Problem statement

A lung cancer is a type of cancer that begins in the lungs and most often occurs in people who smoke.

Causes of lung cancer include smoking, second-hand smoke, exposure to certain toxins and family history.

In this project, we want to predict if a newly administered patient is affected with lung cancer or not using a previous dataset.

Importing the libraries

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

Loading the lung_cancer dataset.csv

```
# Dataset

df = pd.read_csv('lung_cancer.csv')
df
```

ALLERGY	WHEEZING	ALCOHOL CONSUMING	COUGHING	SHORTNESS OF BREATH	SWALLOWING DIFFICULTY	CHEST PAIN	LUNG_CANCER
1	2	2	2	2	2	2	YES
2	1	1	1	2	2	2	YES
1	2	1	2	2	1	2	NO

```
df.shape
```

```
(309, 16)
```

```
df.describe()
```

	AGE	SMOKING	YELLOW_FINGERS	ANXIETY	PEER_PRESSURE	CHRONIC DISEASE
count	309.000000	309.000000	309.000000	309.000000	309.000000	309.000000
mean	62.673139	1.563107	1.569579	1.498382	1.501618	1.504854
std	8.210301	0.496806	0.495938	0.500808	0.500808	0.500787
min	21.000000	1.000000	1.000000	1.000000	1.000000	1.000000
25%	57.000000	1.000000	1.000000	1.000000	1.000000	1.000000
50%	62.000000	2.000000	2.000000	1.000000	2.000000	2.000000
75%	69.000000	2.000000	2.000000	2.000000	2.000000	2.000000
max	87.000000	2.000000	2.000000	2.000000	2.000000	2.000000

```
df.columns
```

```
Index(['GENDER', 'AGE', 'SMOKING', 'YELLOW_FINGERS', 'ANXIETY',
       'PEER_PRESSURE', 'CHRONIC DISEASE', 'FATIGUE ', 'ALLERGY ', 'WHEEZING',
       'ALCOHOL CONSUMING', 'COUGHING', 'SHORTNESS OF BREATH',
       'SWALLOWING DIFFICULTY', 'CHEST PAIN', 'LUNG_CANCER'],
      dtype='object')
```

```
df = df.drop_duplicates()
```

```
df.nunique()
```

```
GENDER                    2
AGE                      39
SMOKING                   2
YELLOW_FINGERS            2
```

```
ANXIETY                  2
PEER_PRESSURE            2
CHRONIC DISEASE          2
FATIGUE                  2
ALLERGY                  2
WHEEZING                 2
ALCOHOL CONSUMING        2
COUGHING                 2
SHORTNESS OF BREATH      2
SWALLOWING DIFFICULTY    2
CHEST PAIN               2
LUNG_CANCER              2
dtype: int64
```

```
# Missing values

df.isnull().sum()
```

```
GENDER                  0
AGE                     0
SMOKING                 0
YELLOW_FINGERS          0
ANXIETY                 0
PEER_PRESSURE           0
CHRONIC DISEASE         0
FATIGUE                 0
ALLERGY                 0
WHEEZING                0
ALCOHOL CONSUMING       0
COUGHING                0
SHORTNESS OF BREATH     0
SWALLOWING DIFFICULTY   0
CHEST PAIN              0
LUNG_CANCER             0
dtype: int64
```

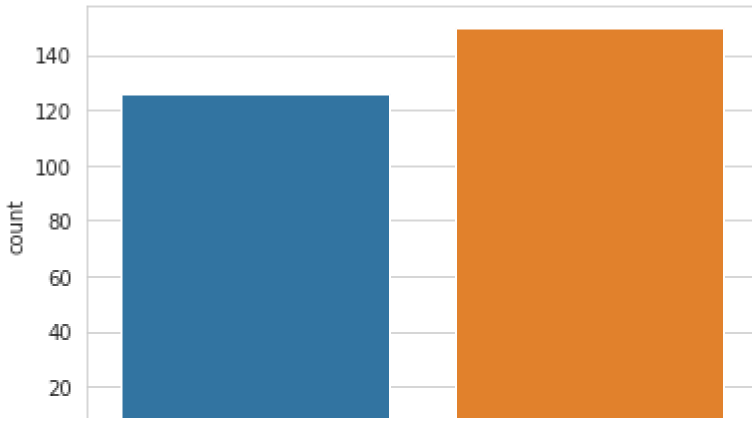
Visualization

```
print(df.GENDER.value_counts())
sns.countplot('GENDER',data=df)
```

```
M    142
F    134
Name: GENDER, dtype: int64
```

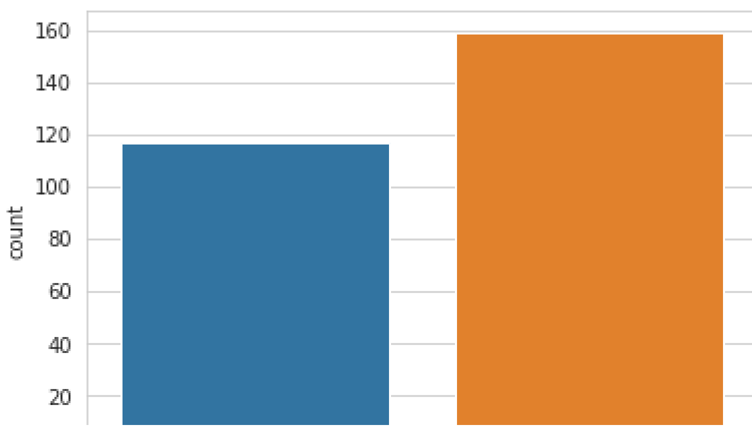
```
print(df.SMOKING.value_counts())
sns.countplot('SMOKING', data=df)
```

```
2    150
1    126
Name: SMOKING, dtype: int64
<matplotlib.axes._subplots.AxesSubplot at 0x7f5d0962c810>
```



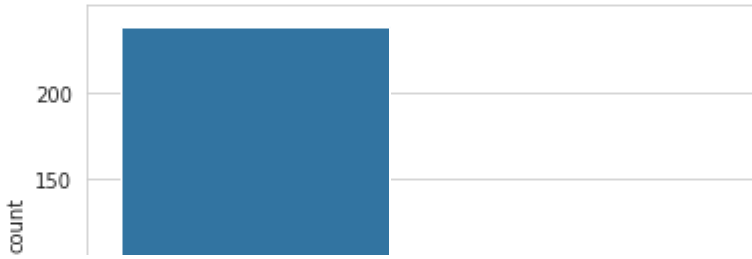

```
print(df.YELLOW_FINGERS.value_counts())
sns.countplot('YELLOW_FINGERS', data=df)
```

```
2    159
1    117
Name: YELLOW_FINGERS, dtype: int64
<matplotlib.axes._subplots.AxesSubplot at 0x7f5d0961ac50>
```




```
print(df.LUNG_CANCER.value_counts())
sns.countplot('LUNG_CANCER', data=df)
```

```
YES    238
NO      38
Name: LUNG_CANCER, dtype: int64
<matplotlib.axes._subplots.AxesSubplot at 0x7f5d09577cd0>
```



Label Encoding

```
# Label Encoding

from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
df['GENDER'] = encoder.fit_transform(df['GENDER'])
df['LUNG_CANCER'] = encoder.fit_transform(df['LUNG_CANCER'])
```

```
df
```

	GENDER	AGE	SMOKING	YELLOW_FINGERS	ANXIETY	PEER_PRESSURE	CHRONIC DISEASE	FATI(
0	1	69	1	2	2	1	1	
1	1	74	2	1	1	1	2	
2	0	59	1	1	1	2	1	
3	1	63	2	2	2	1	1	
4	0	63	1	2	1	1	1	
...	...	...	...	...	...	...	...	
279	0	59	1	2	2	2	1	
280	0	59	2	1	1	1	2	
281	1	55	2	1	1	1	1	
282	1	46	1	2	2	1	1	
283	1	60	1	2	2	1	1	

276 rows × 16 columns

```
# Feature Selection
```

```
# Using Backward Elimination

# Let's first split the dataset into Dependent and Independent variable

X = df.iloc[:,:-1].values
y = df.iloc[:, 15].values

# Print
print(X.shape)
print(y.shape)
```

```
(276, 15)
(276,)
```

Correlation features

```
corr = df.corr()
print(corr)
```

```
                          GENDER       AGE   SMOKING  YELLOW_FINGERS   ANXIETY
GENDER                  1.000000 -0.013120  0.041131       -0.202506 -0.152032
AGE                    -0.013120  1.000000 -0.073410        0.025773  0.050605
SMOKING                 0.041131 -0.073410  1.000000       -0.020799  0.153389
YELLOW_FINGERS         -0.202506  0.025773 -0.020799        1.000000  0.558344
ANXIETY                -0.152032  0.050605  0.153389        0.558344  1.000000
PEER_PRESSURE          -0.261427  0.037848 -0.030364        0.313067  0.210278
CHRONIC DISEASE        -0.189925 -0.003431 -0.149415        0.015316 -0.006938
FATIGUE                -0.079020  0.021606 -0.037803       -0.099644 -0.181474
ALLERGY                 0.150174  0.037139 -0.030179       -0.147130 -0.159451
WHEEZING                0.121047  0.052803 -0.147081       -0.058756 -0.174009
ALCOHOL CONSUMING       0.434264  0.052049 -0.052771       -0.273643 -0.152228
COUGHING                0.120228  0.168654 -0.138553        0.020803 -0.218843
SHORTNESS OF BREATH    -0.052893 -0.009189  0.051761       -0.109959 -0.155678
SWALLOWING DIFFICULTY -0.048959  0.003199  0.042152        0.333349  0.478820
CHEST PAIN              0.361547 -0.035806  0.106984       -0.099169 -0.123182
LUNG_CANCER             0.053666  0.106305  0.034878        0.189192  0.144322

                       PEER_PRESSURE  CHRONIC DISEASE  FATIGUE   ALLERGY   \
GENDER                     -0.261427        -0.189925 -0.079020  0.150174
AGE                         0.037848        -0.003431  0.021606  0.037139
SMOKING                    -0.030364        -0.149415 -0.037803 -0.030179
YELLOW_FINGERS              0.313067         0.015316 -0.099644 -0.147130
ANXIETY                     0.210278        -0.006938 -0.181474 -0.159451
PEER_PRESSURE               1.000000         0.042893  0.094661 -0.066887
CHRONIC DISEASE             0.042893         1.000000 -0.099411  0.134309
FATIGUE                     0.094661        -0.099411  1.000000 -0.001841
ALLERGY                    -0.066887         0.134309 -0.001841  1.000000
WHEEZING                   -0.037769        -0.040546  0.152151  0.166517
ALCOHOL CONSUMING          -0.132603         0.010144 -0.181573  0.378125
COUGHING                   -0.068224        -0.160813  0.148538  0.206367
SHORTNESS OF BREATH        -0.214115        -0.011760  0.407027 -0.018030
SWALLOWING DIFFICULTY       0.327764         0.068263 -0.115727 -0.037581
CHEST PAIN                 -0.074655        -0.048895  0.013757  0.245440
LUNG_CANCER                 0.195086         0.143692  0.160078  0.333552
```

```
                         WHEEZING  ALCOHOL CONSUMING  COUGHING  \
GENDER                   0.121047           0.434264  0.120228   
AGE                      0.052803           0.052049  0.168654   
SMOKING                 -0.147081          -0.052771 -0.138553   
YELLOW_FINGERS          -0.058756          -0.273643  0.020803   
ANXIETY                 -0.174009          -0.152228 -0.218843   
PEER_PRESSURE           -0.037769          -0.132603 -0.068224   
CHRONIC DISEASE         -0.040546           0.010144 -0.160813   
FATIGUE                  0.152151          -0.181573  0.148538   
ALLERGY                  0.166517           0.378125  0.206367   
WHEEZING                 1.000000           0.261061  0.353657   
ALCOHOL CONSUMING        0.261061           1.000000  0.198023   
COUGHING                 0.353657           0.198023  1.000000   
SHORTNESS OF BREATH      0.042289          -0.163370  0.284968   
SWALLOWING DIFFICULTY    0.108304          -0.000635 -0.136885   
CHEST PAIN               0.142846           0.310767  0.077988   
LUNG_CANCER              0.249054           0.294422  0.253027   

                         SHORTNESS OF BREATH  SWALLOWING DIFFICULTY  CHEST PAIN  
GENDER                             -0.052893              -0.048959    0.361547  
AGE                                -0.009189               0.003199   -0.035806  
SMOKING                             0.051761               0.042152    0.106984  
YELLOW_FINGERS                     -0.109959               0.333349   -0.099169  
```

```
# Visualize correlation features
sns.heatmap(corr, annot = True)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f5cf6adce10>

Building a model

```
# Backward Elimination
# Import the library
import statsmodels.api as sm

# Set an index to the independent variable
X = np.append(arr = np.ones((276,1)).astype(int), values = X, axis = 1)
```

```
pd.DataFrame(X)
```

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	1	1	69	1	2	2	1	1	2	1	2	2	2	2	2	2
1	1	1	74	2	1	1	1	2	2	2	1	1	1	2	2	2
2	1	0	59	1	1	1	2	1	2	1	2	1	2	2	1	2
3	1	1	63	2	2	2	1	1	1	1	1	2	1	1	2	2
4	1	0	63	1	2	1	1	1	1	1	2	1	2	2	1	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
271	1	0	59	1	2	2	2	1	1	2	2	1	2	1	2	1
272	1	0	59	2	1	1	1	2	2	2	1	1	1	2	1	1
273	1	1	55	2	1	1	1	1	2	2	1	1	1	2	1	2
274	1	1	46	1	2	2	1	1	1	1	1	1	1	1	2	2
275	1	1	60	1	2	2	1	1	2	1	2	2	2	2	2	2

276 rows × 16 columns

```
X_optimal = X[:, [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15]]
# Fitting the data to statsmodels
regressor_OLS = sm.OLS(endog = y, exog = X_optimal).fit()
# Calling the library
regressor_OLS.summary()
```

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.405
Model:	OLS	**Adj. R-squared:**	0.370
Method:	Least Squares	**F-statistic:**	11.79
Date:	Fri, 10 Jun 2022	**Prob (F-statistic):**	5.47e-22
Time:	13:32:55	**Log-Likelihood:**	-25.964
No. Observations:	276	**AIC:**	83.93
Df Residuals:	260	**BIC:**	141.9
Df Model:	15		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-1.2794	0.208	-6.141	0.000	-1.690	-0.869
x1	-0.0066	0.040	-0.166	0.869	-0.085	0.072
x2	0.0018	0.002	0.897	0.371	-0.002	0.006
x3	0.0702	0.035	1.994	0.047	0.001	0.139
x4	0.1263	0.045	2.835	0.005	0.039	0.214
x5	0.0735	0.047	1.579	0.116	-0.018	0.165
x6	0.0825	0.039	2.120	0.035	0.006	0.159
x7	0.1116	0.036	3.125	0.002	0.041	0.182
x8	0.1562	0.041	3.785	0.000	0.075	0.237
x9	0.1438	0.037	3.847	0.000	0.070	0.217
x10	0.0559	0.038	1.461	0.145	-0.019	0.131
x11	0.1960	0.043	4.505	0.000	0.110	0.282
x12	0.1084	0.042	2.607	0.010	0.027	0.190
x13	0.0406	0.042	0.968	0.334	-0.042	0.123
x14	0.1037	0.041	2.499	0.013	0.022	0.185
x15	0.0372	0.038	0.980	0.328	-0.038	0.112

In the summary above, was can easily remove the variables with the p-value greater than 0.05

```
# We run the command again as well have removed the variables with p-value > 0.05
X_optimal = X[:, [0,1,4,5,7,8,9,10,12,13,15]]
# Fitting the data to statsmodels
regressor_OLS = sm.OLS(endog = y, exog = X_optimal).fit()
# Calling the library
regressor_OLS.summary()
```

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.313
Model:	OLS	**Adj. R-squared:**	0.287
Method:	Least Squares	**F-statistic:**	12.09
Date:	Fri, 10 Jun 2022	**Prob (F-statistic):**	3.32e-17
Time:	13:32:55	**Log-Likelihood:**	-45.679
No. Observations:	276	**AIC:**	113.4
Df Residuals:	265	**BIC:**	153.2
Df Model:	10		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-0.7204	0.159	-4.541	0.000	-1.033	-0.408
x1	0.0262	0.040	0.659	0.510	-0.052	0.104
x2	0.0978	0.045	2.196	0.029	0.010	0.186
x3	0.1578	0.045	3.535	0.000	0.070	0.246
x4	0.1208	0.037	3.240	0.001	0.047	0.194
x5	0.1408	0.042	3.362	0.001	0.058	0.223
x6	0.1854	0.038	4.821	0.000	0.110	0.261
x7	0.0988	0.039	2.550	0.011	0.023	0.175
x8	0.1287	0.042	3.032	0.003	0.045	0.212
x9	-0.0133	0.042	-0.316	0.753	-0.096	0.069
x10	0.0898	0.039	2.301	0.022	0.013	0.167

Omnibus:	39.871	**Durbin-Watson:**	1.848
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	52.561
Skew:	-1.008	**Prob(JB):**	3.86e-12
Kurtosis:	3.712	**Cond. No.**	45.1

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
# We run the command again as well have removed the variables with p-value > 0.05
X_optimal = X[:, [0,1,5,8,9,10,12,13,15]]
# Fitting the data to statsmodels
regressor_OLS = sm.OLS(endog = y, exog = X_optimal).fit()
# Calling the library
regressor_OLS.summary()
```

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.272
Model:	OLS	**Adj. R-squared:**	0.250
Method:	Least Squares	**F-statistic:**	12.46
Date:	Fri, 10 Jun 2022	**Prob (F-statistic):**	3.61e-15
Time:	13:32:55	**Log-Likelihood:**	-53.786
No. Observations:	276	**AIC:**	125.6
Df Residuals:	267	**BIC:**	158.2
Df Model:	8		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-0.4279	0.144	-2.972	0.003	-0.711	-0.144
x1	-0.0129	0.039	-0.328	0.744	-0.091	0.065
x2	0.2043	0.038	5.353	0.000	0.129	0.279
x3	0.1232	0.043	2.890	0.004	0.039	0.207
x4	0.2010	0.038	5.225	0.000	0.125	0.277
x5	0.1026	0.040	2.585	0.010	0.024	0.181
x6	0.1236	0.042	2.961	0.003	0.041	0.206
x7	-0.0118	0.043	-0.275	0.783	-0.096	0.072
x8	0.0904	0.040	2.259	0.025	0.012	0.169

Omnibus:	52.829	**Durbin-Watson:**	1.823
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	78.565
Skew:	-1.176	**Prob(JB):**	8.71e-18
Kurtosis:	4.141	**Cond. No.**	35.9

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

!!! Okay, so we have a perfect numbers of variables whose p-values is < 0.05

```
print(X_optimal.shape)
Y = np.reshape(y, (-1,1))
print(Y.shape)
```

```
(276, 9)
(276, 1)
```

```
# Split into Training set and Testing set
# Import the library
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(
    X_optimal, Y,
    test_size=0.25,
    random_state=0)
# Print
print(X_train.shape)
```

```
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(207, 9)
(69, 9)
(207, 1)
(69, 1)
```

Logistic Regression

```
# Let's Create the model
# Import the model
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
lr.fit(X_train,y_train)
```

```
LogisticRegression()
```

```
# Prediction
y_pred = lr.predict(X_test)
pd.DataFrame((y_pred).astype(int))
```

	0
0	0
1	1
2	1
3	1
4	1
...	...
64	1
65	1
66	1
67	1
68	0

69 rows × 1 columns

Evaluation

```
# Checking for the Accuracy
```

```
print("Training Accuracy =", lr.score(X_train,y_train))
print("Testing Accuracy =", lr.score(X_test,y_test))
```

```
Training Accuracy = 0.9082125603864735
Testing Accuracy = 0.855072463768116
```

```
from sklearn.metrics import mean_squared_error as mse
print("MSE Value =", mse(y_test,y_pred))
```

```
MSE Value = 0.14492753623188406
```

```
lr.coef_
```

```
array([[-2.39038155e-06, -1.73706568e-01,  1.81555550e+00,
         1.07902857e+00,  1.79256745e+00,  1.01502282e+00,
         8.83392179e-01,  4.23355013e-01,  9.13399027e-01]])
```

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier()
dtc.fit(X_train,y_train)
```

```
DecisionTreeClassifier()
```

```
# Prediction
dtc_pred = dtc.predict(X_test)
pd.DataFrame((dtc_pred).astype(int))
```

0

Evaluation

```
# Checking the Accuracy
print("Training Accuracy =", dtc.score(X_train,y_train))
print("Testing Accuracy =", dtc.score(X_test,y_test))
```

```
Training Accuracy = 0.9323671497584541
Testing Accuracy = 0.8695652173913043
```

```
# MSE value for Decision tree
print("MSE Value =", mse(y_test,dtc_pred))
```

```
MSE Value = 0.13043478260869565
```

Scales Vector Machine

```
from sklearn.svm import SVC
svc = SVC(kernel = 'linear', random_state = 0)
svc.fit(X_train,y_train)
```

```
SVC(kernel='linear', random_state=0)
```

```
# Prediction
svc_pred = svc.predict(X_test)
pd.DataFrame(svc_pred)
```

Evaluation

```
# Checking the Accuracy
print("Training Accuracy =", svc.score(X_train,y_train))
print("Testing Accuracy =", svc.score(X_test,y_test))
```

```
Training Accuracy = 0.8985507246376812
Testing Accuracy = 0.855072463768116
```

GaussianNB

```
from sklearn.naive_bayes import GaussianNB
gb = GaussianNB()
gb.fit(X_train,y_train)
```

```
GaussianNB()
```

```
# Prediction
gb_pred = gb.predict(X_test)
pd.DataFrame(gb_pred)
```

	0
0	0
1	1
2	1
3	1
4	0
...	...
64	1
65	1
66	1
67	1
68	0

69 rows × 1 columns

Evaluation

```
# Checking the Accuracy
```

```
print("Training Accuracy =", gb.score(X_train,y_train))
print("Testing Accuracy =", gb.score(X_test,y_test))
```

```
Training Accuracy = 0.8743961352657005
Testing Accuracy = 0.7971014492753623
```

Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(X_train,y_train)
```

```
RandomForestClassifier()
```

```
# Prediction
rfc_pred = rfc.predict(X_test)
pd.DataFrame(rfc_pred)
```

	0
0	0
1	1
2	1
3	1
4	1
...	...
64	1
65	1
66	1
67	1
68	0

69 rows × 1 columns

```
# Checking the Accuracy
print("Training Accuracy =", rfc.score(X_train,y_train))
print("Testing Accuracy =", rfc.score(X_test,y_test))
```

```
Training Accuracy = 0.9323671497584541
Testing Accuracy = 0.8695652173913043
```

Overview

After applying the different types of algorithm models, we got the below accuracies with different method used

Logistic Regression = 90%

Decision Tree algorithm = 93%

Scalar Vector Machine = 89%

GaussianNB algorithm = 87%

Random Forest Classifier = 93%