Importing Necessary Libraries

In [1]:

```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
import missingno as msno
import pickle
from imblearn.over_sampling import RandomOverSampler
from sklearn.compose import ColumnTransformer, make_column_selector as selector
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OrdinalEncoder
```

In [3]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, roc_auc_score, roc_curve, confusion_matrix,
from sklearn.model_selection import GridSearchCV
```

In [4]:

```
import keras
from keras.callbacks import EarlyStopping
from keras.models import Sequential
from keras.layers import Dense
```

In [5]:

```
plt.rc('font', size=15)
```

Importing the Input Dataset

In [6]:

```
thyroid_data = pd.read_csv('input/thyroid0387.data', header=None)
```

Data Inspection and Cleaning

In [7]:

```
thyroid_data
```

Out[7]:

	0	1	2	3	4	5	6	7	8	9	...	20	21	22	23	24	25	26	27	28	
0	29	F	f	f	f	f	f	f	f	t	...	f	?	f	?	f	?	f	?	other	-[84(
1	29	F	f	f	f	f	f	f	f	f	...	t	128	f	?	f	?	f	?	other	-[84(
2	41	F	f	f	f	f	f	f	f	f	...	f	?	f	?	f	?	t	11	other	-[84(
3	36	F	f	f	f	f	f	f	f	f	...	f	?	f	?	f	?	t	26	other	-[84(
4	32	F	f	f	f	f	f	f	f	f	...	f	?	f	?	f	?	t	36	other	S[84(
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
9167	56	M	f	f	f	f	f	f	f	f	...	t	64	t	0.83	t	77	f	?	SVI	-[87(
9168	22	M	f	f	f	f	f	f	f	f	...	t	91	t	0.92	t	99	f	?	SVI	-[87(
9169	69	M	f	f	f	f	f	f	f	f	...	t	113	t	1.27	t	89	f	?	SVI	I[87(
9170	47	F	f	f	f	f	f	f	f	f	...	t	75	t	0.85	t	88	f	?	other	-[87(
9171	31	M	f	f	f	f	f	f	f	t	...	t	66	t	1.02	t	65	f	?	other	-[87(

9172 rows × 30 columns

In [8]:

```
thyroid_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9172 entries, 0 to 9171
Data columns (total 30 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   0       9172 non-null   int64
 1   1       9172 non-null   object
 2   2       9172 non-null   object
 3   3       9172 non-null   object
 4   4       9172 non-null   object
 5   5       9172 non-null   object
 6   6       9172 non-null   object
 7   7       9172 non-null   object
 8   8       9172 non-null   object
 9   9       9172 non-null   object
 10  10      9172 non-null   object
 11  11      9172 non-null   object
 12  12      9172 non-null   object
 13  13      9172 non-null   object
```

In [7]:

```
#Name of the Variables in order, gathered from the Raw Data
feature_list = ['age', 'sex', 'on_thyroxine', 'query_on_thyroxine', 'on_antithyroid_medi
len(feature_list)
```

Out[7]:

30

In [8]:

```
thyroid_data.columns = feature_list
thyroid_data.head()
```

Out[8]:

	age	sex	on_thyroxine	query_on_thyroxine	on_antithyroid_medication	sick	pregnant	th
0	29	F	f	f	f	f	f	
1	29	F	f	f	f	f	f	
2	41	F	f	f	f	f	f	
3	36	F	f	f	f	f	f	
4	32	F	f	f	f	f	f	

5 rows × 30 columns

Remvoing useless variables

In [9]:

```
thyroid_data.drop(columns=['referral source', 'TSH_measured', 'T3_measured', 'TT4_measur
```

Removing variables which are vague and without context

In [10]:

```
thyroid_data.drop(columns=['on_thyroxine', 'query_on_thyroxine', 'on_antithyroid_medicat
```

Missing values are denoted by '?', so we will replace it with np.nan to them

In [11]:

```
thyroid_data = thyroid_data.apply(lambda x: np.where(x=='?', np.nan, x))
thyroid_data.head()
```

Out[11]:

	age	sex	sick	pregnant	thyroid_surgery	lithium	goitre	tumor	hypopituitary	psych	T
0	29.0	F	f	f	f	f	f	f	f	f	
1	29.0	F	f	f	f	f	f	f	f	f	
2	41.0	F	f	f	f	f	f	f	f	f	N
3	36.0	F	f	f	f	f	f	f	f	f	N
4	32.0	F	f	f	f	f	f	f	f	f	N

Type Conversion

Converting Data Type of Numerical Variables to float

In [12]:

```
num_vars = ['age', 'TSH', 'T3', 'TT4', 'T4U', 'FTI', 'TBG']
```

In [13]:

```
thyroid_data[num_vars] = thyroid_data[num_vars].apply(lambda x: x.astype('float64'))
```

Encoding Categorical Variables

Encoding 't' - True and 'f' - False

In [14]:

```
cat_vars = ['sex', 'sick', 'pregnant', 'thyroid_surgery', 'lithium',
       'goitre', 'tumor', 'hypopituitary', 'psych']
```

In [15]:

```
thyroid_data[cat_vars] = thyroid_data[cat_vars].apply(lambda x: np.where(x=='t', True, n
thyroid_data[cat_vars].head()
```

Out[15]:

	sex	sick	pregnant	thyroid_surgery	lithium	goitre	tumor	hypopituitary	psych
0	F	False	False	False	False	False	False	False	False
1	F	False	False	False	False	False	False	False	False
2	F	False	False	False	False	False	False	False	False
3	F	False	False	False	False	False	False	False	False
4	F	False	False	False	False	False	False	False	False

Derive Variable Creation

In [16]:

```
# Creating a Dictionary about Diagnoses Variable from the information given in the Raw Da
diagnoses_dict = {
    'hyperthyroid':['A', 'B', 'C', 'D'],
    'hypothyroid':['E', 'F', 'G', 'H'],
    'normal':['-']
}
```

In [17]:

```
temp_list = []
for i in range(thyroid_data.shape[0]):
    if thyroid_data.Diagnoses[i][0] in diagnoses_dict['hyperthyroid']:
        temp_list.append('hyperthyroid')
    elif thyroid_data.Diagnoses[i][0] in diagnoses_dict['hypothyroid']:
        temp_list.append('hypothyroid')
    elif thyroid_data.Diagnoses[i][0] in diagnoses_dict['normal']:
        temp_list.append('normal')
    else:
        temp_list.append('others')

thyroid_data['condition'] = temp_list
```

In [18]:

```
# Dropping Diagnoses as it is not needed anymore
thyroid_data.drop(columns=['Diagnoses'], inplace=True)
```

In [19]:

```
thyroid_data.condition.value_counts()
```

Out[19]:

```
normal          6771
others          1493
hypothyroid      667
hyperthyroid     241
Name: condition, dtype: int64
```

Deriving the Dependent Variable

In [20]:

```
thyroid_data['thyroid_disease'] = np.where((thyroid_data.condition == 'hypothyroid')|(th
```

In [21]:

```
thyroid_data.thyroid_disease.value_counts()
```

Out[21]:

```
False    8264
True      908
Name: thyroid_disease, dtype: int64
```

Duplicate Value Inspection

In [22]:

```
thyroid_data.duplicated().sum()
```

Out[22]:

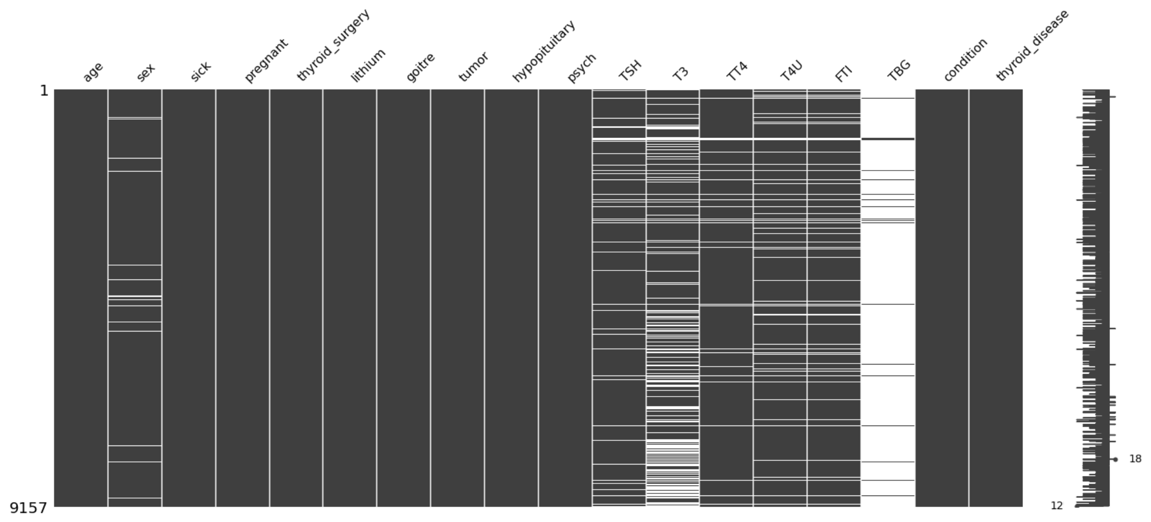
```
15
```

In [23]:

```
# Dropping the Duplicate Observations
thyroid_data.drop_duplicates(ignore_index=True, inplace=True)
```

In [44]:

```
msno.matrix(thyroid_data)
plt.savefig('plots/missing_value_matrix.png', bbox_inches='tight')
plt.show()
```



In [45]:

```
thyroid_data.isna().sum()
```

Out[45]:

```
age                    0
sex                  306
sick                   0
pregnant               0
thyroid_surgery        0
lithium                0
goitre                 0
tumor                  0
hypopituitary          0
psych                  0
TSH                  830
T3                  2593
TT4                  430
T4U                  796
FTI                  789
TBG                 8819
condition              0
thyroid_disease        0
dtype: int64
```

Dropping TBG due to High amount of Missing Values

In [24]:

```
thyroid_data.drop(columns=['TBG'], inplace=True)
```

Now, Dropping all the observations which have missing values in more than 2 out of 5 Numerical Variables

In [25]:

```
num_vars = ['age', 'TSH', 'T3', 'TT4', 'T4U', 'FTI']
index_to_drop = [i for i, value in enumerate(thyroid_data[num_vars].isna().sum(axis=1).v
print('No. of observations to be dropped :',len(index_to_drop))
```

```
No. of observations to be dropped : 454
```

In [26]:

```
thyroid_data = thyroid_data.drop(index=index_to_drop).reset_index(drop=True)
thyroid_data
```

Out[26]:

	age	sex	sick	pregnant	thyroid_surgery	lithium	goitre	tumor	hypopituitary	psyc
0	29.0	F	False	False	False	False	False	False	False	Fals
1	28.0	F	False	False	False	False	False	False	False	Fals
2	28.0	F	False	False	False	False	False	False	False	Fals
3	28.0	F	False	False	False	False	False	False	False	Fals
4	54.0	F	False	False	False	False	False	False	False	Fals
...	...	...	...	...	...	...	...	...	...	
8698	56.0	M	False	False	False	False	False	False	False	Fals
8699	22.0	M	False	False	False	False	False	False	False	Fals
8700	69.0	M	False	False	False	False	False	False	False	Fals
8701	47.0	F	False	False	False	False	False	False	False	Fals
8702	31.0	M	False	False	False	False	False	False	False	Fals

8703 rows × 17 columns

Separating Features and Target Variable

In [27]:

```
X = thyroid_data[thyroid_data.columns.difference(['condition', 'thyroid_disease'])]
y = thyroid_data['thyroid_disease']
print('Thyroid Data : {}\nFeatures :{}\nTarget : {}'.format(thyroid_data.shape, X.shape,
```

```
Thyroid Data : (8703, 17)
Features :(8703, 15)
Target : (8703,)
```

In [28]:

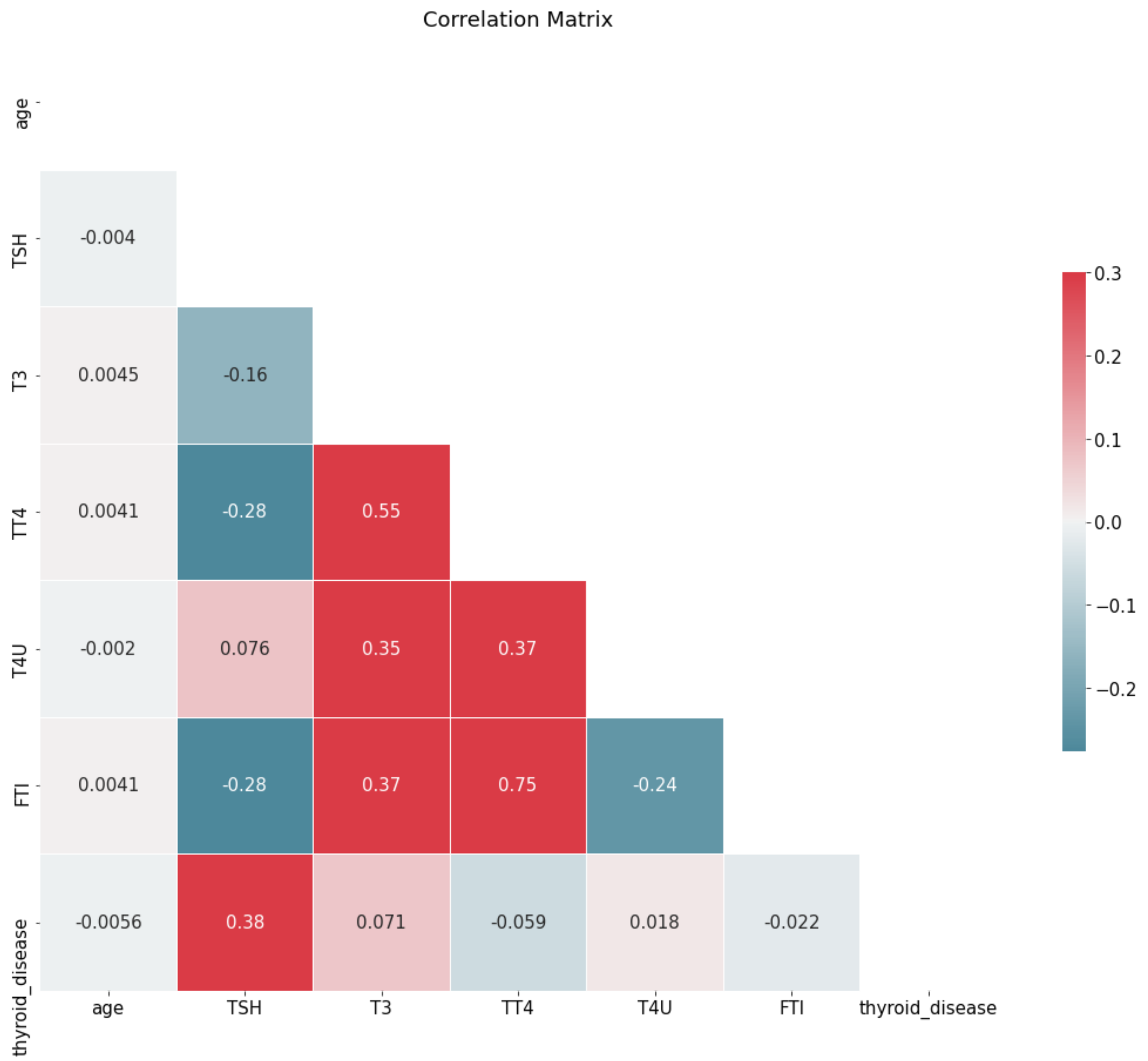
```
cat_vars = [var for var in X.columns if var not in num_vars]
binary_vars = [var for var in cat_vars if var != 'sex']
print('Numerical Variables : {} \nLength : {}'.format(num_vars, len(num_vars)))
print('Categorical Variables : {} \nLength : {}'.format(cat_vars, len(cat_vars)))
print('Binary Variables : {} \nLength : {}'.format(binary_vars, len(binary_vars)))
```

```
Numerical Variables : ['age', 'TSH', 'T3', 'TT4', 'T4U', 'FTI']
Length : 6
Categorical Variables : ['goitre', 'hypopituitary', 'lithium', 'pregnant',
'psych', 'sex', 'sick', 'thyroid_surgery', 'tumor']
Length : 9
Binary Variables : ['goitre', 'hypopituitary', 'lithium', 'pregnant', 'psy
ch', 'sick', 'thyroid_surgery', 'tumor']
Length : 8
```

Exploratory Data Analysis

In [60]:

```
corr_matrix = thyroid_data.corr()

mask = np.triu(np.ones_like(corr_matrix, dtype=np.bool))

f, ax = plt.subplots(figsize=(20, 15))

cmap = sns.diverging_palette(220, 10, as_cmap=True)

plt.title('Correlation Matrix')

sns.heatmap(corr_matrix, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}, annot=True)

plt.show()
```



In [52]:

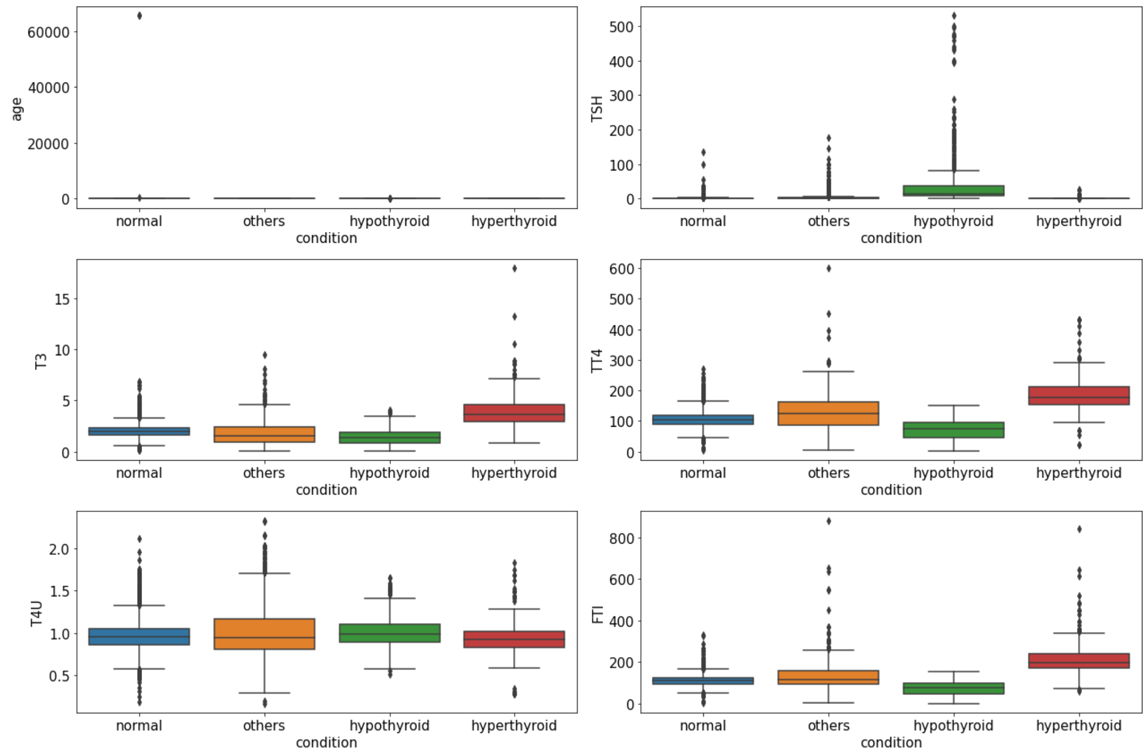
```
thyroid_data[num_vars].iloc[:,1]
```

Out[52]:

```
0       0.3
1       1.6
2       NaN
3       NaN
4       NaN
       ...
9167    NaN
9168    NaN
9169    NaN
9170    NaN
9171    NaN
Name: TSH, Length: 9172, dtype: float64
```

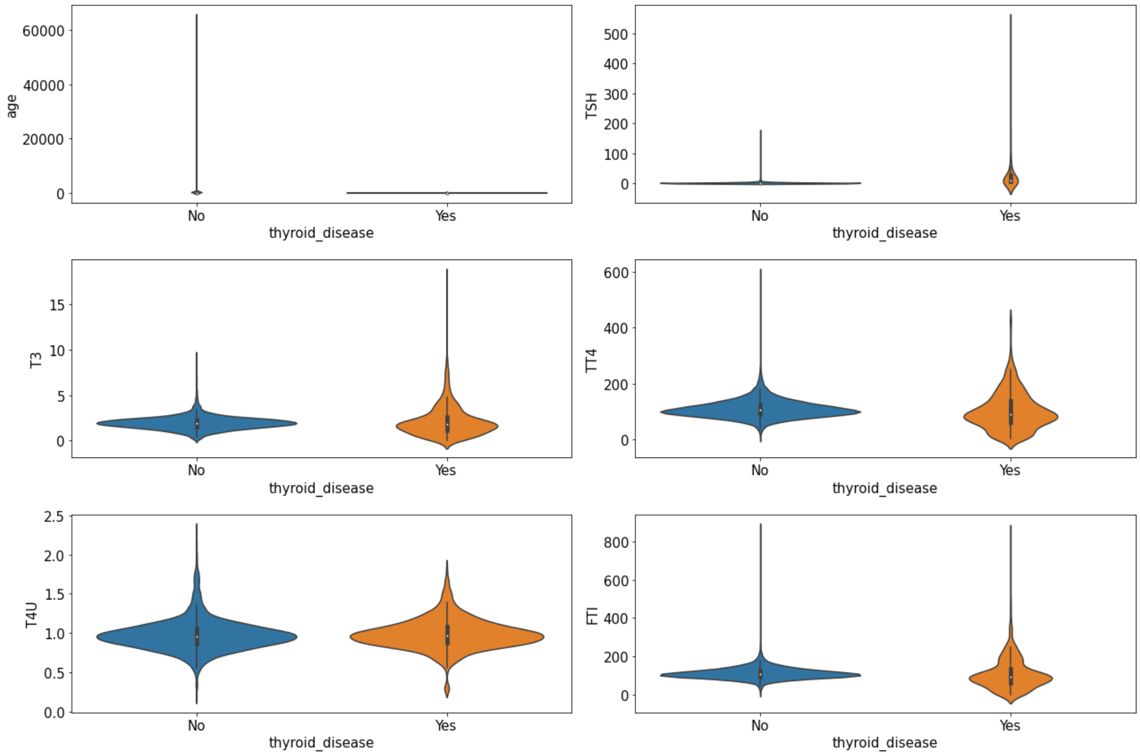
In [71]:

```
fig, ax = plt.subplots(nrows=3, ncols=2, figsize=(18,12))
ax = ax.flatten()

for i in range(len(ax)):
    ax[i] = sns.boxplot(data=thyroid_data, x='condition', y=thyroid_data[num_vars].iloc[
plt.tight_layout()
plt.show()
```



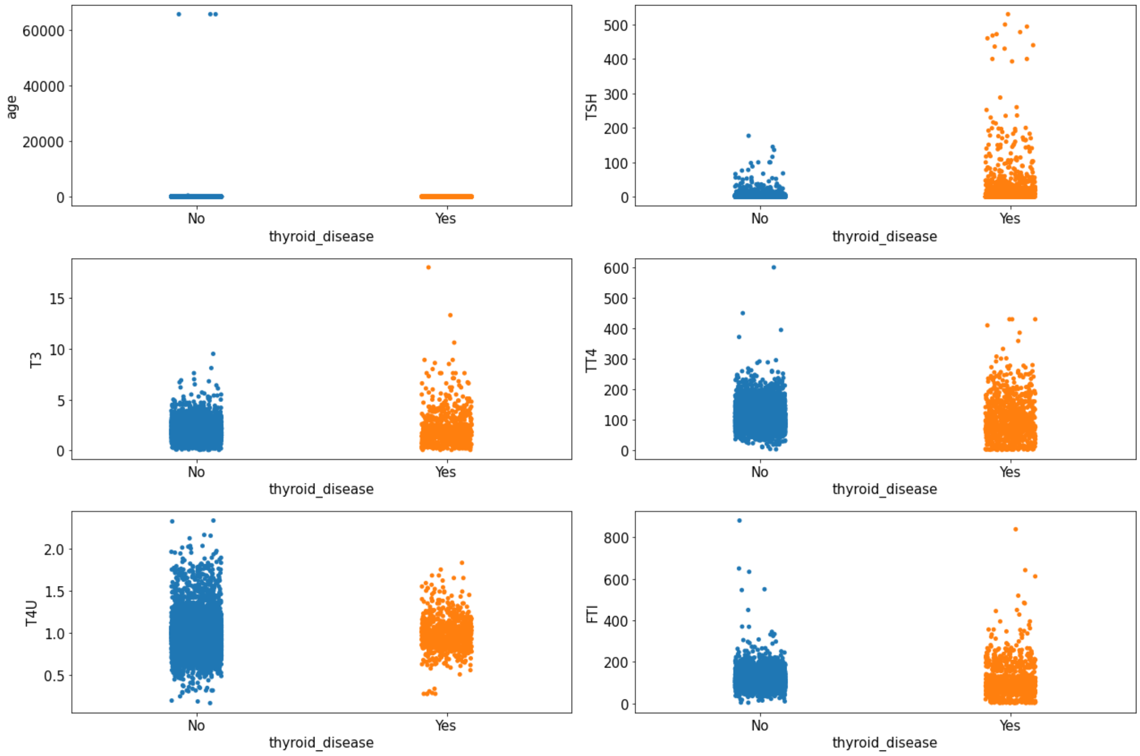
In [82]:

```
fig, ax = plt.subplots(nrows=3, ncols=2, figsize=(18,12))
ax = ax.flatten()

for i in range(len(ax)):
    ax[i] = sns.violinplot(data=thyroid_data, x='thyroid_disease', y=thyroid_data[num_va
plt.tight_layout()
plt.show()
```



In [83]:

```
fig, ax = plt.subplots(nrows=3, ncols=2, figsize=(18,12))
ax = ax.flatten()

for i in range(len(ax)):
    ax[i] = sns.stripplot(data=thyroid_data, x='thyroid_disease', y=thyroid_data[num_var
plt.tight_layout()
plt.show()
```

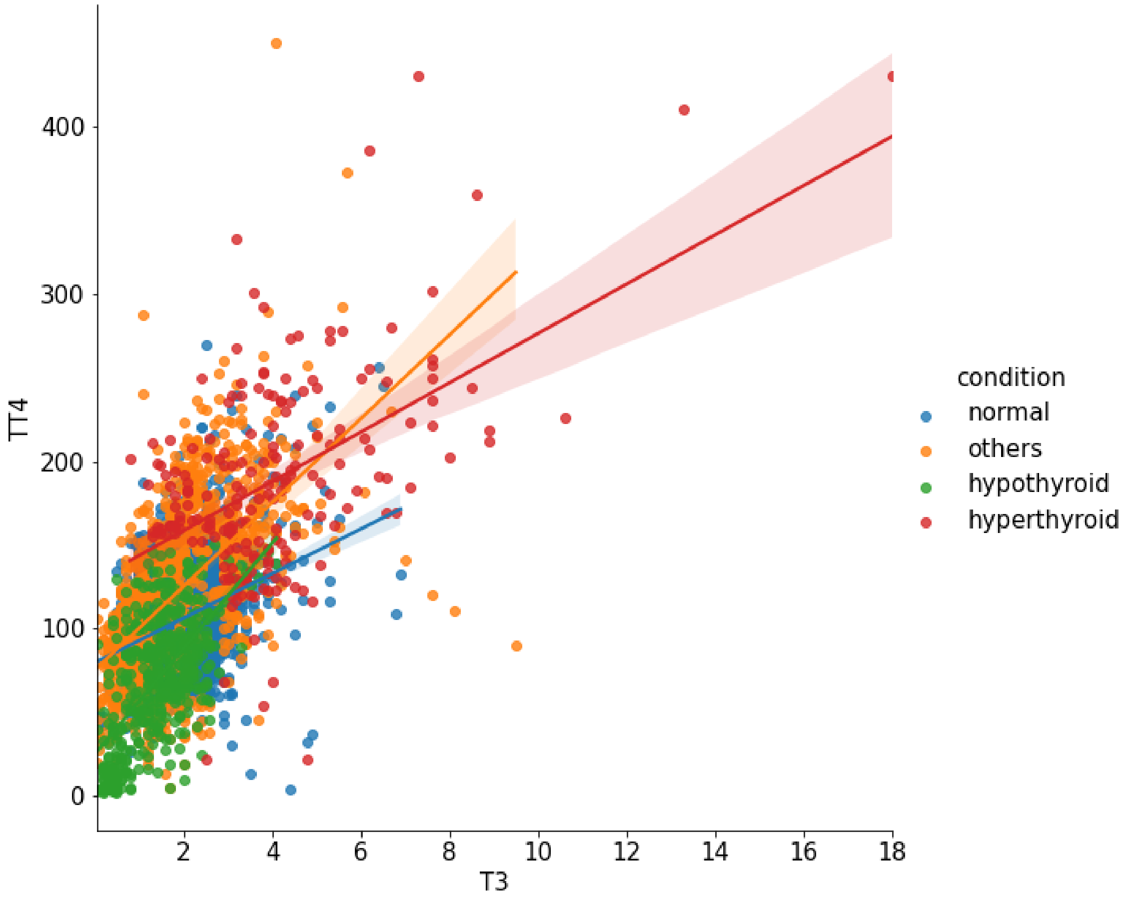


In [77]:

```
sns.lmplot(data=thyroid_data, x='T3', y='TT4', hue='condition', height=8)
```

Out[77]:

```
<seaborn.axisgrid.FacetGrid at 0x252e10d28e0>
```

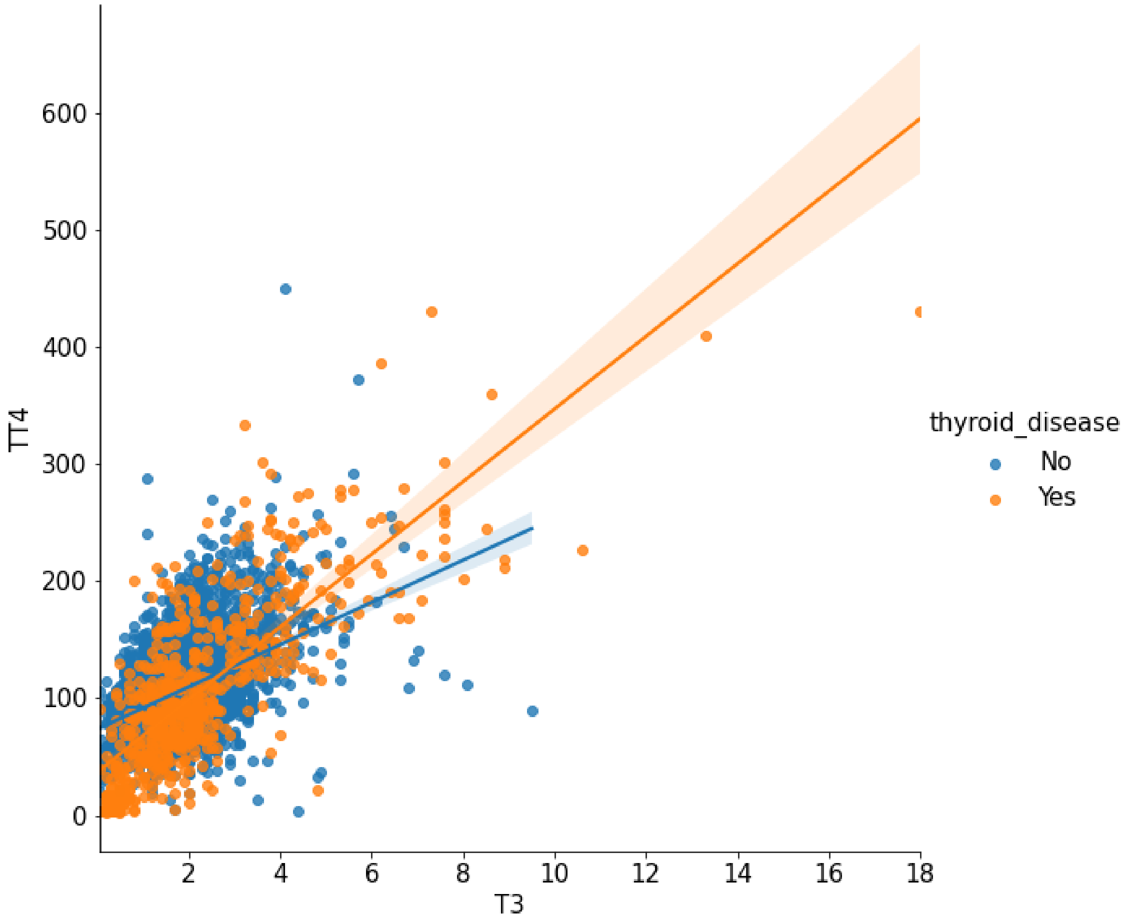


In [73]:

```
sns.lmplot(data=thyroid_data, x='T3', y='TT4', hue='thyroid_disease', height=8)
```

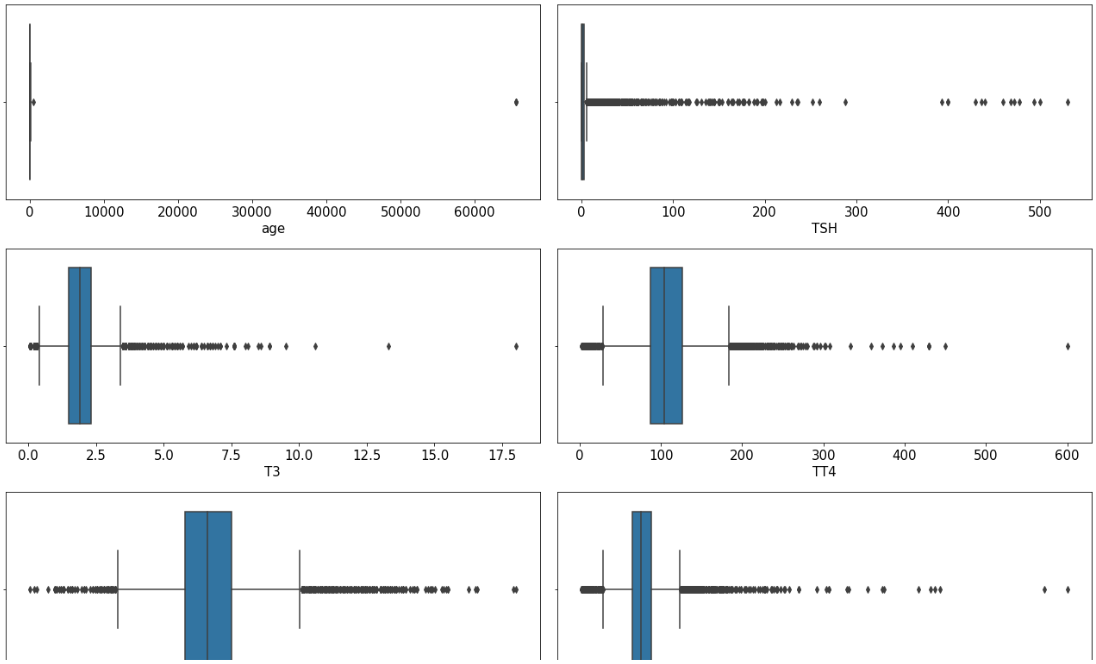
Out[73]:

```
<seaborn.axisgrid.FacetGrid at 0x252de1356a0>
```



In [105]:

```
fig, ax = plt.subplots(nrows=3, ncols=2, figsize=(18,12))
ax = ax.flatten()

for i in range(len(ax)):
    ax[i] = sns.boxplot(X[num_vars].iloc[:,i], ax=ax[i])
plt.tight_layout()
plt.show()
```



Thyroid disease can affect anyone — men, women, infants, teenagers and the elderly. It can be present at birth (typically hypothyroidism) and it can develop as you age (often after menopause in women). source - [https://my.clevelandclinic.org/ (https://my.clevelandclinic.org/health/diseases/8541-thyroid-disease#:~:text=Thyroid%20disease%20can%20affect%20anyone,often%20after%20menopause%20in%20w](https://my.clevelandclinic.org/health/diseases/8541-thyroid-disease#:~:text=Thyroid%20disease%20can%20affect%20anyone,often%20after%20menopause%20in%20w)

Data Pre-Processing

Separating Training and Testing Datasets

In [30]:

```
train_x, test_x, train_y, test_y = train_test_split(X, y, test_size=0.3, random_state=12
print(train_x.shape)
print(test_x.shape)
print(train_y.shape)
print(test_y.shape)
```

```
(6092, 15)
(2611, 15)
(6092,)
(2611,)
```

Outlier Treatment

Clipping the age variable at 1st & 99th permilles and all the other variables at 1st and 99th percentile

In [31]:

```
outliers_ucap = {}
outliers_lcap = {}
for num_var in num_vars:
    if num_var == 'age':
        outliers_lcap[num_var] = round(train_x[num_var].dropna().quantile(0.001),2)
        outliers_ucap[num_var] = round(train_x[num_var].dropna().quantile(0.999),2)
    else:
        outliers_lcap[num_var] = round(train_x[num_var].dropna().quantile(0.01),2)
        outliers_ucap[num_var] = round(train_x[num_var].dropna().quantile(0.99),2)
print('Lower Cap :',outliers_lcap)
print('Upper Cap :',outliers_ucap)
```

```
Lower Cap : {'age': 1.0, 'TSH': 0.02, 'T3': 0.3, 'TT4': 14.87, 'T4U': 0.5
5, 'FTI': 15.0}
Upper Cap : {'age': 96.82, 'TSH': 98.0, 'T3': 5.04, 'TT4': 230.0, 'T4U':
1.69, 'FTI': 251.0}
```

Dumping the information about treating outliers into pickle files

In [38]:

```
# For outliers_lcap
# create a binary pickle file
f1 = open("object instances/outliers_lcap.pkl","wb")

# write the python object (dict) to pickle file
pickle.dump(outliers_lcap,f1)

# close file
f1.close()

# For outliers_ucap
f2 = open("object instances/outliers_ucap.pkl","wb")
pickle.dump(outliers_ucap,f2)
f2.close()
```

In [32]:

```
# For Training Data
for num_var in num_vars:
    if num_var == 'age':
        train_x[num_var] = train_x[num_var].clip(lower=train_x[num_var].dropna().quantil
    else:
        train_x[num_var] = train_x[num_var].clip(lower=train_x[num_var].dropna().quantil
```

In [33]:

```
# For Testing Data
for num_var in num_vars:
    test_x[num_var] = test_x[num_var].clip(lower= outliers_lcap[num_var], upper=outliers_
```

Missing Values Treatment

In [54]:

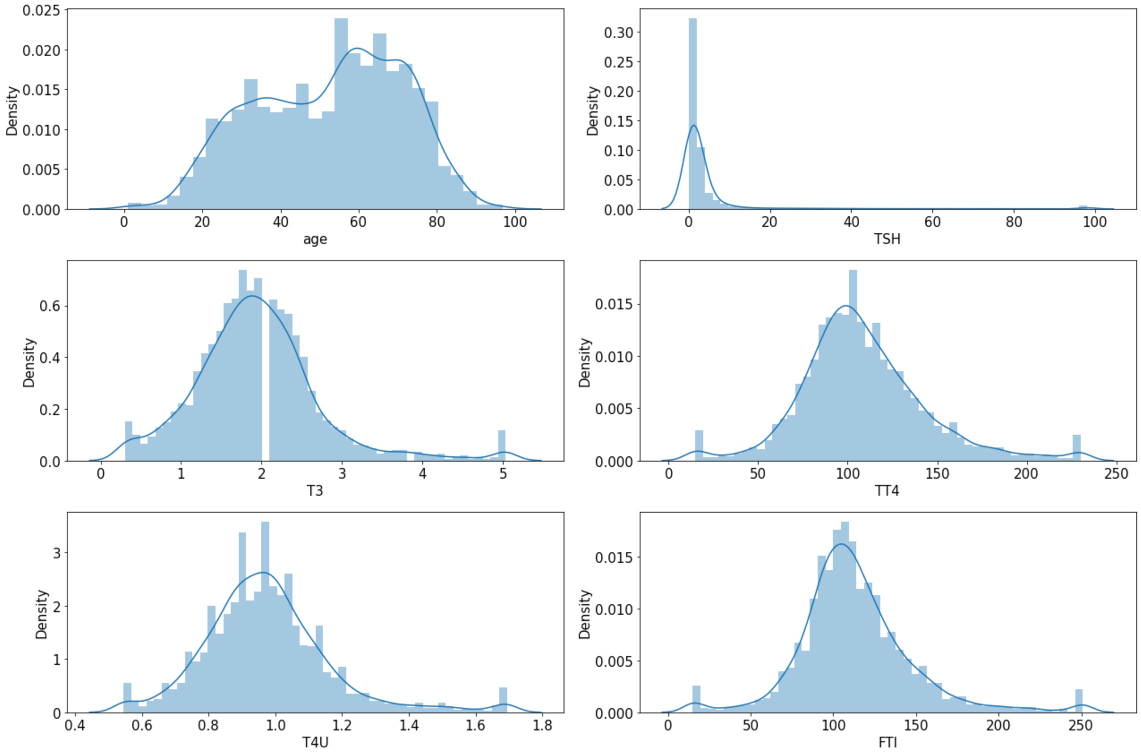
```
train_x.isna().sum()
```

Out[54]:

```
FTI                  237
T3                  1527
T4U                  241
TBG                 6062
TSH                  307
TT4                    4
age                    0
goitre                 0
hypopituitary          0
lithium                0
pregnant               0
psych                  0
sex                  202
sick                   0
thyroid_surgery        0
tumor                  0
dtype: int64
```

In [42]:

```
fig, ax = plt.subplots(nrows=3, ncols=2, figsize=(18,12))
ax = ax.flatten()

for i in range(len(ax)):
    ax[i] = sns.distplot(train_x[num_vars].iloc[:,i], kde=True, ax=ax[i])
plt.tight_layout()
plt.savefig('plots/Distribution Plots for Numerical Data.png', bbox_inches = 'tight')
plt.show()
```



All the Numerical Variables seems to be normally distributed except TSH, so we will impute TSH with median and all others with mean whereas, There is only one Categorical Variable i.e. 'sex', so we will impute it with mode.

In [34]:

```
num_vars
```

Out[34]:

```
['age', 'TSH', 'T3', 'TT4', 'T4U', 'FTI']
```

In [35]:

```
missing_imputation = {}
for num_var in train_x.columns:
    if num_var in ['age', 'T3', 'TT4', 'T4U', 'FTI']:
        missing_imputation[num_var] = round(train_x[num_var].dropna().mean(),2)
    elif num_var == 'TSH':
        missing_imputation[num_var] = round(train_x[num_var].dropna().median(),2)
    elif num_var == 'sex':
        missing_imputation[num_var] = train_x[num_var].dropna().mode()[0]
    else:
        continue
print(missing_imputation)
```

```
{'FTI': 113.08, 'T3': 1.94, 'T4U': 0.97, 'TSH': 1.4, 'TT4': 108.38, 'age':
52.46, 'sex': 'F'}
```

In [45]:

```
# Dumping the information about Missing Value Imputation into a pickle file
f = open("object instances/missing_imputation.pkl","wb")
pickle.dump(missing_imputation,f)
f.close()
```

In [36]:

```
for num_var in train_x.columns:
    if num_var in missing_imputation.keys():
        train_x[num_var] = train_x[num_var].fillna(missing_imputation[num_var])
        test_x[num_var] = test_x[num_var].fillna(missing_imputation[num_var])
    else:
        continue
if train_x.isna().sum().sum() == 0:
    print('Missing Value Imputation on Training Data is Done')
if test_x.isna().sum().sum() == 0:
    print('Missing Value Imputation on Testing Data is Done')
```

```
Missing Value Imputation on Training Data is Done
Missing Value Imputation on Testing Data is Done
```

Encoing the Categorical Variables

In [37]:

```
# For 'Sex' Variable : 'M' - 1 and 'F' - 0
train_x.sex = train_x.sex.map({'M':1, 'F':0})
test_x.sex = test_x.sex.map({'M':1, 'F':0})
```

In [38]:

```
# For all the other Variables : 'True' - 1 and 'False' - 0
train_x[cat_vars] = train_x[cat_vars].apply(lambda x: np.where(x==True, 1, 0))
test_x[cat_vars] = test_x[cat_vars].apply(lambda x: np.where(x==True, 1, 0))
train_x.head()
```

Out[38]:

	FTI	T3	T4U	TSH	TT4	age	goitre	hypopituitary	lithium	pregnant	psych	s
8547	90.0	1.94	0.63	1.20	57.0	75.0	0	0	0	0	0	
8571	97.0	2.50	0.98	1.10	95.0	65.0	0	0	0	0	1	
4757	200.0	2.60	1.01	0.02	203.0	42.0	0	0	0	0	0	
6323	156.0	0.40	0.68	4.30	106.0	81.0	0	0	0	0	0	
1412	82.0	1.94	0.82	16.00	67.0	58.0	0	0	0	0	0	

Standardization

In [39]:

```
scaler = StandardScaler()
```

In [40]:

```
scaler = ColumnTransformer([('scaler', StandardScaler(), ['FTI', 'T3', 'T4U', 'TSH', 'TT
```

In [41]:

```
train_x_scaled = pd.DataFrame(scaler.fit_transform(train_x), columns=train_x.columns)
train_x_scaled.head()
```

Out[41]:

	FTI	T3	T4U	TSH	TT4	age	goitre	hypopituitary	lithi
0	-0.675459	0.000310	-1.840230	-0.237613	-1.463851	1.197936	0.0	0.0	
1	-0.470589	0.825060	0.031386	-0.245930	-0.381304	0.666459	0.0	0.0	
2	2.543923	0.972337	0.191810	-0.335756	2.695408	-0.555937	0.0	0.0	
3	1.256170	-2.267751	-1.572856	0.020219	-0.067935	1.516822	0.0	0.0	
4	-0.909596	0.000310	-0.824210	0.993326	-1.178970	0.294426	0.0	0.0	

In [50]:

```
# Dumping the scaler into a pickle file
file = open('models/scaler.pkl', 'wb' )

pickle.dump(scaler, file)

file.close()
```

In [42]:

```
test_x_scaled = pd.DataFrame(scaler.transform(test_x), columns=train_x.columns)
test_x_scaled.head()
```

Out[42]:

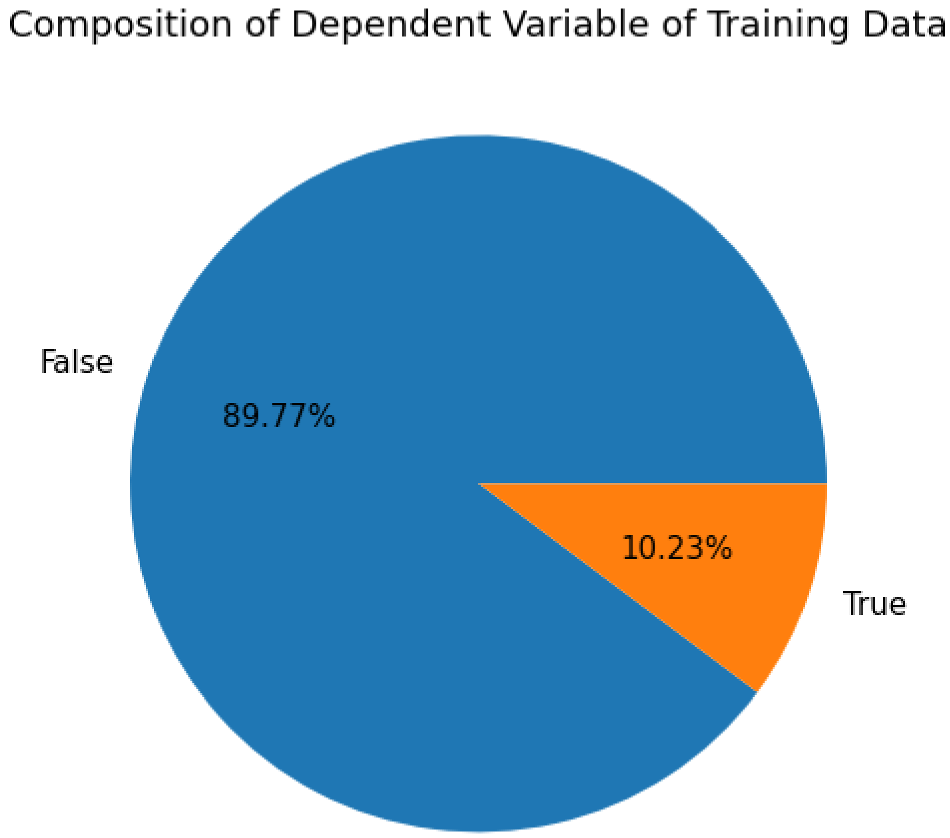
	FTI	T3	T4U	TSH	TT4	age	goitre	hypopituitary	lithi
0	0.524492	-0.647707	0.405709	-0.310804	0.843683	-0.130755	0.0	0.0	
1	-0.207185	0.000310	0.512659	-0.304150	0.131481	1.304231	0.0	0.0	
2	0.904965	0.000310	0.405709	-0.220979	1.214028	-1.618890	0.0	0.0	
3	-1.231534	0.000310	-0.931159	0.061805	-1.463851	-0.555937	0.0	0.0	
4	-0.675459	0.000310	-1.038109	0.244782	-1.065018	1.623117	0.0	0.0	

OverSampling

using RandomOverSampler from imblearning

In [50]:

```
plt.figure(figsize=(8,8))
plt.pie(train_y.value_counts(), autopct='%.2f%%', labels=train_y.value_counts().index)
plt.title('Composition of Dependent Variable of Training Data')
plt.savefig('plots/Piechart_train_y.png', bboxes_inches='tight')
plt.show()
```



In [51]:

```
train_y.value_counts()
```

Out[51]:

```
False    5469
True      623
Name: thyroid_disease, dtype: int64
```

Classes are Highly Imbalanced, so we will use RandomOverSampler to OverSample the Class with low proportion

In [52]:

```
oversampler = RandomOverSampler(random_state=12345)
train_x_os, train_y_os = oversampler.fit_resample(train_x, train_y)
train_y_os.value_counts()
```

Out[52]:

```
False    5469
True     5469
Name: thyroid_disease, dtype: int64
```

The Classes are Balanced Now, so we can move on to Modelling

Data Modelling

Logistic Regression

In [53]:

```
log_reg = LogisticRegression(random_state=12345)

log_reg.fit(train_x_os, train_y_os)
```

Out[53]:

```
LogisticRegression(random_state=12345)
```

In [94]:

```
# Dumping the log_reg model into a pickle file
file = open('models/LogisticRegression.pkl', 'wb' )

pickle.dump(rf_clf2, file)

file.close()
```

In [156]:

```
# Creating a Dataframe to save all the Predictions
train_predictions_df = pd.DataFrame({'log_reg_pred': log_reg.predict(train_x_os), 'log_r
test_predictions_df = pd.DataFrame({'log_reg_pred': log_reg.predict(test_x_scaled), 'log
```

In [55]:

```
logreg_train_acc = accuracy_score(train_y_os, train_predictions_df.log_reg_pred)
logreg_test_acc = accuracy_score(test_y, test_predictions_df.log_reg_pred)
logreg_train_auc = roc_auc_score(train_y_os, train_predictions_df.log_reg_proba)
logreg_test_auc = roc_auc_score(test_y, test_predictions_df.log_reg_proba)
print('Training Accuracy :{} | Testing Accuracy :{}'.format(logreg_train_acc, logreg_tes
print('Training AUC :{} | Testing AUC :{}'.format(logreg_train_auc, logreg_test_auc ))
```

```
Training Accuracy :0.8880051197659535 | Testing Accuracy :0.87131367292225
2
Training AUC :0.9470374100454362 | Testing AUC :0.5759391734584206
```

In [56]:

```
target_names = ['False', 'True']
```

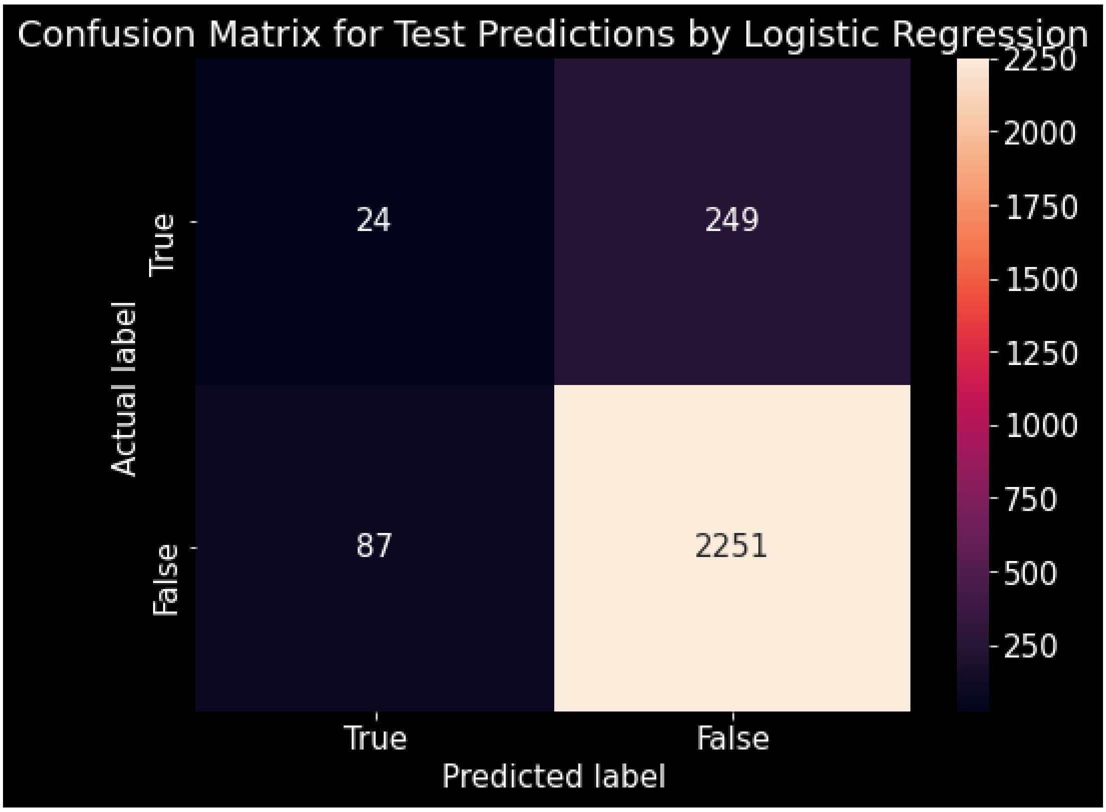
In [85]:

```
print(classification_report(test_y, test_predictions_df.log_reg_pred, target_names=targe
```

```
              precision    recall  f1-score   support

       False       0.90      0.96      0.93      2338
        True       0.22      0.09      0.12       273

    accuracy                           0.87      2611
   macro avg       0.56      0.53      0.53      2611
weighted avg       0.83      0.87      0.85      2611
```

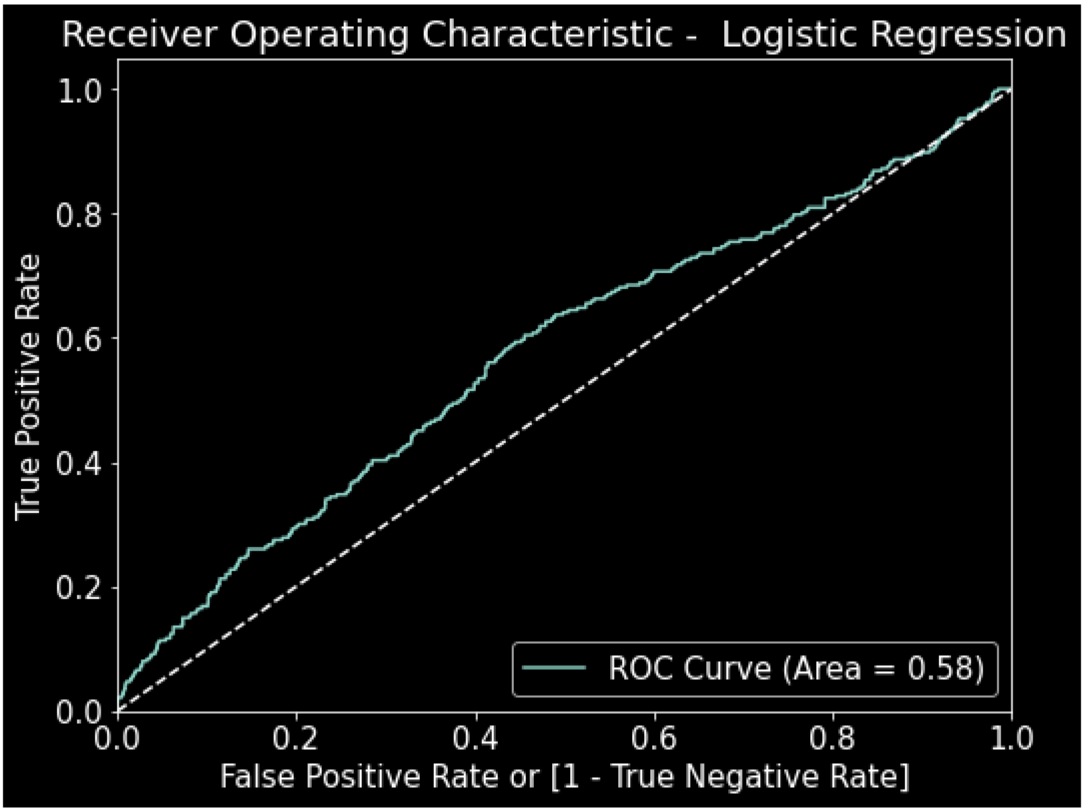
In [108]:

```
cm_log_reg = confusion_matrix(test_y, test_predictions_df.log_reg_pred, labels=[True,Fal
with plt.style.context('dark_background'):
    plt.figure(figsize=(8,6))
    sns.heatmap(cm_log_reg, annot=True,  fmt='d', xticklabels = ["True", "False"] , ytic
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')
    plt.title('Confusion Matrix for Test Predictions by Logistic Regression')
    plt.savefig('plots/Confusion Matrix - Logistic Regression.png', bbox_inches='tight')
    plt.show()
```



In [109]:

```
fpr, tpr, thresholds = roc_curve(test_y, test_predictions_df.log_reg_proba, drop_interme
with plt.style.context('dark_background'):
    plt.figure(figsize=(8, 6))
    plt.plot( fpr, tpr, label='ROC Curve (Area = %0.2f)' % logreg_test_auc)
    plt.plot([0, 1], [0, 1], 'w--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic -  Logistic Regression')
    plt.legend(loc="lower right")
    plt.savefig('plots/ROC Curve - Logistic Regression.png', bbox_inches='tight')
    plt.show()
```



Support Vector Machine

In [57]:

```
lsvc = SVC(kernel='linear', gamma='auto', probability=True, random_state=12345)

lsvc.fit(train_x_os, train_y_os)
```

Out[57]:

```
SVC(gamma='auto', kernel='linear', probability=True, random_state=12345)
```

In [58]:

```
# Dumping the lsvc model into a pickle file
file = open('models/LinearSupportVectorMachine.pkl', 'wb' )

pickle.dump(lsvc, file)

file.close()
```

In [157]:

```
train_predictions_df = pd.concat([train_predictions_df, pd.Series(lsvc.predict(train_x_o
test_predictions_df = pd.concat([test_predictions_df, pd.Series(lsvc.predict(test_x_scal
```

In [60]:

```
lsvc_train_acc = accuracy_score(train_y_os, train_predictions_df.lsvc_pred)
lsvc_test_acc = accuracy_score(test_y, test_predictions_df.lsvc_pred)
lsvc_train_auc = roc_auc_score(train_y_os, train_predictions_df.lsvc_proba)
lsvc_test_auc = roc_auc_score(test_y, test_predictions_df.lsvc_proba)
print('Training Accuracy :{} | Testing Accuracy :{}'.format(lsvc_train_acc, lsvc_test_ac
print('Training AUC :{} | Testing AUC :{}'.format(lsvc_train_auc, lsvc_test_auc ))
```

```
Training Accuracy :0.8993417443773999 | Testing Accuracy :0.89505936422826
5
Training AUC :0.9506724198002131 | Testing AUC :0.670719784919956
```

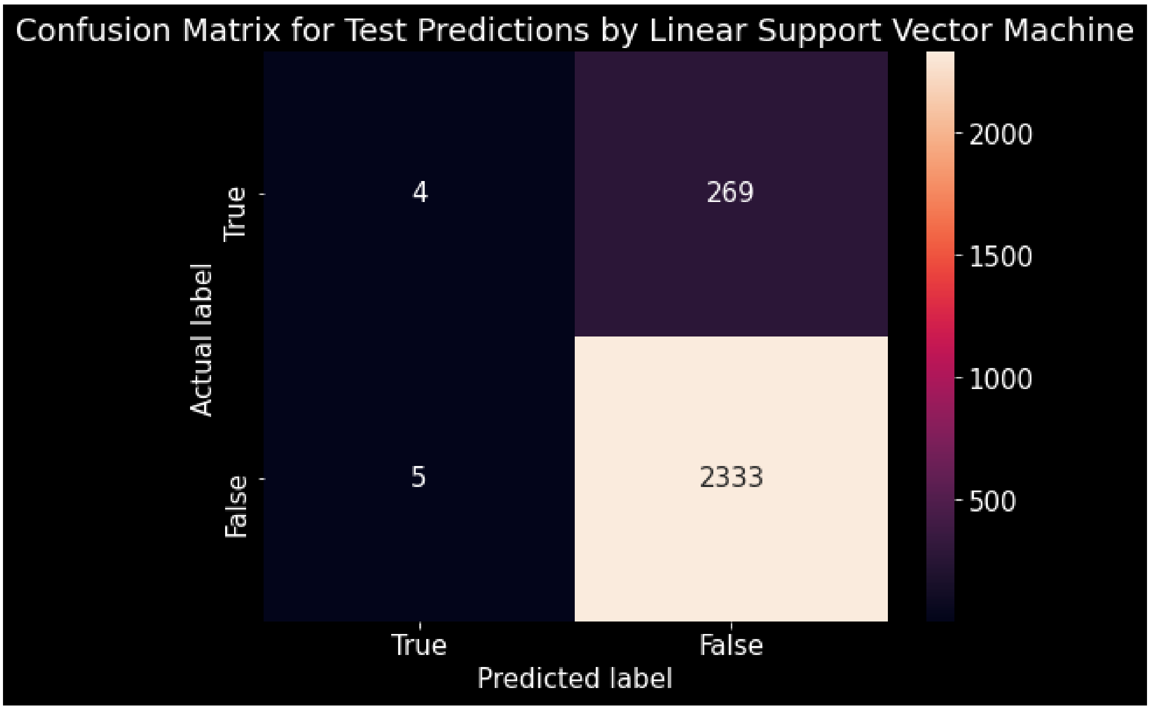
In [61]:

```
print(classification_report(test_y, test_predictions_df.lsvc_pred, target_names=target_n
```

```
              precision    recall  f1-score   support

       False       0.90      1.00      0.94      2338
        True       0.44      0.01      0.03       273

    accuracy                           0.90      2611
   macro avg       0.67      0.51      0.49      2611
weighted avg       0.85      0.90      0.85      2611
```

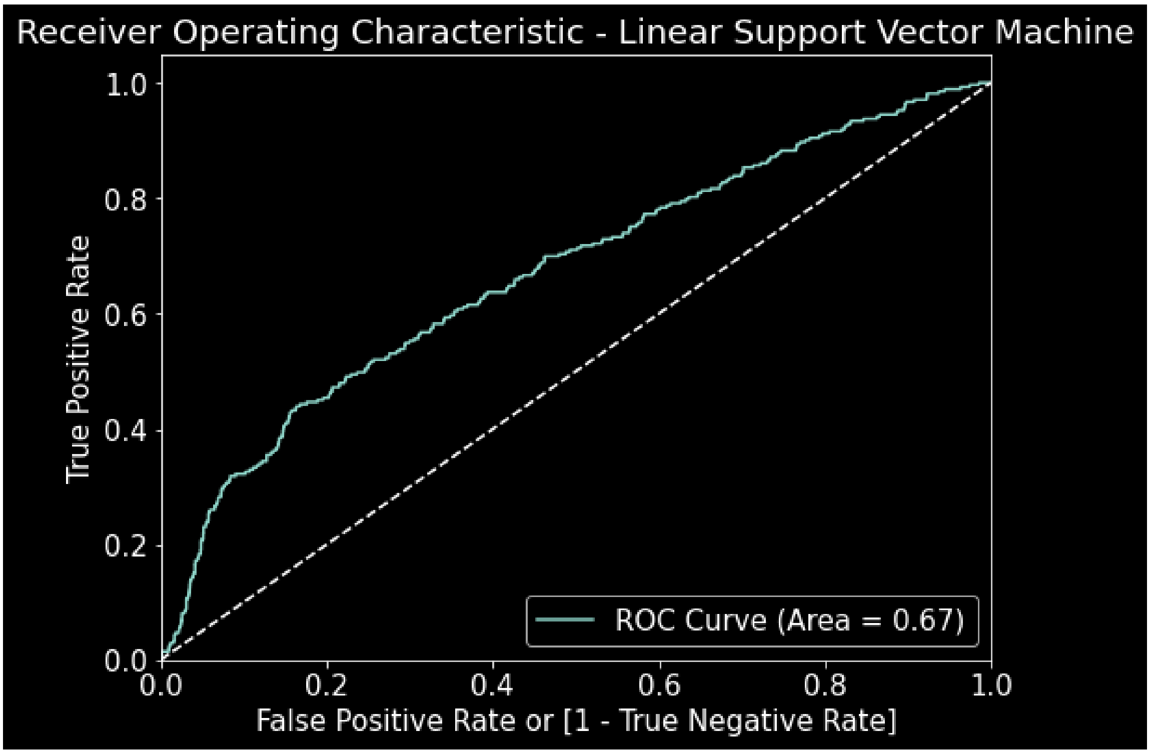
In [62]:

```
cm_lsvc = confusion_matrix(test_y, test_predictions_df.lsvc_pred, labels=[True,False])
with plt.style.context('dark_background'):
    plt.figure(figsize=(8,6))
    sns.heatmap(cm_lsvc, annot=True,  fmt='d', xticklabels = ["True", "False"] , ytickla
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')
    plt.title('Confusion Matrix for Test Predictions by Linear Support Vector Machine')
    plt.savefig('plots/Confusion Matrix - LinearSVC.png', bbox_inches='tight')
    plt.show()
```



In [63]:

```
fpr, tpr, thresholds = roc_curve(test_y, test_predictions_df.lsvc_proba, drop_intermedia
with plt.style.context('dark_background'):
    plt.figure(figsize=(8, 6))
    plt.plot( fpr, tpr, label='ROC Curve (Area = %0.2f)' % lsvc_test_auc)
    plt.plot([0, 1], [0, 1], 'w--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic - Linear Support Vector Machine')
    plt.legend(loc="lower right")
    plt.savefig('plots/ROC Curve - LinearSVC.png', bbox_inches='tight')
    plt.show()
```



Random Forest Classifier

In [64]:

```
rf_clf = RandomForestClassifier(random_state=12345)

rf_clf.fit(train_x_os, train_y_os)
```

Out[64]:

```
RandomForestClassifier(random_state=12345)
```

In [65]:

```
file  = open('models/RandomForest.pkl', 'wb' )

pickle.dump(rf_clf, file)

file.close()
```

In [158]:

```
train_predictions_df = pd.concat([train_predictions_df, pd.Series(rf_clf.predict(train_x
test_predictions_df = pd.concat([test_predictions_df, pd.Series(rf_clf.predict(test_x_sc
```

In [67]:

```
rf_clf_train_acc = accuracy_score(train_y_os, train_predictions_df.rf_clf_pred)
rf_clf_test_acc = accuracy_score(test_y, test_predictions_df.rf_clf_pred)
rf_clf_train_auc = roc_auc_score(train_y_os, train_predictions_df.rf_clf_proba)
rf_clf_test_auc = roc_auc_score(test_y, test_predictions_df.rf_clf_proba)
print('Training Accuracy :{} | Testing Accuracy :{}'.format(rf_clf_train_acc, rf_clf_tes
print('Training AUC :{} | Testing AUC :{}'.format(rf_clf_train_auc, rf_clf_test_auc ))
```

```
Training Accuracy :1.0 | Testing Accuracy :0.907698199923401
Training AUC :1.0 | Testing AUC :0.5986245718923221
```

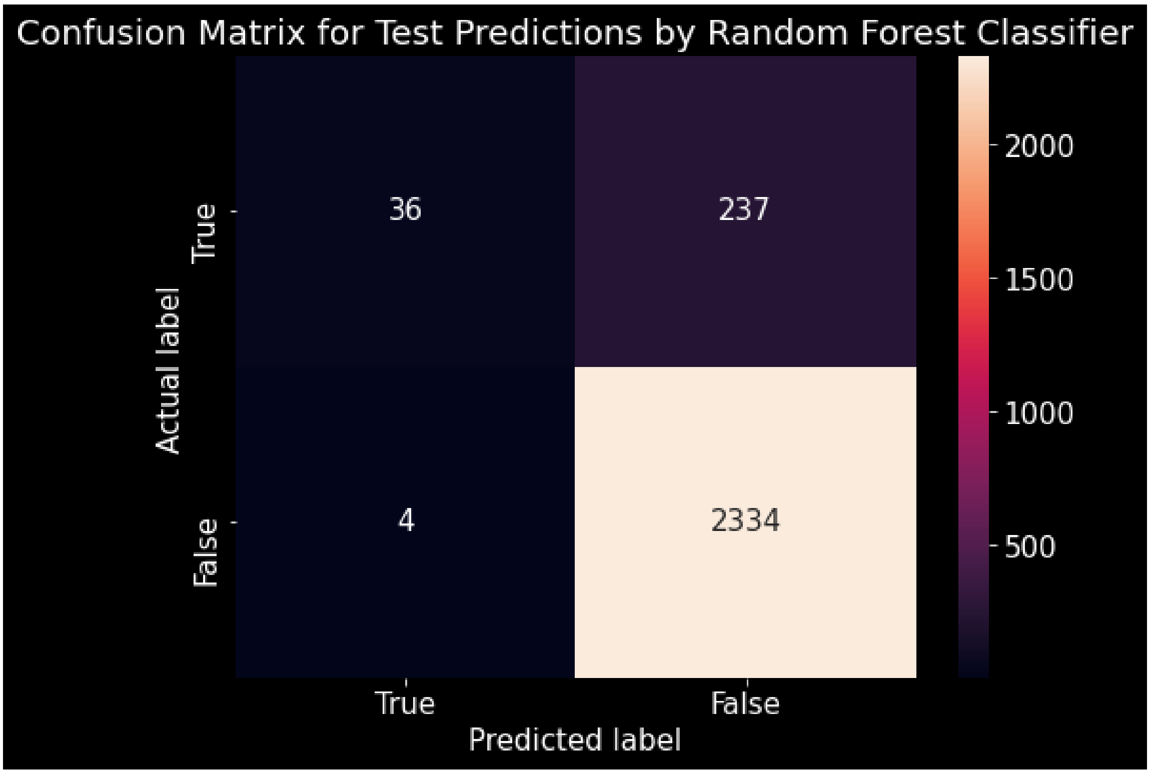
In [69]:

```
print(classification_report(test_y, test_predictions_df.rf_clf_pred, target_names=target
```

```
              precision    recall  f1-score   support

       False       0.91      1.00      0.95      2338
        True       0.90      0.13      0.23       273

    accuracy                           0.91      2611
   macro avg       0.90      0.57      0.59      2611
weighted avg       0.91      0.91      0.88      2611
```

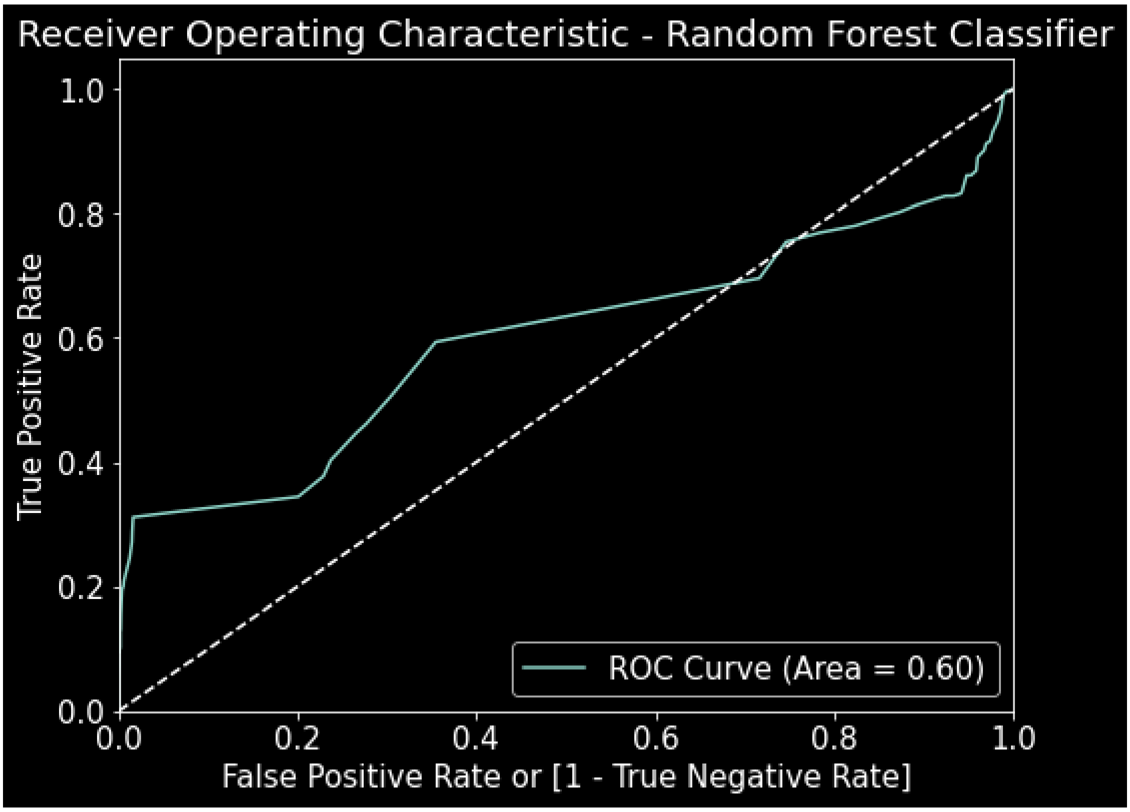
In [70]:

```
cm_rf_clf = confusion_matrix(test_y, test_predictions_df.rf_clf_pred, labels=[True,False
with plt.style.context('dark_background'):
    plt.figure(figsize=(8,6))
    sns.heatmap(cm_rf_clf, annot=True,  fmt='d', xticklabels = ["True", "False"] , ytick
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')
    plt.title('Confusion Matrix for Test Predictions by Random Forest Classifier')
    plt.savefig('plots/Confusion Matrix - Random Forest.png', bbox_inches='tight')
    plt.show()
```



In [71]:

```
fpr, tpr, thresholds = roc_curve(test_y, test_predictions_df.rf_clf_proba, drop_intermed
with plt.style.context('dark_background'):
    plt.figure(figsize=(8, 6))
    plt.plot( fpr, tpr, label='ROC Curve (Area = %0.2f)' % rf_clf_test_auc)
    plt.plot([0, 1], [0, 1], 'w--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic - Random Forest Classifier')
    plt.legend(loc="lower right")
    plt.savefig('plots/ROC Curve - Random Forest.png', bbox_inches='tight')
    plt.show()
```



Tuning Random Forest Classifier

Tune Model 1 : For Best Accuracy

In [72]:

```
rf_params ={
    'n_estimators': [20,50,100,150],
    'max_depth': [5,10,15],
    'max_features': [5,10,15]
}
```

In [73]:

```
rfCV1 = GridSearchCV(RandomForestClassifier(random_state=12345), param_grid=rf_params, c

rfCV1 .fit(train_x_os, train_y_os)
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits
```

Out[73]:

```
GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=12345),
             n_jobs=-1,
             param_grid={'max_depth': [5, 10, 15], 'max_features': [5, 10,
15],
                         'n_estimators': [20, 50, 100, 150]},
             scoring='accuracy', verbose=10)
```

In [76]:

```
print('Best Score :{} | Best Parameters :{}'.format(rfCV1.best_score_, rfCV1.best_params
```

```
Best Score :0.9821720336808246 | Best Parameters :{'max_depth': 15, 'max_f
eatures': 5, 'n_estimators': 20}
```

In [77]:

```
cv_results_rf1 = pd.DataFrame(rfCV1.cv_results_)
cv_results_rf1 = cv_results_rf1.sort_values("mean_test_score", ascending=False)
cv_results_rf1[
    [
        "mean_test_score",
        "std_test_score",
        "param_n_estimators",
        "param_max_depth",
        "param_max_features"
    ]
].head(5)
```

Out[77]:

	mean_test_score	std_test_score	param_n_estimators	param_max_depth	param_max_fea
24	0.982172	0.002005	20	15	
25	0.982081	0.002135	50	15	
27	0.981989	0.002483	150	15	
26	0.981715	0.002421	100	15	
28	0.981075	0.002253	20	15	

In [78]:

```
# Using the Best Estimator to Create a New RF Model
rf_clf1 = rfCV1.best_estimator_

rf_clf1.fit(train_x_os, train_y_os)
```

Out[78]:

```
RandomForestClassifier(max_depth=15, max_features=5, n_estimators=20,
                       random_state=12345)
```

In [79]:

```
file  = open('models/RandomForestTuned1.pkl', 'wb' )

pickle.dump(rf_clf1, file)

file.close()
```

In [159]:

```
train_predictions_df = pd.concat([train_predictions_df, pd.Series(rf_clf1.predict(train_
test_predictions_df = pd.concat([test_predictions_df, pd.Series(rf_clf1.predict(test_x_s
```

In [81]:

```
rf_clf1_train_acc = accuracy_score(train_y_os, train_predictions_df.rf_clf1_pred)
rf_clf1_test_acc = accuracy_score(test_y, test_predictions_df.rf_clf1_pred)
rf_clf1_train_auc = roc_auc_score(train_y_os, train_predictions_df.rf_clf1_proba)
rf_clf1_test_auc = roc_auc_score(test_y, test_predictions_df.rf_clf1_proba)
print('Training Accuracy :{} | Testing Accuracy :{}'.format(rf_clf1_train_acc, rf_clf1_t
print('Training AUC :{} | Testing AUC :{}'.format(rf_clf1_train_auc, rf_clf1_test_auc ))
```

```
Training Accuracy :0.9937831413421101 | Testing Accuracy :0.90923018000765
99
Training AUC :0.9999876295392027 | Testing AUC :0.5836255275947321
```

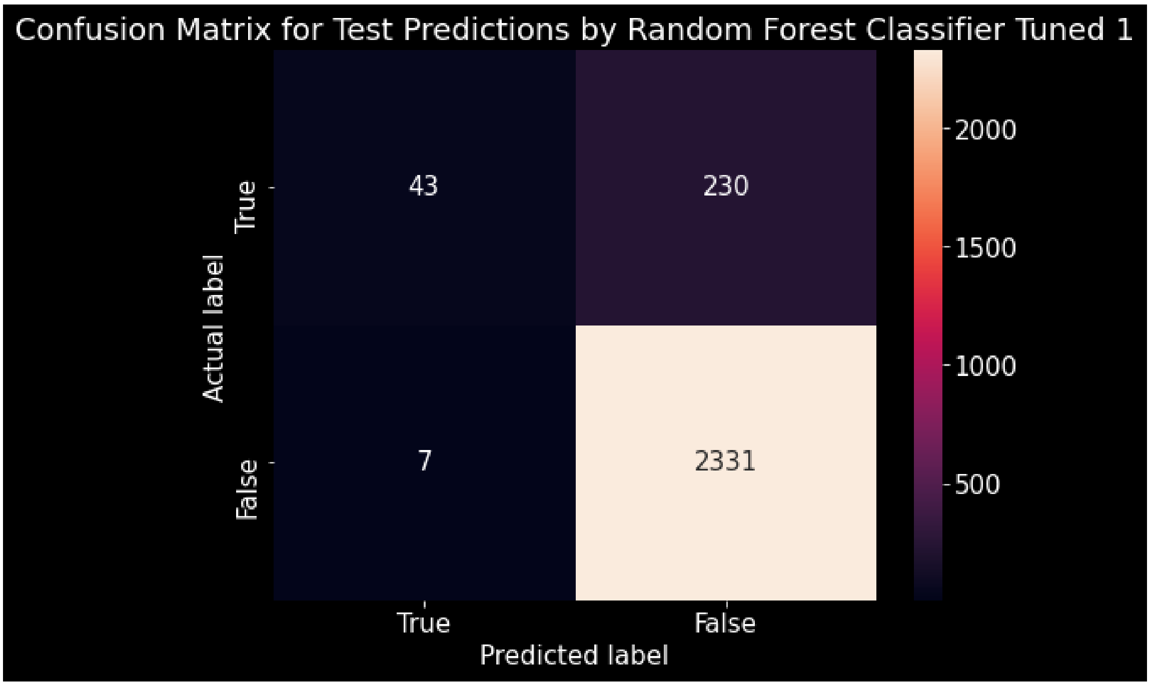
In [83]:

```
print(classification_report(test_y, test_predictions_df.rf_clf1_pred, target_names=targe
```

```
              precision    recall  f1-score   support

       False       0.91      1.00      0.95      2338
        True       0.86      0.16      0.27       273

    accuracy                           0.91      2611
   macro avg       0.89      0.58      0.61      2611
weighted avg       0.90      0.91      0.88      2611
```

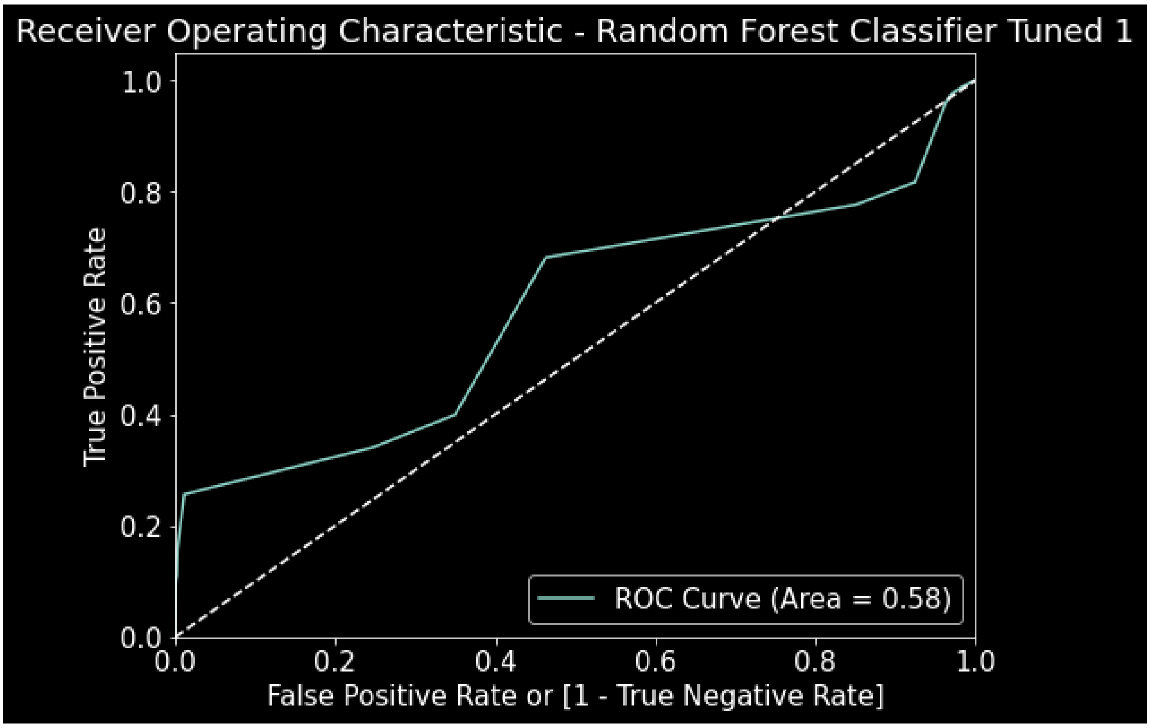
In [84]:

```
cm_rf_clf1 = confusion_matrix(test_y, test_predictions_df.rf_clf1_pred, labels=[True,Fal
with plt.style.context('dark_background'):
    plt.figure(figsize=(8,6))
    sns.heatmap(cm_rf_clf1, annot=True,  fmt='d', xticklabels = ["True", "False"] , ytic
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')
    plt.title('Confusion Matrix for Test Predictions by Random Forest Classifier Tuned 1
    plt.savefig('plots/Confusion Matrix - Random Forest Tuned 1.png', bbox_inches='tight
    plt.show()
```



In [85]:

```
fpr, tpr, thresholds = roc_curve(test_y, test_predictions_df.rf_clf1_proba, drop_interme
with plt.style.context('dark_background'):
    plt.figure(figsize=(8, 6))
    plt.plot( fpr, tpr, label='ROC Curve (Area = %0.2f)' % rf_clf1_test_auc)
    plt.plot([0, 1], [0, 1], 'w--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic - Random Forest Classifier Tuned 1')
    plt.legend(loc="lower right")
    plt.savefig('plots/ROC Curve - Random Forest Tuned 1.png', bbox_inches='tight')
    plt.show()
```



Tune Model 2: For Best AUC

In [86]:

```
rfCV2 = GridSearchCV(RandomForestClassifier(random_state=12345), param_grid=rf_params, c

rfCV2 .fit(train_x_os, train_y_os)
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits
```

Out[86]:

```
GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=12345),
             n_jobs=-1,
             param_grid={'max_depth': [5, 10, 15], 'max_features': [5, 10,
15],
                         'n_estimators': [20, 50, 100, 150]},
             scoring='roc_auc', verbose=10)
```

In [87]:

```
print('Best Score :{} | Best Parameters :{}'.format(rfCV2.best_score_, rfCV2.best_params_
```

```
Best Score :0.999508545613667 | Best Parameters :{'max_depth': 15, 'max_fe
atures': 5, 'n_estimators': 150}
```

In [88]:

```
cv_results_rf2 = pd.DataFrame(rfCV2.cv_results_)
cv_results_rf2 = cv_results_rf2.sort_values("mean_test_score", ascending=False)
cv_results_rf2[
    [
        "mean_test_score",
        "std_test_score",
        "param_n_estimators",
        "param_max_depth",
        "param_max_features"
    ]
].head(5)
```

Out[88]:

	mean_test_score	std_test_score	param_n_estimators	param_max_depth	param_max_fea
27	0.999509	0.000371	150	15	
26	0.999392	0.000395	100	15	
25	0.999169	0.000768	50	15	
30	0.998848	0.000925	100	15	
31	0.998820	0.000941	150	15	

In [89]:

```
# Creating a new RF model using the Best Estimator
rf_clf2 = rfCV2.best_estimator_

rf_clf2.fit(train_x_os, train_y_os)
```

Out[89]:

```
RandomForestClassifier(max_depth=15, max_features=5, n_estimators=150,
                       random_state=12345)
```

In [93]:

```
file = open('models/RandomForestTuned2.pkl', 'wb' )

pickle.dump(rf_clf2, file)

file.close()
```

In [160]:

```
train_predictions_df = pd.concat([train_predictions_df, pd.Series(rf_clf2.predict(train_
test_predictions_df = pd.concat([test_predictions_df, pd.Series(rf_clf2.predict(test_x_s
```

In [91]:

```
rf_clf2_train_acc = accuracy_score(train_y_os, train_predictions_df.rf_clf2_pred)
rf_clf2_test_acc = accuracy_score(test_y, test_predictions_df.rf_clf2_pred)
rf_clf2_train_auc = roc_auc_score(train_y_os, train_predictions_df.rf_clf2_proba)
rf_clf2_test_auc = roc_auc_score(test_y, test_predictions_df.rf_clf2_proba)
print('Training Accuracy :{} | Testing Accuracy :{}'.format(rf_clf2_train_acc, rf_clf2_t
print('Training AUC :{} | Testing AUC :{}'.format(rf_clf2_train_auc, rf_clf2_test_auc ))
```

```
Training Accuracy :0.9937831413421101 | Testing Accuracy :0.91995404059747
22
Training AUC :1.0 | Testing AUC :0.7025023735887722
```

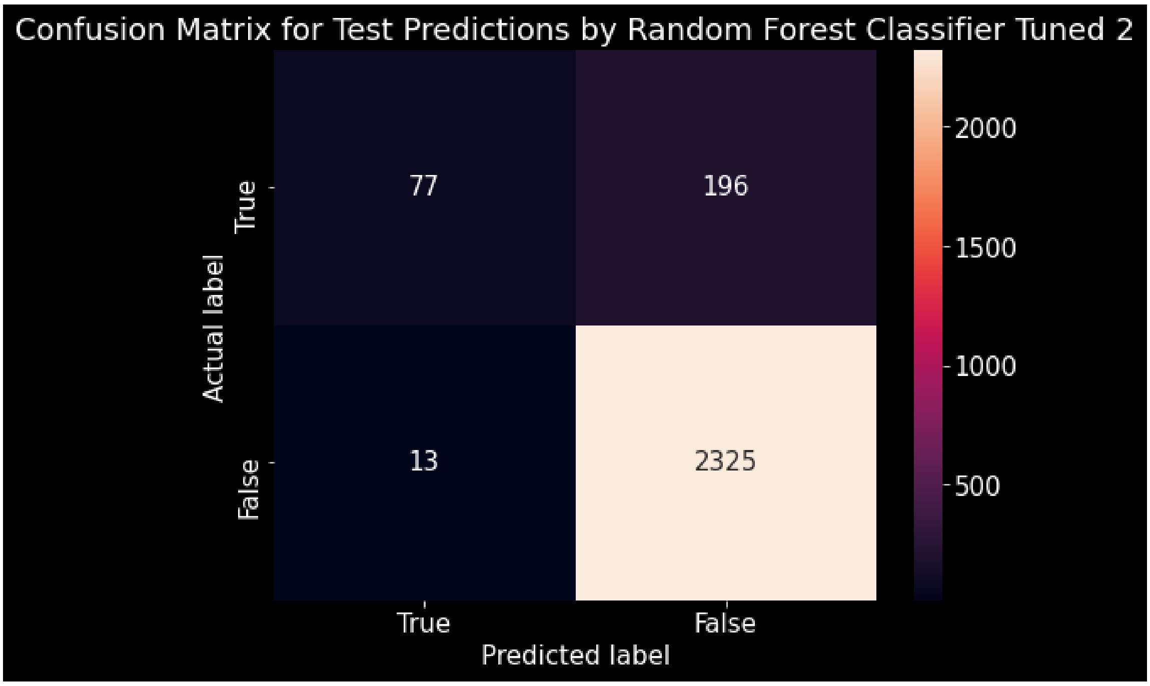
In [92]:

```
print(classification_report(test_y, test_predictions_df.rf_clf2_pred, target_names=targe
```

```
              precision    recall  f1-score   support

       False       0.92      0.99      0.96      2338
        True       0.86      0.28      0.42       273

    accuracy                           0.92      2611
   macro avg       0.89      0.64      0.69      2611
weighted avg       0.92      0.92      0.90      2611
```

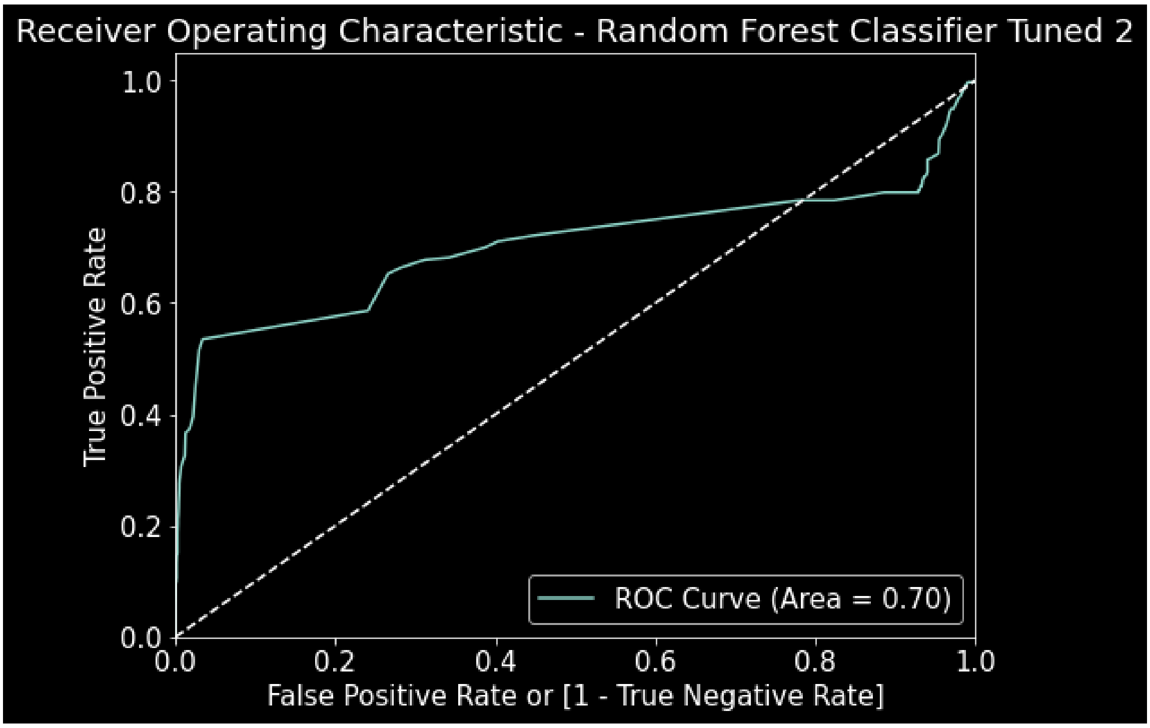
In [88]:

```
cm_rf_clf2 = confusion_matrix(test_y, test_predictions_df.rf_clf2_pred, labels=[True,Fal
with plt.style.context('dark_background'):
    plt.figure(figsize=(8,6))
    sns.heatmap(cm_rf_clf2, annot=True,  fmt='d', xticklabels = ["True", "False"] , ytic
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')
    plt.title('Confusion Matrix for Test Predictions by Random Forest Classifier Tuned 2
    plt.savefig('plots/Confusion Matrix - Random Forest Tuned 2.png', bbox_inches='tight
    plt.show()
```



In [93]:

```
fpr, tpr, thresholds = roc_curve(test_y, test_predictions_df.rf_clf2_proba, drop_interme
with plt.style.context('dark_background'):
    plt.figure(figsize=(8, 6))
    plt.plot( fpr, tpr, label='ROC Curve (Area = %0.2f)' % rf_clf2_test_auc)
    plt.plot([0, 1], [0, 1], 'w--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic - Random Forest Classifier Tuned 2')
    plt.legend(loc="lower right")
    plt.savefig('plots/ROC Curve - Random Forest Tuned 2.png', bbox_inches='tight')
    plt.show()
```



Gradient Boosting Classifier

In [94]:

```
gb_clf = GradientBoostingClassifier(random_state=12345)

gb_clf.fit(train_x_os, train_y_os)
```

Out[94]:

```
GradientBoostingClassifier(random_state=12345)
```

In [95]:

```
file = open('models/GradientBoostingMachine.pkl', 'wb' )

pickle.dump(gb_clf, file)

file.close()
```

In [161]:

```
train_predictions_df = pd.concat([train_predictions_df, pd.Series(gb_clf.predict(train_x
test_predictions_df = pd.concat([test_predictions_df, pd.Series(gb_clf.predict(test_x_sc
```

In [97]:

```
gb_clf_train_acc = accuracy_score(train_y_os, train_predictions_df.gb_clf_pred)
gb_clf_test_acc = accuracy_score(test_y, test_predictions_df.gb_clf_pred)
gb_clf_train_auc = roc_auc_score(train_y_os, train_predictions_df.gb_clf_proba)
gb_clf_test_auc = roc_auc_score(test_y, test_predictions_df.gb_clf_proba)
print('Training Accuracy :{} | Testing Accuracy :{}'.format(gb_clf_train_acc, gb_clf_tes
print('Training AUC :{} | Testing AUC :{}'.format(gb_clf_train_auc, gb_clf_test_auc ))
```

```
Training Accuracy :0.9758639605046626 | Testing Accuracy :0.30333205668326
313
Training AUC :0.991923911234789 | Testing AUC :0.7533943102805378
```

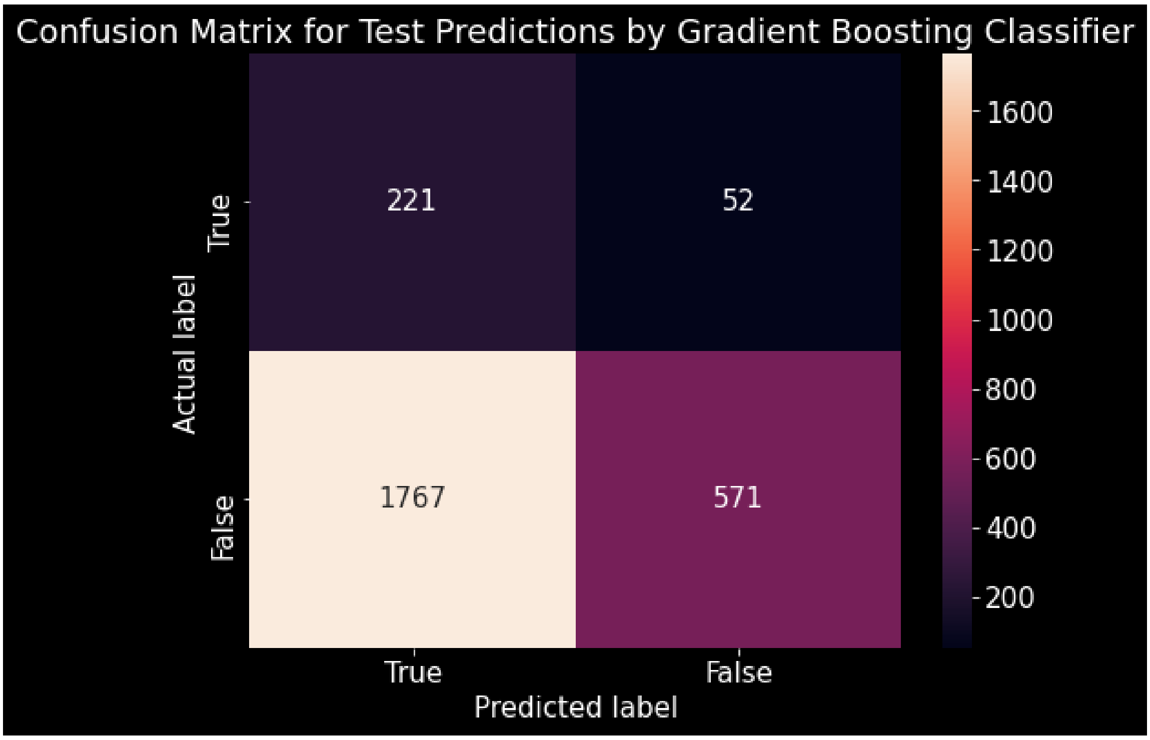
In [98]:

```
print(classification_report(test_y, test_predictions_df.gb_clf_pred, target_names=target
```

```
              precision    recall  f1-score   support

       False       0.92      0.24      0.39      2338
        True       0.11      0.81      0.20       273

    accuracy                           0.30      2611
   macro avg       0.51      0.53      0.29      2611
weighted avg       0.83      0.30      0.37      2611
```

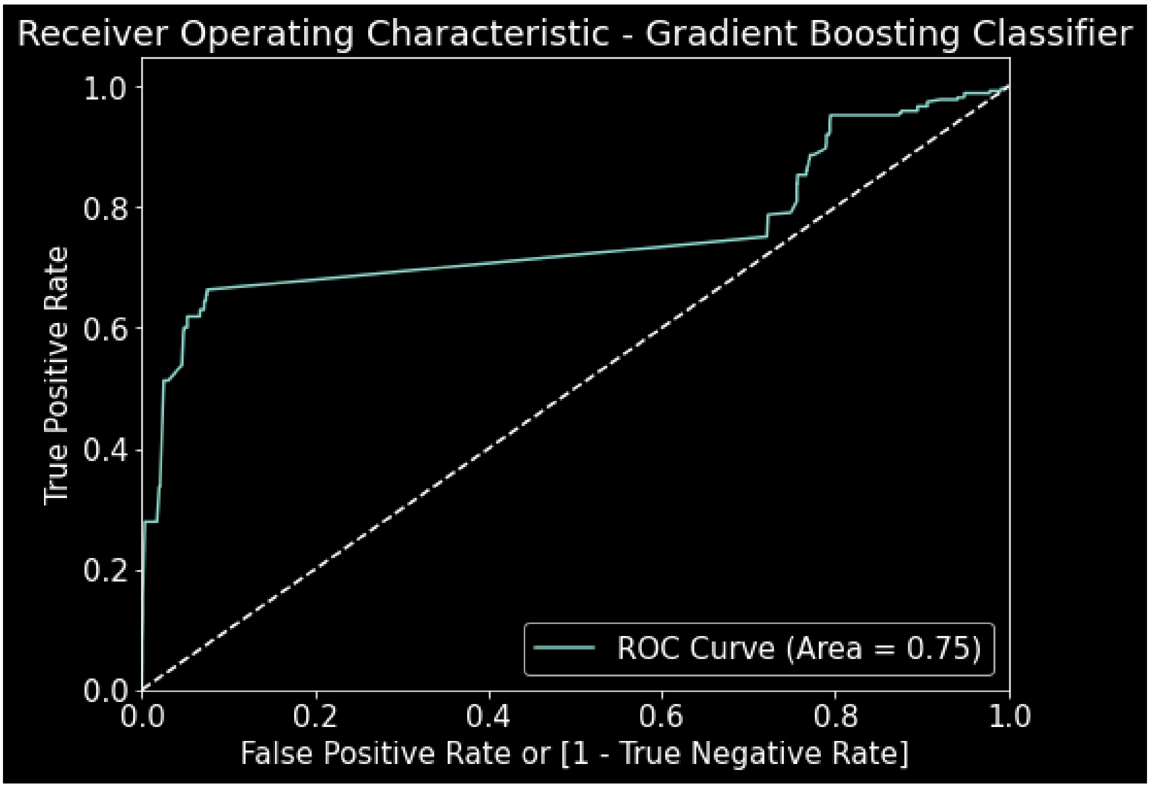
In [100]:

```
cm_gb_clf = confusion_matrix(test_y, test_predictions_df.gb_clf_pred, labels=[True,False
with plt.style.context('dark_background'):
    plt.figure(figsize=(8,6))
    sns.heatmap(cm_gb_clf, annot=True,  fmt='d', xticklabels = ["True", "False"] , ytick
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')
    plt.title('Confusion Matrix for Test Predictions by Gradient Boosting Classifier')
    plt.savefig('plots/Confusion Matrix - Gradient Boosting.png', bbox_inches='tight')
    plt.show()
```



In [101]:

```
fpr, tpr, thresholds = roc_curve(test_y, test_predictions_df.gb_clf_proba, drop_intermed
with plt.style.context('dark_background'):
    plt.figure(figsize=(8, 6))
    plt.plot( fpr, tpr, label='ROC Curve (Area = %0.2f)' % gb_clf_test_auc)
    plt.plot([0, 1], [0, 1], 'w--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic - Gradient Boosting Classifier')
    plt.legend(loc="lower right")
    plt.savefig('plots/ROC Curve - Gradient Boosting.png', bbox_inches='tight')
    plt.show()
```



Tuning Gradient Boosting Classifier

In [102]:

```
gb_params ={
    'n_estimators': [20,50,100,150],
    'max_depth': [5,10,15],
    'max_features': [5,10,15],
    'learning_rate': [0.1,0.5,0.9]
}
```

In [103]:

```
gbCV1 = GridSearchCV(GradientBoostingClassifier(random_state=12345), param_grid=gb_param

gbCV1.fit(train_x_os, train_y_os)
```

```
Fitting 5 folds for each of 108 candidates, totalling 540 fits
```

Out[103]:

```
GridSearchCV(cv=5, estimator=GradientBoostingClassifier(random_state=1234
5),
             n_jobs=-1,
             param_grid={'learning_rate': [0.1, 0.5, 0.9],
                         'max_depth': [5, 10, 15], 'max_features': [5, 10,
15],
                         'n_estimators': [20, 50, 100, 150]},
             scoring='accuracy', verbose=10)
```

In [105]:

```
print('Best Score :{} | Best Parameters :{}'.format(gbCV1.best_score_, gbCV1.best_params_
```

```
Best Score :0.9946971843760162 | Best Parameters :{'learning_rate': 0.9,
'max_depth': 15, 'max_features': 5, 'n_estimators': 150}
```

In [106]:

```
cv_results_gb1 = pd.DataFrame(gbCV1.cv_results_)
cv_results_gb1 = cv_results_gb1.sort_values("mean_test_score", ascending=False)
cv_results_gb1[
    [
        "mean_test_score",
        "std_test_score",
        "param_n_estimators",
        "param_max_depth",
        "param_max_features",
        "param_learning_rate"
    ]
].head(5)
```

Out[106]:

	mean_test_score	std_test_score	param_n_estimators	param_max_depth	param_max_fe
99	0.994697	0.000943	150	15	
103	0.994240	0.001345	150	15	
98	0.992869	0.000849	100	15	
107	0.992412	0.001974	150	15	
102	0.991954	0.001179	100	15	

In [107]:

```
# Creating a new GB model using the Best Estimator
gb_clf1 = gbCV1.best_estimator_

gb_clf1.fit(train_x_os, train_y_os)
```

Out[107]:

```
GradientBoostingClassifier(learning_rate=0.9, max_depth=15, max_features=
5,
                           n_estimators=150, random_state=12345)
```

In [109]:

```
file = open('models/GradientBoostingMachineTuned1.pkl', 'wb' )

pickle.dump(gb_clf1, file)

file.close()
```

In [162]:

```
train_predictions_df = pd.concat([train_predictions_df, pd.Series(gb_clf1.predict(train_
test_predictions_df = pd.concat([test_predictions_df, pd.Series(gb_clf1.predict(test_x_s
```

In [111]:

```
gb_clf1_train_acc = accuracy_score(train_y_os, train_predictions_df.gb_clf1_pred)
gb_clf1_test_acc = accuracy_score(test_y, test_predictions_df.gb_clf1_pred)
gb_clf1_train_auc = roc_auc_score(train_y_os, train_predictions_df.gb_clf1_proba)
gb_clf1_test_auc = roc_auc_score(test_y, test_predictions_df.gb_clf1_proba)
print('Training Accuracy :{} | Testing Accuracy :{}'.format(gb_clf1_train_acc, gb_clf1_t
print('Training AUC :{} | Testing AUC :{}'.format(gb_clf1_train_auc, gb_clf1_test_auc ))
```

```
Training Accuracy :1.0 | Testing Accuracy :0.8981233243967829
Training AUC :1.0 | Testing AUC :0.6621678150762839
```

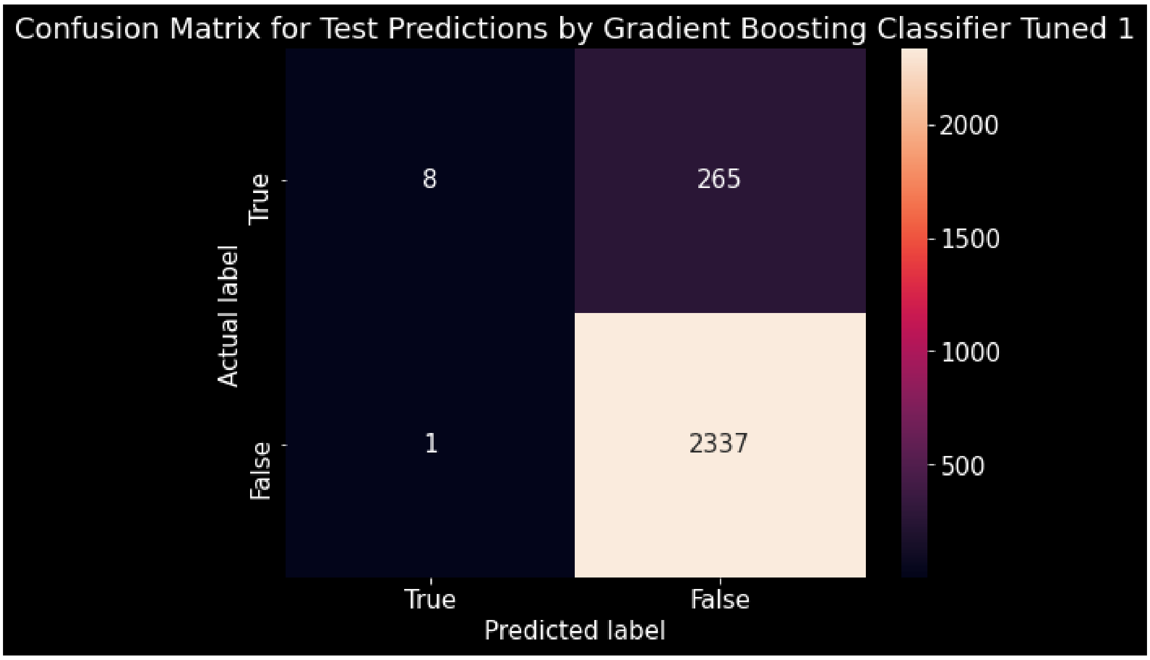
In [112]:

```
print(classification_report(test_y, test_predictions_df.gb_clf1_pred, target_names=targe
```

```
              precision    recall  f1-score   support

       False       0.90      1.00      0.95      2338
        True       0.89      0.03      0.06       273

    accuracy                           0.90      2611
   macro avg       0.89      0.51      0.50      2611
weighted avg       0.90      0.90      0.85      2611
```

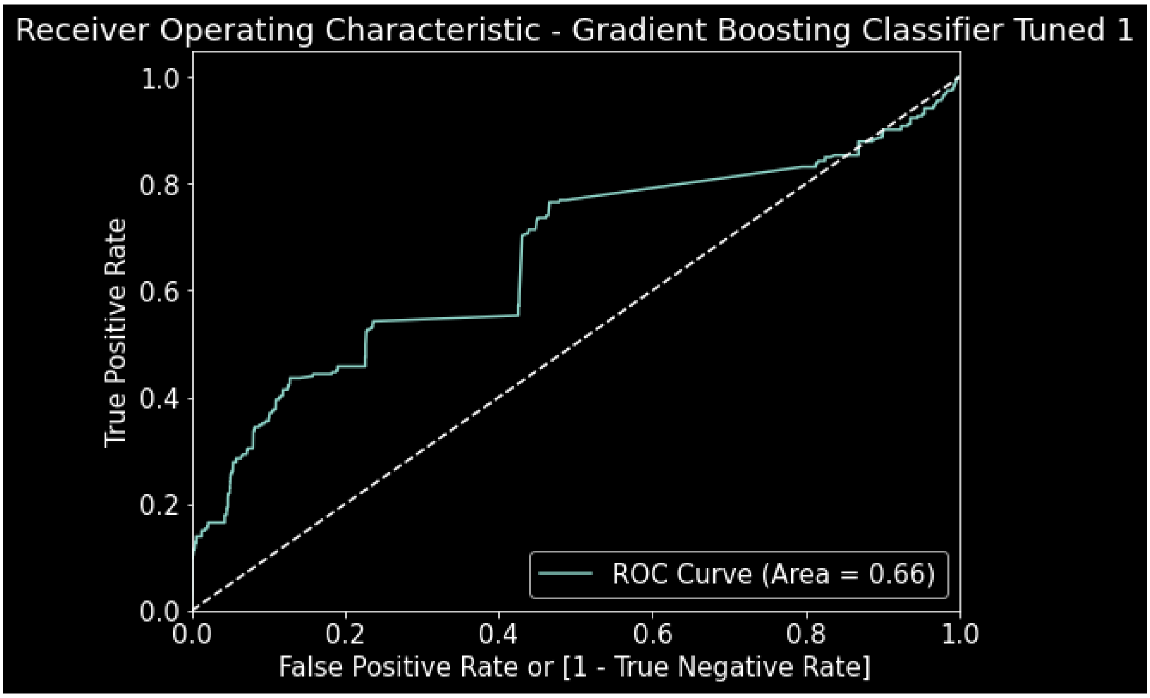
In [113]:

```
cm_gb_clf1 = confusion_matrix(test_y, test_predictions_df.gb_clf1_pred, labels=[True,Fal
with plt.style.context('dark_background'):
    plt.figure(figsize=(8,6))
    sns.heatmap(cm_gb_clf1, annot=True,  fmt='d', xticklabels = ["True", "False"] , ytic
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')
    plt.title('Confusion Matrix for Test Predictions by Gradient Boosting Classifier Tun
    plt.savefig('plots/Confusion Matrix - Gradient Boosting Tuned 1.png', bbox_inches='t
    plt.show()
```



In [114]:

```
fpr, tpr, thresholds = roc_curve(test_y, test_predictions_df.gb_clf1_proba, drop_interme
with plt.style.context('dark_background'):
    plt.figure(figsize=(8, 6))
    plt.plot( fpr, tpr, label='ROC Curve (Area = %0.2f)' % gb_clf1_test_auc)
    plt.plot([0, 1], [0, 1], 'w--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic - Gradient Boosting Classifier Tuned 1'
    plt.legend(loc="lower right")
    plt.savefig('plots/ROC Curve - Gradient Boosting Tuned 1.png', bbox_inches='tight')
    plt.show()
```



XGBoost Classifier

In [116]:

```
xgbc = XGBClassifier(random_state=12345)

xgbc.fit(train_x_os, train_y_os)
```

```
[00:10:46] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release
_1.5.1/src/learner.cc:1115: Starting in XGBoost 1.3.0, the default evaluat
ion metric used with the objective 'binary:logistic' was changed from 'err
or' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
```

Out[116]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=F
alse,
              gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_delta_step=0, max_depth=6, min_child_weight=1, missing=n
an,
              monotone_constraints='()', n_estimators=100, n_jobs=2,
              num_parallel_tree=1, predictor='auto', random_state=12345,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

In [117]:

```
file = open('models/XGBoostClassifier.pkl', 'wb' )

pickle.dump(xgbc, file)

file.close()
```

In [163]:

```
train_predictions_df = pd.concat([train_predictions_df, pd.Series(xgbc.predict(train_x_o
test_predictions_df = pd.concat([test_predictions_df, pd.Series(xgbc.predict(test_x_scal
```

In [119]:

```
xgbc_train_acc = accuracy_score(train_y_os, train_predictions_df.xgbc_pred)
xgbc_test_acc = accuracy_score(test_y, test_predictions_df.xgbc_pred)
xgbc_train_auc = roc_auc_score(train_y_os, train_predictions_df.xgbc_proba)
xgbc_test_auc = roc_auc_score(test_y, test_predictions_df.xgbc_proba)
print('Training Accuracy :{} | Testing Accuracy :{}'.format(xgbc_train_acc, xgbc_test_ac
print('Training AUC :{} | Testing AUC :{}'.format(xgbc_train_auc, xgbc_test_auc ))
```

```
Training Accuracy :0.9994514536478333 | Testing Accuracy :0.12638835695135
964
Training AUC :1.0 | Testing AUC :0.32750981553376757
```

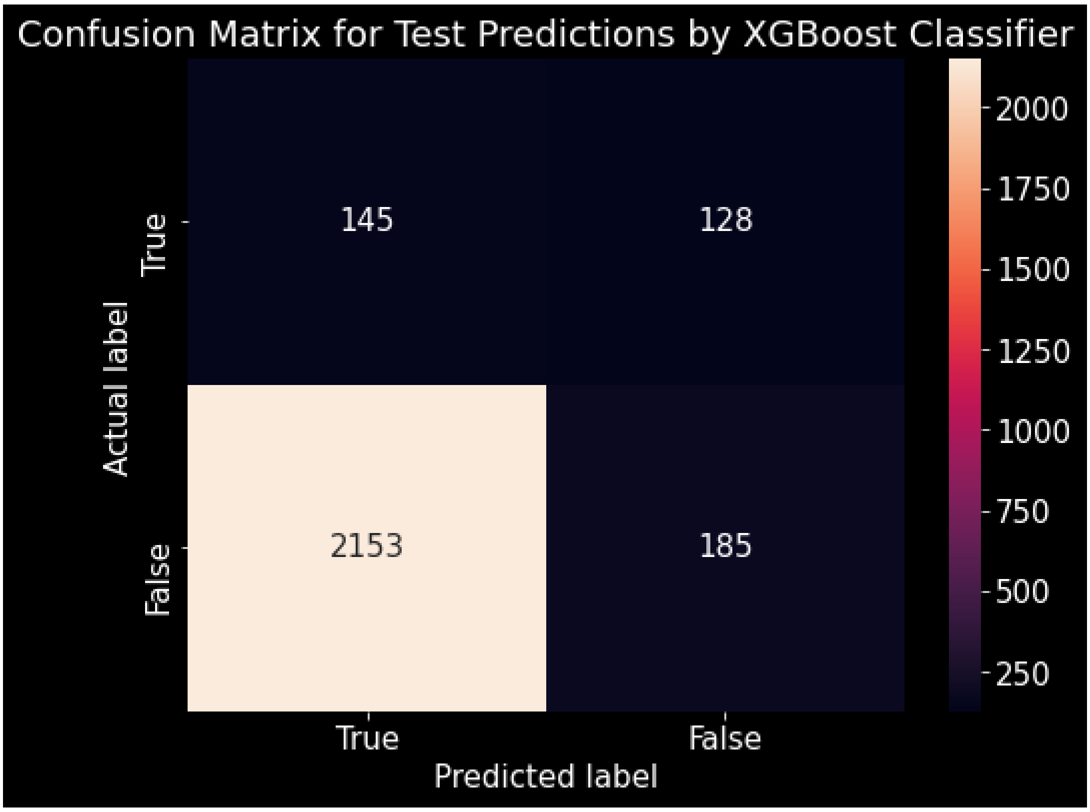
In [120]:

```
print(classification_report(test_y, test_predictions_df.xgbc_pred, target_names=target_n
```

```
              precision    recall  f1-score   support

       False       0.59      0.08      0.14      2338
        True       0.06      0.53      0.11       273

    accuracy                           0.13      2611
   macro avg       0.33      0.31      0.13      2611
weighted avg       0.54      0.13      0.14      2611
```

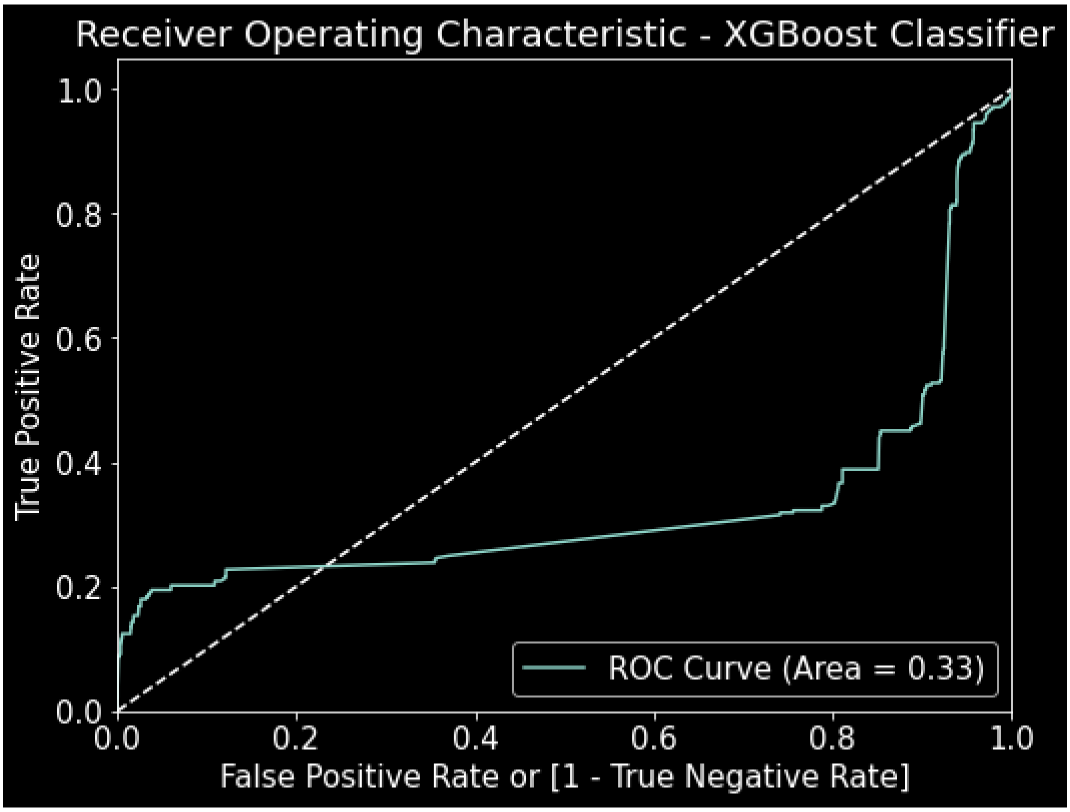
In [121]:

```
cm_xgbc = confusion_matrix(test_y, test_predictions_df.xgbc_pred, labels=[True,False])
with plt.style.context('dark_background'):
    plt.figure(figsize=(8,6))
    sns.heatmap(cm_xgbc, annot=True,  fmt='d', xticklabels = ["True", "False"] , ytickla
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')
    plt.title('Confusion Matrix for Test Predictions by XGBoost Classifier')
    plt.savefig('plots/Confusion Matrix - XGBoost Classifier.png', bbox_inches='tight')
    plt.show()
```



In [122]:

```
fpr, tpr, thresholds = roc_curve(test_y, test_predictions_df.xgbc_proba, drop_intermedia
with plt.style.context('dark_background'):
    plt.figure(figsize=(8, 6))
    plt.plot( fpr, tpr, label='ROC Curve (Area = %0.2f)' % xgbc_test_auc)
    plt.plot([0, 1], [0, 1], 'w--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic - XGBoost Classifier')
    plt.legend(loc="lower right")
    plt.savefig('plots/ROC Curve - XGBoost Classifier.png', bbox_inches='tight')
    plt.show()
```



Multi Layer Perceptron

using Sequential Model with Dense Layers

In [123]:

```
# using Earlystopping rounds to avoid overfitting on training
callback = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=5)
```

In [124]:

```
# Instantiating the Model
mlp_clf = Sequential()
```

In [125]:

```
print('Input Dimensions should be :',train_x_os.shape[1])
print('Maximum Number of Nodes per Layer Should be around :',2/3*train_x_os.shape[1] + t
print('Nodes for the output layer should be around :',train_y_os.nunique()-1)
```

```
Input Dimensions should be : 15
Maximum Number of Nodes per Layer Should be around : 11.0
Nodes for the output layer should be around : 1
```

In [126]:

```
# Adding the Input Layer and the First Hidden Layer
mlp_clf.add(Dense(units = 11, kernel_initializer = 'uniform', activation = 'softmax', in

# Adding the Second Hidden Layer
mlp_clf.add(Dense(units = 8, kernel_initializer = 'uniform', activation = 'softmax'))

# Adding the Third Hidden Layer
mlp_clf.add(Dense(units = 4, kernel_initializer = 'uniform', activation = 'softmax'))

# Adding the Output Layer
mlp_clf.add(Dense(units = 1, kernel_initializer = 'uniform', activation = 'sigmoid'))
```

In [127]:

```
# Compiling Neural Network
mlp_clf.compile(optimizer = 'adam', loss = 'binary_crossentropy', weighted_metrics = ['a
```

In [128]:

```
# Fitting our Model
mlp_clf.fit(train_x_os, train_y_os, batch_size = 10, epochs = 100, callbacks=callback, v
```

```
Epoch 1/100
1094/1094 [==============================] - 5s 3ms/step - loss: 0.6636 -
accuracy: 0.6685 - val_loss: 0.6994 - val_accuracy: 0.2823
Epoch 2/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.4884 -
accuracy: 0.8342 - val_loss: 0.6189 - val_accuracy: 0.8108
Epoch 3/100
1094/1094 [==============================] - 3s 3ms/step - loss: 0.4333 -
accuracy: 0.8343 - val_loss: 0.5922 - val_accuracy: 0.8093
Epoch 4/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.4183 -
accuracy: 0.8363 - val_loss: 0.5205 - val_accuracy: 0.8767
Epoch 5/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.4116 -
accuracy: 0.8376 - val_loss: 0.4980 - val_accuracy: 0.8843
Epoch 6/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.4075 -
accuracy: 0.8374 - val_loss: 0.4899 - val_accuracy: 0.8843
Epoch 7/100
1094/1094 [==============================] - 2s 2ms/step - loss: 0.4043 -
accuracy: 0.8405 - val_loss: 0.4696 - val_accuracy: 0.8836
Epoch 8/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.4069 -
accuracy: 0.8364 - val_loss: 0.5866 - val_accuracy: 0.7867
Epoch 9/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.3827 -
accuracy: 0.8461 - val_loss: 0.3950 - val_accuracy: 0.8866
Epoch 10/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.3309 -
accuracy: 0.8805 - val_loss: 0.3517 - val_accuracy: 0.8840
Epoch 11/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.2841 -
accuracy: 0.9007 - val_loss: 0.3627 - val_accuracy: 0.8705
Epoch 12/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.2541 -
accuracy: 0.9136 - val_loss: 0.3456 - val_accuracy: 0.8709
Epoch 13/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.2322 -
accuracy: 0.9179 - val_loss: 0.3457 - val_accuracy: 0.8682
Epoch 14/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.2163 -
accuracy: 0.9257 - val_loss: 0.3332 - val_accuracy: 0.8705
Epoch 15/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.2179 -
accuracy: 0.9221 - val_loss: 0.3186 - val_accuracy: 0.8809
Epoch 16/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.2097 -
accuracy: 0.9252 - val_loss: 0.3138 - val_accuracy: 0.8874
Epoch 17/100
1094/1094 [==============================] - 3s 2ms/step - loss: 0.2035 -
accuracy: 0.9302 - val_loss: 0.3182 - val_accuracy: 0.8847
Epoch 18/100
1094/1094 [==============================] - 2s 2ms/step - loss: 0.2072 -
accuracy: 0.9274 - val_loss: 0.3208 - val_accuracy: 0.8870
Epoch 19/100
1094/1094 [==============================] - 2s 2ms/step - loss: 0.2098 -
accuracy: 0.9239 - val_loss: 0.3213 - val_accuracy: 0.8893
Epoch 20/100
1094/1094 [==============================] - 2s 2ms/step - loss: 0.2067 -
accuracy: 0.9241 - val_loss: 0.3274 - val_accuracy: 0.8874
Epoch 21/100
```

```
1094/1094 [==============================] - 2s 2ms/step - loss: 0.2046 -
accuracy: 0.9271 - val_loss: 0.3325 - val_accuracy: 0.8836
Epoch 21: early stopping
```

Out[128]:

```
<keras.callbacks.History at 0x25f808fd070>
```

In [130]:

```
file = open('models/MplClassifier.pkl', 'wb' )

pickle.dump(mlp_clf, file)

file.close()
```

```
INFO:tensorflow:Assets written to: ram://9c8213fd-1023-4a7b-82d1-cf3cf70c5
714/assets
```

In [168]:

```
mlp_clf.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 11)                176

 dense_1 (Dense)             (None, 8)                 96

 dense_2 (Dense)             (None, 4)                 36

 dense_3 (Dense)             (None, 1)                 5

=================================================================
Total params: 313
Trainable params: 313
Non-trainable params: 0
_________________________________________________________________
```

In [164]:

```
train_predictions_df = pd.concat([train_predictions_df, pd.Series(mlp_clf.predict(train_
test_predictions_df = pd.concat([test_predictions_df, pd.Series(mlp_clf.predict(test_x_s
```

In [147]:

```
mlp_clf_train_auc = roc_auc_score(train_y_os, train_predictions_df.mlp_clf_proba)
mlp_clf_test_auc = roc_auc_score(test_y, test_predictions_df.mlp_clf_proba)

mlp_clf_train_acc = accuracy_score(train_y_os, train_predictions_df.mlp_clf_proba>0.5)
mlp_clf_test_acc = accuracy_score(test_y, test_predictions_df.mlp_clf_proba>0.5)

print('Training AUC :{} | Testing AUC :{}'.format(mlp_clf_train_auc, mlp_clf_test_auc))
print('Training Accuracy :{} | Testing Accuracy :{}'.format((mlp_clf_train_acc), (mlp_cl
```

```
Training AUC :0.9717566499000115 | Testing AUC :0.7463307294359476
Training Accuracy :0.9261290912415432 | Testing Accuracy :0.88356951359632
33
```

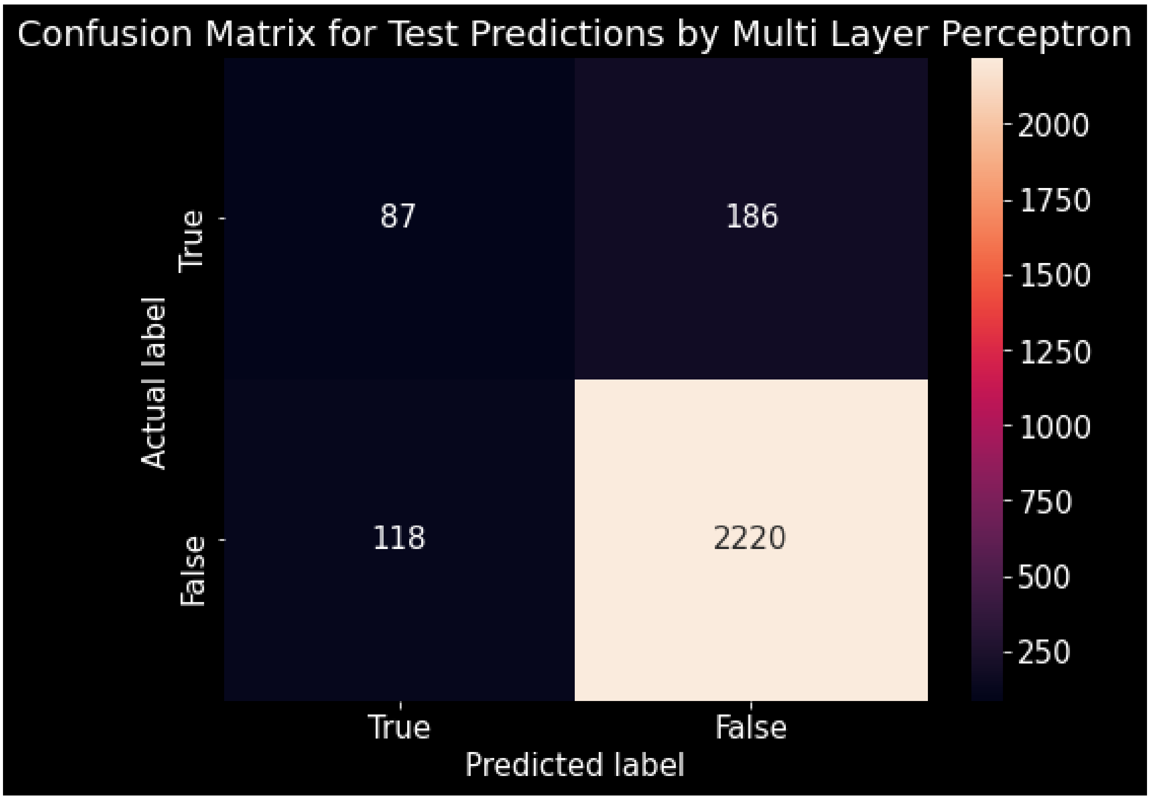
In [149]:

```
print(classification_report(test_y, test_predictions_df.mlp_clf_proba>0.5, target_names=
```

```
              precision    recall  f1-score   support

       False       0.92      0.95      0.94      2338
        True       0.42      0.32      0.36       273

    accuracy                           0.88      2611
   macro avg       0.67      0.63      0.65      2611
weighted avg       0.87      0.88      0.88      2611
```

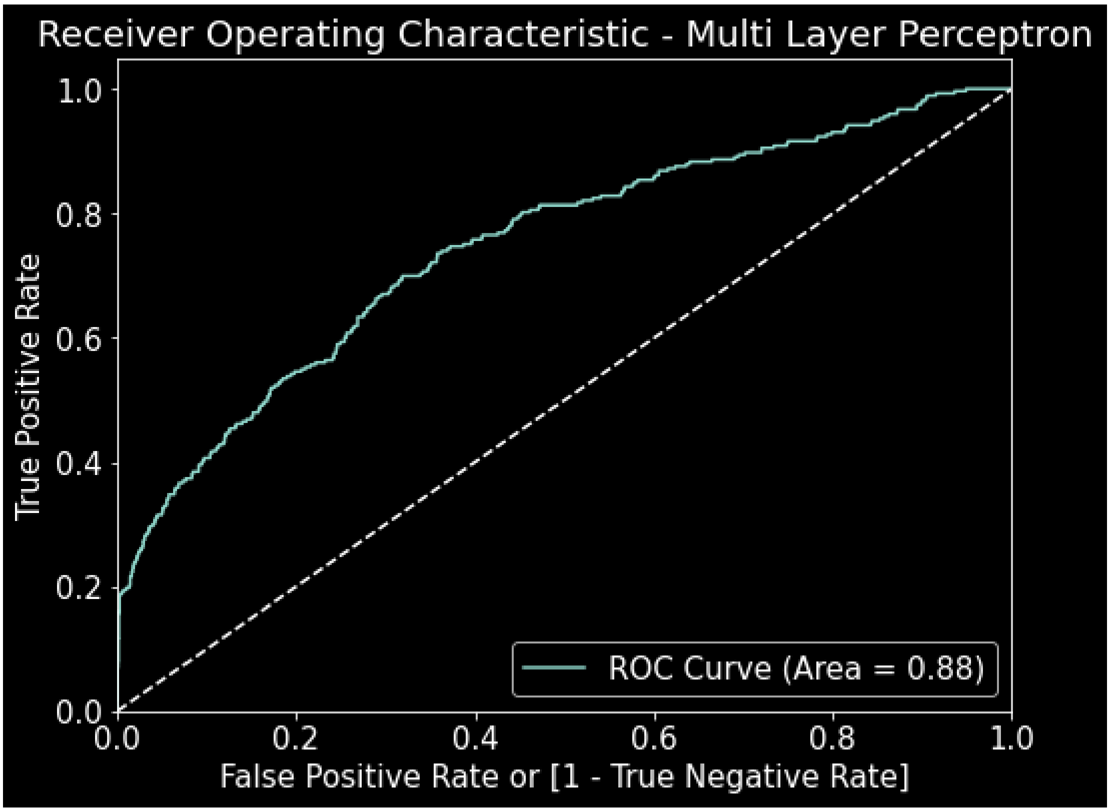
In [150]:

```
cm_mlp_clf = confusion_matrix(test_y, test_predictions_df.mlp_clf_proba>0.5, labels=[Tru
with plt.style.context('dark_background'):
    plt.figure(figsize=(8,6))
    sns.heatmap(cm_mlp_clf, annot=True,  fmt='d', xticklabels = ["True", "False"] , ytic
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')
    plt.title('Confusion Matrix for Test Predictions by Multi Layer Perceptron')
    plt.savefig('plots/Confusion Matrix - Multi Layer Perceptron.png', bbox_inches='tigh
    plt.show()
```



In [151]:

```
fpr, tpr, thresholds = roc_curve(test_y, test_predictions_df.mlp_clf_proba, drop_interme
with plt.style.context('dark_background'):
    plt.figure(figsize=(8, 6))
    plt.plot( fpr, tpr, label='ROC Curve (Area = %0.2f)' % mlp_clf_test_acc)
    plt.plot([0, 1], [0, 1], 'w--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate or [1 - True Negative Rate]')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic - Multi Layer Perceptron')
    plt.legend(loc="lower right")
    plt.savefig('plots/ROC Curve - Multi Layer Perceptron.png', bbox_inches='tight')
    plt.show()
```



Choosing the Best Model

In [165]:

```
train_predictions_df.head()
```

Out[165]:

	log_reg_pred	log_reg_proba	lsvc_pred	lsvc_proba	rf_clf_pred	rf_clf_proba	rf_clf1_pred
0	False	0.169124	False	0.097648	False	0.00	False
1	False	0.076764	False	0.062516	False	0.00	False
2	True	0.525438	False	0.452142	False	0.25	False
3	False	0.471750	True	0.516739	False	0.00	False
4	True	0.986558	True	0.990351	False	0.42	True

In [166]:

```
test_predictions_df.head()
```

Out[166]:

	log_reg_pred	log_reg_proba	lsvc_pred	lsvc_proba	rf_clf_pred	rf_clf_proba	rf_clf1_pred
0	False	0.005361	False	0.000471	False	0.29	False
1	False	0.007964	False	0.000855	False	0.34	False
2	False	0.010865	False	0.000778	False	0.34	False
3	False	0.251215	False	0.000154	False	0.36	False
4	False	0.324433	False	0.000151	False	0.33	False

In [154]:

```
pd.DataFrame({
    'Accuracy':[logreg_test_acc, lsvc_test_acc, rf_clf_test_acc, rf_clf1_test_acc, rf_cl
    'AUC':[logreg_test_auc, lsvc_test_auc, rf_clf_test_auc, rf_clf1_test_auc, rf_clf2_te
}, index=['Logistic Regression', 'LinearSVC', 'Random Forest', 'Random Forest Tuned 1',
```

Out[154]:

	Accuracy	AUC
Logistic Regression	0.871314	0.575939
LinearSVC	0.895059	0.670720
Random Forest	0.907698	0.598625
Random Forest Tuned 1	0.909230	0.583626
Random Forest Tuned 2	0.919954	0.702502
Gradient Boosting	0.303332	0.753394
Gradient Boosting Tuned 1	0.898123	0.662168
XGBoost	0.126388	0.327510
MLP	0.883570	0.746331

The 2nd Tune Model of Random Forest Classifier seems to be performing well both Accuracy and AUC wise. so we will be finalizing it as our Final Model for Predictions

In [ ]:

```

```

In [100]:

```
age = None
```

In [102]:

```
if age:
    print('T')
else:
    print('false')
```

```
false
```

In [108]:

```
train_x.head()
```

Out[108]:

	FTI	T3	T4U	TSH	TT4	age	goitre	hypopituitary	lithium	pregnant	psych	s
8547	90.0	1.94	0.63	1.20	57.0	75.0	0	0	0	0	0	
8571	97.0	2.50	0.98	1.10	95.0	65.0	0	0	0	0	1	
4757	200.0	2.60	1.01	0.02	203.0	42.0	0	0	0	0	0	
6323	156.0	0.40	0.68	4.30	106.0	81.0	0	0	0	0	0	
1412	82.0	1.94	0.82	16.00	67.0	58.0	0	0	0	0	0	

In [52]:

```
FTI, T3, T4U, TSH, TT4, age, goitre, hypopituitary, lithium, pregnant, psych, sex, sick,
```

In [59]:

```
scaler_transformer.transform([[FTI, T3, T4U, TSH, TT4, age, goitre, hypopituitary, lithi
```

```
---------------------------------------------------------------------------
----
Empty                                     Traceback (most recent call l
ast)
File ~\anaconda3\lib\site-packages\joblib\parallel.py:827, in Parallel.
dispatch_one_batch(self, iterator)
    826 try:
--> 827     tasks = self._ready_batches.get(block=False)
    828 except queue.Empty:
    829     # slice the iterator n_jobs * batchsize items at a time. If
the
    830     # slice returns less than that, then the current batchsize
puts
   (...)
    833     # accordingly to distribute evenly the last items between a
ll
    834     # workers.

File ~\anaconda3\lib\queue.py:167, in Queue.get(self, block, timeout)
```

In [125]:

```
[[FTI, T3, T4U, TSH, TT4, age, goitre, hypopituitary, lithium, pregnant, psych, sex, sic
```

Out[125]:

```
[[90.0,
  1.94,
  0.63,
  1.2,
  57.0,
  75.0,
  0.0,
  0.0,
  0.0,
  0.0,
  0.0,
  1.0,
  0.0,
  0.0,
  0.0]]
```

In [53]:

```
temp_dict ={
    'FTI':90.0,
    'T3':1.94,
    'T4U':0.63,
    'TSH':1.2,
    'TT4':57.0,
    'age':75.0,
    'goitre':0.0,
    'hypopituitary':0.0,
    'lithium':0.0,
    'pregnant':0.0,
    'psych':0.0,
    'sex':1.0,
    'sick':0.0,
    'thyroid_surgery':0.0,
    'tumor':0.0
}
```

In [54]:

```
temp_df = pd.DataFrame(columns=temp_dict.keys(), index = [0])
```

In [55]:

```
for var in temp_dict.keys():
    temp_df.loc[0,[var]] = temp_dict[var]
temp_df
```

Out[55]:

	FTI	T3	T4U	TSH	TT4	age	goitre	hypopituitary	lithium	pregnant	psych	sex	si
0	90.0	1.94	0.63	1.2	57.0	75.0	0.0	0.0	0.0	0.0	0.0	1.0	0

In [61]:

```
temp_df = pd.DataFrame(scaler.transform(temp_df), columns=temp_df.columns)
```

In [63]:

```
log_reg.predict(temp_df)[0]
```

Out[63]:

```
True
```

In [72]:

```
train_x_scaled.head(1)
```

Out[72]:

	FTI	T3	T4U	TSH	TT4	age	goitre	hypopituitary	lithium
0	-0.675459	0.00031	-1.84023	-0.237613	-1.463851	1.197936	0.0	0.0	0.0

In [72]:

```
a = True
```

In [73]:

```
if a:
    print('T')
else:
    print('F')
```

```
T
```

In [86]:

```
test_x
```

Out[86]:

	FTI	T3	T4U	TSH	TT4	age	goitre	hypopituitary	lithium	pregnant	psych	se
5700	131.0	1.50	1.05	0.32	138.0	50.0	0	0	0	0	0	
15	106.0	1.94	1.07	0.40	113.0	77.0	0	0	0	0	0	
3928	144.0	1.94	1.05	1.40	151.0	22.0	0	0	0	0	0	
7375	71.0	1.94	0.80	4.80	57.0	42.0	0	0	0	0	0	
4699	90.0	1.94	0.78	7.00	71.0	83.0	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	
861	101.0	1.50	0.84	4.00	85.0	72.0	0	0	0	0	0	
6569	128.0	2.40	0.72	0.47	92.0	64.0	0	0	0	0	0	
5747	93.0	2.30	0.94	2.20	87.0	60.0	0	0	0	0	0	
4075	152.0	1.94	0.83	0.02	126.0	49.0	0	0	0	0	0	
7998	86.0	1.10	0.98	2.10	84.0	39.0	0	0	0	0	0	

2611 rows × 15 columns

In [87]:

```
test_y
```

Out[87]:

```
5700     False
15       False
3928     False
7375     False
4699      True
         ...
861      False
6569     False
5747     False
4075     False
7998     False
Name: thyroid_disease, Length: 2611, dtype: bool
```