

Predicting Cervical Cancer From Biopsy Results

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A thorough protocol for cervical cancer detection hinges on cytological tests in conjunction with other methodologies; The focus is narrowed to patients that are healthy vs. unhealthy (based on biopsy results). This predictive modeling endeavor stems from the selection of 858 female patients ages 13-84 from a Venezuelan inpatient clinic. The data is preprocessed; feature selection is based on removal of highly correlated and near zero variance predictors. The data is subsequently partitioned using an 80:20 train-test split ratio to evaluate the model performance of data outside the training set. The class imbalance scenario whereby the majority of cases (healthy) is rebalanced with oversampling. Three models are proposed to aide in establishing the likelihood of being diagnosed with cervical cancer. Results vary based on key performance indicators of the receiver operating characteristics' areas under their curves. Furthermore, each model is holistically evaluated based on its predictive ability.

Keywords: cervical cancer, machine learning, ensemble methods, predictive modeling

Loading, Pre-Processing, and Exploring Data

```
[1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from prettytable import PrettyTable

from imblearn.over_sampling import SMOTE, ADASYN
from sklearn.decomposition import PCA
import statsmodels.api as sm
from sklearn.model_selection import train_test_split, \
RepeatedStratifiedKFold, RandomizedSearchCV
from sklearn import metrics
from sklearn.metrics import roc_curve, auc, mean_squared_error, \
precision_score, recall_score, f1_score, accuracy_score, \
confusion_matrix, plot_confusion_matrix, classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC

from scipy.stats import loguniform, uniform, truncnorm, randint

import warnings
warnings.filterwarnings('ignore')
```

```
[2]: url = 'https://raw.githubusercontent.com/lshpaner/\
MSADS_503_Predictive_Modeling_Predicting_Cervical_Cancer/main/\
code_files/risk_factors_cervical_cancer.csv'
```

Now, we proceed to read in the flat .csv file, and examine the first 5 rows of data.

```
[3]: df = pd.read_csv(url)
df.head()
```

```
[3]: Age Number of sexual partners First sexual intercourse Num of pregnancies \
0    18                      4.0                      15.0          1.0
1    15                      1.0                      14.0          1.0
2    34                      1.0                      ?            1.0
3    52                      5.0                      16.0          4.0
4    46                      3.0                      21.0          4.0
```

```
Smokes Smokes (years) Smokes (packs/year) Hormonal Contraceptives \
0    0.0          0.0          0.0          0.0
1    0.0          0.0          0.0          0.0
2    0.0          0.0          0.0          0.0
3    1.0          37.0         37.0          1.0
4    0.0          0.0          0.0          1.0
```

```
Hormonal Contraceptives (years) IUD ... STDs: Time since first diagnosis \
0          0.0  0.0 ... ?
1          0.0  0.0 ... ?
2          0.0  0.0 ... ?
3          3.0  0.0 ... ?
4         15.0  0.0 ... ?
```

```
STDs: Time since last diagnosis Dx:Cancer Dx:CIN Dx:HPV Dx Hinselmann \
0          ?          0          0          0  0          0
1          ?          0          0          0  0          0
2          ?          0          0          0  0          0
3          ?          1          0          1  0          0
4          ?          0          0          0  0          0
```

```
Schiller Citology Biopsy
0          0          0          0
1          0          0          0
2          0          0          0
3          0          0          0
4          0          0          0
```

[5 rows x 36 columns]

```
[4]: # replace original dataframe's ? symbol with nulls
df = df.replace('?', np.nan)
```

Features' Data Types and Their Respective Null Counts

```
[5]: print('Number of Rows:', df.shape[0])
print('Number of Columns:', df.shape[1], '\n')
data_types = df.dtypes

data_types = pd.DataFrame(data_types)
data_types = data_types.assign(Null_Values =
                                df.isnull().sum())
total_null = data_types['Null_Values'].sum()
data_types.reset_index(inplace = True)
```

```
data_types = data_types.rename(columns={0: 'Data Type',
                                     'index': 'Column/Variable',
                                     'Null_Values': "# of Nulls"})
data_types
```

Number of Rows: 858

Number of Columns: 36

```
[5]:
```

	Column/Variable	Data Type	# of Nulls
0	Age	int64	0
1	Number of sexual partners	object	26
2	First sexual intercourse	object	7
3	Num of pregnancies	object	56
4	Smokes	object	13
5	Smokes (years)	object	13
6	Smokes (packs/year)	object	13
7	Hormonal Contraceptives	object	108
8	Hormonal Contraceptives (years)	object	108
9	IUD	object	117
10	IUD (years)	object	117
11	STDs	object	105
12	STDs (number)	object	105
13	STDs:condylomatosis	object	105
14	STDs:cervical condylomatosis	object	105
15	STDs:vaginal condylomatosis	object	105
16	STDs:vulvo-perineal condylomatosis	object	105
17	STDs:syphilis	object	105
18	STDs:pelvic inflammatory disease	object	105
19	STDs:genital herpes	object	105
20	STDs:molluscum contagiosum	object	105
21	STDs:AIDS	object	105
22	STDs:HIV	object	105
23	STDs:Hepatitis B	object	105
24	STDs:HPV	object	105
25	STDs: Number of diagnosis	int64	0
26	STDs: Time since first diagnosis	object	787
27	STDs: Time since last diagnosis	object	787
28	Dx:Cancer	int64	0
29	Dx:CIN	int64	0
30	Dx:HPV	int64	0
31	Dx	int64	0
32	Hinselmann	int64	0
33	Schiller	int64	0
34	Citology	int64	0
35	Biopsy	int64	0

```
[6]: print ('Total # of Missing Values:', total_null)
```

Total # of Missing Values: 3622

The following columns have #NA values

```
[7]: df.columns[df.isnull().any()].tolist()
```

```
[7]: ['Number of sexual partners',
      'First sexual intercourse',
      'Num of pregnancies',
      'Smokes',
      'Smokes (years)',
      'Smokes (packs/year)',
      'Hormonal Contraceptives',
      'Hormonal Contraceptives (years)',
      'IUD',
      'IUD (years)',
      'STDs',
      'STDs (number)',
      'STDs:condylomatosis',
      'STDs:cervical condylomatosis',
      'STDs:vaginal condylomatosis',
      'STDs:vulvo-perineal condylomatosis',
      'STDs:syphilis',
      'STDs:pelvic inflammatory disease',
      'STDs:genital herpes',
      'STDs:molluscum contagiosum',
      'STDs:AIDS',
      'STDs:HIV',
      'STDs:Hepatitis B',
      'STDs:HPV',
      'STDs: Time since first diagnosis',
      'STDs: Time since last diagnosis']
```

```
[8]: # drop columns with tests other than Biopsy
cervdat = df.drop(columns=['Citology', 'Schiller', 'Hinselmann'])
```

```
[9]: # nunmericize features
cervdat = cervdat.apply(pd.to_numeric)
cervdat.dtypes
```

```
[9]: Age                                int64
      Number of sexual partners         float64
      First sexual intercourse          float64
      Num of pregnancies                float64
      Smokes                           float64
      Smokes (years)                   float64
      Smokes (packs/year)              float64
      Hormonal Contraceptives           float64
      Hormonal Contraceptives (years)   float64
      IUD                              float64
      IUD (years)                      float64
      STDs                             float64
      STDs (number)                    float64
      STDs:condylomatosis               float64
```

```

STDs:cervical condylomatosis      float64
STDs:vaginal condylomatosis      float64
STDs:vulvo-perineal condylomatosis float64
STDs:syphilis                    float64
STDs:pelvic inflammatory disease float64
STDs:genital herpes              float64
STDs:molluscum contagiosum       float64
STDs:AIDS                       float64
STDs:HIV                        float64
STDs:Hepatitis B                float64
STDs:HPV                        float64
STDs: Number of diagnosis        int64
STDs: Time since first diagnosis float64
STDs: Time since last diagnosis  float64
Dx:Cancer                       int64
Dx:CIN                          int64
Dx:HPV                          int64
Dx                              int64
Biopsy                          int64
dtype: object

```

```

[10]: # inspect number of rows, columns
print('Number of Rows:', cervdat.shape[0])
print('Number of Columns:', cervdat.shape[1], '\n')

```

Number of Rows: 858
Number of Columns: 33

Imputing Missing Values by Median

```

[11]: cervdat = cervdat.fillna(cervdat.median())

```

```

[12]: var = pd.DataFrame(cervdat.var())
var.reset_index(inplace = True)
var = var.rename(columns={0:'Variance',
                        'index': 'Column/Variable'})
var

```

```

[12]:
      Column/Variable  Variance
0                Age  72.215121
1  Number of sexual partners  2.705232
2    First sexual intercourse  7.794611
3      Num of pregnancies    1.962749
4                Smokes    0.122949
5      Smokes (years)    16.488655
6  Smokes (packs/year)    4.885653
7  Hormonal Contraceptives    0.215476
8  Hormonal Contraceptives (years)  12.723776
9                IUD    0.087481
10      IUD (years)    3.291387

```

11	STDs	0.083694
12	STDs (number)	0.280494
13	STDs:condylomatosis	0.048709
14	STDs:cervical condylomatosis	0.000000
15	STDs:vaginal condylomatosis	0.004646
16	STDs:vulvo-perineal condylomatosis	0.047660
17	STDs:syphilis	0.020563
18	STDs:pelvic inflammatory disease	0.001166
19	STDs:genital herpes	0.001166
20	STDs:molluscum contagiosum	0.001166
21	STDs:AIDS	0.000000
22	STDs:HIV	0.020563
23	STDs:Hepatitis B	0.001166
24	STDs:HPV	0.002328
25	STDs: Number of diagnosis	0.091533
26	STDs: Time since first diagnosis	3.186782
27	STDs: Time since last diagnosis	3.308495
28	Dx:Cancer	0.020563
29	Dx:CIN	0.010392
30	Dx:HPV	0.020563
31	Dx	0.027221
32	Biopsy	0.060063

[13]: *# drop columns with near zero variance and get shape*

```
cervdat = cervdat.drop(columns=['Smokes (years)', 'Smokes (packs/year)',
                                'IUD (years)', 'STDs:cervical condylomatosis',
                                'STDs:vaginal condylomatosis',
                                'STDs:syphilis', 'STDs:pelvic inflammatory disease',
                                'STDs:genital herpes', 'STDs:molluscum contagiosum',
                                'STDs:AIDS', 'STDs:HIV', 'STDs:Hepatitis B', 'STDs:HPV',
                                'STDs: Time since first diagnosis', 'Dx:Cancer', 'Dx:HPV',
                                'Dx'])

cervdat.shape
```

[13]: (858, 16)

[14]: *# encode target to categorical variable*

```
cervdat['Biopsy_Res'] = np.where(cervdat['Biopsy'] > 0, 'Cancer', 'Healthy')
```

[15]: *# create dictionary for age ranges*

```
cervdat['Age_Range'] = cervdat['Age'].map({13: '13-17', 14: '13-17',
15: '13-17', 16: '13-17', 17: '13-17', 18: '18-21', 19: '18-21', 20: '18-21',
21: '18-21', 22: '22-30', 23: '22-30', 24: '22-30', 25: '22-30', 26: '22-30',
27: '22-30', 28: '22-30', 29: '22-30', 30: '22-30', 31: '31-40', 32: '31-40',
33: '31-40', 34: '31-40', 35: '31-40', 36: '31-40', 37: '31-40', 38: '31-40',
39: '31-40', 40: '31-40', 41: '41-50', 42: '41-50', 43: '41-50', 44: '41-50',
45: '41-50', 46: '41-50', 47: '41-50', 48: '41-50', 49: '41-50', 50: '41-50',
51: '51-60', 52: '51-60', 53: '51-60', 53: '51-60', 54: '51-60', 55: '51-60',
56: '51-60', 57: '51-60', 58: '51-60', 58: '51-60', 59: '51-60', 60: '51-60',
```

```

61: '61-70', 62: '61-70', 63: '61-70', 64: '61-70', 65: '61-70', 66: '61-70',
67: '61-70', 68: '61-70', 69: '61-70', 70: '61-70', 71: '71-80', 72: '71-80',
73: '71-80', 74: '71-80', 75: '71-80', 76: '71-80', 77: '71-80', 78: '71-80',
79: '71-80', 80: '71-80', 81: '81-90', 82: '81-90', 83: '81-90', 84: '81-90',
85: '81-90', 86: '81-90', 87: '81-90', 87: '81-90', 88: '81-90', 89: '81-90',
90: '81-90'})

```

Exploratory Data Analysis (EDA)

Distribution: Histograms

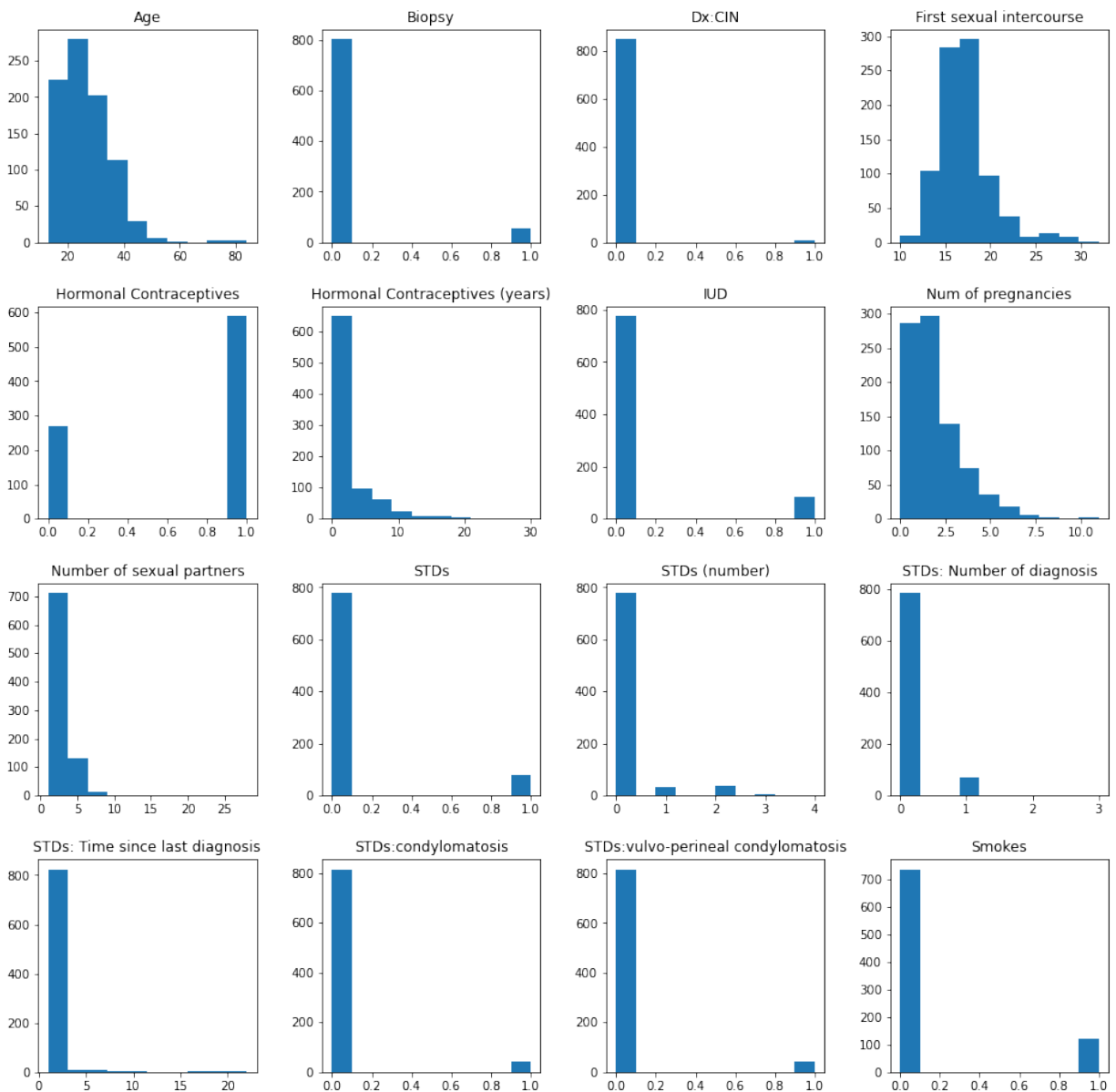
[16]: # checking for degenerate distributions

```

cervdat.hist(grid=False,
             figsize=(16,16))

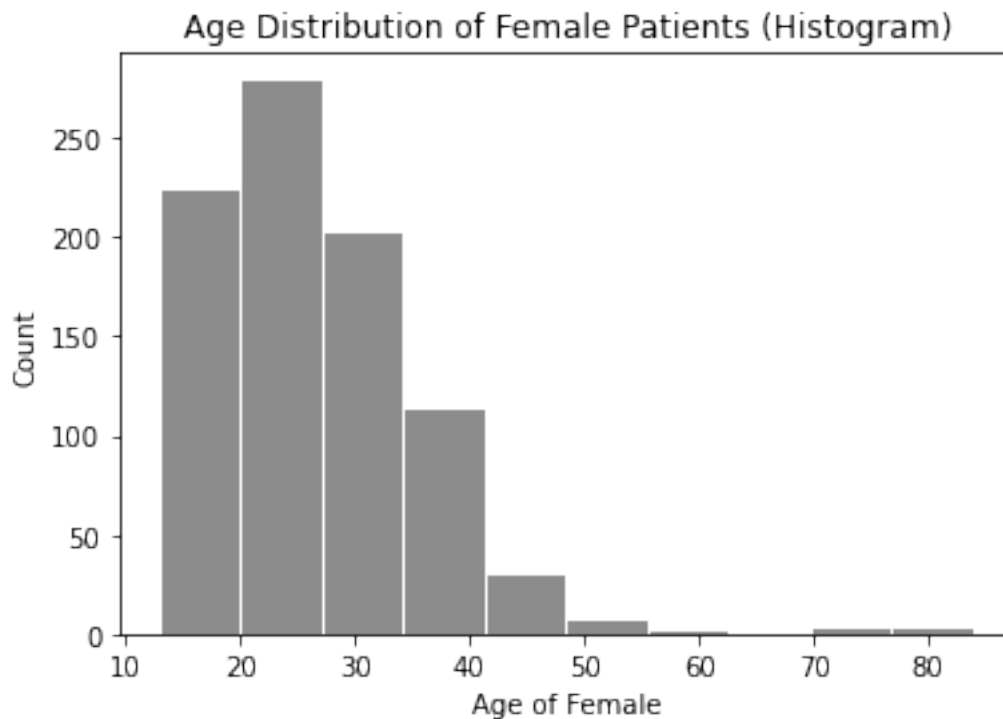
plt.show()

```



Selected Histogram - Age of Female

```
[17]: # age bar graph
plt.hist(cervdat['Age'], bins=10, color='gray', alpha=0.9, rwidth=.97)
plt.title('Age Distribution of Female Patients (Histogram)')
plt.xlabel('Age of Female')
plt.ylabel('Count')
plt.show()
```



Five Number Summary

```
[18]: # five number summary
age_summary = pd.DataFrame(cervdat['Age'].describe()).T
age_summary
```

```
[18]:
```

	count	mean	std	min	25%	50%	75%	max
Age	858.0	26.820513	8.497948	13.0	20.0	25.0	32.0	84.0

```
[19]: print("\033[1m" + 'Age Range Summary' + "\033[1m")
def cerv_stats_by_age():
    pd.options.display.float_format = '{:,.2f}'.format
    new2 = cervdat.groupby('Age_Range')['Age']\
        .agg(["mean", "median", "std", "min", "max"])
    new2.loc['Total'] = new2.sum(numeric_only=True, axis=0)
    column_rename = {'mean': 'Mean', 'median': 'Median',
```



```

        'std': 'Standard Deviation',\
        'min': 'Minimum', 'max': 'Maximum'}
    dfsummary = new2.rename(columns = column_rename)
    return dfsummary
cerv_stats_age = cerv_stats_by_age()
cerv_stats_by_age()

```

Age Range Summary

```

[19]:

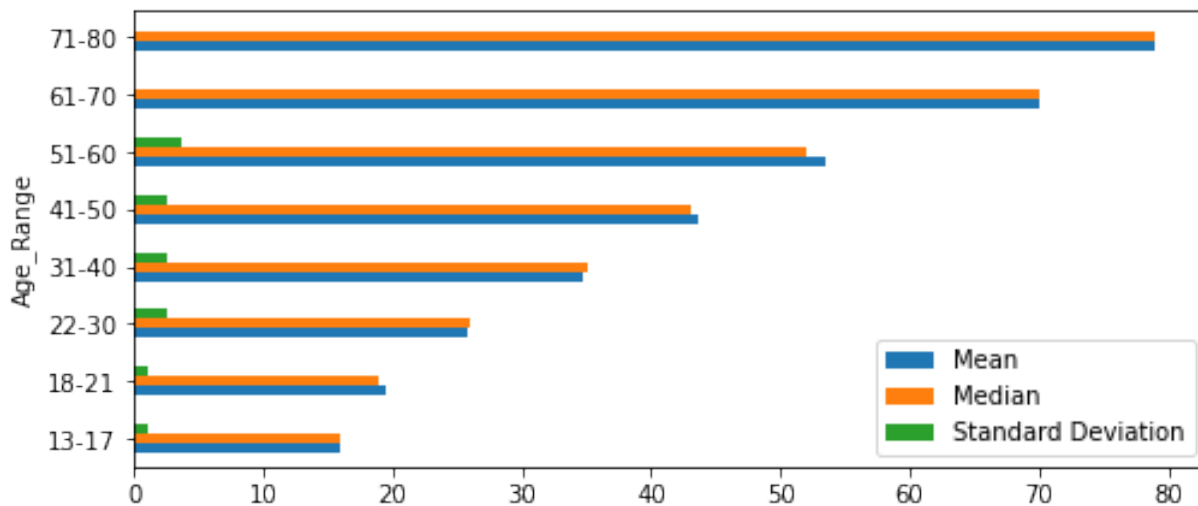
```

	Mean	Median	Standard Deviation	Minimum	Maximum
Age_Range					
13-17	16.01	16.00	1.01	13.00	17.00
18-21	19.47	19.00	1.14	18.00	21.00
22-30	25.84	26.00	2.55	22.00	30.00
31-40	34.69	35.00	2.60	31.00	40.00
41-50	43.62	43.00	2.54	41.00	50.00
51-60	53.50	52.00	3.70	51.00	59.00
61-70	70.00	70.00	0.00	70.00	70.00
71-80	79.00	79.00	nan	79.00	79.00
81-90	84.00	84.00	nan	84.00	84.00
Total	426.14	424.00	13.54	409.00	450.00

```

[20]: cerv_stats_age.iloc[:, 0:3][0:8].plot.barh(figsize=(8,3.5))
plt.show()

```



Boxplot

```

[21]: # selected boxplot distributions
print("\033[1m" + 'Boxplot Distribution' + "\033[1m")

# Boxplot of age as one way of showing distribution
fig = plt.figure(figsize = (10,1.5))
plt.title ('Boxplot: Age Distribution')

```

```

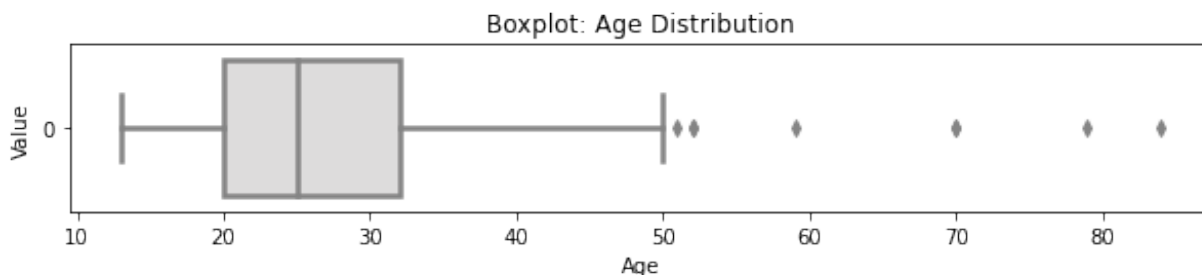
plt.xlabel('Age')
plt.ylabel('Value')
sns.boxplot(data=cervdat['Age'],
            palette="coolwarm", orient='h',
            linewidth=2.5)
plt.show()

IQR = age_summary['75%'][0] - age_summary['25%'][0]

print('The first quartile is %s. '%age_summary['25%'][0])
print('The third quartile is %s. '%age_summary['75%'][0])
print('The IQR is %s. '%round(IQR,2))
print('The mean is %s. '%round(age_summary['mean'][0],2))
print('The standard deviation is %s. '%round(age_summary['std'][0],2))
print('The median is %s. '%round(age_summary['50%'][0],2))

```

Boxplot Distribution



The first quartile is 20.0.
 The third quartile is 32.0.
 The IQR is 12.0.
 The mean is 26.82.
 The standard deviation is 8.5.
 The median is 25.0.

Contingency Table

```

[22]: def age_biopsy():

    Biopsy_Res_healthy = cervdat.loc[cervdat.Biopsy_Res == 'Healthy'].groupby(
        ['Age_Range'])[['Biopsy_Res']].count()
    Biopsy_Res_healthy.rename(columns = {'Biopsy_Res':'Healthy'}, inplace=True)
    Biopsy_Res_cancer= cervdat.loc[cervdat.Biopsy_Res == 'Cancer'].groupby(
        ['Age_Range'])[['Biopsy_Res']].count()
    Biopsy_Res_cancer.rename(columns = {'Biopsy_Res':'Cancer'}, inplace=True)
    Biopsy_Res_comb = pd.concat([Biopsy_Res_healthy, Biopsy_Res_cancer], axis=1)
    # sum row totals
    Biopsy_Res_comb['Total']=Biopsy_Res_comb.sum(axis=1)
    Biopsy_Res_comb.loc['Total']=Biopsy_Res_comb.sum(numeric_only=True, axis=0)
    # get % total of each row

```

```

Biopsy_Res_comb['% Cancer']=round((Biopsy_Res_comb['Cancer'] /
(Biopsy_Res_comb['Cancer']+Biopsy_Res_comb['Healthy']))* 100, 2)
Biopsy_Res_comb['Cancer']=Biopsy_Res_comb['Cancer'].fillna(0)
Biopsy_Res_comb['% Cancer']=Biopsy_Res_comb['% Cancer'].fillna(0)
return Biopsy_Res_comb.style.format("{:,.0f}")
age_biopsy()
age_biopsy = age_biopsy().data; age_biopsy

```

```

[22]:
Healthy  Cancer  Total  % Cancer
13-17    83.00    2.00  85.00    2.35
18-21   171.00   14.00 185.00    7.57
22-30   318.00   20.00 338.00    5.92
31-40   182.00   15.00 197.00    7.61
41-50    43.00    2.00  45.00    4.44
51-60     2.00    2.00   4.00   50.00
61-70     2.00    0.00   2.00    0.00
71-80     1.00    0.00   1.00    0.00
81-90     1.00    0.00   1.00    0.00
Total   803.00   55.00 858.00    6.41

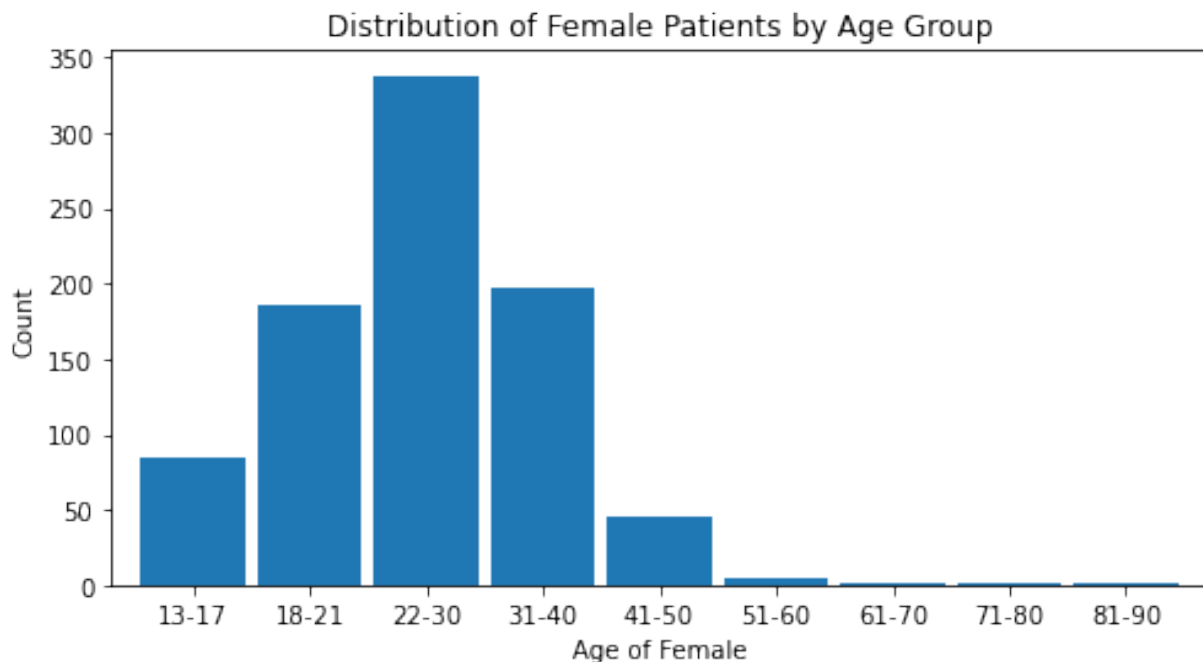
```

Bar Graphs

```

[23]: age_range_plt = age_biopsy['Total'][0:9]
age_range_plt.plot(kind='bar', width=0.90, figsize=(8,4))
plt.title('Distribution of Female Patients by Age Group')
plt.xlabel('Age of Female'); plt.xticks(rotation = 0)
plt.ylabel('Count'); plt.show()

```

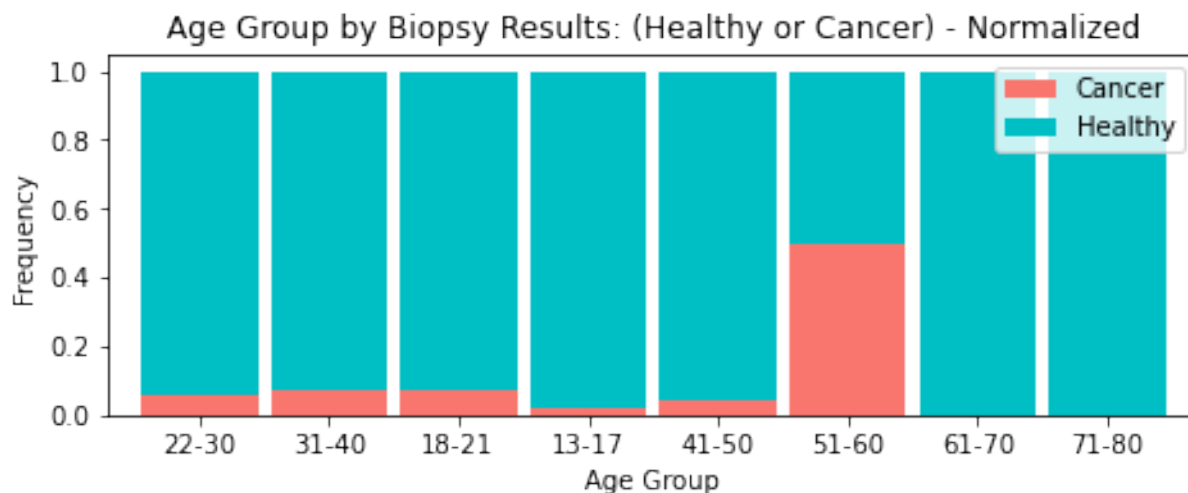
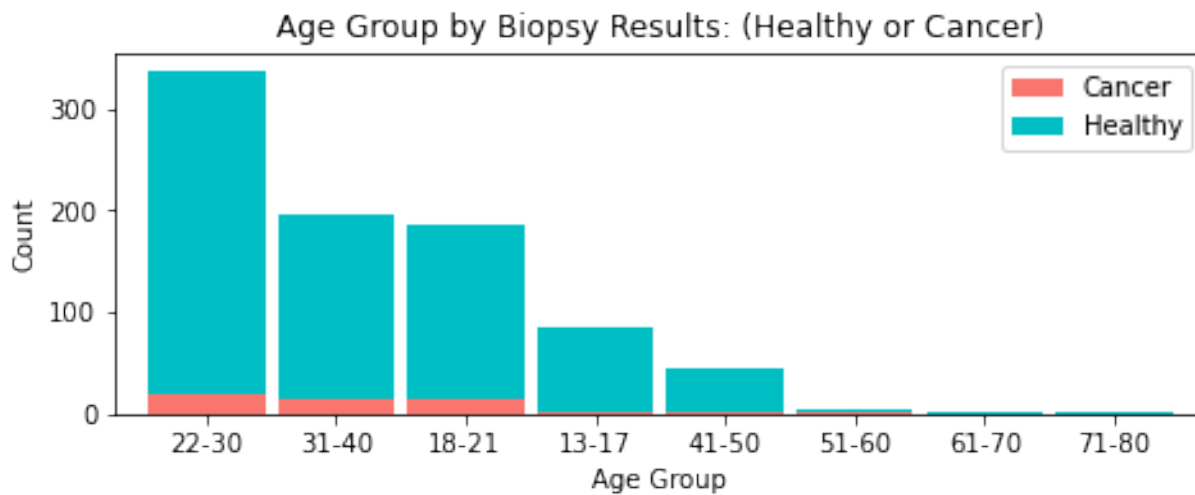


Note. The age range 22-30 has the largest number of observations in this dataset.

```
[24]: fig = plt.figure(figsize=(8,7))
ax1 = fig.add_subplot(211); ax2 = fig.add_subplot(212); fig.tight_layout(pad=6)
age_range_plt2= age_biopsy [['Cancer', 'Healthy']][0:8].sort_values(by=['Cancer'],
                                                                    ascending=False)

age_range_plt2.plot(kind='bar', stacked=True,
                    ax=ax1, color = ['#F8766D', '#00BFC4'], width = 0.90)
ax1.set_title('Age Group by Biopsy Results: (Healthy or Cancer)')
ax1.set_xlabel('Age Group'); ax1.set_ylabel('Count')
for tick in ax1.get_xticklabels():
    tick.set_rotation(0)

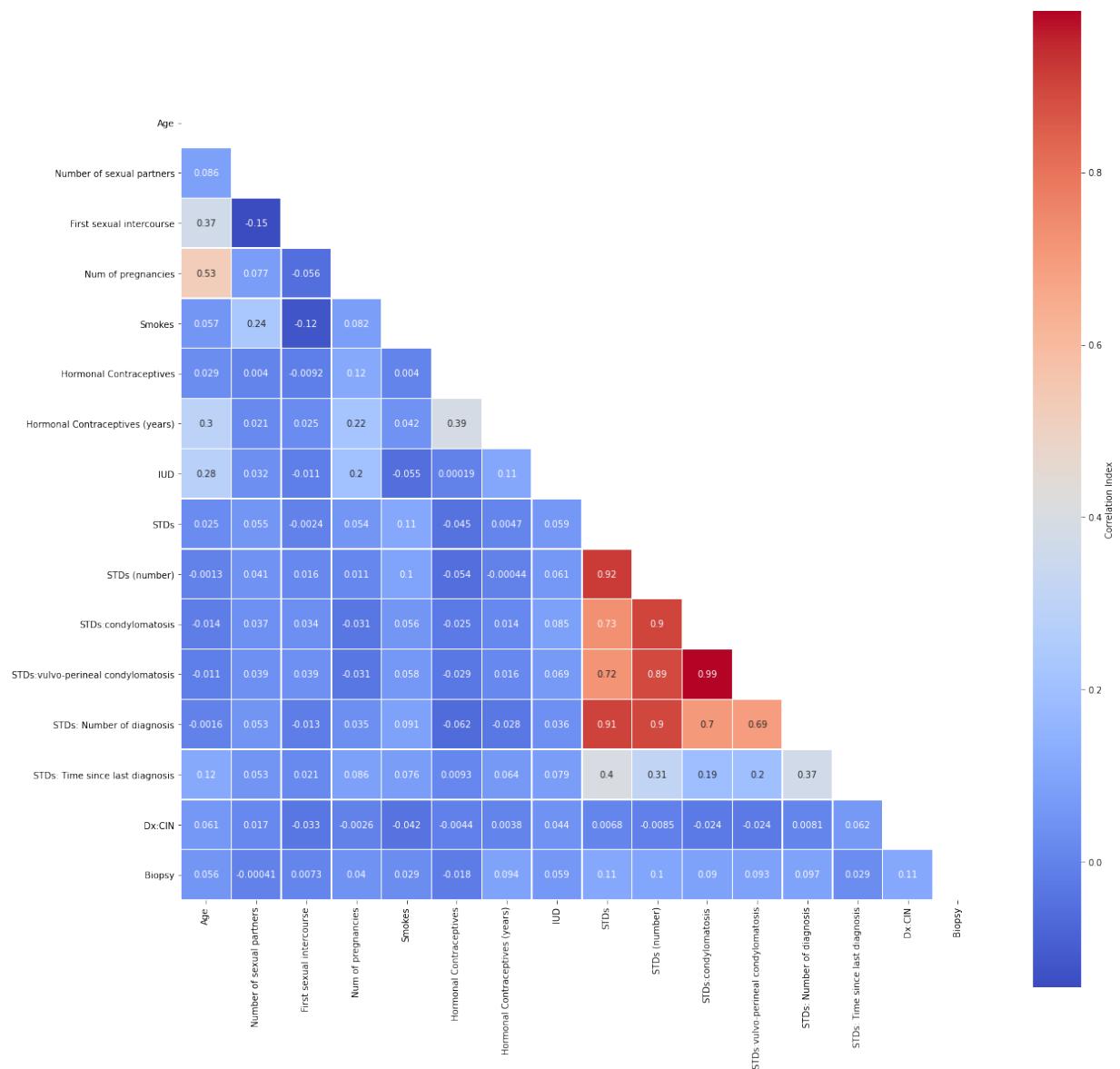
# normalize the plot
age_range_plt_norm = age_range_plt2.div(age_range_plt2.sum(1), axis = 0)
age_range_plt_norm.plot(kind='bar', stacked=True,
                        ax=ax2,color = ['#F8766D', '#00BFC4'], width = 0.90)
ax2.set_title('Age Group by Biopsy Results: (Healthy or Cancer) - Normalized')
ax2.set_xlabel('Age Group'); ax2.set_ylabel('Frequency')
for tick in ax2.get_xticklabels():
    tick.set_rotation(0)
```



Addressing Multicollinearity

```
[25]: # correlation matrix title
print("\033[1m" + 'Cervical Cancer Data: Correlation Matrix' + "\033[1m")
# assign correlation function to new variable
corr = cervdat.corr()
matrix = np.triu(corr) # for triangular matrix
plt.figure(figsize=(20,20))
# parse corr variable into triangular matrix
sns.heatmap(cervdat.corr(method='pearson'),
            annot=True, linewidths=.5, cmap="coolwarm", mask=matrix,
            square = True,
            cbar_kws={'label': 'Correlation Index'})
plt.show()
```

Cervical Cancer Data: Correlation Matrix



Let us narrow our focus by removing highly correlated predictors and passing the rest into a new dataframe.

```
[26]: cor_matrix = cervdat.corr().abs()
upper_tri = cor_matrix.where(np.triu(np.ones(cor_matrix.shape),
                                         k=1).astype(np.bool))
to_drop = [column for column in upper_tri.columns if
            any(upper_tri[column] > 0.75)]
print('These are the columns we should drop: %s'%to_drop)
```

These are the columns we should drop: ['STDs (number)', 'STDs:condylomatosis', 'STDs:vulvo-perineal condylomatosis', 'STDs: Number of diagnosis']

```
[27]: cervdat1 = cervdat.drop(columns = ['STDs (number)', 'STDs:condylomatosis',
                                         'STDs:vulvo-perineal condylomatosis',
                                         'STDs: Number of diagnosis', 'Age_Range',
                                         'Biopsy_Res'])

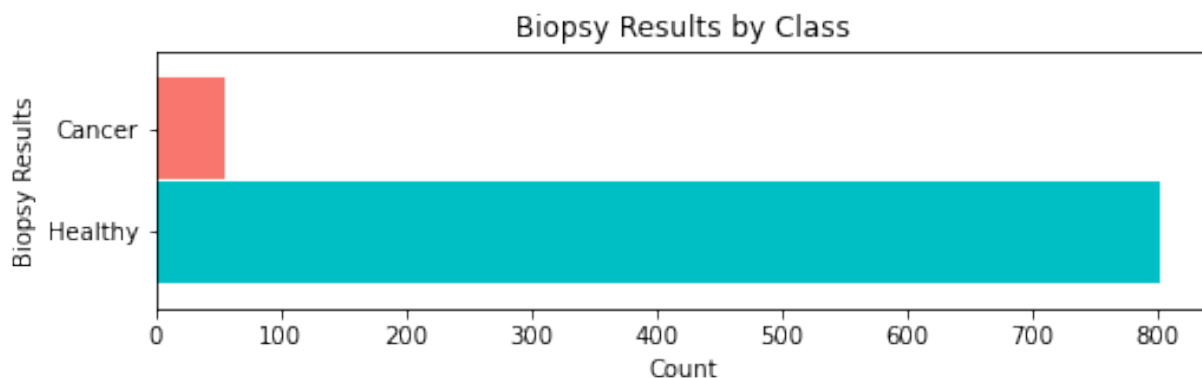
cervdat1.shape[1]
```

[27]: 12

Class Imbalance

```
[28]: # biopsy bar graph
biopsy_count = cervdat['Biopsy_Res'].value_counts()

biopsy_count.plot.barh(x='lab', y='val', rot=0, width=0.99,
                      color = ['#00BFC4', '#F8766D'], figsize=(8,2))
plt.title('Biopsy Results by Class')
plt.xlabel('Count'); plt.ylabel('Biopsy Results')
plt.show()
print(biopsy_count)
```



```
Healthy    803
Cancer      55
Name: Biopsy_Res, dtype: int64
```

```
[29]: pca = PCA(n_components=2, random_state=222)
data_2d = pd.DataFrame(pca.fit_transform(cervdat1.iloc[:,0:11]))
```

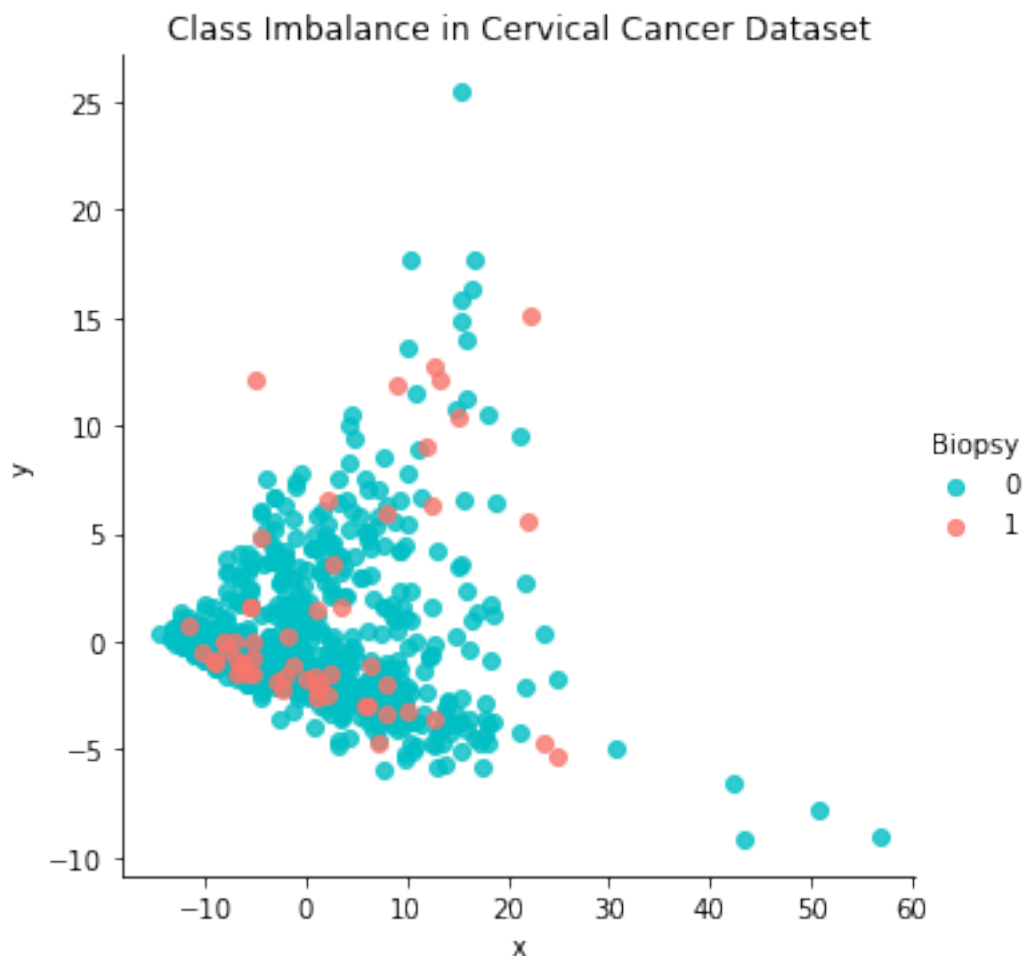
```
[30]: data_2d= pd.concat([data_2d, cervdat1['Biopsy']], axis=1)
data_2d.columns = ['x', 'y', 'Biopsy']; data_2d
```

```
[30]:
```

	x	y	Biopsy
0	-9.26	-0.58	0
1	-12.36	-0.06	0
2	6.59	-2.93	0
3	24.80	-1.71	0
4	21.25	9.54	0
..
853	6.66	-3.15	0
854	6.04	4.70	0
855	-2.26	-1.76	0
856	6.62	-4.09	0
857	2.17	-2.42	0

```
[858 rows x 3 columns]
```

```
[31]: sns.lmplot('x','y',data_2d,fit_reg=False,hue='Biopsy',palette=['#00BFC4','#F8766D'])
plt.title('Class Imbalance in Cervical Cancer Dataset'); plt.show()
```



```
[32]: ada = ADASYN(random_state=222)
      X_resampled, y_resampled = ada.fit_resample(cervdat1.iloc[:,0:11], cervdat1['Biopsy'])

[33]: cervdat2 = pd.concat([pd.DataFrame(X_resampled), pd.DataFrame(y_resampled)], axis=1)
      cervdat2.columns = cervdat1.columns

[34]: cervdat2['Biopsy'].value_counts()

[34]: 0      803
      1      799
      Name: Biopsy, dtype: int64
```

Checking for Statistical Significance Via Baseline Mode

The logistic regression model is introduced as a baseline because establishing impact of coefficients on each independent feature can be carried with relative ease. Moreover, it is possible to gauge statistical significance from the reported p -values of the summary output table below.

Generalized Linear Model - Logistic Regression Baseline

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon$$

Logistic Regression - Parametric Form

$$p(y) = \frac{\exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p)}{1 + \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p)} + \varepsilon$$

Logistic Regression - Descriptive Form

$$\hat{p}(\text{Cancer}) = \frac{\exp(b_0 + b_1(\text{Age}) + b_2(\text{No. Partners}) + \cdots + b_p x_p)}{1 + \exp(b_0 + b_1(\text{Age}) + b_2(\text{No. Partners}) + \cdots + b_p x_p)}$$

```
[35]: X1 = cervdat2.drop(columns=['Biopsy'])
      X1 = sm.add_constant(X1)
      y1 = pd.DataFrame(cervdat2[['Biopsy']])
      log_results = sm.Logit(y1,X1, random_state=222).fit()
      log_results.summary()
```

Optimization terminated successfully.

Current function value: 0.644722

Iterations 5

```
[35]: <class 'statsmodels.iolib.summary.Summary'>
      """
```

Logit Regression Results

```
=====
Dep. Variable:          Biopsy   No. Observations:          1602
Model:                Logit     Df Residuals:              1590
Method:                MLE       Df Model:                 11
```



```

Date: Thu, 03 Mar 2022 Pseudo R-squ.: 0.06986
Time: 22:44:38 Log-Likelihood: -1032.8
converged: True LL-Null: -1110.4
Covariance Type: nonrobust LLR p-value: 1.322e-27

```

```

=====
=====

```

	coef	std err	z	P> z	[0.025
0.975]					

const	-0.0388	0.443	-0.087	0.930	-0.908
0.830					
Age	-0.0239	0.010	-2.471	0.013	-0.043
-0.005					
Number of sexual partners	0.0210	0.039	0.541	0.588	-0.055
0.097					
First sexual intercourse	0.0216	0.026	0.845	0.398	-0.029
0.072					
Num of pregnancies	0.1540	0.054	2.877	0.004	0.049
0.259					
Smokes	-0.0910	0.172	-0.530	0.596	-0.428
0.246					
Hormonal Contraceptives	-0.5927	0.134	-4.421	0.000	-0.855
-0.330					
Hormonal Contraceptives (years)	0.1042	0.016	6.456	0.000	0.073
0.136					
IUD	0.6167	0.196	3.154	0.002	0.234
1.000					
STDs	1.7231	0.200	8.606	0.000	1.331
2.115					
STDs: Time since last diagnosis	-0.0800	0.031	-2.555	0.011	-0.141
-0.019					
Dx:CIN	-0.4723	0.722	-0.654	0.513	-1.887
0.943					
=====					
=====					
"""					

From the summary output table, we observe that Number of sexual partners, First sexual intercourse, Smokes, and Dx:CIN have p -values of 0.588, 0.398, 0.596, and 0.513, respectively, thereby making these variables non-statistically significant where $\alpha = 0.05$. We will thus remove them from the refined dataset.

```
[36]: cervdat2 = cervdat2.drop(columns=['Number of sexual partners', 'First sexual_
↪intercourse', 'Smokes', 'Dx:CIN'])
```

Train_Test_Split

```
[37]: X = cervdat2.drop(columns=['Biopsy'])
y = pd.DataFrame(cervdat2['Biopsy'])
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,
                                                    random_state=42)

# confirming train_test_split proportions
print('training size:', round(len(X_train)/len(X),2))
print('test size:', round(len(X_test)/len(X),2))
```

training size: 0.8
test size: 0.2

```
[38]: # confirm dimensions (size of newly partitioned data)
print('Training:', len(X_train))
print('Test:', len(X_test))
print('Total:', len(X_train) + len(X_test))
```

Training: 1281
Test: 321
Total: 1602

Model Building Strategies

Logistic Regression

```
[39]: from scipy.stats import loguniform
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import RandomizedSearchCV

model = LogisticRegression(random_state=222)
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=222)
space = dict()
# define search space
space['solver'] = ['newton-cg', 'lbfgs', 'liblinear']
space['penalty'] = ['none', 'l1', 'l2', 'elasticnet']
space['C'] = loguniform(1e-5, 100)
# define search
search = RandomizedSearchCV(model, space, n_iter=500, scoring='accuracy',
n_jobs=-1, cv=cv, random_state=222)
# execute search
result = search.fit(X_train, y_train)
# summarize result
print('Best Score: %s' % result.best_score_)
print('Best Hyperparameters: %s' % result.best_params_)
```

Best Score: 0.6434875645994832
Best Hyperparameters: {'C': 0.07972630225526722, 'penalty': 'l1', 'solver': 'liblinear'}

```
[40]: # Manually Tuning The Logistic Regression Model
C = [0.01, 0.1, 0.2, 0.5, 0.8, 1, 5, 10, 20, 50]
LRtrainAcc = []
LRtestAcc = []
for param in C:
    tuned_lr = LogisticRegression(solver = 'liblinear',
```

```

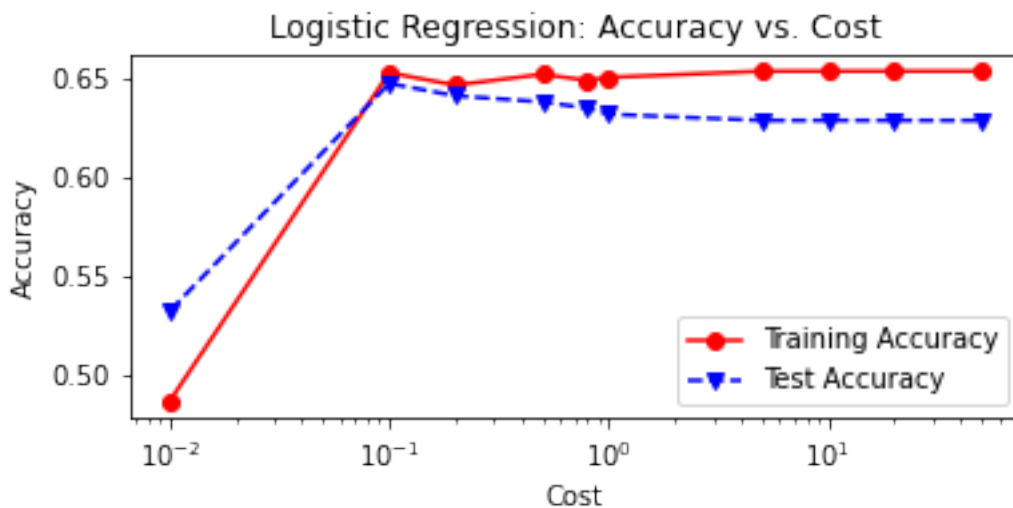
C = param,
max_iter = 500,
penalty = 'l1',
n_jobs = -1,
random_state = 222)

tuned_lr.fit(X_train, y_train)
# Predict on train set
tuned_lr_pred_train = tuned_lr.predict(X_train)
# Predict on test set
tuned_lr1 = tuned_lr.predict(X_test)
LRtrainAcc.append(accuracy_score(y_train, tuned_lr_pred_train))
LRtestAcc.append(accuracy_score(y_test, tuned_lr1))
print('Cost = %2.2f \t Testing Accuracy = %2.2f \t \
Training Accuracy = %2.2f' % (param, accuracy_score(y_test, tuned_lr1),
                             accuracy_score(y_train, tuned_lr_pred_train)))

# plot cost by accuracy
fig, ax = plt.subplots(figsize=(6,2.5))
ax.plot(C, LRtrainAcc, 'ro-', C, LRtestAcc, 'bv--')
ax.legend(['Training Accuracy', 'Test Accuracy'])
plt.title('Logistic Regression: Accuracy vs. Cost')
ax.set_xlabel('Cost'); ax.set_xscale('log')
ax.set_ylabel('Accuracy'); plt.show()

```

Cost = 0.01	Testing Accuracy = 0.53	Training Accuracy = 0.49
Cost = 0.10	Testing Accuracy = 0.65	Training Accuracy = 0.65
Cost = 0.20	Testing Accuracy = 0.64	Training Accuracy = 0.65
Cost = 0.50	Testing Accuracy = 0.64	Training Accuracy = 0.65
Cost = 0.80	Testing Accuracy = 0.64	Training Accuracy = 0.65
Cost = 1.00	Testing Accuracy = 0.63	Training Accuracy = 0.65
Cost = 5.00	Testing Accuracy = 0.63	Training Accuracy = 0.65
Cost = 10.00	Testing Accuracy = 0.63	Training Accuracy = 0.65
Cost = 20.00	Testing Accuracy = 0.63	Training Accuracy = 0.65
Cost = 50.00	Testing Accuracy = 0.63	Training Accuracy = 0.65



```
[41]: # Un-Tuned Logistic Regression Model
logit_reg = LogisticRegression(random_state=222)
logit_reg.fit(X_train, y_train)

# Predict on test set
logit_reg_pred1 = logit_reg.predict(X_test)

# accuracy and classification report (Untuned Model)
print('Untuned Logistic Regression Model')
print('Accuracy Score')
print(accuracy_score(y_test, logit_reg_pred1))
print('Classification Report \n',
      classification_report(y_test, logit_reg_pred1))

# Tuned Logistic Regression Model

tuned_logreg = LogisticRegression(solver = 'liblinear',
                                  C = 0.08,
                                  penalty = 'l1',
                                  max_iter = 500,
                                  n_jobs = -1,
                                  random_state=42)

tuned_logreg.fit(X_train, y_train)
logreg_pred = tuned_logreg.predict(X_test)

# accuracy and classification report (Tuned Model)
print('Tuned Logistic Regression Model')
print('Accuracy Score')
print(accuracy_score(y_test, logreg_pred))
print('Classification Report \n',
      classification_report(y_test, logreg_pred))
```

Untuned Logistic Regression Model

Accuracy Score

0.6292834890965732

Classification Report

	precision	recall	f1-score	support
0	0.64	0.72	0.67	172
1	0.62	0.53	0.57	149
accuracy			0.63	321
macro avg	0.63	0.62	0.62	321
weighted avg	0.63	0.63	0.63	321

Tuned Logistic Regression Model

Accuracy Score

0.6510903426791277

Classification Report					
	precision	recall	f1-score	support	
0	0.65	0.75	0.70	172	
1	0.65	0.54	0.59	149	
accuracy			0.65	321	
macro avg	0.65	0.64	0.64	321	
weighted avg	0.65	0.65	0.65	321	

Random Forest

```
[42]: model_params = {
    # randomly sample numbers from 4 to 204 estimators
    'n_estimators': randint(4,200),
    # normally distributed max_features,
    # with mean .25 stddev 0.1, bounded between 0 and 1
    'max_features': truncnorm(a=0, b=1, loc=0.25, scale=0.1),
    # uniform distribution from 0.01 to 0.2 (0.01 + 0.199)
    'min_samples_split': uniform(0.01, 0.199)
}
# create random forest classifier model
rf_model = RandomForestClassifier()

# set up random search meta-estimator
# this will train 100 models over 5 folds of cross validation
# (500 models total)
clf = RandomizedSearchCV(rf_model, model_params, n_iter=100,
                        cv=5, scoring='accuracy', random_state=222)

# train the random search meta-estimator to find the
# best model out of 100 candidates
result2 = clf.fit(X_train, y_train)

# print winning set of hyperparameters
from pprint import pprint
print('Best Score: %s' % result2.best_score_)
pprint(result2.best_estimator_.get_params())
```

Best Score: 0.9187986381322958

```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': None,
 'max_features': 0.3050233553233379,
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 1,
 'min_samples_split': 0.01760707355810456,
```

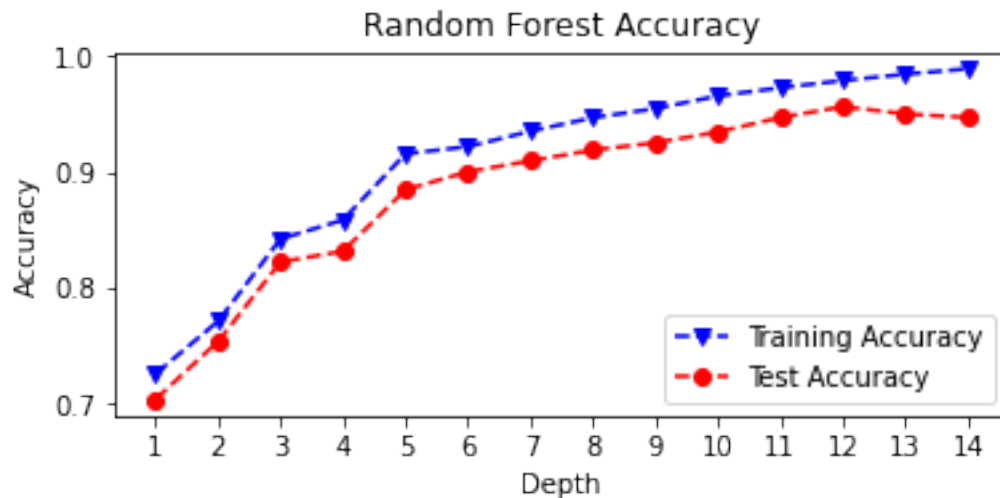
```
'min_weight_fraction_leaf': 0.0,
'n_estimators': 68,
'n_jobs': None,
'oob_score': False,
'random_state': None,
'verbose': 0,
'warm_start': False}
```

```
[43]: # Random Forest Tuning (Manual)
rf_train_accuracy = []
rf_test_accuracy = []
for n in range(1, 15):
    rf = RandomForestClassifier(max_depth = n,
                               random_state=222)
    rf = rf.fit(X_train, y_train)
    rf_pred_train = rf.predict(X_train)
    rf_pred_test = rf.predict(X_test)
    rf_train_accuracy.append(accuracy_score(y_train,
                                             rf_pred_train))
    rf_test_accuracy.append(accuracy_score(y_test,
                                           rf_pred_test))
    print('Max Depth = %2.0f \t Test Accuracy = %2.2f \t \
Training Accuracy = %2.2f' % (n, accuracy_score(y_test,
                                                  rf_pred_test),
                              accuracy_score(y_train,
                                              rf_pred_train)))
max_depth = list(range(1, 15))
fig, plt.subplots(figsize=(6,2.5))
plt.plot(max_depth, rf_train_accuracy, 'bv--',
         label='Training Accuracy')
plt.plot(max_depth, rf_test_accuracy, 'ro--',
         label='Test Accuracy')
plt.title('Random Forest Accuracy')
plt.xlabel('Depth')
plt.ylabel('Accuracy')
plt.xticks(max_depth)
plt.legend()
plt.show()
```

Max Depth = 1	Test Accuracy = 0.70	Training Accuracy = 0.73
Max Depth = 2	Test Accuracy = 0.75	Training Accuracy = 0.77
Max Depth = 3	Test Accuracy = 0.82	Training Accuracy = 0.84
Max Depth = 4	Test Accuracy = 0.83	Training Accuracy = 0.86
Max Depth = 5	Test Accuracy = 0.88	Training Accuracy = 0.92
Max Depth = 6	Test Accuracy = 0.90	Training Accuracy = 0.92
Max Depth = 7	Test Accuracy = 0.91	Training Accuracy = 0.94
Max Depth = 8	Test Accuracy = 0.92	Training Accuracy = 0.95
Max Depth = 9	Test Accuracy = 0.93	Training Accuracy = 0.95
Max Depth = 10	Test Accuracy = 0.93	Training Accuracy = 0.97
Max Depth = 11	Test Accuracy = 0.95	Training Accuracy = 0.97
Max Depth = 12	Test Accuracy = 0.96	Training Accuracy = 0.98
Max Depth = 13	Test Accuracy = 0.95	Training Accuracy = 0.98

Max Depth = 14 Test Accuracy = 0.95

Training Accuracy = 0.99



```
[44]: # Untuned Random Forest
untuned_rf = RandomForestClassifier(random_state=222)
untuned_rf = untuned_rf.fit(X_train, y_train)

# Predict on test set
untuned_rf1 = untuned_rf.predict(X_test)

# accuracy and classification report
print('Untuned Random Forest Model')
print('Accuracy Score')
print(accuracy_score(y_test, untuned_rf1))
print('Classification Report \n',
      classification_report(y_test, untuned_rf1))

# Tuned Random Forest
tuned_rf = RandomForestClassifier(random_state=222,
                                max_depth = 12)
tuned_rf = tuned_rf.fit(X_train, y_train)

# Predict on test set
tuned_rf1 = tuned_rf.predict(X_test)

# accuracy and classification report
print('Tuned Random Forest Model')
print('Accuracy Score')
print(accuracy_score(y_test, tuned_rf1))
print('Classification Report \n',
      classification_report(y_test, tuned_rf1))
```

Untuned Random Forest Model
Accuracy Score
0.9532710280373832

Classification Report				
	precision	recall	f1-score	support
0	0.94	0.97	0.96	172
1	0.97	0.93	0.95	149
accuracy			0.95	321
macro avg	0.95	0.95	0.95	321
weighted avg	0.95	0.95	0.95	321

Tuned Random Forest Model

Accuracy Score

0.956386292834891

Classification Report				
	precision	recall	f1-score	support
0	0.94	0.98	0.96	172
1	0.97	0.93	0.95	149
accuracy			0.96	321
macro avg	0.96	0.95	0.96	321
weighted avg	0.96	0.96	0.96	321

Support Vector Machines

Similar to that of logistic regression, a linear support vector machine model relies on estimating (w^*, b^*) via constrained optimization of the following form:

$$\begin{aligned} \min_{w^*, b^*, \{\xi_i\}} \quad & \frac{\|w\|^2}{2} + \frac{1}{C} \sum_i \xi_i \\ \text{s.t.} \quad & \forall i : y_i \left[w^T \phi(x_i) + b \right] \geq 1 - \xi_i, \quad \xi_i \geq 0 \end{aligned}$$

However, our endeavor relies on the radial basis function kernel:

$$K(x, x') = \exp \left(-\frac{\|x - x'\|^2}{2\sigma^2} \right)$$

where $\|x - x'\|^2$ is the squared Euclidean distance between the two feature vectors, and $\gamma = \frac{1}{2\sigma^2}$.

Simplifying the equation we have:

$$K(x, x') = \exp(-\gamma \|x - x'\|^2)$$

SVM (Radial Basis Function) Model

```
[45]: svm1 = SVC(kernel='rbf', random_state=222)
      svm1.fit(X_train, y_train)
      svm1_pred_test = svm1.predict(X_test)
```



```
print('accuracy = %2.2f ' % accuracy_score(y_test, svm1_pred_test))
```

accuracy = 0.56

Setting (tuning) the gamma hyperparameter to “auto”

```
[46]: svm2 = SVC(kernel='rbf', gamma='auto', random_state=222)
      svm2.fit(X_train, y_train)
      svm2_pred_test = svm2.predict(X_test)
      print('accuracy = %2.2f ' % accuracy_score(svm2_pred_test,y_test))
```

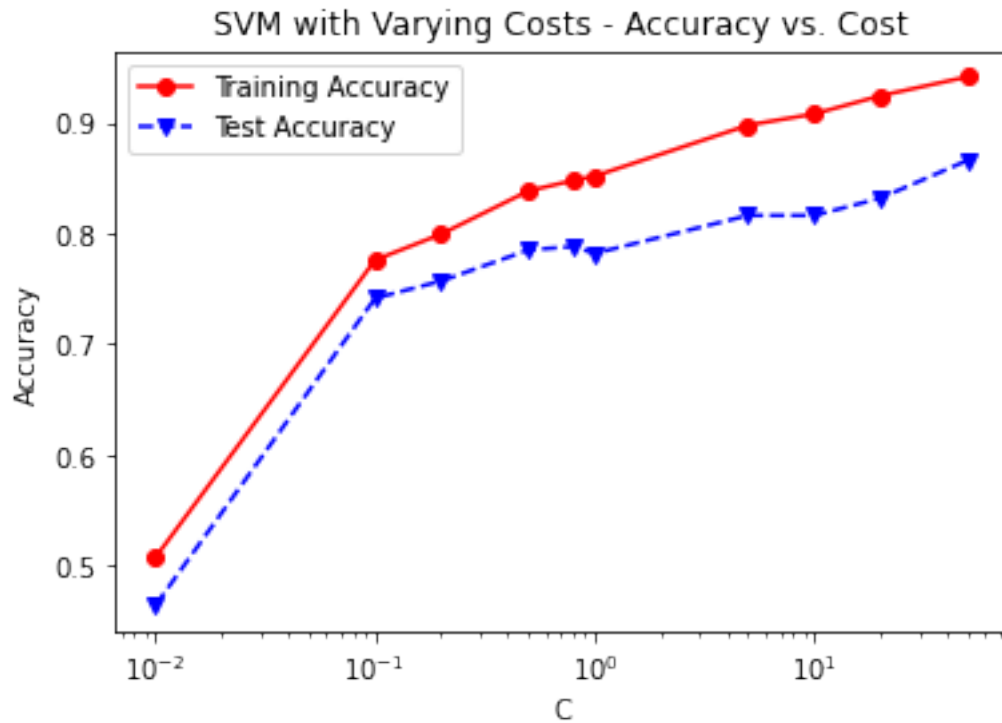
accuracy = 0.78

```
[47]: C = [0.01, 0.1, 0.2, 0.5, 0.8, 1, 5, 10, 20, 50]
      svm3_trainAcc = []
      svm3_testAcc = []

      for param in C:
          svm3 = SVC(C=param,kernel='rbf', gamma = 'auto', random_state=42)
          svm3.fit(X_train, y_train)
          svm3_pred_train = svm3.predict(X_train)
          svm3_pred_test = svm3.predict(X_test)
          svm3_trainAcc.append(accuracy_score(y_train, svm3_pred_train))
          svm3_testAcc.append(accuracy_score(y_test, svm3_pred_test))
          print('Cost = %2.2f \t Testing Accuracy = %2.2f \t \
                Training Accuracy = %2.2f' % (param,accuracy_score(y_test,svm3_pred_test),
                                                accuracy_score(y_train,svm3_pred_train)))

      fig, ax = plt.subplots()
      ax.plot(C, svm3_trainAcc, 'ro-', C, svm3_testAcc,'bv--')
      ax.legend(['Training Accuracy','Test Accuracy'])
      plt.title('SVM with Varying Costs - Accuracy vs. Cost')
      ax.set_xlabel('C')
      ax.set_xscale('log')
      ax.set_ylabel('Accuracy')
      plt.show()
```

Cost = 0.01	Testing Accuracy = 0.46	Training Accuracy = 0.51
Cost = 0.10	Testing Accuracy = 0.74	Training Accuracy = 0.78
Cost = 0.20	Testing Accuracy = 0.76	Training Accuracy = 0.80
Cost = 0.50	Testing Accuracy = 0.79	Training Accuracy = 0.84
Cost = 0.80	Testing Accuracy = 0.79	Training Accuracy = 0.85
Cost = 1.00	Testing Accuracy = 0.78	Training Accuracy = 0.85
Cost = 5.00	Testing Accuracy = 0.82	Training Accuracy = 0.90
Cost = 10.00	Testing Accuracy = 0.82	Training Accuracy = 0.91
Cost = 20.00	Testing Accuracy = 0.83	Training Accuracy = 0.92
Cost = 50.00	Testing Accuracy = 0.87	Training Accuracy = 0.94



```
[48]: # Untuned Support Vector Machine
untuned_svm = SVC(random_state=222)
untuned_svm = untuned_svm.fit(X_train, y_train)

# Predict on test set
untuned_svm1 = untuned_svm.predict(X_test)

# accuracy and classification report
print('Untuned Support Vector Machine Model')
print('Accuracy Score')
print(accuracy_score(y_test, untuned_svm1))
print('Classification Report \n',
      classification_report(y_test, untuned_svm1))

# Tuned Support Vector Machine
tuned_svm = SVC(kernel='rbf',
                gamma='auto',
                random_state=222,
                C = 50, probability = True)
tuned_svm = tuned_svm.fit(X_train, y_train)

# Predict on test set
tuned_svm1 = tuned_svm.predict(X_test)

# accuracy and classification report
print('Tuned Support Vector Machine Model')
print('Accuracy Score')
```

```
print(accuracy_score(y_test, tuned_svm1))
print('Classification Report \n',
      classification_report(y_test, tuned_svm1))
```

Untuned Support Vector Machine Model

Accuracy Score

0.557632398753894

Classification Report

	precision	recall	f1-score	support
0	0.56	0.87	0.68	172
1	0.57	0.20	0.30	149
accuracy			0.56	321
macro avg	0.56	0.53	0.49	321
weighted avg	0.56	0.56	0.50	321

Tuned Support Vector Machine Model

Accuracy Score

0.8660436137071651

Classification Report

	precision	recall	f1-score	support
0	0.91	0.84	0.87	172
1	0.83	0.90	0.86	149
accuracy			0.87	321
macro avg	0.87	0.87	0.87	321
weighted avg	0.87	0.87	0.87	321

Model Evaluation

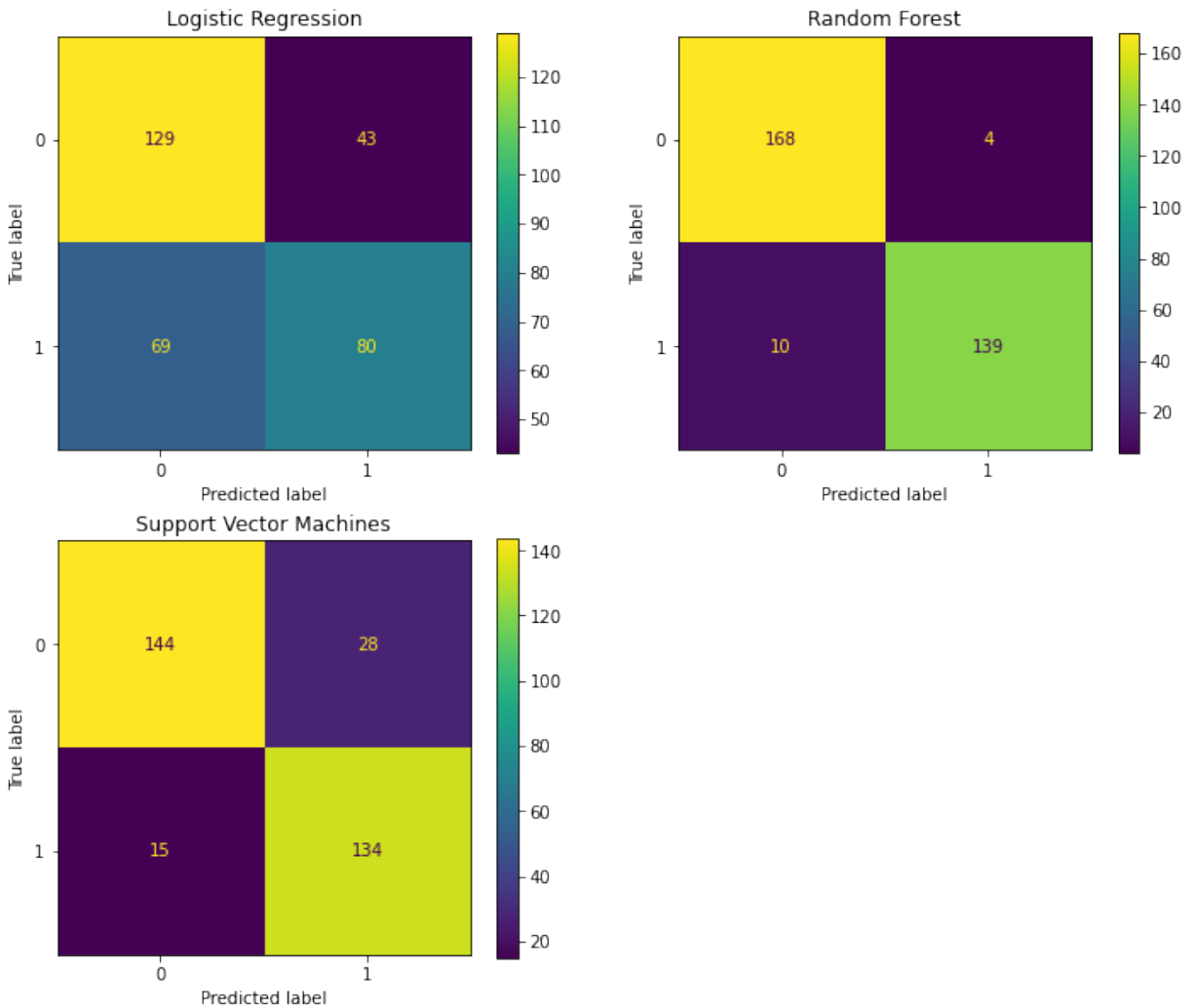
Confusion Matrices

```
[49]: fig = plt.figure(figsize=(12,10))
ax1 = fig.add_subplot(221)
ax2 = fig.add_subplot(222)
ax3 = fig.add_subplot(223)

# logistic regression confusion matrix
plot_confusion_matrix(tuned_logreg, X_test, y_test, ax=ax1)
ax1.set_title('Logistic Regression')

# Decision tree confusion matrix
plot_confusion_matrix(tuned_rf, X_test, y_test, ax=ax2)
ax2.set_title('Random Forest')

# random forest confusion matrix
plot_confusion_matrix(tuned_svm, X_test, y_test, ax=ax3)
ax3.set_title('Support Vector Machines')
plt.show()
```



ROC Curves

```
[50]: lr_pred = tuned_logreg.predict_proba(X_test)[: , 1]
      rf_pred = tuned_rf.predict_proba(X_test)[: , 1]
      svm_pred = tuned_svm.predict_proba(X_test)[: , 1]
```

```
[51]: # plot all of the roc curves on one graph
      tuned_lr_roc = metrics.roc_curve(y_test,lr_pred)
      fpr,tpr,thresholds = metrics.roc_curve(y_test,lr_pred)
      tuned_lr_auc = metrics.auc(fpr, tpr)
      tuned_lr_plot = metrics.RocCurveDisplay(fpr=fpr,tpr=tpr,
      roc_auc = tuned_lr_auc,
      estimator_name = 'Logistic Regression')

      tuned_rf1_roc = metrics.roc_curve(y_test,rf_pred)
      fpr,tpr,thresholds = metrics.roc_curve(y_test,rf_pred)
      tuned_rf1_auc = metrics.auc(fpr, tpr)
      tuned_rf1_plot = metrics.RocCurveDisplay(fpr=fpr,tpr=tpr,
      roc_auc=tuned_rf1_auc,
```

```

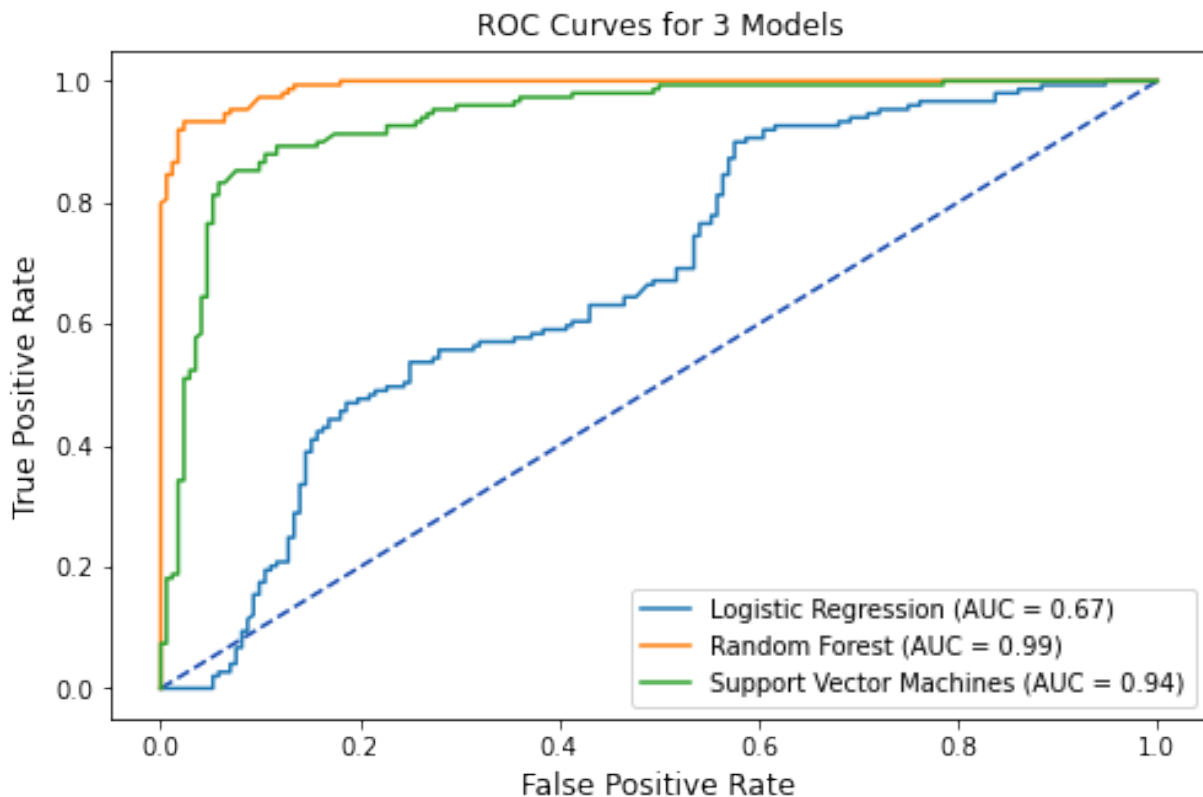
estimator_name = 'Random Forest')

tuned_svm1_roc = metrics.roc_curve(y_test, svm_pred)
fpr,tpr,thresholds = metrics.roc_curve(y_test,svm_pred)
tuned_svm1_auc = metrics.auc(fpr, tpr)
tuned_svm1_plot = metrics.RocCurveDisplay(fpr=fpr,tpr=tpr,
roc_auc=tuned_svm1_auc,
estimator_name = 'Support Vector Machines')

# plot set up
fig, ax = plt.subplots(figsize=(8,5))
plt.title('ROC Curves for 3 Models',fontsize=12)
plt.plot([0, 1], [0, 1], linestyle = '--',
         color = '#174ab0')
plt.xlabel('',fontsize=12)
plt.ylabel('',fontsize=12)

# Model ROC Plots Defined above
tuned_lr_plot.plot(ax)
tuned_rf1_plot.plot(ax)
tuned_svm1_plot.plot(ax)
plt.show()

```



Performance Metrics

```
[52]: # Logistic Regression Performance Metrics
report1 = classification_report(y_test, logreg_pred, output_dict=True)
accuracy1 = round(report1['accuracy'],4)
precision1 = round(report1['1']['precision'],4)
recall1 = round(report1['1']['recall'],4)
f1_score1 = round(report1['1']['f1-score'],4)

# Decision Tree Performance Metrics
report2 = classification_report(y_test,tuned_rf1, output_dict=True)
accuracy2 = round(report2['accuracy'],4)
precision2 = round(report2['1']['precision'],4)
recall2 = round(report2['1']['recall'],4)
f1_score2 = round(report2['1']['f1-score'],4)

# Random Forest Performance Metrics
report3 = classification_report(y_test,tuned_svm1,output_dict=True)
accuracy3 = round(report3['accuracy'],4)
precision3 = round(report3['1']['precision'],4)
recall3 = round(report3['1']['recall'],4)
f1_score3 = round(report3['1']['f1-score'],4)
```

```
[53]: table1 = PrettyTable()
table1.field_names = ['Model', 'Test Accuracy',
'Precision', 'Recall',
'F1-score']
table1.add_row(['Logistic Regression', accuracy1,
precision1, recall1, f1_score1])
table1.add_row(['Random Forest', accuracy2,
precision2, recall2, f1_score2])
table1.add_row(['Support Vector Machines', accuracy3,
precision3, recall3, f1_score3])
print(table1)
```

Model	Test Accuracy	Precision	Recall	F1-score
Logistic Regression	0.6511	0.6504	0.5369	0.5882
Random Forest	0.9564	0.972	0.9329	0.9521
Support Vector Machines	0.866	0.8272	0.8993	0.8617

```
[54]: # Mean-Squared Errors
mse1 = round(mean_squared_error(y_test, logreg_pred),4)
mse2 = round(mean_squared_error(y_test, tuned_rf1),4)
mse3 = round(mean_squared_error(y_test, tuned_svm1),4)

table2 = PrettyTable()
table2.field_names = ['Model', 'AUC', 'MSE']
table2.add_row(['Logistic Regression',
round(tuned_lr_auc,4), mse1])
```

```
table2.add_row(['Random Forest',
               round(tuned_rf1_auc,4), mse2])
table2.add_row(['Support Vector Machines',
               round(tuned_svm1_auc,4), mse3])
print(table2)
```

Model	AUC	MSE
Logistic Regression	0.6744	0.3489
Random Forest	0.9913	0.0436
Support Vector Machines	0.9378	0.134

References

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