Dane: - Aniket Kumay 100 100/100 11/100 11/100 11/100 SR. No: - 30 ROII No: - PP 45 MAR PORT AND INTO MARCHAN TO COMPANY PRN NO: - 1032171203 it ideas the isolo of localis ones 2001394 4004 July soll Problem Statement: - To study l'implement SYM Algorithm: SVM: Through mary inch our sund was friend at not nated attendants on planes. SVM:

9+ is highly pre-terored by many as it produces dignificant accuracy with less computational power It can be used for both regression and classification - The line that maximizes the minimum margin is a good best.

The maximum margin separator is determined by a dubset of datapoints. April 10 10000 110 15000 10000 DUR S Sampropining 211 ing prices of son was sill ad could be smill the super the state of the services of . Formor pio

- Data points in this subset one called support Vectors
 - It will be useful computionally it only a small fraction of the datapoints are support vectors!
 - The support vectors are used to alicide which side of the departer a test case is on.

Hypen plane:

Hyper plane are decision boundaries that help classify the data points. Data points failing on either dide of the hyperplane can be attributed to different classes. Also, the dimension of the hyper plane different classes whon the number of features.

Main Ideas behind the kernel function.

- 1. Starts with data in low dimension
- 2. Moves the data into a higher dimension if it is not linearly departed the hyperplane
 - · Dupport Vector Machines work very well in practice.
 The user must choose the kernel function and
 its parameters.

the test penformance is very good.

. They can be expensive in time and space for big dataset.

in a much higher-dimensional space, thus giving a non-linear version of PCA in the original space.

conclusion

SVM classifier was studied and the implementation was performed for the keanel functions.

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Subject: AML Lab Assignment 4

Problem Statement: Implement SVM

Import the required libraries

```
In [1]: import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    from matplotlib.colors import ListedColormap
    import seaborn as sns
    from sklearn.impute import SimpleImputer
    from sklearn.preprocessing import StandardScaler
    from sklearn.ensemble import RandomForestClassifier
    from sklearn.model_selection import train_test_split
    from sklearn.svm import SVC
    from sklearn.metrics import confusion_matrix
```

```
warnings.filterwarnings("ignore")
SEED = 42
```

Import the data

Display the info about dataset

```
In [3]: df.shape
```

Out[3]: (768, 9)

In [4]: df.head()

Out[4]:

pregnant	glucose	bp	skin	insulin	bmi	pedigree	age	label
6	148	72	35	0	33.6	0.627	50	1
1 1	85	66	29	0	26.6	0.351	31	0
2 8	183	64	0	0	23.3	0.672	32	1
3 1	89	66	23	94	28.1	0.167	21	0
1 0	137	40	35	168	43.1	2.288	33	1
	0 6 1 1 2 8 3 1	0 6 148 1 1 85 2 8 183 3 1 89	0 6 148 72 1 1 85 66 2 8 183 64 3 1 89 66	0 6 148 72 35 1 1 85 66 29 2 8 183 64 0 3 1 89 66 23	0 6 148 72 35 0 1 1 85 66 29 0 2 8 183 64 0 0 3 1 89 66 23 94	0 6 148 72 35 0 33.6 1 1 85 66 29 0 26.6 2 8 183 64 0 0 23.3 3 1 89 66 23 94 28.1	0 6 148 72 35 0 33.6 0.627 1 1 85 66 29 0 26.6 0.351 2 8 183 64 0 0 23.3 0.672 3 1 89 66 23 94 28.1 0.167	1 1 85 66 29 0 26.6 0.351 31 2 8 183 64 0 0 23.3 0.672 32 3 1 89 66 23 94 28.1 0.167 21

```
In [5]: df.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
pregnant 768 non-null int64
glucose 768 non-null int64

bp 768 non-null int64 skin 768 non-null int64 insulin 768 non-null int64 bmi 768 non-null float64 pedigree 768 non-null float64 age 768 non-null int64 768 non-null int64 label dtypes: float64(2), int64(7) memory usage: 54.1 KB

In [6]: df.describe()

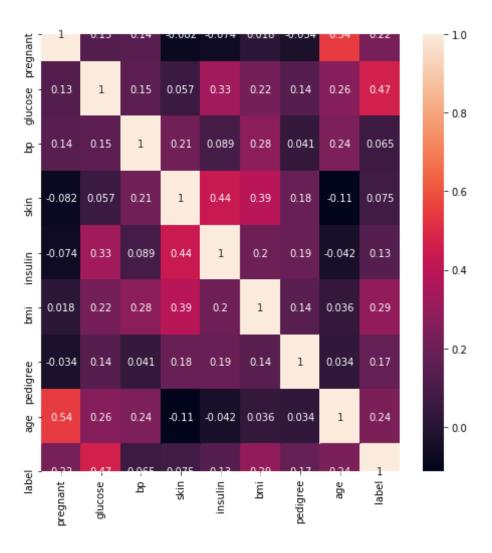
Out[6]:

		pregnant	glucose	bp	skin	insulin	bmi	pedigree	
	count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.0
ı	mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.2
	std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.7
	min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.0
	25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.0
	50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.0
	75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.0
	max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.0
4									•

Correlation Matrix

```
In [7]: fig = plt.figure(figsize = (8, 8))
    correlationmatrix = df.corr()
    sns.heatmap(correlationmatrix, annot = True)
```

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x15b39bf59c8>



Data Preprocessing

```
qlucose
                                                                                       5
                                                                                    35
                                   bp
                                                                                227
                                   skin
                                   insulin
                                                                                374
                                   bmi
                                                                                    11
                                   pedigree
                                                                                       0
                                   age
                                   label
                                   dtype: int64
   In [9]: imputer = SimpleImputer(missing values = np.nan, strategy = 'mean')
                                   df[['qlucose', 'bp']] = imputer.fit transform(df[['qlucose', 'bp']])
                                   imputer = SimpleImputer(missing_values = np.nan, strategy = 'median')
                                   df[['skin', 'insulin', 'bmi']] = imputer.fit transform(df[['skin', 'insulin', 'insu
                                   ulin', 'bmi']])
In [10]: df.isnull().sum()
Out[10]: pregnant
                                                                                 0
                                   glucose
                                                                                 0
                                   bp
                                   skin
                                   insulin
                                   bmi
                                   pedigree
                                                                                0
                                   age
                                   label
                                   dtype: int64
                                   Dependant and Independant variables
In [11]: # Independant variables
                                   feature columns = ['pregnant', 'glucose', 'bp', 'skin', 'insulin', 'bm
                                   i', 'pedigree', 'age']
                                   X = df[feature columns]
                                   print("FEATURES: ", X.shape)
```

```
# Dependant variables
y = df.label
print("LABEL: ", y.shape)

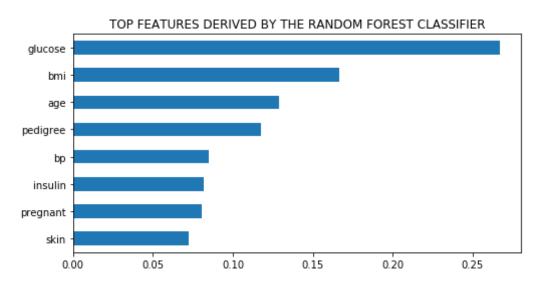
FEATURES: (768, 8)
LABEL: (768,)
```

Feature Selection

```
In [12]: rfc = RandomForestClassifier(random_state = SEED, n_estimators = 100)
    model = rfc.fit(X, y)

(pd.Series(model.feature_importances_, index = X.columns)
    .nlargest(10)
    .plot(kind = 'barh', figsize = [8, 4])
    .invert_yaxis())
plt.title('TOP FEATURES DERIVED BY THE RANDOM FOREST CLASSIFIER')
```

Out[12]: Text(0.5, 1.0, 'TOP FEATURES DERIVED BY THE RANDOM FOREST CLASSIFIER')



```
In [13]: feature_columns = ['glucose', 'bmi']
```

```
X = X[feature_columns]
          X.head()
Out[13]:
             glucose bmi
          0
               148.0 33.6
                85.0 26.6
               183.0 23.3
           3
                89.0 28.1
               137.0 43.1
          Feature Scaling
In [14]: scaler = StandardScaler()
          standardized_X = pd.DataFrame(scaler.fit_transform(X), columns = featur
          e columns)
          X = standardized_X
          X.head()
Out[14]:
              glucose
                          bmi
          0 0.865108 0.166619
          1 -1.206162 -0.852200
          2 2.015813 -1.332500
           3 -1.074652 -0.633881
           4 0.503458 1.549303
In [15]: X.describe()
Out[15]:
                     glucose
                                    bmi
```

bmi	glucose	
7.680000e+02	7.680000e+02	count
2.815312e-16	-3.301757e-16	mean
1.000652e+00	1.000652e+00	std
-2.074783e+00	-2.554131e+00	min
-7.212087e-01	-7.212214e-01	25%
-2.258989e-02	-1.540881e-01	50%
6.032562e-01	6.103090e-01	75%
5.042397e+00	2.541850e+00	max

Split the data into Train and Test sets

```
In [16]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
    0.2, random_state = SEED, stratify = y)
    print('The shape of the of the resultant data sets are as follows...')
    print('X_train: ', X_train.shape)
    print('y_train: ', y_train.shape)
    print('X_test : ', X_test.shape)

The shape of the of the resultant data sets are as follows...
    X_train: (614, 2)
    y_train: (614,)
    X test : (154, 2)
```

Linear SVM

y test : (154,)

```
In [17]: svc_linear = SVC(kernel = 'linear', random_state = SEED)
model = svc_linear.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

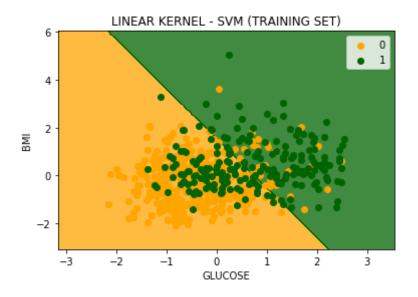
```
cm = confusion_matrix(y_test, y_pred)
print('CONFUSION MATRIX: \n', cm)

CONFUSION MATRIX:
[[85 15]
[29 25]]
```

Vizualising Training dataset

```
In [18]: X set = X train.to numpy()
         y set = y train.to numpy()
         X1, X2 = np.meshgrid(np.arange(start = X set[:, 0].min() - 1, stop = X
         set[:, 0].max() + 1, step = 0.01),
                              np.arange(start = X set[:, 1].min() - 1, stop = X
         set[:, 1].max() + 1, step = 0.01))
         plt.contourf(X1, X2, model.predict(np.array([X1.ravel(), X2.ravel()]).T
         ).reshape(X1.shape),
                      alpha = 0.75, cmap = ListedColormap(('orange', 'darkgreen'
         )))
         plt.xlim(X1.min(), X1.max())
         plt.ylim(X2.min(), X2.max())
         for i, j in enumerate(np.unique(v set)):
             plt.scatter(X set[y set == j, 0], X set[y set == j, 1],
                         c = ListedColormap(('orange', 'darkgreen'))(i), label =
         plt.title('LINEAR KERNEL - SVM (TRAINING SET)')
         plt.xlabel('GLUCOSE')
         plt.vlabel('BMI')
         plt.legend()
         plt.show()
```

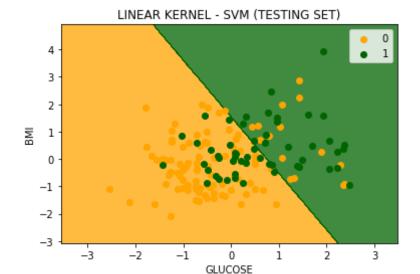
'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its lengt h matches with 'x' & 'y'. Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points. 'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its lengt h matches with 'x' & 'y'. Please use a 2-D array with a single row if



Vizualising Test dataset

```
j)
plt.title('LINEAR KERNEL - SVM (TESTING SET)')
plt.xlabel('GLUCOSE')
plt.ylabel('BMI')
plt.legend()
plt.show()
```

'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its lengt h matches with 'x' & 'y'. Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points. 'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its lengt h matches with 'x' & 'y'. Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.



RBF SVM

```
In [20]: svc_rbf = SVC(kernel = 'rbf', random_state = SEED)
model = svc_rbf.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

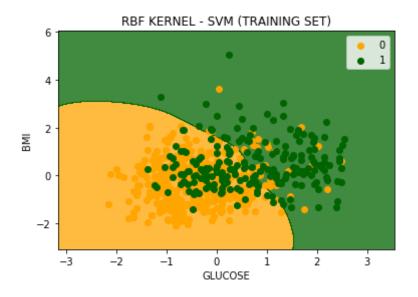
```
cm = confusion_matrix(y_test, y_pred)
print('CONFUSION MATRIX: \n', cm)

CONFUSION MATRIX:
[[84 16]
[31 23]]
```

Vizualising Training dataset

```
In [21]: X set = X train.to numpy()
         y set = y train.to numpy()
         X1, X2 = np.meshgrid(np.arange(start = X set[:, 0].min() - 1, stop = X
         set[:, 0].max() + 1, step = 0.01),
                              np.arange(start = X set[:, 1].min() - 1, stop = X
         set[:, 1].max() + 1, step = 0.01))
         plt.contourf(X1, X2, model.predict(np.array([X1.ravel(), X2.ravel()]).T
         ).reshape(X1.shape),
                      alpha = 0.75, cmap = ListedColormap(('orange', 'darkgreen'
         )))
         plt.xlim(X1.min(), X1.max())
         plt.ylim(X2.min(), X2.max())
         for i, j in enumerate(np.unique(v set)):
             plt.scatter(X set[y set == j, 0], X set[y set == j, 1],
                         c = ListedColormap(('orange', 'darkgreen'))(i), label =
         plt.title('RBF KERNEL - SVM (TRAINING SET)')
         plt.xlabel('GLUCOSE')
         plt.vlabel('BMI')
         plt.legend()
         plt.show()
```

'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its lengt h matches with 'x' & 'y'. Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points. 'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its lengt h matches with 'x' & 'y'. Please use a 2-D array with a single row if



Vizualising Test dataset

```
j)
plt.title('RBF KERNEL - SVM (TESTING SET)')
plt.xlabel('GLUCOSE')
plt.ylabel('BMI')
plt.legend()
plt.show()
```

'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its lengt h matches with 'x' & 'y'. Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points. 'c' argument looks like a single numeric RGB or RGBA sequence, which should be avoided as value-mapping will have precedence in case its lengt h matches with 'x' & 'y'. Please use a 2-D array with a single row if you really want to specify the same RGB or RGBA value for all points.



