CS156 (Introduction to AI), Spring 2022

Final term project

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Any special notes or anything you would like to communicate to me about this project submission goes in here.

Project description/introduction text (the background information)

Parkinson's disease is a progressive nervous system disorder that affects movement, commonly causing stiffness or slowness of movement. It affects nearly 6 million people, resulting in a range of both motor and non-motor symptoms. Symptoms of this disease may be reflected in many activities in everyday life - potentially, in particularly intricate movements like typing. The goal of this project is to predict whether a particular person may have Parkinson's by analyzing their keystroke data (positional changes and press/release delays).

Machine learning algorithm selected for this project

Poly SVC was selected for this project. It is ideal for taking advantage of the large feature space of the dataset, utilizing kernels to find a hyperplane that best separates instances of the classes.

Dataset source

https://www.physionet.org/content/tappy/1.0.0/

References and sources

[1] Adams, Warwick R. "High-Accuracy Detection of Early Parkinson's Disease Using Multiple Characteristics of Finger Movement While Typing." PLOS ONE, Public Library of Science, 30 Nov. 2017, https://journals.plos.org/plosone/article?id=10.1371%2Fjournal.pone.0188226.

[2] Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation [Online]. 101 (23), pp. e215–e220.

Solution

Load libraries and set random number generator seed

```
import numpy as np
from google.colab import drive
import pandas as pd
import os
import csv

import statistics
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.svm import LinearSVC
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import accuracy_score, precision_score,
recall_score
from sklearn.model_selection import StratifiedKFold
from sklearn import linear_model

from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.manifold import TSNE
from matplotlib.colors import ListedColormap
from mpl_toolkits.mplot3d import Axes3D
import warnings
warnings.filterwarnings("ignore")

np.random.seed(42)
```

Code the solution

Pre-processing

```
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
users = []
df = pd.DataFrame()

# read data from text files
root = '/content/drive/MyDrive/SJSU/CS156/Keystroke Data'
for fn in os.listdir(root + '/Archived users'):
    user_file = open(root + '/Archived users/' + fn, "r")
    data = user_file.read()
```

```
    content = data.split("\n")
    #print(content)
    users.append(str(fn)[5:-4])

# combine data into singular dataframe
for fn in os.listdir(root + '/Tappy Data'):
    if fn[:-9] in users:
        new = pd.read_csv(root + '/Tappy Data/' + fn, delimiter="\t",
names = ['UserKey', 'Date', 'Timestamp', 'Hand', 'Hold time',
'Direction', 'Latency time', 'Flight time'], index_col=False)
        try:
            new['Hold time'] = pd.to_numeric(new['Hold time'],
errors='coerce')
            new['Latency time'] = pd.to_numeric(new['Latency time'],
errors='coerce')
            new['Flight time'] = pd.to_numeric(new['Flight time'],
errors='coerce')
            new = new.dropna()

            indexNames = new[(abs(new['Hold time']) >= 1000)].index
            new = new.drop(indexNames)
            indexNames = new[(abs(new['Latency time']) >= 1000)].index
            new = new.drop(indexNames)
            indexNames = new[(abs(new['Flight time']) >= 1000)].index
            new = new.drop(indexNames)
            df = df.append(new)
        except:
            pass

display(df)
```

```
         UserKey    Date     Timestamp Hand  Hold time Direction  \
0     0EA27ICBLF  160722  18:41:04.336    L      101.6        LL
1     0EA27ICBLF  160722  18:42:14.070    L       85.9        LL
2     0EA27ICBLF  160722  18:42:14.273    L       78.1        LL
3     0EA27ICBLF  160722  18:42:14.617    L       62.5        LL
4     0EA27ICBLF  160722  18:42:15.586    S      125.0        LS
...          ...     ...           ...  ...        ...       ...
8649  ZYWLN4JVLA  170126  13:56:20.117    L      195.3        RL
8650  ZYWLN4JVLA  170126  13:56:20.242    R      105.5        LR
8651  ZYWLN4JVLA  170126  13:56:33.625    L      168.0        LL
8652  ZYWLN4JVLA  170126  13:56:33.836    L       97.7        LL
8653  ZYWLN4JVLA  170126  13:56:34.066    L      168.0        LL

      Latency time  Flight time
0            234.4        156.3
1            437.5        359.4
2            210.9        125.0
3            359.4        281.3
4            187.5         93.8
```

```
...           ...          ...
8649        425.8        261.7
8650        214.8         19.5
8651        332.0         15.6
8652        281.3        113.3
8653        160.2         62.5

[9013244 rows x 8 columns]
```

Data cleansing

```
# remove irrelevant columns for data processing (date, timestamp)
df_1 = df.drop('Date', axis='columns').drop('Timestamp',
axis='columns')
print("Number of unique users: " + str(df_1.UserKey.nunique()))
display(df_1)
```

```
Number of unique users: 276

         UserKey Hand  Hold time Direction  Latency time  Flight time
0     0EA27ICBLF    L      101.6        LL         234.4        156.3
1     0EA27ICBLF    L       85.9        LL         437.5        359.4
2     0EA27ICBLF    L       78.1        LL         210.9        125.0
3     0EA27ICBLF    L       62.5        LL         359.4        281.3
4     0EA27ICBLF    S      125.0        LS         187.5         93.8
...          ...  ...        ...       ...           ...          ...
8649  ZYWLN4JVLA    L      195.3        RL         425.8        261.7
8650  ZYWLN4JVLA    R      105.5        LR         214.8         19.5
8651  ZYWLN4JVLA    L      168.0        LL         332.0         15.6
8652  ZYWLN4JVLA    L       97.7        LL         281.3        113.3
8653  ZYWLN4JVLA    L      168.0        LL         160.2         62.5

[9013244 rows x 6 columns]
```

```
# remove participants with fewer than 1000 keystrokes to avoid small
sample bias
df_2 = df_1.groupby('UserKey').filter(lambda x : len(x)>1000)
print("Number of unique users: " + str(df_2.UserKey.nunique()))
display(df_2)
```

```
Number of unique users: 155

         UserKey Hand  Hold time Direction  Latency time  Flight time
0     0EA27ICBLF    L      101.6        LL         234.4        156.3
1     0EA27ICBLF    L       85.9        LL         437.5        359.4
2     0EA27ICBLF    L       78.1        LL         210.9        125.0
3     0EA27ICBLF    L       62.5        LL         359.4        281.3
4     0EA27ICBLF    S      125.0        LS         187.5         93.8
...          ...  ...        ...       ...           ...          ...
8649  ZYWLN4JVLA    L      195.3        RL         425.8        261.7
8650  ZYWLN4JVLA    R      105.5        LR         214.8         19.5
```

```
8651  ZYWLN4JVLA    L      168.0        LL          332.0          15.6
8652  ZYWLN4JVLA    L       97.7        LL          281.3         113.3
8653  ZYWLN4JVLA    L      168.0        LL          160.2          62.5

[8996101 rows x 6 columns]
```

```
unique_users = df_2.UserKey.unique()
```

Dependent variable encoding

```
# binary encoding of Parkinson status (0 = negative, 1 = positive)
parkinsons_list = []
for fn in os.listdir(root + '/Archived users'):
  if (str(fn)[5:-4] in unique_users):
    user_file = open(root + '/Archived users/' + fn, "r")
    data = user_file.read()
    content = data.split("\n")
    #print(content)
    if content[2][12:] == 'True':
      parkinsons_list.append(1)
    elif content[2][12:] == 'False':
      parkinsons_list.append(0)

print(parkinsons_list)
```

```
[1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0,
1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0,
1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1,
1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1,
0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0,
1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1]
```

Feature extraction

```
# combine individual keystrokes into combined statistical data for
each participant (mean, standard deviation, skewness, kurtosis) for
hold time and latency time, as well as assymetry between L-side/R-side
# thousands of entries are condensed into one row for each participant
to extract important features
user_info = pd.DataFrame(columns=np.arange(28))
user_info.columns = ['HT Mean (L)', 'HT Mean (R)', 'HT STD (L)', 'HT
STD (R)', 'HT Skew (L)', 'HT Skew (R)', 'HT Kurt (L)', 'HT Kurt (R)',
'Mean difference', 'LT Mean (LR)', 'LT Mean (RL)', 'LT Mean (LL)', 'LT
Mean (RR)', 'LT STD (LR)', 'LT STD (RL)', 'LT STD (LL)', 'LT STD
(RR)', 'LT Skew (LR)', 'LT Skew (RL)', 'LT Skew (LL)', 'LT Skew (RR)',
'LT Kurt (LR)', 'LT Kurt (RL)', 'LT Kurt (LL)', 'LT Kurt (RR)', 'Mean
diff (LR-RL)', 'Mean diff (LL-RR)', 'Parkinson\'s']
for i in range(len(unique_users)):
  user = unique_users[i]
  user_values = []
  curr_df = df_2[df_2["UserKey"].str.contains(user)]
```

```
  curr_df = curr_df.reset_index()
  #curr_df = curr_df.drop('Discount', axis='columns').drop('index',
axis='columns')
  #print(curr_df['Direction'][1:])
  HT_L = curr_df.loc[(curr_df['Hand'] == 'L'), 'Hold time']
  HT_R = curr_df.loc[(curr_df['Hand'] == 'R'), 'Hold time']
  HT_list = [HT_L, HT_R]

  for j in range(2):
    user_values.append(statistics.mean(HT_list[j]))
    user_values.append(statistics.stdev(HT_list[j]))
    user_values.append(stats.skew(HT_list[j], bias=False))
    user_values.append(stats.kurtosis(HT_list[j], bias=False))
  user_values.append(abs(statistics.mean(HT_L) -
statistics.mean(HT_R)))

  LT_LR = curr_df.loc[(curr_df['Direction'] == 'LR'), 'Latency time']
  LT_RL = curr_df.loc[(curr_df['Direction'] == 'RL'), 'Latency time']
  LT_LL = curr_df.loc[(curr_df['Direction'] == 'LL'), 'Latency time']
  LT_RR = curr_df.loc[(curr_df['Direction'] == 'RR'), 'Latency time']
  LT_list = [LT_LR, LT_RL, LT_LL, LT_RR]

  for j in range(4):
    user_values.append(statistics.mean(LT_list[j]))
    user_values.append(statistics.stdev(LT_list[j]))
    user_values.append(stats.skew(LT_list[j], bias=False))
    user_values.append(stats.kurtosis(LT_list[j], bias=False))
  user_values.append(abs(statistics.mean(LT_LR) -
statistics.mean(LT_RL)))
  user_values.append(abs(statistics.mean(LT_LL) -
statistics.mean(LT_RR)))

  user_values.append(parkinsons_list[i])
  user_info.loc[len(user_info)] = user_values

display(user_info)
```

```
     HT Mean (L)  HT Mean (R)  HT STD (L)  HT STD (R)  HT Skew (L)  \
0      77.749454    17.598336    1.585134   11.522029    79.306669
1      98.931818    23.869914    0.236835    0.859236   101.595749
2     153.702407    53.213749    0.264980    0.625664   105.622423
3     153.521655    43.931450    1.352828    2.623331   149.722970
4      89.355483    22.041569    0.795804    7.209476    90.890535
..           ...          ...         ...         ...          ...
150   144.550351    51.964212   -0.343776    0.077503   115.651657
151   111.271697    25.435708    1.847418    9.510130   109.022713
152   112.056034    20.694022    0.392660    2.998890   111.744260
153    93.671032    51.082657   -0.061584   -0.282887    90.009187
154   144.792909    81.351678    0.698503    1.496581   132.569886
```

	HT Skew (R)	HT Kurt (L)	HT Kurt (R)	Mean difference	LT Mean (LR)
0	24.609195	4.130419	44.944694	1.557215	277.610541
1	37.219557	7.495779	110.960777	2.663930	411.718182
2	27.036622	2.797976	24.142310	48.079984	313.541489
3	37.167793	1.152588	1.756346	3.798685	604.100000
4	34.355843	0.508098	2.215637	1.535052	351.215053
..	...	...	...	...	...
150	36.921484	0.727193	2.084348	28.898694	416.058555
151	22.563197	1.350504	13.981419	2.248984	353.507881
152	26.670033	0.517080	0.690160	0.311773	378.445122
153	51.725588	0.139027	-0.156771	3.661845	152.749177
154	71.298522	0.609289	2.423355	12.223022	195.494628

	...	LT Skew (RL)	LT Skew (LL)	LT Skew (RR)	LT Kurt (LR)
0	...	97.920148	0.481528	-0.700290	273.864624
1	...	162.606085	0.377702	-0.511024	365.736471
2	...	101.977747	-1.342300	2.022551	322.170833
3	...	154.972292	0.301000	-1.013709	489.507095
4	...	120.015100	0.514506	1.248726	338.282118
..	...	...	...	...	...
150	...	162.173494	0.532466	-0.256977	423.811620
151	...	70.945323	-0.265956	0.292382	359.141169
152	...	144.463350	0.810516	0.083938	379.116725
153	...	79.460218	1.213004	1.737602	168.250427
154	...	134.652202	1.446668	2.631722	206.760194

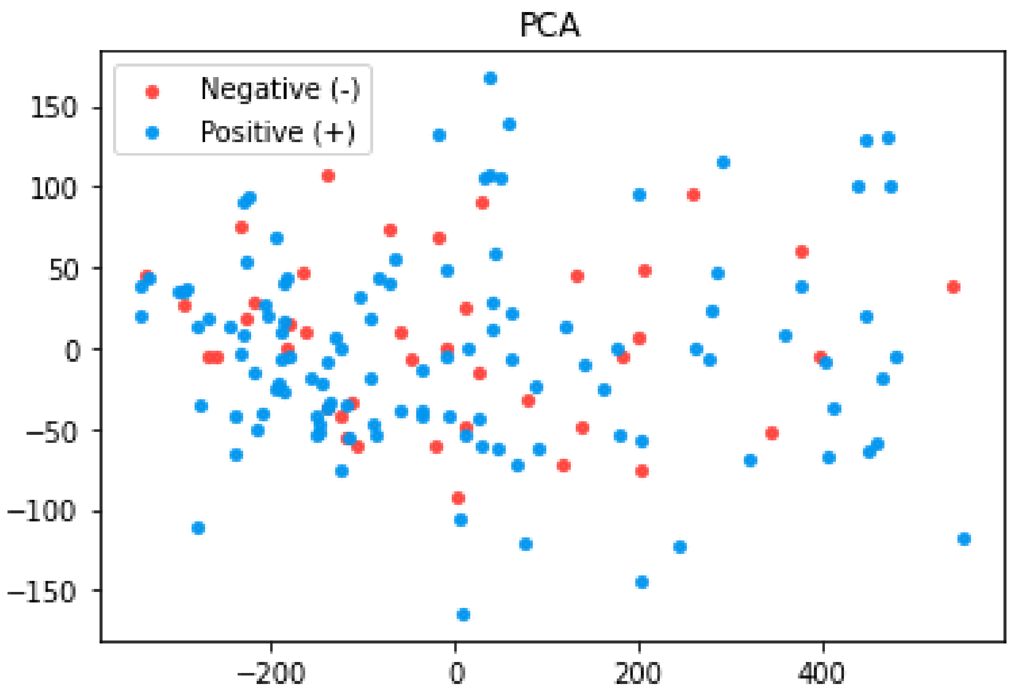
	LT Kurt (RL)	LT Kurt (LL)	LT Kurt (RR)	Mean diff (LR-RL)
0	117.423836	0.148535	-1.237983	139.245790
1	155.345904	0.575523	-0.246378	18.540793
2	82.901327	-0.286635	0.765983	2.742036
3	154.531992	0.140075	-1.051458	30.863529
4	148.919332	0.476318	-0.014178	39.519115
..	...	...	...	...
150	170.111380	0.419322	-0.779357	10.369051
151	89.251047	-0.588214	-0.184743	5.966590
152	138.788763	0.918057	0.923714	55.907015
153	93.145271	1.141790	0.986675	10.795979
154	138.685190	1.412620	2.716789	15.209416

```
     Mean diff (LL-RR)  Parkinson's
0            10.284312          1.0
1            40.979771          0.0
2            25.711714          0.0
3             0.345793          1.0
4            21.948033          0.0
..                 ...          ...
150          28.607444          1.0
151           5.378925          1.0
152           1.699700          1.0
153          10.642127          1.0
154           3.627122          1.0

[155 rows x 28 columns]
```

Principal component analysis (PCA)

```
# simplify high-dimensional data to find greatest variance
X = user_info
#X = X.drop(user_info.iloc[:, 9:27], axis = 1)
#X = X.drop(user_info.iloc[:, 0:9], axis = 1)

Y = X[X.columns[27:]].to_numpy().flatten().astype(int)
#print(Y)
X = X.drop("Parkinson's",axis=1)

pca = PCA(n_components=2)
pca.fit(X)
print(pca.explained_variance_ratio_)

X_transformed = pca.transform(X)

colors = ['#FE433C','#0095EF']
lw = 2

class_names = ["Negative (-)", "Positive (+)"]
cn = np.array(class_names)

for color, i, class_names in zip(colors, list(range(0, 2)),
class_names):
    plt.scatter(X_transformed[Y == i, 0], X_transformed[Y == i, 1],
color=color, alpha=.9, lw=lw, s=10,
                label=class_names)
plt.legend(loc='best', shadow=False, scatterpoints=1)
plt.title('PCA')
plt.figure()
x_scaled = StandardScaler().fit_transform(X)
```

```
[0.81978855 0.05749631]
```




```
<Figure size 432x288 with 0 Axes>
```

```
X.to_csv('data.csv')
!cp data.csv "drive/My Drive/SJSU"
```

Linear SVC Model training

```
X_final_train, X_final_test, Y_final_train, Y_final_test =
train_test_split(x_scaled, Y, test_size=0.2, random_state=100)

skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=1)
lst_accu_stratified = []
lr = linear_model.LogisticRegression()

accs = []
for train_index, test_index in skf.split(X_final_train,
Y_final_train):
    x_train, x_test = X_final_train[train_index],
X_final_train[test_index]
    y_train, y_test = Y_final_train[train_index],
Y_final_train[test_index]

    model = LinearSVC(multi_class='ovr',
class_weight='balanced').fit(x_train, y_train)
    accs.append(model.score(x_test, y_test))

print("Individual cross-validation accuracies: " + str(accs))
print("Mean cross-validation accuracy: {:.3f}".format(sum(accs) /
len(accs)))
```

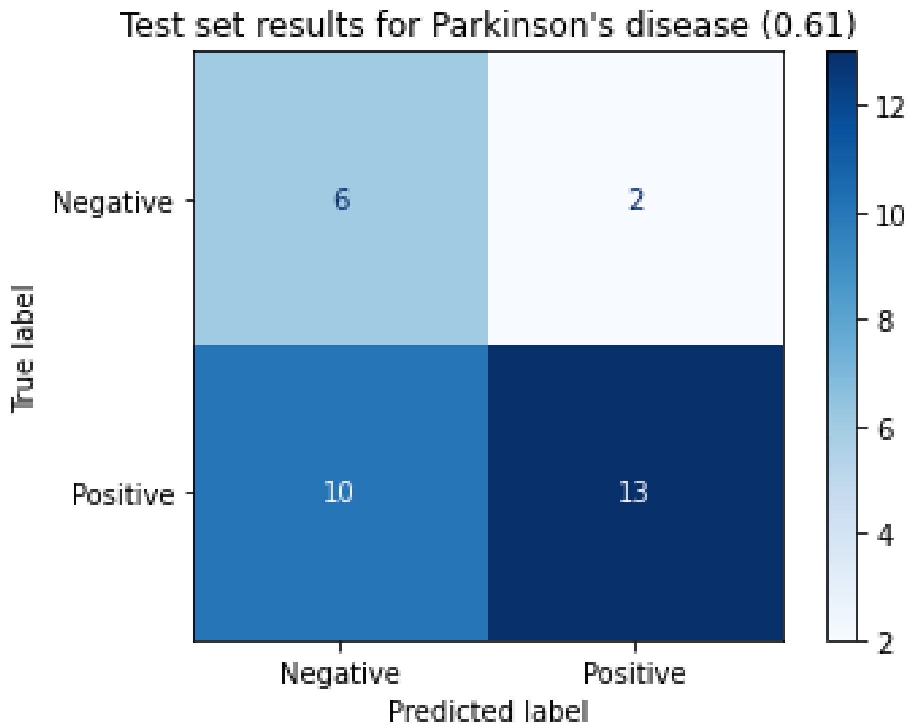
```
Individual cross-validation accuracies: [0.48, 0.56, 0.56, 0.6,
0.5833333333333334]
Mean cross-validation accuracy: 0.557
```

```
model.fit(X_final_train,Y_final_train)

print('Accuracy of linear SVC on test set:
{:.2f}'.format(model.score(X_final_test, Y_final_test)))
```

```
Accuracy of linear SVC on test set: 0.61
```

Linear SVC Results

```
np.set_printoptions(precision=2)

for i in range(1):
  labels = []
  for j in range(len(Y)):
    if Y[j] == i:
      labels.append(1)
    else:
      labels.append(0)
  Y_digit = np.array(labels)
 # X_train, X_test, Y_train, Y_test = train_test_split(X, Y_digit,
test_size=0.2, random_state=0, stratify=Y_digit)
  model.fit(X_final_train, Y_final_train)

  disp = plot_confusion_matrix(model, X_final_test, Y_final_test,
display_labels=["Negative".format(i), "Positive".format(i)],
cmap=plt.cm.Blues)
  disp.ax_.set_title("Test set results for Parkinson's disease
({score:.2f})".format(i, score=model.score(X_final_test,
Y_final_test)))
  plt.show()
```

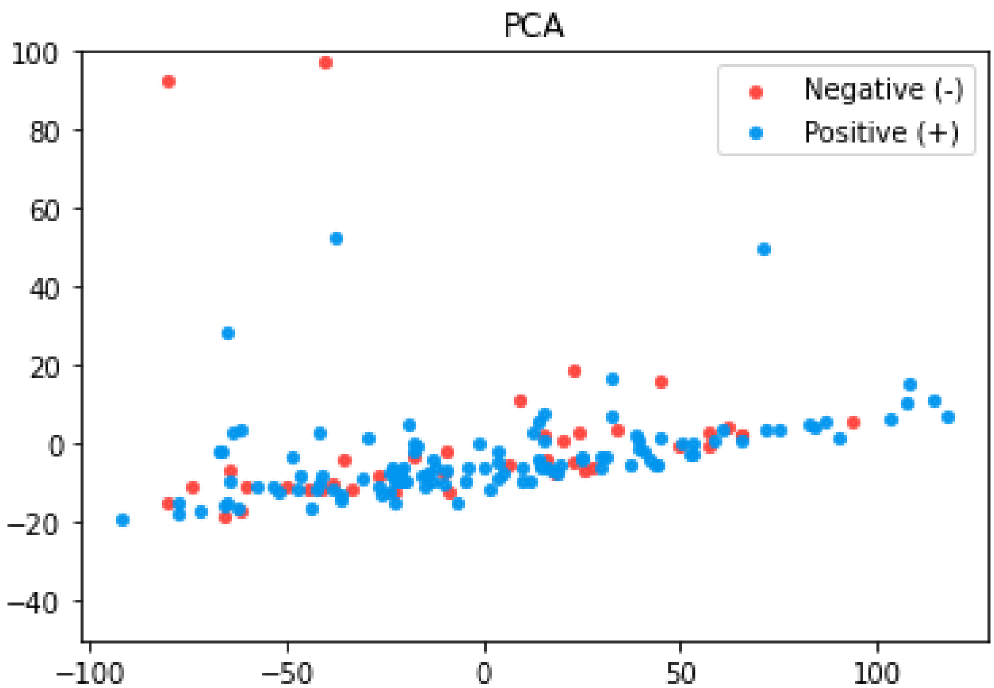


Poly SVC Model training

```
# simplify high-dimensional data to find greatest variance
X = user_info
X = X.drop(user_info.iloc[:, 9:27], axis = 1)
#X = X.drop(user_info.iloc[:, 0:9], axis = 1)

Y = X[X.columns[9:]].to_numpy().flatten().astype(int)
#print(Y)
X = X.drop("Parkinson's",axis=1)

pca = PCA(n_components=2)
pca.fit(X)
print(pca.explained_variance_ratio_)

X_transformed = pca.transform(X)

colors = ['#FE433C','#0095EF']
lw = 2

class_names = ["Negative (-)", "Positive (+)"]
cn = np.array(class_names)

for color, i, class_names in zip(colors, list(range(0, 2)),
class_names):
    plt.scatter(X_transformed[Y == i, 0], X_transformed[Y == i, 1],
color=color, alpha=.9, lw=lw, s=10,
```

```
                    label=class_names)
plt.legend(loc='best', shadow=False, scatterpoints=1)
plt.title('PCA')
plt.ylim([-50, 100])
plt.figure()
#plt.xlim([-3, 3])
x_scaled = StandardScaler().fit_transform(X)
```

```
[0.59 0.24]
```




```
<Figure size 432x288 with 0 Axes>
```

```
X_final_train, X_final_test, Y_final_train, Y_final_test = 
train_test_split(x_scaled, Y, test_size=0.2, random_state=100)

skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=1)
lst_accu_stratified = []
lr = linear_model.LogisticRegression()

accs = []
for train_index, test_index in skf.split(X_final_train, 
Y_final_train):
    x_train, x_test = X_final_train[train_index], 
X_final_train[test_index]
    y_train, y_test = Y_final_train[train_index], 
Y_final_train[test_index]

    model = SVC(kernel='poly', class_weight='balanced').fit(x_train, 
y_train)
```

```
    accs.append(model.score(x_test, y_test))

print("Individual cross-validation accuracies: " + str(accs))
print("Mean cross-validation accuracy: {:.3f}".format(sum(accs) /
len(accs)))
```

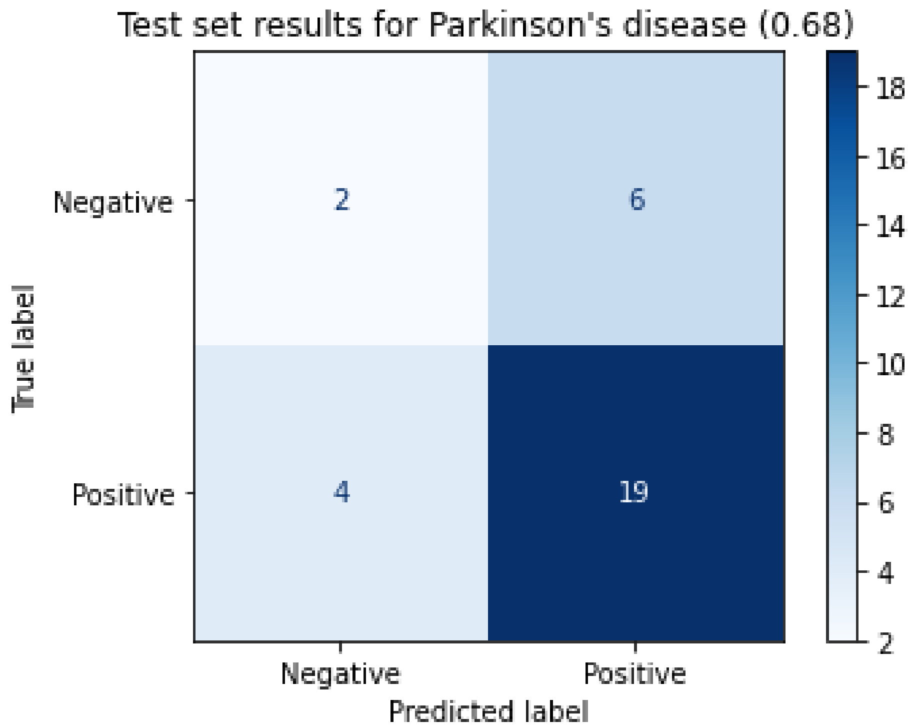
```
Individual cross-validation accuracies: [0.72, 0.76, 0.72, 0.52, 0.75]
Mean cross-validation accuracy: 0.694
```

```
model.fit(X_final_train,Y_final_train)

print('Accuracy of poly SVC on test set:
{:.2f}'.format(model.score(X_final_test, Y_final_test)))
```

```
Accuracy of poly SVC on test set: 0.68
```

Poly SVC Results

```
np.set_printoptions(precision=2)

for i in range(1):
  labels = []
  for j in range(len(Y)):
    if Y[j] == i:
      labels.append(1)
    else:
      labels.append(0)
  Y_digit = np.array(labels)
 # X_train, X_test, Y_train, Y_test = train_test_split(X, Y_digit,
test_size=0.2, random_state=0, stratify=Y_digit)
  model.fit(X_final_train, Y_final_train)

  disp = plot_confusion_matrix(model, X_final_test, Y_final_test,
display_labels=["Negative".format(i), "Positive".format(i)],
cmap=plt.cm.Blues)
  disp.ax_.set_title("Test set results for Parkinson's disease
({score:.2f})".format(i, score=model.score(X_final_test,
Y_final_test)))
  plt.show()
```



Test set results for Parkinson's disease (0.68)
True label
Negative
Positive
2
6
4
19
Negative
Positive
Predicted label
18
16
14
12
10
8
6
4
2