In [232]:

```
# Spring 2022
# IE7275- Data Mining in Engineering
# Project Group 24
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import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
```

In [233]:

```
# Importing the csv file of the dataset
stroke_df = pd.read_csv("C:/Sam/Sem2/Data mining/Project/Healthcare dataset/archive/healt
hcare-dataset-stroke-data.csv")
print(stroke_df)
```

```
         id  gender   age  hypertension  heart_disease ever_married  \
0      9046    Male  67.0             0              1          Yes   
1     51676  Female  61.0             0              0          Yes   
2     31112    Male  80.0             0              1          Yes   
3     60182  Female  49.0             0              0          Yes   
4      1665  Female  79.0             1              0          Yes   
...     ...     ...   ...           ...            ...          ...   
5105  18234  Female  80.0             1              0          Yes   
5106  44873  Female  81.0             0              0          Yes   
5107  19723  Female  35.0             0              0          Yes   
5108  37544    Male  51.0             0              0          Yes   
5109  44679  Female  44.0             0              0          Yes   

          work_type Residence_type  avg_glucose_level   bmi   smoking_status  \
0           Private          Urban             228.69  36.6  formerly smoked   
1     Self-employed          Rural             202.21   NaN     never smoked   
2           Private          Rural             105.92  32.5     never smoked   
3           Private          Urban             171.23  34.4           smokes   
4     Self-employed          Rural             174.12  24.0     never smoked   
...             ...            ...                ...   ...              ...   
5105        Private          Urban              83.75   NaN     never smoked   
5106  Self-employed          Urban             125.20  40.0     never smoked   
5107  Self-employed          Rural              82.99  30.6     never smoked   
5108        Private          Rural             166.29  25.6  formerly smoked   
5109       Govt_job          Urban              85.28  26.2          Unknown   

      stroke  
0          1  
1          1  
2          1  
3          1  
4          1  
...      ...  
5105       0  
5106       0  
5107       0  
5108       0  
5109       0  

[5110 rows x 12 columns]
```

In [234]:

```
# Printing the descriptive statistics of the dataset
stroke_df.describe()
```

Out[234]:

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke
count	5110.000000	5110.000000	5110.000000	5110.000000	5110.000000	4909.000000	5110.000000
mean	36517.829354	43.226614	0.097456	0.054012	106.147677	28.893237	0.048728
std	21161.721625	22.612647	0.296607	0.226063	45.283560	7.854067	0.215320
min	67.000000	0.080000	0.000000	0.000000	55.120000	10.300000	0.000000
25%	17741.250000	25.000000	0.000000	0.000000	77.245000	23.500000	0.000000
50%	36932.000000	45.000000	0.000000	0.000000	91.885000	28.100000	0.000000
75%	54682.000000	61.000000	0.000000	0.000000	114.090000	33.100000	0.000000
max	72940.000000	82.000000	1.000000	1.000000	271.740000	97.600000	1.000000

In [235]:

```
# Printing the information of column name and datatype
stroke_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 5110 non-null   int64  
 1   gender             5110 non-null   object 
 2   age                5110 non-null   float64
 3   hypertension       5110 non-null   int64  
 4   heart_disease      5110 non-null   int64  
 5   ever_married       5110 non-null   object 
 6   work_type          5110 non-null   object 
 7   Residence_type     5110 non-null   object 
 8   avg_glucose_level  5110 non-null   float64
 9   bmi                4909 non-null   float64
 10  smoking_status     5110 non-null   object 
 11  stroke             5110 non-null   int64  
dtypes: float64(3), int64(4), object(5)
memory usage: 479.2+ KB
```

In [236]:

```
# Checking for null values in the dataset
stroke_df.isna().sum()
```

Out[236]:

```
id                     0
gender                 0
age                    0
hypertension           0
heart_disease          0
ever_married           0
work_type              0
Residence_type         0
avg_glucose_level      0
bmi                  201
smoking_status         0
stroke                 0
dtype: int64
```

In [237]:

```
# We see that bmi has 201 NA rows, which we can fill with median values
stroke_df['bmi'].fillna(stroke_df['bmi'].median(), inplace=True)
# Checking again for null values
stroke_df.isna().sum()
# The output confirms all the null values were filled with median values
```

Out[237]:

```
id                   0
gender               0
age                  0
hypertension         0
heart_disease        0
ever_married         0
work_type            0
Residence_type       0
avg_glucose_level    0
bmi                  0
smoking_status       0
stroke               0
dtype: int64
```

In [238]:

```
# Identifying and removing redundant data
# We can drop the id column as it is redundant
stroke_df.drop('id',axis=1,inplace=True)
stroke_df
```

Out[238]:

	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_s
0	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	for sn
1	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	28.1	never sn
2	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never sn
3	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	sr
4	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never sn
...	...	...	...	...	...	...	...	...	...	
5105	Female	80.0	1	0	Yes	Private	Urban	83.75	28.1	never sn
5106	Female	81.0	0	0	Yes	Self-employed	Urban	125.20	40.0	never sn
5107	Female	35.0	0	0	Yes	Self-employed	Rural	82.99	30.6	never sn
5108	Male	51.0	0	0	Yes	Private	Rural	166.29	25.6	for sn
5109	Female	44.0	0	0	Yes	Govt_job	Urban	85.28	26.2	Unk

5110 rows × 11 columns

In [239]:

```
# Determining unique values of all categorical columns
print(stroke_df.gender.unique())
print(stroke_df.ever_married.unique())
print(stroke_df.work_type.unique())
print(stroke_df.Residence_type.unique())
print(stroke_df.smoking_status.unique())
```

```
['Male' 'Female' 'Other']
['Yes' 'No']
['Private' 'Self-employed' 'Govt_job' 'children' 'Never_worked']
['Urban' 'Rural']
['formerly smoked' 'never smoked' 'smokes' 'Unknown']
```

In [240]:

```
# From the above categories we can see that the 'Other' category in Gender field has just
```

```
one entry which we can remove
stroke_df.drop(stroke_df.index[stroke_df['gender'] == 'Other'], inplace = True)
print(stroke_df.gender.unique())
```

```
['Male' 'Female']
```

In [241]:

```
# Finding duplicate rows in the dataset
duplicate = stroke_df[stroke_df.duplicated()]

print("Duplicate Rows :")
duplicate
stroke_df
# From the output it is clear that there are no duplicate data in the dataset
```

```
Duplicate Rows :
```

Out[241]:

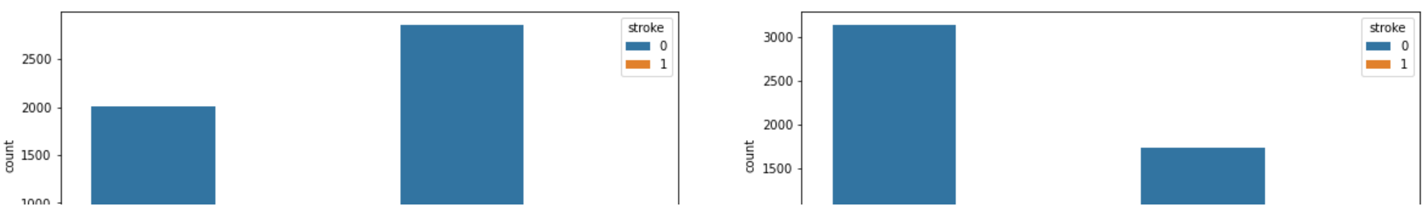
	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_s
0	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	for sn
1	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	28.1	never sn
2	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never sn
3	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	sr
4	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never sn
...	...	...	...	...	...	...	...	...	...	
5105	Female	80.0	1	0	Yes	Private	Urban	83.75	28.1	never sn
5106	Female	81.0	0	0	Yes	Self-employed	Urban	125.20	40.0	never sn
5107	Female	35.0	0	0	Yes	Self-employed	Rural	82.99	30.6	never sn
5108	Male	51.0	0	0	Yes	Private	Rural	166.29	25.6	for sn
5109	Female	44.0	0	0	Yes	Govt_job	Urban	85.28	26.2	Unk

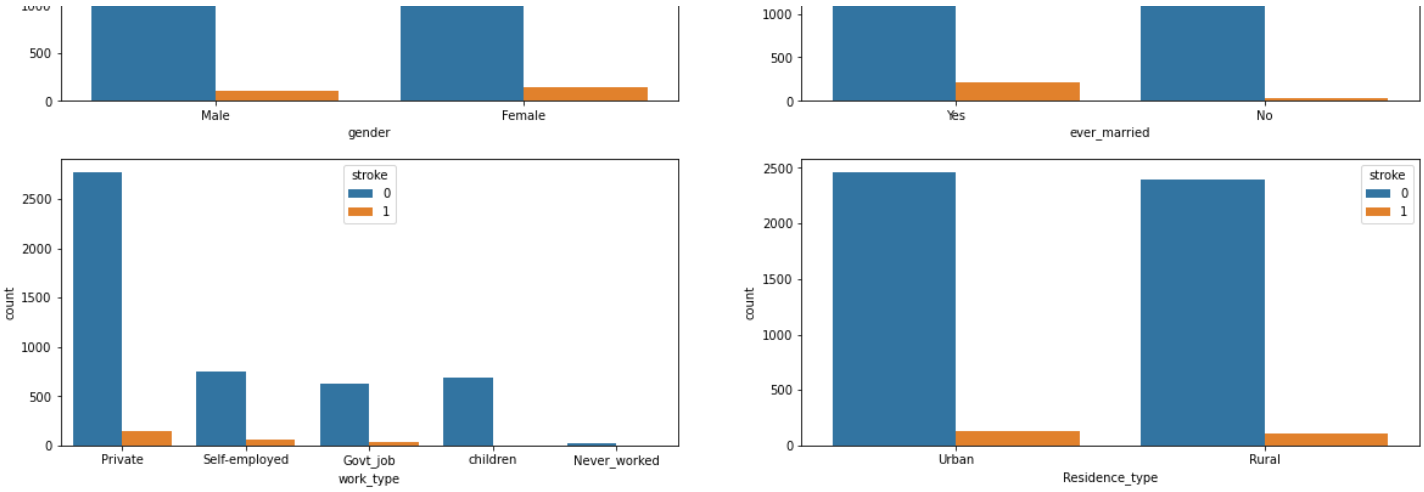
5109 rows × 11 columns

In [242]:

```
# Plotting barplots of stroke vs categorical fields
categorical = stroke_df.select_dtypes('object').columns
print(categorical)
plt.figure(figsize = (20,20))
i = 1
for column in categorical[:-1]:
    plt.subplot(4, 2, i)
    sns.countplot(x = stroke_df[column], hue = stroke_df["stroke"])
    i+=1
plt.show()
```

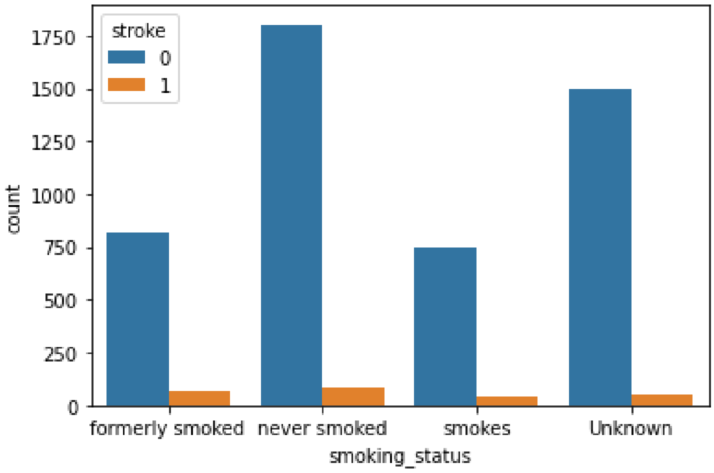
```
Index(['gender', 'ever_married', 'work_type', 'Residence_type',
       'smoking_status'],
      dtype='object')
```





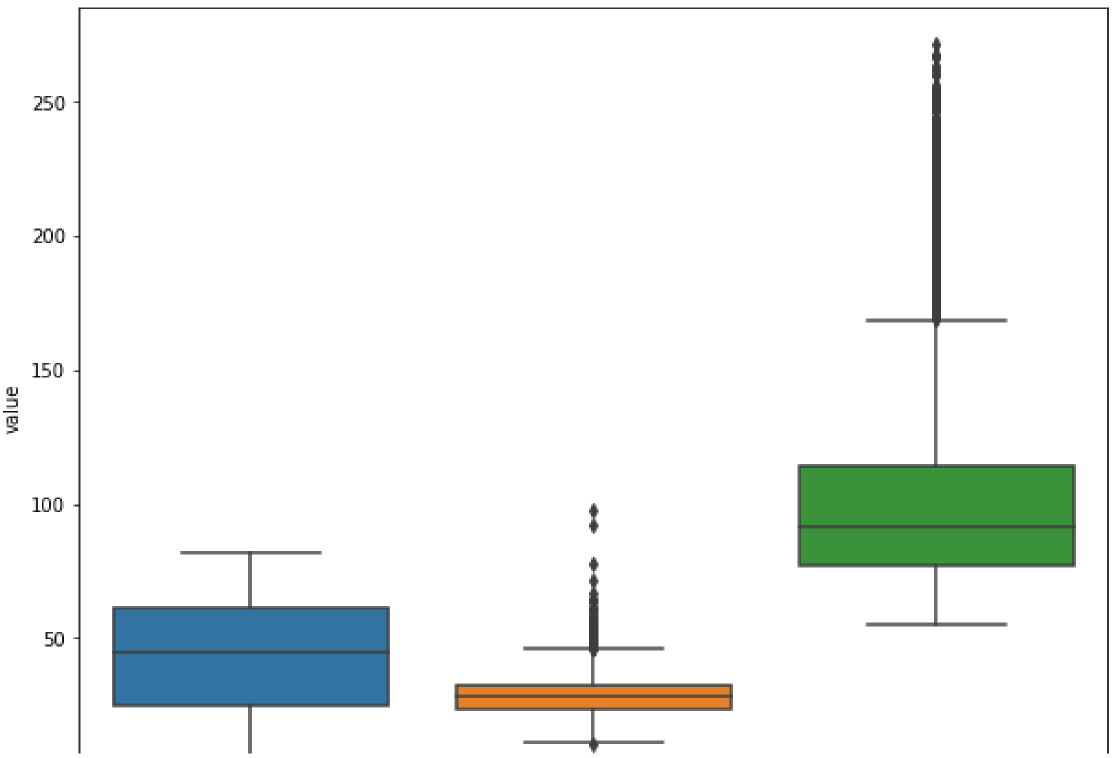
In [243]:

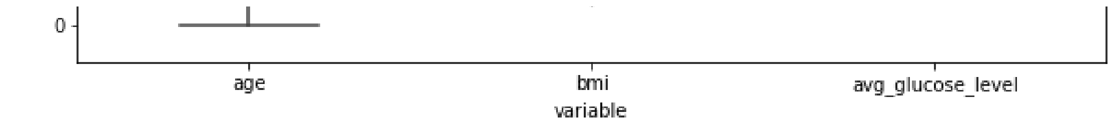
```
# Plotting barplot of stroke vs smoking_status field
sns.countplot(x = stroke_df["smoking_status"], hue = stroke_df["stroke"])
plt.show()
```



In [244]:

```
# Plotting boxplots of numerical fields like age, bmi, average glucose level of patients
plt.figure(figsize = (10,8))
df2 = pd.DataFrame(data=stroke_df, columns=["age", "bmi", "avg_glucose_level"])
sns.boxplot(x="variable", y="value", data=pd.melt(df2))
plt.show()
```





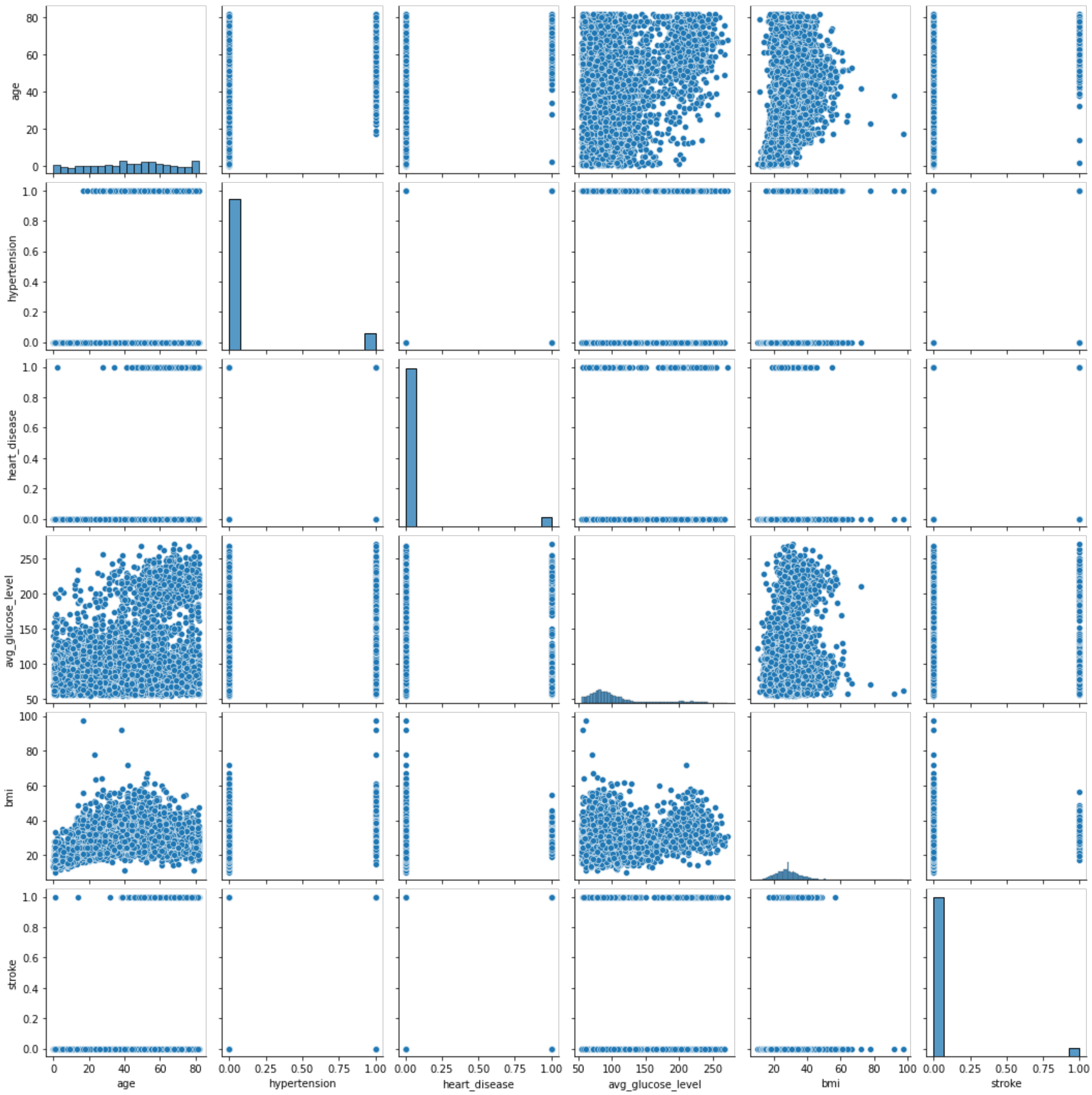
In [245]:

```
# Plotting pairplots the fields
plt.figure(figsize = (15,15))
sns.pairplot(stroke_df)
```

Out[245]:

```
<seaborn.axisgrid.PairGrid at 0x1a58439fbe0>
```

```
<Figure size 1080x1080 with 0 Axes>
```



In [246]:

```
!pip install plotly
```

```
Requirement already satisfied: plotly in c:\users\samru\anaconda3\lib\site-packages (5.7.0)
Requirement already satisfied: six in c:\users\samru\anaconda3\lib\site-packages (from plotly) (1.16.0)
Requirement already satisfied: tenacity>=6.2.0 in c:\users\samru\anaconda3\lib\site-packa
```

```
Requirement already satisfied: tenacity>=6.2.0 in c:\users\samru\anaconda3\lib\site-packa
ges (from plotly) (8.0.1)
```

In [247]:

```
# Ploting scatterplot of age vs stroke
import plotly.express as px
plt.figure(figsize = (5,5))
fig = px.scatter( stroke_df, x = 'age', y = 'stroke')
fig.show()
```

```
<Figure size 360x360 with 0 Axes>
```

In [248]:

```
# Some fields in the dataset have object datatype
# For applying k-NN to categorical variables, we need to convert them to binary dummy var
iables
stroke_df.gender = stroke_df.gender.astype('category').cat.codes
stroke_df.ever_married = stroke_df.ever_married.astype('category').cat.codes
stroke_df.Residence_type = stroke_df.Residence_type.astype('category').cat.codes
stroke_df = pd.get_dummies(data=stroke_df, prefix=['work_type','smoking_status'], column
s=['work_type','smoking_status'], drop_first=True)
stroke_df.head(10)
#print(stroke_df[['age','bmi','avg_glucose_level']])
```

Out[248]:

	gender	age	hypertension	heart_disease	ever_married	Residence_type	avg_glucose_level	bmi	stroke	work_type_Never_
0	1	67.0	0	1	1	1	228.69	36.6	1	
1	0	61.0	0	0	1	0	202.21	28.1	1	
2	1	80.0	0	1	1	0	105.92	32.5	1	
3	0	49.0	0	0	1	1	171.23	34.4	1	
4	0	79.0	1	0	1	0	174.12	24.0	1	
5	1	81.0	0	0	1	1	186.21	29.0	1	

	gender	age	hypertension	heart_disease	ever_married	Residence_type	avg_glucose_level	bmi	stroke	work_type_Never_
6	1	74.0	1	1	1	0	70.09	27.4	1	
~~7~~	~~0~~	~~69.0~~	~~0~~	~~0~~	~~0~~	~~1~~	~~94.39~~	~~22.8~~	~~1~~	
8	0	59.0	0	0	1	0	76.15	28.1	1	
9	0	78.0	0	0	1	1	58.57	24.2	1	

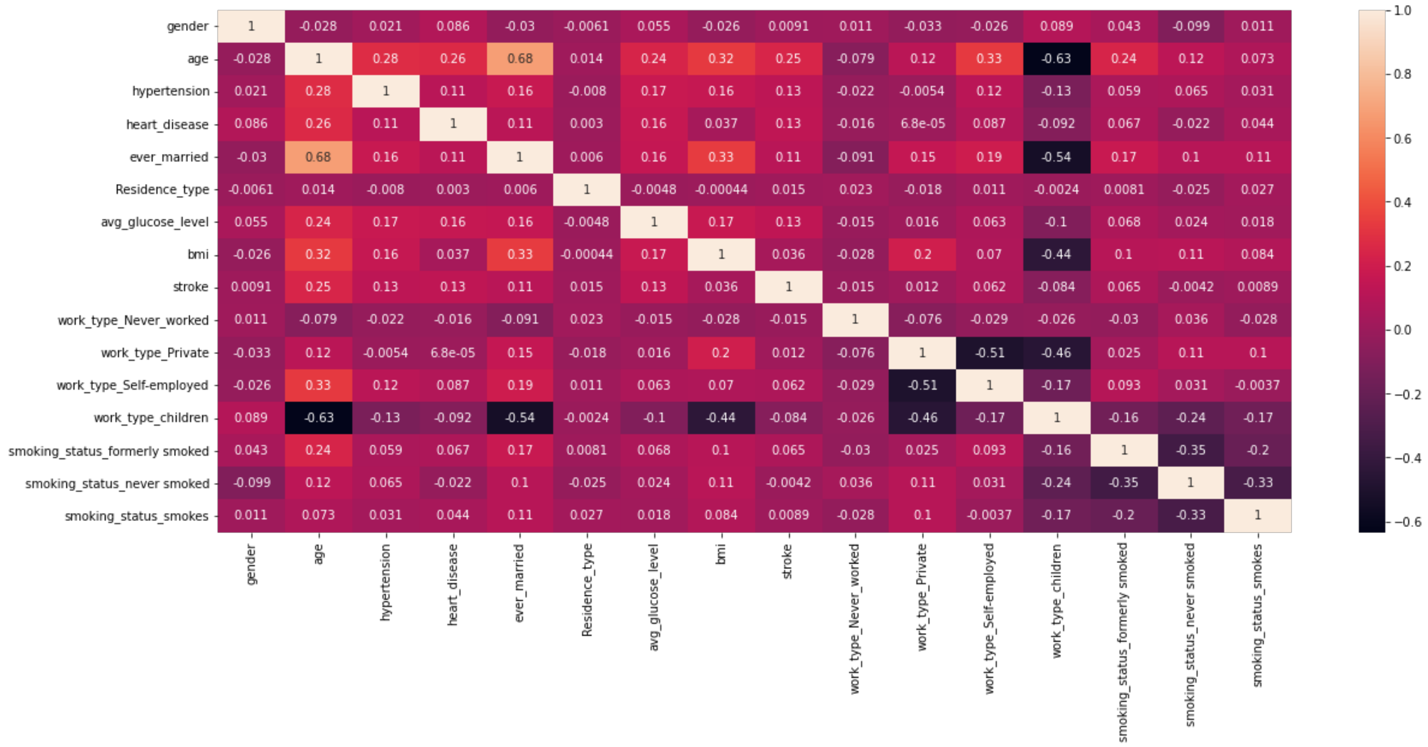
In [249]:

```
print(stroke_df[['age','bmi','avg_glucose_level']].describe())
```

```
               age          bmi  avg_glucose_level
count  5109.000000  5109.000000        5109.000000
mean     43.229986    28.863300         106.140399
std      22.613575     7.699785          45.285004
min       0.080000    10.300000          55.120000
25%      25.000000    23.800000          77.240000
50%      45.000000    28.100000          91.880000
75%      61.000000    32.800000         114.090000
max      82.000000    97.600000         271.740000
```

In [278]:

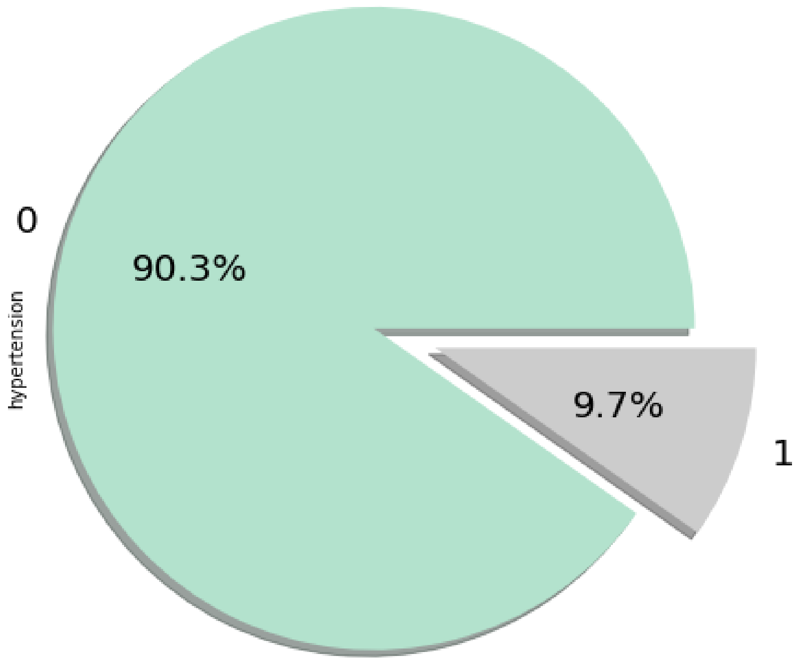
```
# Plotting heatmap of correlation of fields in the dataset
corrMatrix = stroke_df.corr()
# print (corrMatrix)
plt.figure(figsize=(20,8))
sns.heatmap(corrMatrix, annot=True)
plt.show()
```



In [251]:

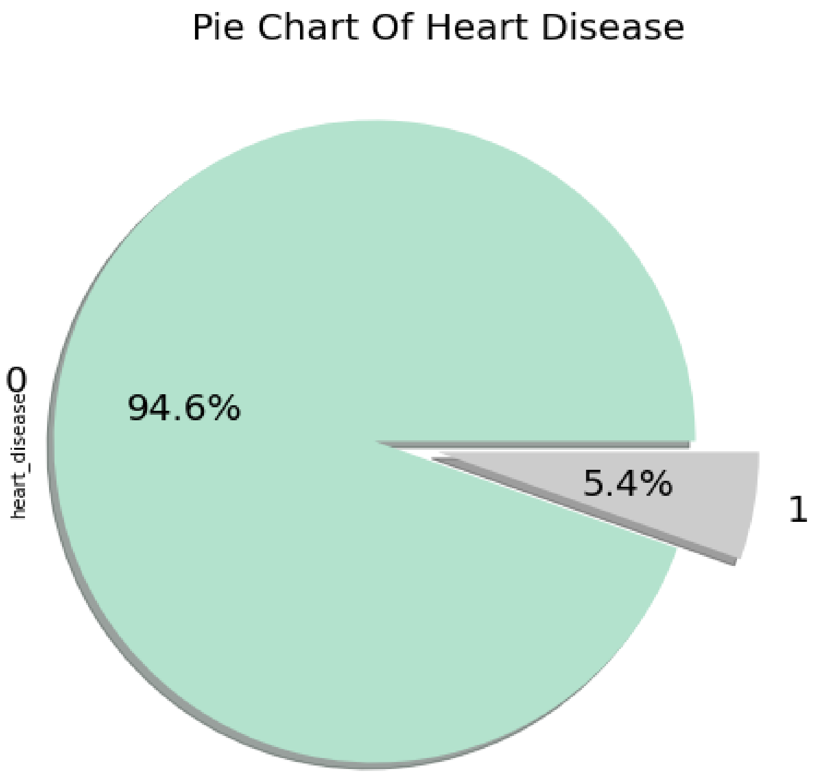
```
# Pieplot of Hypertension patients distribution
fig, axes = plt.subplots(figsize=(8,8))
stroke_df['hypertension'].value_counts().plot.pie(autopct='%1.1f%%',
                                                  colormap='Pastel2',
                                                  fontsize=20,
                                                  shadow=True,
                                                  explode=[0.2,0])
axes.set_title("Pie Chart Of Hypertension", fontsize=20)
axes.set_xlabel(None)
plt.show()
```

Pie Chart Of Hypertension



In [252]:

```
# Pieplot of Heart disease patients distribution
fig, axes = plt.subplots(figsize=(8,8))
stroke_df['heart_disease'].value_counts().plot.pie(autopct='%1.1f%%',
                                                    colormap='Pastel2',
                                                    fontsize=20,
                                                    shadow=True,
                                                    explode=[0.2,0])
axes.set_title("Pie Chart Of Heart Disease", fontsize=20)
axes.set_xlabel(None)
plt.show()
```



In [253]:

```
#Standardizing the numerical columns
```

```
col = ['age','avg_glucose_level', 'bmi']
min_max_scaler = preprocessing.MinMaxScaler()

column_names_to_normalize = ['age','avg_glucose_level', 'bmi']
x = stroke_df[column_names_to_normalize].values
x_scaled = min_max_scaler.fit_transform(x)
df_temp = pd.DataFrame(x_scaled, columns=column_names_to_normalize, index = stroke_df.in
dex)
stroke_df[column_names_to_normalize] = df_temp
# Verifying the operation through describe function
stroke_df.describe()
print(stroke_df[['age','bmi','avg_glucose_level']].describe())
```

```
               age          bmi  avg_glucose_level
count  5109.000000  5109.000000        5109.000000
mean      0.526733     0.212638           0.235529
std       0.276045     0.088199           0.209053
min       0.000000     0.000000           0.000000
25%       0.304199     0.154639           0.102114
50%       0.548340     0.203895           0.169698
75%       0.743652     0.257732           0.272228
max       1.000000     1.000000           1.000000
```

In [254]:

```
# Forming feature and target dataframes
X = stroke_df.drop(['stroke'],axis=1)
y = stroke_df['stroke']
```

In [255]:

```
# Splitting data as training = 75% and testing = 25%
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=4
2)
```

In [256]:

```
# transform the dataset by oversampling
from imblearn.over_sampling import SMOTE
oversample = SMOTE()
X_oversample, y_oversample = oversample.fit_resample(X, y)
X_train_os, X_test_os, y_train_os, y_test_os = train_test_split(X_oversample, y_oversamp
le, test_size=0.20, random_state=42)
```

In [257]:

```
from sklearn.metrics import accuracy_score,precision_score, recall_score, f1_score
from sklearn.neighbors import NearestNeighbors, KNeighborsClassifier

# KNN Classifier before oversampling
results = []
for k in range(1, 40):
 knn = KNeighborsClassifier(n_neighbors=k).fit(X_train, y_train)
 results.append({'k': k, 'accuracy': accuracy_score(y_test, knn.predict(X_test)) })
# Convert results to a pandas data frame
results = pd.DataFrame(results)
print(results)

# KNN Classifier after oversampling
results1 = []
print('After oversampling')
for k in range(1, 40):
 knn = KNeighborsClassifier(n_neighbors=k).fit(X_train_os, y_train_os)
 results1.append({'k': k, 'accuracy': accuracy_score(y_test_os, knn.predict(X_test_os))
})
# Convert results to a pandas data frame
results1 = pd.DataFrame(results1)
print(results1)
```

```
     k  accuracy
0    1  0.904538
```

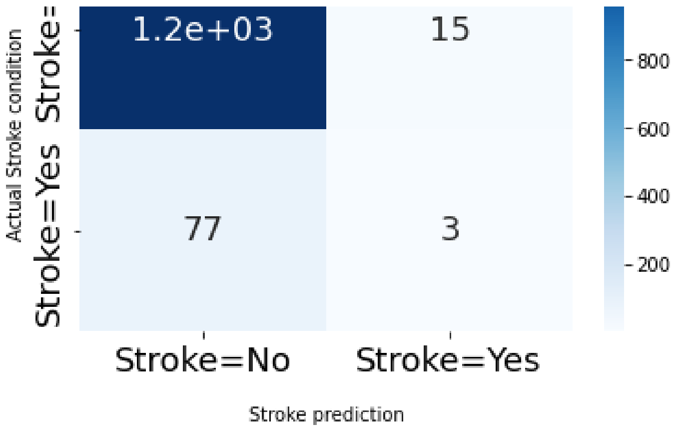
```
1    2  0.935055
2    3  0.928013
3    4  0.938185
4    5  0.937402
5    6  0.938185
6    7  0.937402
7    8  0.938185
8    9  0.938967
9   10  0.938185
10  11  0.938967
11  12  0.937402
12  13  0.938185
13  14  0.937402
14  15  0.937402
15  16  0.937402
16  17  0.937402
17  18  0.937402
18  19  0.937402
19  20  0.937402
20  21  0.937402
21  22  0.937402
22  23  0.937402
23  24  0.937402
24  25  0.937402
25  26  0.937402
26  27  0.937402
27  28  0.937402
28  29  0.937402
29  30  0.937402
30  31  0.937402
31  32  0.937402
32  33  0.937402
33  34  0.937402
34  35  0.937402
35  36  0.937402
36  37  0.937402
37  38  0.937402
38  39  0.937402
After oversampling
      k  accuracy
0    1  0.899691
1    2  0.889918
2    3  0.887346
3    4  0.889403
4    5  0.873971
5    6  0.874486
6    7  0.867284
7    8  0.871399
8    9  0.860597
9   10  0.866255
10  11  0.858539
11  12  0.858025
12  13  0.850309
13  14  0.852366
14  15  0.843621
15  16  0.844136
16  17  0.842078
17  18  0.842593
18  19  0.835905
19  20  0.834877
20  21  0.828189
21  22  0.827160
22  23  0.823560
23  24  0.819444
24  25  0.816358
25  26  0.821502
26  27  0.812243
27  28  0.815329
28  29  0.814300
29  30  0.814815
30  31  0.810700
31  32  0.812757
32  33  0.810185
```

```
32  33  0.810185
33  34  0.812757
34  35  0.810700
35  36  0.811728
36  37  0.809671
37  38  0.813786
38  39  0.806070
```

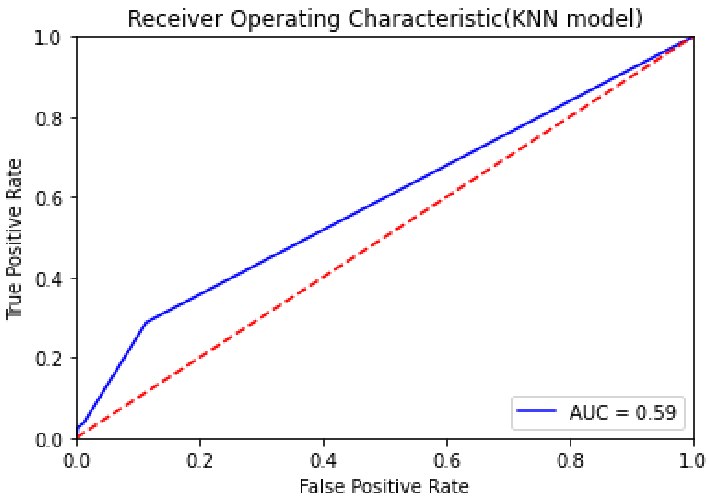
In [258]:

```
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
knn4 = KNeighborsClassifier()
knn4.set_params(n_neighbors = 3)
knn_model = knn4.fit(X_train, y_train)
y_pred_knn = knn4.predict(X_test)
y_pred_knn

# Get the confusion matrix
cf_matrix_knn = confusion_matrix(y_test, y_pred_knn)

print('Confusion Matrix - KNN')
print(cf_matrix_knn)

cf_matrix_plot = sns.heatmap(cf_matrix_knn, annot=True, cmap='Blues',annot_kws={"fontsize
":18})

cf_matrix_plot.set_title('Confusion Matrix for KNN\n\n');
cf_matrix_plot.set_xlabel('\nStroke prediction')
cf_matrix_plot.set_ylabel('Actual Stroke condition ');

# Ticket labels
cf_matrix_plot.xaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
cf_matrix_plot.yaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)

# Display the visualization of the Confusion Matrix.
plt.show()

print(classification_report(y_test, y_pred_knn))

class_probabilities = knn_model.predict_proba(X_test)
preds = class_probabilities[:, 1]

fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)

# Printing AUC
print(f"AUC for KNN classifier is: {roc_auc}")

# Plotting the ROC
plt.title('Receiver Operating Characteristic(KNN model)')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
Confusion Matrix - KNN
[[1183   15]
 [  77    3]]
```




```
              precision    recall  f1-score   support

           0       0.94      0.99      0.96      1198
           1       0.17      0.04      0.06        80

    accuracy                           0.93      1278
   macro avg       0.55      0.51      0.51      1278
weighted avg       0.89      0.93      0.91      1278

AUC for KNN classifier is: 0.5874426126878131
```

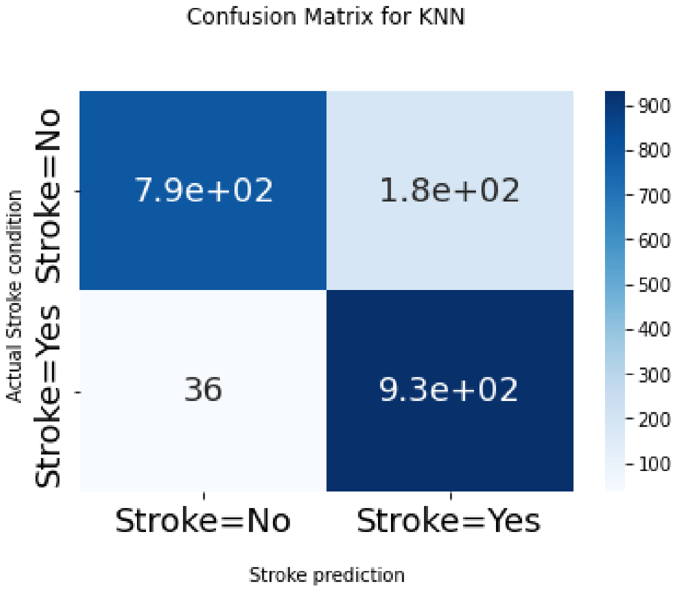


In [259]:

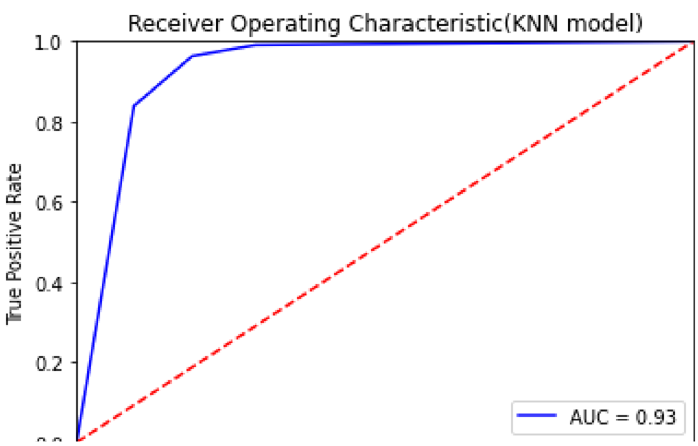
```python
#KNN model performance testing with oversampled data
knn4 = KNeighborsClassifier()
knn4.set_params(n_neighbors = 3)
knn_model = knn4.fit(X_train_os, y_train_os)
y_pred_knn = knn4.predict(X_test_os)
y_pred_knn

# Get the confusion matrix
cf_matrix_knn = confusion_matrix(y_test_os, y_pred_knn)

print('Confusion Matrix - KNN')
print(cf_matrix_knn)

cf_matrix_plot = sns.heatmap(cf_matrix_knn, annot=True, cmap='Blues', annot_kws={"fontsiz
e":18})

cf_matrix_plot.set_title('Confusion Matrix for KNN\n\n');
cf_matrix_plot.set_xlabel('\nStroke prediction')
cf_matrix_plot.set_ylabel('Actual Stroke condition ');

# Ticket labels
cf_matrix_plot.xaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
cf_matrix_plot.yaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)

# Display the visualization of the Confusion Matrix.
plt.show()
```

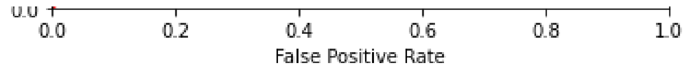
```
print(classification_report(y_test_os, y_pred_knn))

class_probabilities = knn_model.predict_proba(X_test_os)
preds = class_probabilities[:, 1]

fpr, tpr, threshold = roc_curve(y_test_os, preds)
roc_auc = auc(fpr, tpr)

# Printing AUC
print(f"AUC for KNN classifier is: {roc_auc}")

# Plotting the ROC
plt.title('Receiver Operating Characteristic(KNN model)')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
Confusion Matrix - KNN
[[793 183]
 [ 36 932]]
```




```
              precision    recall  f1-score   support

           0       0.96      0.81      0.88       976
           1       0.84      0.96      0.89       968

    accuracy                           0.89      1944
   macro avg       0.90      0.89      0.89      1944
weighted avg       0.90      0.89      0.89      1944

AUC for KNN classifier is: 0.9308375177821433
```





In [260]:

```
# Performing Hyper-parameter tuning to find the best model parameter. In case case, findi
ng the best k value using GridSearcgCV
from sklearn.model_selection import GridSearchCV
knn = KNeighborsClassifier()
params = {
    'n_neighbors': [3,5,7,9,11,13],
    'weights': ['uniform', 'distance'],
    'p': [1,2]
}

clf = GridSearchCV(
    estimator=knn,
    param_grid=params,
    cv=5,
    n_jobs=5,
    verbose=1
)
# Fitting our GridSearchCV Object
clf.fit(X_train, y_train)
# Printing the best parameters
print(clf.best_params_)
```

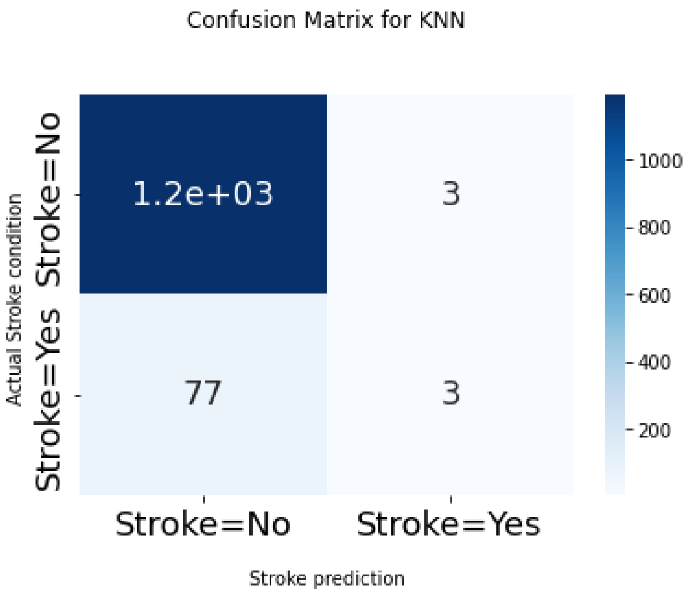
```
Fitting 5 folds for each of 24 candidates, totalling 120 fits
{'n_neighbors': 9, 'p': 2, 'weights': 'uniform'}
```

In [261]:

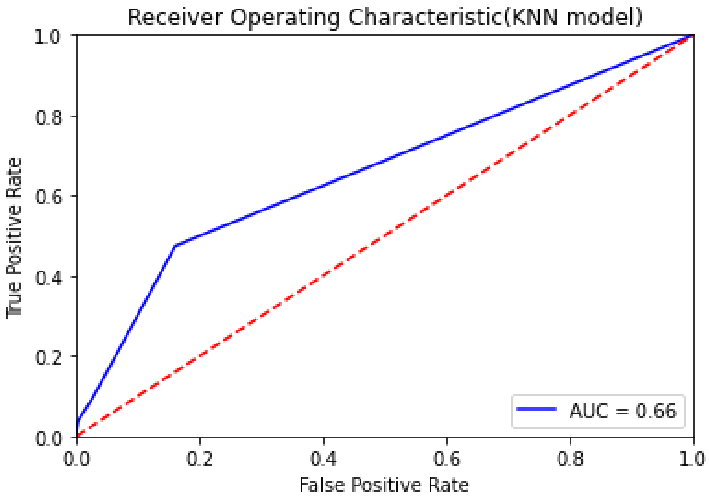
```
knn4 = KNeighborsClassifier()
knn4.set_params(n_neighbors = 5)
knn_model = knn4.fit(X_train, y_train)
y_pred_knn = knn4.predict(X_test)
y_pred_knn

# Get the confusion matrix
cf_matrix_knn = confusion_matrix(y_test, y_pred_knn)

print('Confusion Matrix - KNN')
print(cf_matrix_knn)

cf_matrix_plot = sns.heatmap(cf_matrix_knn, annot=True, cmap='Blues',annot_kws={"fontsize
":18})

cf_matrix_plot.set_title('Confusion Matrix for KNN\n\n');
cf_matrix_plot.set_xlabel('\nStroke prediction')
cf_matrix_plot.set_ylabel('Actual Stroke condition ');

# Ticket labels
cf_matrix_plot.xaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
cf_matrix_plot.yaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)

# Display the visualization of the Confusion Matrix.
plt.show()

print(classification_report(y_test, y_pred_knn))

class_probabilities = knn_model.predict_proba(X_test)
preds = class_probabilities[:, 1]

fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)

# Printing AUC
print(f"AUC for KNN classifier is: {roc_auc}")

# Plotting the ROC
plt.title('Receiver Operating Characteristic(KNN model)')
```

```python
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
Confusion Matrix - KNN
[[1195    3]
 [  77    3]]
```




```
              precision    recall  f1-score   support

           0       0.94      1.00      0.97      1198
           1       0.50      0.04      0.07        80

    accuracy                           0.94      1278
   macro avg       0.72      0.52      0.52      1278
weighted avg       0.91      0.94      0.91      1278

AUC for KNN classifier is: 0.6586863522537563
```



In [262]:

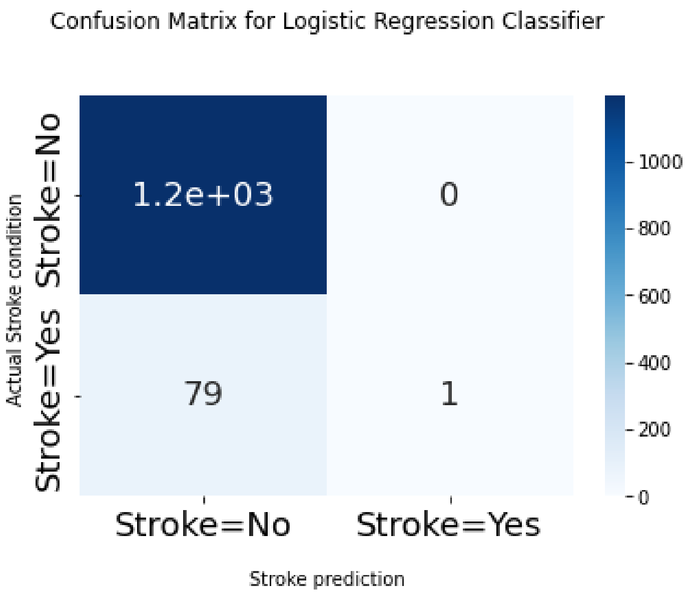
```python
# !pip install imbalanced-learn
```

In [263]:

```python
# Logistic Regression Classifier

from sklearn.linear_model import LogisticRegression
lrc_classifier = LogisticRegression(random_state = 1)
```

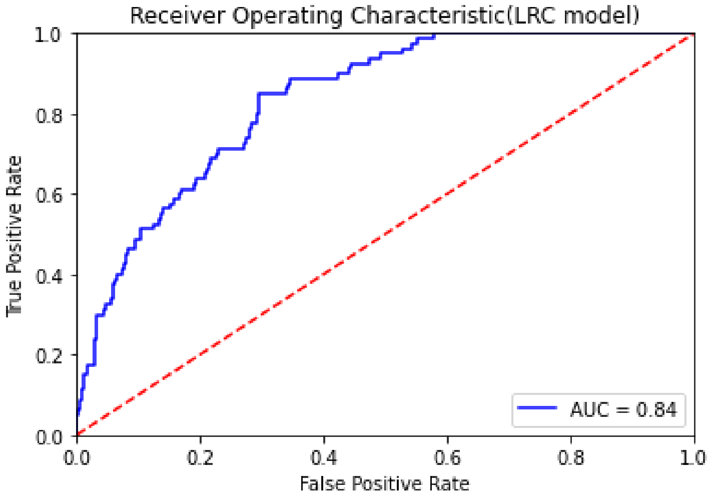
```
lrc_model = lrc_classifier.fit(X_train, y_train)
y_pred_lrc = lrc_classifier.predict(X_test)
y_pred_lrc
# Get the confusion matrix
cf_matrix_lrc = confusion_matrix(y_test, y_pred_lrc)
print('Confusion Matrix - LRC')
print(cf_matrix_lrc)

cf_matrix_plot = sns.heatmap(cf_matrix_lrc, annot=True, cmap='Blues',annot_kws={"fontsize
":18})

cf_matrix_plot.set_title('Confusion Matrix for Logistic Regression Classifier\n\n');
cf_matrix_plot.set_xlabel('\nStroke prediction')
cf_matrix_plot.set_ylabel('Actual Stroke condition ');

# Ticket labels
cf_matrix_plot.xaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
cf_matrix_plot.yaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)

# Display the visualization of the Confusion Matrix.
plt.show()

print(classification_report(y_test, y_pred_lrc))

class_probabilities = lrc_model.predict_proba(X_test)
preds = class_probabilities[:, 1]

fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)

# Printing AUC
print(f"AUC for Logistic Regression classifier is: {roc_auc}")

# Plotting the ROC
plt.title('Receiver Operating Characteristic(LRC model)')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
Confusion Matrix - LRC
[[1198    0]
 [  79    1]]
```




```
              precision    recall  f1-score   support

           0       0.94      1.00      0.97      1198
           1       1.00      0.01      0.02        80
```

```
    accuracy                           0.94      1278
   macro avg       0.97      0.51      0.50      1278
weighted avg       0.94      0.94      0.91      1278

AUC for Logistic Regression classifier is: 0.8351106010016695
```

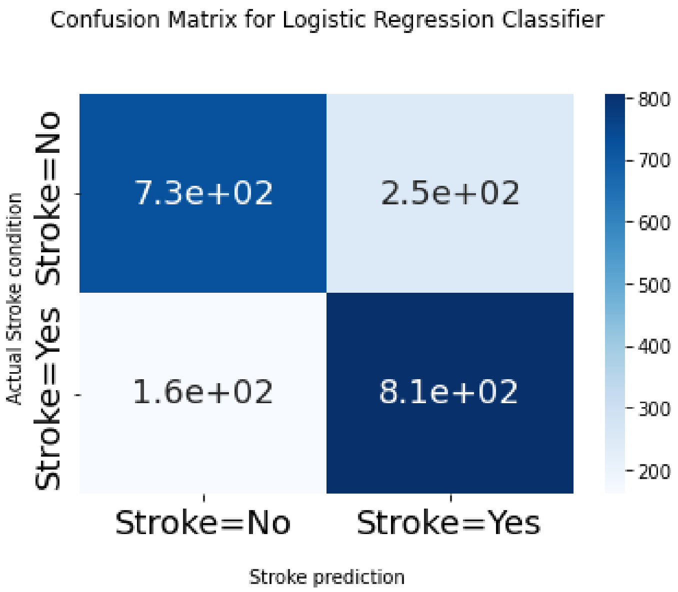


In [264]:

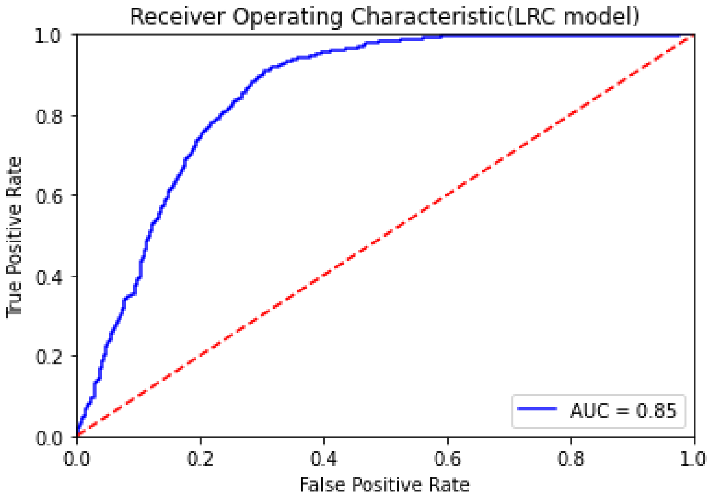
```
# LRC model performance testing with oversampled data

lrc_classifier = LogisticRegression(random_state = 1)
lrc_model = lrc_classifier.fit(X_train_os, y_train_os)
y_pred_lrc = lrc_classifier.predict(X_test_os)
y_pred_lrc
# Get the confusion matrix
cf_matrix_lrc = confusion_matrix(y_test_os, y_pred_lrc)
print('Confusion Matrix - LRC')
print(cf_matrix_lrc)

cf_matrix_plot = sns.heatmap(cf_matrix_lrc, annot=True, cmap='Blues',annot_kws={"fontsize
":18})

cf_matrix_plot.set_title('Confusion Matrix for Logistic Regression Classifier\n\n');
cf_matrix_plot.set_xlabel('\nStroke prediction')
cf_matrix_plot.set_ylabel('Actual Stroke condition ');

# Ticket labels
cf_matrix_plot.xaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
cf_matrix_plot.yaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)

# Display the visualization of the Confusion Matrix.
plt.show()

print(classification_report(y_test_os, y_pred_lrc))

class_probabilities = lrc_model.predict_proba(X_test_os)
preds = class_probabilities[:, 1]

fpr, tpr, threshold = roc_curve(y_test_os, preds)
roc_auc = auc(fpr, tpr)

# Printing AUC
print(f"AUC for Logistic Regression classifier is: {roc_auc}")

# Plotting the ROC
plt.title('Receiver Operating Characteristic(LRC model)')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
```

```
plt.show()
```

```
Confusion Matrix - LRC
[[726 250]
 [161 807]]
```




```
              precision    recall  f1-score   support

           0       0.82      0.74      0.78       976
           1       0.76      0.83      0.80       968

    accuracy                           0.79      1944
   macro avg       0.79      0.79      0.79      1944
weighted avg       0.79      0.79      0.79      1944

AUC for Logistic Regression classifier is: 0.8498763717653435
```

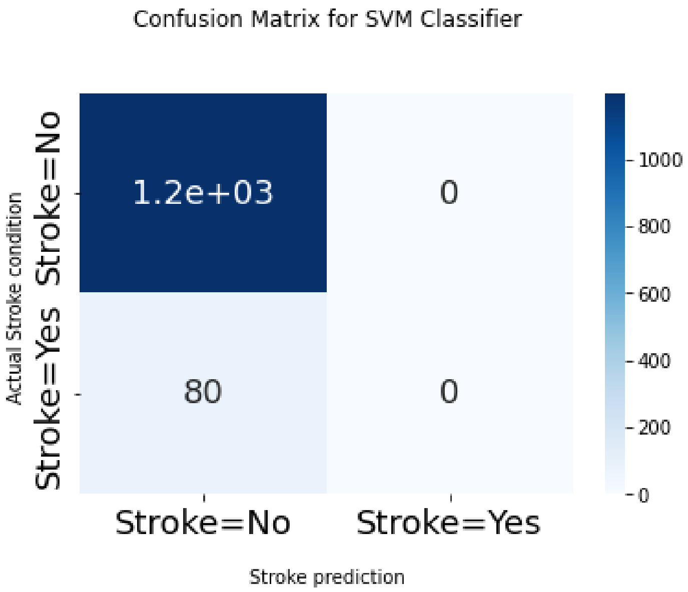


In [265]:

```
# SVM Classifier

from sklearn.svm import SVC
classifier_svc = SVC(kernel = 'linear', random_state = 0,probability=True) #class_weight
='balanced',
svm_model = classifier_svc.fit(X_train, y_train)
y_pred_svm = classifier_svc.predict(X_test)
y_pred_svm
# Get the confusion matrix
cf_matrix_svm = confusion_matrix(y_test, y_pred_svm)
print('Confusion Matrix - SVM')
print(cf_matrix_svm)

cf_matrix_plot = sns.heatmap(cf_matrix_svm, annot=True, cmap='Blues',annot_kws={"fontsize
":18})
```

```
cf_matrix_plot.set_title('Confusion Matrix for SVM Classifier\n\n');
cf_matrix_plot.set_xlabel('\nStroke prediction')
cf_matrix_plot.set_ylabel('Actual Stroke condition ');

# Ticket labels
cf_matrix_plot.xaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
cf_matrix_plot.yaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)

# Display the visualization of the Confusion Matrix.
plt.show()

print(classification_report(y_test, y_pred_svm))

class_probabilities = svm_model.predict_proba(X_test)
preds = class_probabilities[:, 1]

fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)

# Printing AUC
print(f"AUC for SVM classifier is: {roc_auc}")

# Plotting the ROC
plt.title('Receiver Operating Characteristic(SVM model)')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

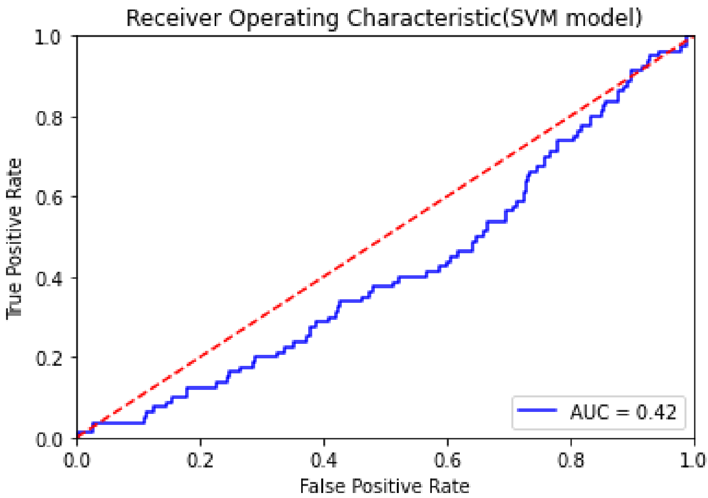
```
Confusion Matrix - SVM
[[1198    0]
 [  80    0]]
```




```
              precision    recall  f1-score   support

           0       0.94      1.00      0.97      1198
           1       0.00      0.00      0.00        80

    accuracy                           0.94      1278
   macro avg       0.47      0.50      0.48      1278
weighted avg       0.88      0.94      0.91      1278

AUC for SVM classifier is: 0.4173935726210351
```

```
C:\Users\samru\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1318: Undef
inedMetricWarning:
```

```
Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted sa
mples. Use `zero_division` parameter to control this behavior.

C:\Users\samru\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1318: Undef
inedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted sa
mples. Use `zero_division` parameter to control this behavior.

C:\Users\samru\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1318: Undef
inedMetricWarning:

Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted sa
mples. Use `zero_division` parameter to control this behavior.
```

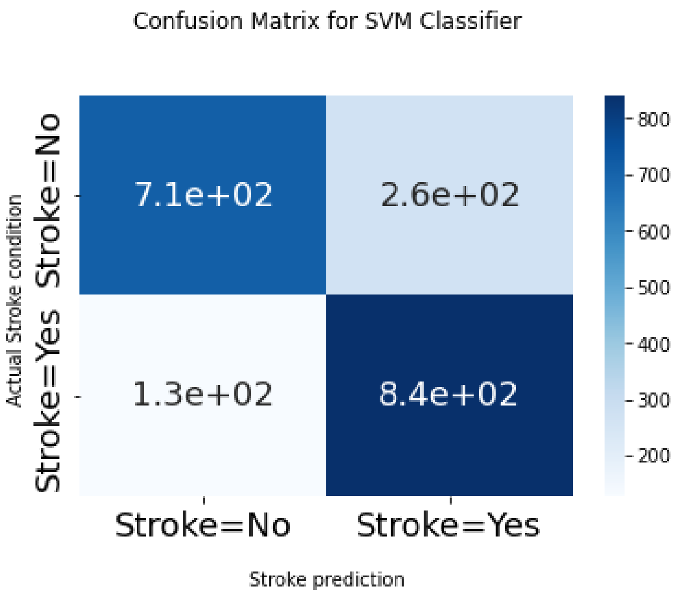


In [266]:

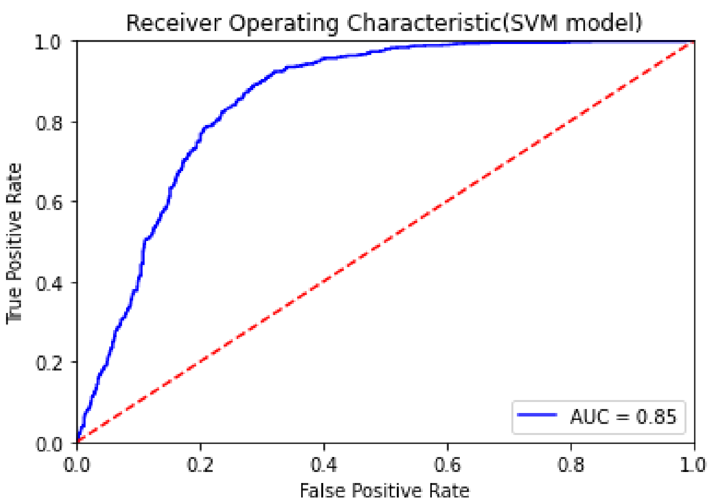
```
# SVM model performance testing with oversampled data

classifier_svc = SVC(kernel = 'linear', random_state = 0,probability=True) #class_weight
='balanced',
svm_model = classifier_svc.fit(X_train_os, y_train_os)
y_pred_svm = classifier_svc.predict(X_test_os)
y_pred_svm

# Get the confusion matrix
cf_matrix_svm = confusion_matrix(y_test_os, y_pred_svm)
print('Confusion Matrix - SVM')
print(cf_matrix_svm)

cf_matrix_plot = sns.heatmap(cf_matrix_svm, annot=True, cmap='Blues',annot_kws={"fontsize
":18})

cf_matrix_plot.set_title('Confusion Matrix for SVM Classifier\n\n');
cf_matrix_plot.set_xlabel('\nStroke prediction')
cf_matrix_plot.set_ylabel('Actual Stroke condition ');

# Ticket labels
cf_matrix_plot.xaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
cf_matrix_plot.yaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)

# Display the visualization of the Confusion Matrix.
plt.show()

print(classification_report(y_test_os, y_pred_svm))

class_probabilities = svm_model.predict_proba(X_test_os)
preds = class_probabilities[:, 1]

fpr, tpr, threshold = roc_curve(y_test_os, preds)
roc_auc = auc(fpr, tpr)

# Printing AUC
```

```
print(f"AUC for SVM classifier is: {roc_auc}")

# Plotting the ROC
plt.title('Receiver Operating Characteristic(SVM model)')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
Confusion Matrix - SVM
[[711 265]
 [127 841]]
```




```
              precision    recall  f1-score   support

           0       0.85      0.73      0.78       976
           1       0.76      0.87      0.81       968

    accuracy                           0.80      1944
   macro avg       0.80      0.80      0.80      1944
weighted avg       0.80      0.80      0.80      1944

AUC for SVM classifier is: 0.8517853060222191
```



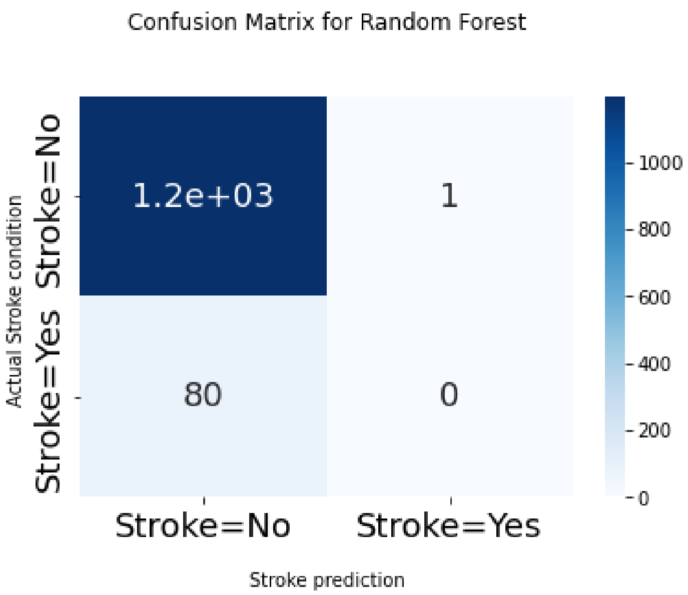
In [267]:

```
# !pip install mlxtend
```

In [268]:

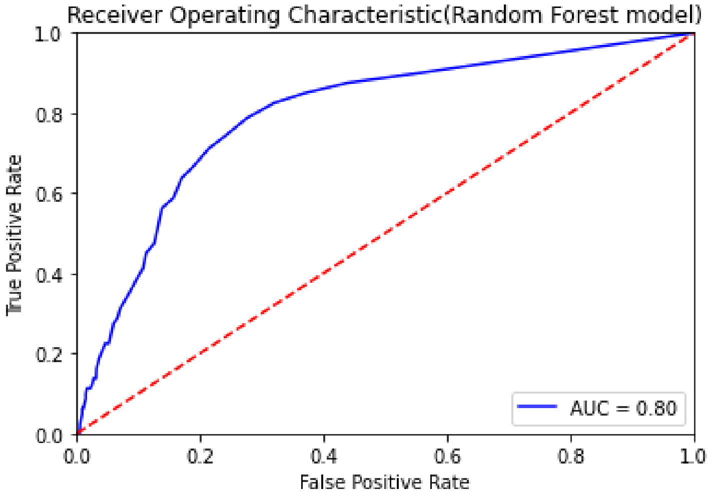
```
# Random Forest Classifier

from sklearn.ensemble import RandomForestClassifier
classifier_rf = RandomForestClassifier( random_state=0)
rf_model = classifier_rf.fit(X_train, y_train)
y_pred_rf = classifier_rf.predict(X_test)
y_pred_rf
# Get the confusion matrix
cf_matrix_rf = confusion_matrix(y_test, y_pred_rf)
print('Confusion Matrix - RF')
print(cf_matrix_rf)

# Plotting Confusion matrix
cf_matrix_plot = sns.heatmap(cf_matrix_rf, annot=True, cmap='Blues',annot_kws={"fontsize
":18})
cf_matrix_plot.set_title('Confusion Matrix for Random Forest\n\n');
cf_matrix_plot.set_xlabel('\nStroke prediction')
cf_matrix_plot.set_ylabel('Actual Stroke condition ');

# Ticket labels - List must be in alphabetical order
cf_matrix_plot.xaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
cf_matrix_plot.yaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
plt.show()

print(classification_report(y_test, y_pred_rf))

class_probabilities = rf_model.predict_proba(X_test)
preds = class_probabilities[:, 1]

fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)

# Printing AUC
print(f"AUC for Random Forest classifier is: {roc_auc}")

# Plotting the ROC
plt.title('Receiver Operating Characteristic(Random Forest model)')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
Confusion Matrix - RF
[[1197    1]
 [  80    0]]
```




```
              precision    recall  f1-score   support
```

```
           0       0.94      1.00      0.97      1198
           1       0.00      0.00      0.00        80

    accuracy                           0.94      1278
   macro avg       0.47      0.50      0.48      1278
weighted avg       0.88      0.94      0.91      1278

AUC for Random Forest classifier is: 0.7967810934891485
```

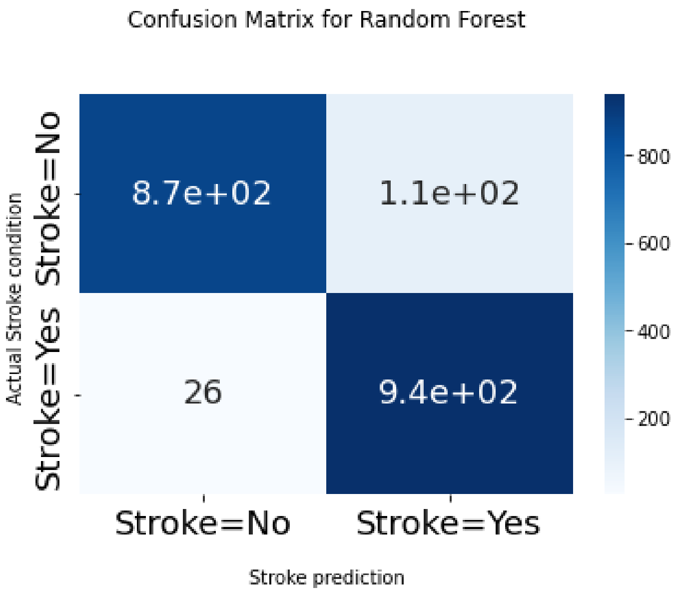


In [269]:

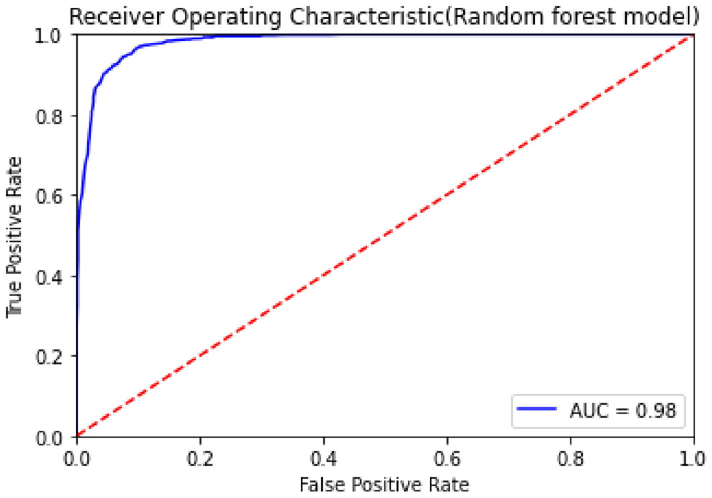
```
# Random Forest Classifier performance testing after oversampling

classifier_rf = RandomForestClassifier( random_state=0)
rf_model = classifier_rf.fit(X_train_os, y_train_os)
y_pred_rf = classifier_rf.predict(X_test_os)
y_pred_rf
# Get the confusion matrix
cf_matrix_rf = confusion_matrix(y_test_os, y_pred_rf)
print('Confusion Matrix - RF')
print(cf_matrix_rf)

# Plotting Confusion matrix
cf_matrix_plot = sns.heatmap(cf_matrix_rf, annot=True, cmap='Blues',annot_kws={"fontsize
":18})
cf_matrix_plot.set_title('Confusion Matrix for Random Forest\n\n');
cf_matrix_plot.set_xlabel('\nStroke prediction')
cf_matrix_plot.set_ylabel('Actual Stroke condition ');

# Ticket labels - List must be in alphabetical order
cf_matrix_plot.xaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
cf_matrix_plot.yaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
plt.show()

print(classification_report(y_test_os, y_pred_rf))

class_probabilities = rf_model.predict_proba(X_test_os)
preds = class_probabilities[:, 1]

fpr, tpr, threshold = roc_curve(y_test_os, preds)
roc_auc = auc(fpr, tpr)

# Printing AUC
print(f"AUC for Random Forest classifier is: {roc_auc}")

# Plotting the ROC
plt.title('Receiver Operating Characteristic(Random forest model)')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
```

```
plt.show()
```

```
Confusion Matrix - RF
[[868 108]
 [ 26 942]]
```




```
              precision    recall  f1-score   support

           0       0.97      0.89      0.93       976
           1       0.90      0.97      0.93       968

    accuracy                           0.93      1944
   macro avg       0.93      0.93      0.93      1944
weighted avg       0.93      0.93      0.93      1944

AUC for Random Forest classifier is: 0.982222090502642
```

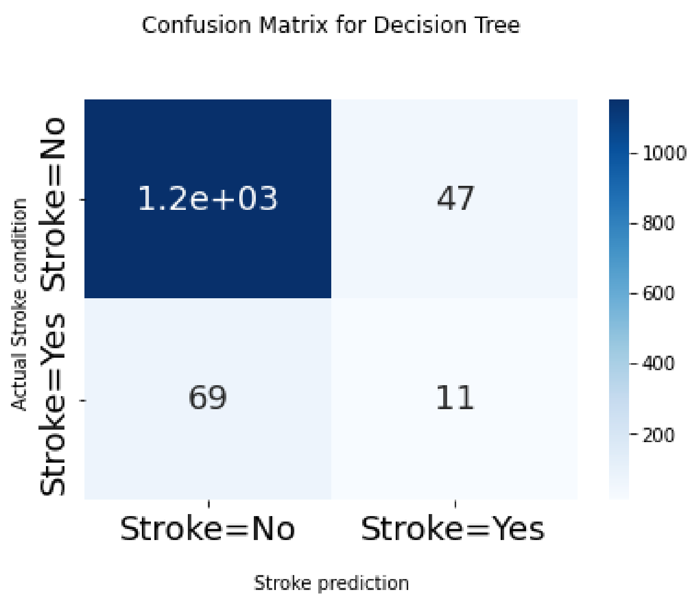


In [270]:

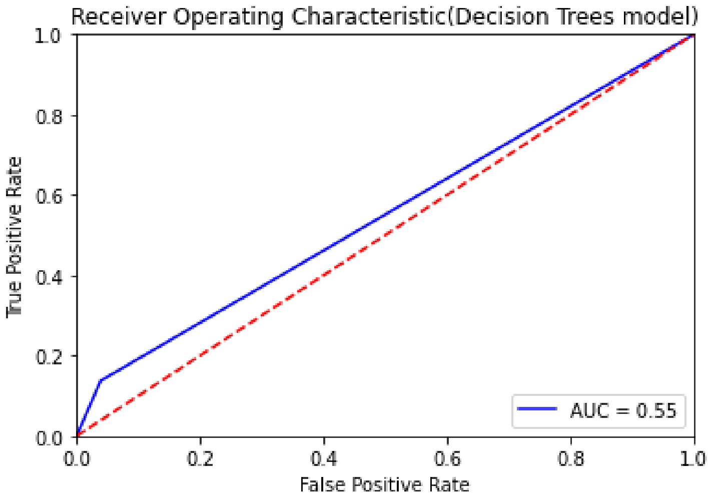
```
# Decision Tree Classifier

from sklearn.tree import DecisionTreeClassifier
from sklearn import tree

dt = DecisionTreeClassifier(random_state= 0)
dt_model = dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)
y_pred_dt

# Get the confusion matrix
cf_matrix_dt = confusion_matrix(y_test, y_pred_dt)
print('Confusion Matrix - RF')
print(cf_matrix_dt)
```

```
cf_matrix_plot = sns.heatmap(cf_matrix_dt, annot=True, cmap='Blues',annot_kws={"fontsize
":18})

cf_matrix_plot.set_title('Confusion Matrix for Decision Tree\n\n');
cf_matrix_plot.set_xlabel('\nStroke prediction')
cf_matrix_plot.set_ylabel('Actual Stroke condition ');

## Ticket labels - List must be in alphabetical order
cf_matrix_plot.xaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
cf_matrix_plot.yaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)

## Display the visualization of the Confusion Matrix.
plt.show()

print(classification_report(y_test, y_pred_dt))

class_probabilities = dt_model.predict_proba(X_test)
preds = class_probabilities[:, 1]

fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)

# Printing AUC
print(f"AUC for Decision Trees classifier is: {roc_auc}")

# Plotting the ROC
plt.title('Receiver Operating Characteristic(Decision Trees model)')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
# plt.figure(figsize=(50,50))
# tree.plot_tree(dt, filled= True,feature_names=X_train.columns, fontsize=10)
```

```
Confusion Matrix - RF
[[1151   47]
 [  69   11]]
```




```
              precision    recall  f1-score   support

           0       0.94      0.96      0.95      1198
           1       0.19      0.14      0.16        80

    accuracy                           0.91      1278
   macro avg       0.57      0.55      0.56      1278
weighted avg       0.90      0.91      0.90      1278

AUC for Decision Trees classifier is: 0.5491339732888147
```

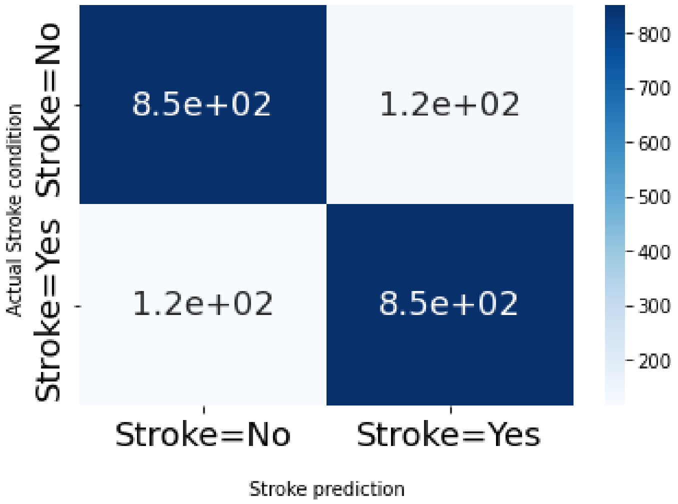


In [271]:

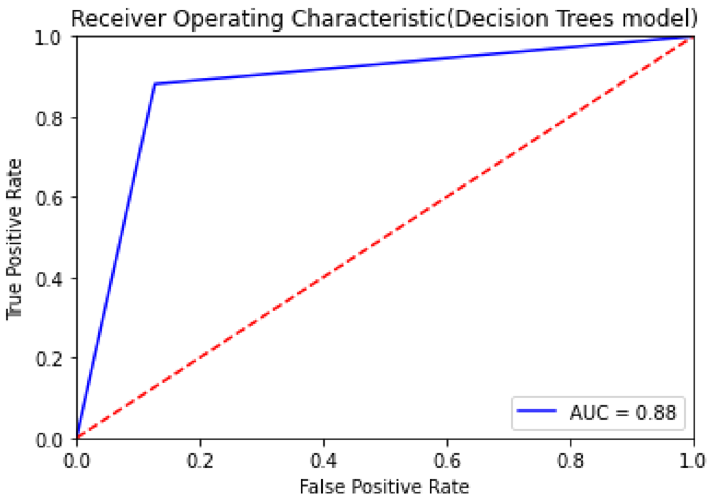
```
# Decision Trees Classifier performance testing after oversampling
dt = DecisionTreeClassifier(random_state= 0)
dt_model = dt.fit(X_train_os, y_train_os)
y_pred_dt = dt.predict(X_test_os)
y_pred_dt

# Get the confusion matrix
cf_matrix_dt = confusion_matrix(y_test_os, y_pred_dt)
print('Confusion Matrix - RF')
print(cf_matrix_dt)

cf_matrix_plot = sns.heatmap(cf_matrix_dt, annot=True, cmap='Blues',annot_kws={"fontsize
":18})

cf_matrix_plot.set_title('Confusion Matrix for Decision Tree\n\n');
cf_matrix_plot.set_xlabel('\nStroke prediction')
cf_matrix_plot.set_ylabel('Actual Stroke condition ');

# Ticket labels - List must be in alphabetical order
cf_matrix_plot.xaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
cf_matrix_plot.yaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)

# Display the visualization of the Confusion Matrix.
plt.show()

print(classification_report(y_test_os, y_pred_dt))

class_probabilities = dt_model.predict_proba(X_test_os)
preds = class_probabilities[:, 1]

fpr, tpr, threshold = roc_curve(y_test_os, preds)
roc_auc = auc(fpr, tpr)

# Printing AUC
print(f"AUC for Decision Trees classifier is: {roc_auc}")

# Plotting the ROC
plt.title('Receiver Operating Characteristic(Decision Trees model)')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
Confusion Matrix - RF
[[852 124]
 [115 853]]
```

Confusion Matrix for Decision Tree




```
              precision    recall  f1-score   support

           0       0.88      0.87      0.88       976
           1       0.87      0.88      0.88       968

    accuracy                           0.88      1944
   macro avg       0.88      0.88      0.88      1944
weighted avg       0.88      0.88      0.88      1944

AUC for Decision Trees classifier is: 0.8770745833897846
```



In [272]:

```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
# selecting top 10 features using chi-square test method
sel_chi2 = SelectKBest(chi2, k=10)
X_train_chi2 = sel_chi2.fit_transform(X_train, y_train)
print(sel_chi2.get_support())
```

```
[False  True  True  True  True  True  True False  True False  True  True
  True False False]
```

In [273]:

```
X_test_chi2 = sel_chi2.transform(X_test)
print(X_test.shape)
print(X_test_chi2.shape)
```

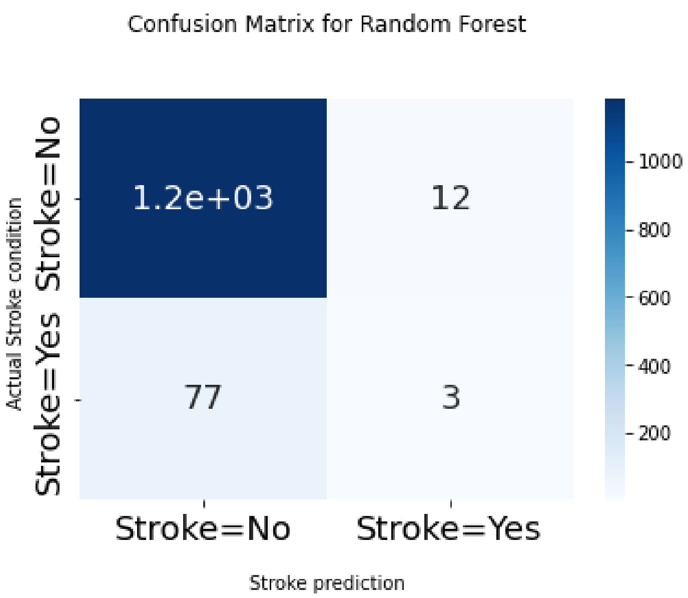
```
(1278, 15)
(1278, 10)
```

In [274]:

```
# Random Forest Classifier performance testing after feature selection
```

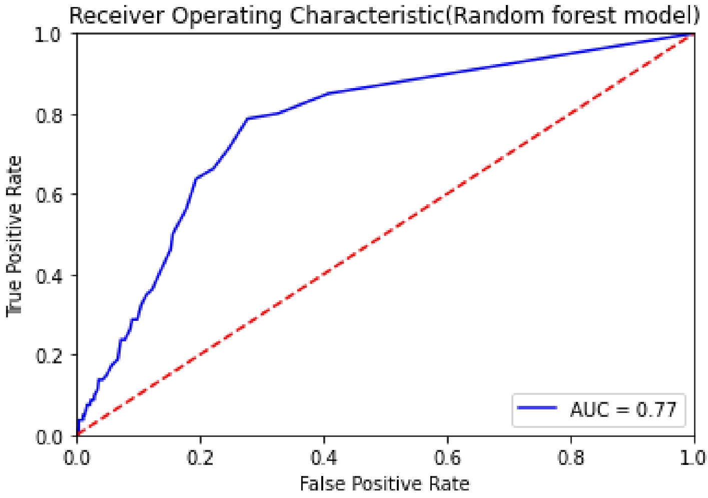
```python
classifier_rf = RandomForestClassifier( random_state=0)
rf_model = classifier_rf.fit(X_train_chi2, y_train)
y_pred_rf = classifier_rf.predict(X_test_chi2)
y_pred_rf
# Get the confusion matrix
cf_matrix_rf = confusion_matrix(y_test, y_pred_rf)
print('Confusion Matrix - RF')
print(cf_matrix_rf)

# Plotting Confusion matrix
cf_matrix_plot = sns.heatmap(cf_matrix_rf, annot=True, cmap='Blues',annot_kws={"fontsize
":18})
cf_matrix_plot.set_title('Confusion Matrix for Random Forest\n\n');
cf_matrix_plot.set_xlabel('\nStroke prediction')
cf_matrix_plot.set_ylabel('Actual Stroke condition ');

# Ticket labels - List must be in alphabetical order
cf_matrix_plot.xaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
cf_matrix_plot.yaxis.set_ticklabels(['Stroke=No','Stroke=Yes'],fontsize = 18)
plt.show()

print(classification_report(y_test, y_pred_rf))

class_probabilities = rf_model.predict_proba(X_test_chi2)
preds = class_probabilities[:, 1]

fpr, tpr, threshold = roc_curve(y_test, preds)
roc_auc = auc(fpr, tpr)

# Printing AUC
print(f"AUC for Random Forest classifier is: {roc_auc}")

# Plotting the ROC
plt.title('Receiver Operating Characteristic(Random forest model)')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
Confusion Matrix - RF
[[1186   12]
 [  77    3]]
```




```
              precision    recall  f1-score   support

           0       0.94      0.99      0.96      1198
           1       0.20      0.04      0.06        80
```

```
    accuracy                           0.93      1278
   macro avg       0.57      0.51      0.51      1278
weighted avg       0.89      0.93      0.91      1278

AUC for Random Forest classifier is: 0.7708785475792989
```



In [ ]: