predict(x_test)

         print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     26114
           1       1.00      1.00      1.00     26074

    accuracy                           1.00     52188
   macro avg       1.00      1.00      1.00     52188
weighted avg       1.00      1.00      1.00     52188
```

In [55]:

```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report

# Create the model
dt_classifier = DecisionTreeClassifier(random_state=1)

# Train
dt_classifier.fit(x_train, y_train)

# Predict
y_pred_dt = dt_classifier.predict(x_test)

# Evaluation
print("Decision Tree Classification Report:")
print(classification_report(y_test, y_pred_dt))
```

```
Decision Tree Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     26114
           1       1.00      1.00      1.00     26074

    accuracy                           1.00     52188
   macro avg       1.00      1.00      1.00     52188
weighted avg       1.00      1.00      1.00     52188
```

In [56]:

```python
from sklearn.ensemble import RandomForestClassifier

# Create the model
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=1)

# Train
rf_classifier.fit(x_train, y_train)

# Predict
y_pred_rf = rf_classifier.predict(x_test)

# Evaluation
print("Random Forest Classification Report:")
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     26114
           1       1.00      1.00      1.00     26074

    accuracy                           1.00     52188
   macro avg       1.00      1.00      1.00     52188
weighted avg       1.00      1.00      1.00     52188
```

In [ ]: