

swetha-pca

May 8, 2023

```
[2]: #Importing required libraries
import numpy as np
import pandas as pd
```

```
[3]: ctg_df=pd.read_csv("ctg_data1.csv")
```

```
[4]: ctg_df.head()
```

```
[4]:
```

	b	e	AC	FM	UC	DL	DS	DP	DR	LB	...	C	D	E	AD	DE	LD	FS	\
0	240	357	0	0	0	0	0	0	0	120	...	-1	-1	-1	-1	-1	-1	1	
1	5	632	4	0	4	2	0	0	0	132	...	-1	-1	-1	1	-1	-1	-1	
2	177	779	2	0	5	2	0	0	0	133	...	-1	-1	-1	1	-1	-1	-1	
3	411	1192	2	0	6	2	0	0	0	134	...	-1	-1	-1	1	-1	-1	-1	
4	533	1147	4	0	5	0	0	0	0	132	...	-1	-1	-1	-1	-1	-1	-1	

	SUSP	CLASS	NSP
0	-1	9	2
1	-1	6	1
2	-1	6	1
3	-1	6	1
4	-1	2	1

[5 rows x 42 columns]

```
[5]: ctg_df.dtypes
```

```
[5]: b          int64
     e          int64
     AC         int64
     FM         int64
     UC         int64
     DL         int64
     DS         int64
     DP         int64
     DR         int64
     LB         int64
     AC.1       float64
```

```

FM.1      float64
UC.1      float64
DL.1      float64
DS.1      float64
DP.1      float64
ASTV      int64
MSTV      float64
ALTV      int64
MLTV      float64
Width     int64
Min       int64
Max       int64
Nmax      int64
Nzeros    int64
Mode      int64
Mean      int64
Median    int64
Variance  int64
Tendency  int64
A         int64
B         int64
C         int64
D         int64
E         int64
AD        int64
DE        int64
LD        int64
FS        int64
SUSP      int64
CLASS     int64
NSP       int64
dtype: object

```

```

[6]: #Checking for null values
ctg_df.isna().sum()

```

```

[6]: b      0
     e      0
     AC     0
     FM     0
     UC     0
     DL     0
     DS     0
     DP     0
     DR     0
     LB     0
     AC.1   0

```

```

FM.1      0
UC.1      0
DL.1      0
DS.1      0
DP.1      0
ASTV      0
MSTV      0
ALTV      0
MLTV      0
Width     0
Min       0
Max       0
Nmax      0
Nzeros    0
Mode      0
Mean      0
Median    0
Variance  0
Tendency  0
A         0
B         0
C         0
D         0
E         0
AD        0
DE        0
LD        0
FS        0
SUSP      0
CLASS     0
NSP       0
dtype: int64

```

```
[7]: ctg_df.dropna()
```

```

[7]:      b      e  AC  FM  UC  DL  DS  DP  DR  LB  ...  C  D  E  AD  DE  LD  \
0      240   357   0   0   0   0   0   0   0  120  ... -1 -1 -1  -1  -1  -1
1        5   632   4   0   4   2   0   0   0  132  ... -1 -1 -1   1  -1  -1
2     177   779   2   0   5   2   0   0   0  133  ... -1 -1 -1   1  -1  -1
3     411  1192   2   0   6   2   0   0   0  134  ... -1 -1 -1   1  -1  -1
4     533  1147   4   0   5   0   0   0   0  132  ... -1 -1 -1  -1  -1  -1
...
2121  2059  2867   0   0   6   0   0   0   0  140  ... -1 -1  1  -1  -1  -1
2122  1576  2867   1   0   9   0   0   0   0  140  ... -1 -1  1  -1  -1  -1
2123  1576  2596   1   0   7   0   0   0   0  140  ... -1 -1  1  -1  -1  -1
2124  1576  3049   1   0   9   0   0   0   0  140  ... -1 -1  1  -1  -1  -1
2125  2796  3415   1   1   5   0   0   0   0  142  ... -1 -1 -1  -1  -1  -1

```

	FS	SUSP	CLASS	NSP
0	1	-1	9	2
1	-1	-1	6	1
2	-1	-1	6	1
3	-1	-1	6	1
4	-1	-1	2	1
...
2121	-1	-1	5	2
2122	-1	-1	5	2
2123	-1	-1	5	2
2124	-1	-1	5	2
2125	-1	-1	1	1

[2126 rows x 42 columns]

```
[8]: ctg_df.isna().sum()
```

```
[8]: b          0
     e          0
     AC         0
     FM         0
     UC         0
     DL         0
     DS         0
     DP         0
     DR         0
     LB         0
     AC.1       0
     FM.1       0
     UC.1       0
     DL.1       0
     DS.1       0
     DP.1       0
     ASTV       0
     MSTV       0
     ALTV       0
     MLTV       0
     Width      0
     Min        0
     Max        0
     Nmax       0
     Nzeros     0
     Mode       0
     Mean       0
     Median     0
     Variance    0
```

```

Tendency    0
A            0
B            0
C            0
D            0
E            0
AD           0
DE           0
LD           0
FS           0
SUSP        0
CLASS       0
NSP         0
dtype: int64

```

```

[9]: Features=ctg_df.drop('NSP', axis=1)
     Label=ctg_df['NSP']

```

PCA

```

[10]: # mean Centering the data
      Features_meaned = Features - np.mean(Features , axis = 0)
      Features_meaned

```

```

[10]:
      b          e          AC          FM          UC          DL \
0    -638.439793 -1345.877234 -2.722484 -7.241298 -3.659925 -1.570085
1    -873.439793 -1070.877234  1.277516 -7.241298  0.340075  0.429915
2    -701.439793 -923.877234 -0.722484 -7.241298  1.340075  0.429915
3    -467.439793 -510.877234 -0.722484 -7.241298  2.340075  0.429915
4    -345.439793 -555.877234  1.277516 -7.241298  1.340075 -1.570085
...
2121 1180.560207 1164.122766 -2.722484 -7.241298  2.340075 -1.570085
2122  697.560207 1164.122766 -1.722484 -7.241298  5.340075 -1.570085
2123  697.560207  893.122766 -1.722484 -7.241298  3.340075 -1.570085
2124  697.560207 1346.122766 -1.722484 -7.241298  5.340075 -1.570085
2125 1917.560207 1712.122766 -1.722484 -6.241298  1.340075 -1.570085

      DS          DP          DR          LB          ...          B          C          D \
0    -0.003293 -0.126058  0.0 -13.303857 ... -0.544685 -0.049859 -0.076199
1    -0.003293 -0.126058  0.0  -1.303857 ... -0.544685 -0.049859 -0.076199
2    -0.003293 -0.126058  0.0  -0.303857 ... -0.544685 -0.049859 -0.076199
3    -0.003293 -0.126058  0.0   0.696143 ... -0.544685 -0.049859 -0.076199
4    -0.003293 -0.126058  0.0  -1.303857 ...  1.455315 -0.049859 -0.076199
...
2121 -0.003293 -0.126058  0.0   6.696143 ... -0.544685 -0.049859 -0.076199
2122 -0.003293 -0.126058  0.0   6.696143 ... -0.544685 -0.049859 -0.076199
2123 -0.003293 -0.126058  0.0   6.696143 ... -0.544685 -0.049859 -0.076199

```

```
2124 -0.003293 -0.126058 0.0 6.696143 ... -0.544685 -0.049859 -0.076199
2125 -0.003293 -0.126058 0.0 8.696143 ... -0.544685 -0.049859 -0.076199
```

```

      E      AD      DE      LD      FS      SUSP      CLASS
0  -0.067733 -0.312324 -0.237065 -0.100659 1.935089 -0.185325 4.490122
1  -0.067733 1.687676 -0.237065 -0.100659 -0.064911 -0.185325 1.490122
2  -0.067733 1.687676 -0.237065 -0.100659 -0.064911 -0.185325 1.490122
3  -0.067733 1.687676 -0.237065 -0.100659 -0.064911 -0.185325 1.490122
4  -0.067733 -0.312324 -0.237065 -0.100659 -0.064911 -0.185325 -2.509878
...
2121 1.932267 -0.312324 -0.237065 -0.100659 -0.064911 -0.185325 0.490122
2122 1.932267 -0.312324 -0.237065 -0.100659 -0.064911 -0.185325 0.490122
2123 1.932267 -0.312324 -0.237065 -0.100659 -0.064911 -0.185325 0.490122
2124 1.932267 -0.312324 -0.237065 -0.100659 -0.064911 -0.185325 0.490122
2125 -0.067733 -0.312324 -0.237065 -0.100659 -0.064911 -0.185325 -3.509878
```

[2126 rows x 41 columns]

```
[11]: # Calculate the co-variance matrix of the mean-centered data.
cov_matrix = np.cov(Features_meaned , rowvar = False)
```

```
[12]: #Calculating Eigenvalues and Eigenvectors of the covariance matrix
eigen_values , eigen_vectors = np.linalg.eigh(cov_matrix)
```

```
[13]: #sort the eigenvalues in descending order
sorted_index = np.argsort(eigen_values)[::-1]

sorted_eigenvalue = eigen_values[sorted_index]
#similarly sort the eigenvectors
sorted_eigenvectors = eigen_vectors[:,sorted_index]
sorted_eigenvectors
```

```
[13]: array([[ 6.91839404e-01,  7.21512407e-01,  1.75656916e-02, ...,
               0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
              [ 7.22033857e-01, -6.91484578e-01, -1.52148770e-02, ...,
               2.42108531e-16, -1.19944670e-16,  9.70778671e-16],
              [ 5.35372127e-05, -5.53091262e-03,  1.35371709e-02, ...,
               3.08198656e-12, -4.15940569e-12, -7.86838897e-11],
              ...,
              [-3.88395017e-05,  1.12232968e-04, -1.40543871e-03, ...,
               -4.51674774e-01,  1.90457665e-01, -2.39697854e-03],
              [-7.85665562e-05,  4.22719070e-05, -3.33119538e-03, ...,
               -5.54477252e-01,  1.58982377e-01, -2.16854955e-03],
              [-1.95401290e-04, -1.98217218e-05,  9.55309887e-03, ...,
               2.05604956e-01,  6.29505765e-02, -4.56858038e-04]])
```

```
[14]: # select the first n eigenvectors, n is desired dimension
# of our final reduced data.

n_components = 30 #you can select any number of components.
eigenvector_subset = sorted_eigenvectors[:,0:n_components]
eigenvector_subset
```

```
[14]: array([[ 6.91839404e-01,  7.21512407e-01,  1.75656916e-02, ...,
        -3.54733462e-05, -3.58086842e-05, -1.13214907e-04],
       [ 7.22033857e-01, -6.91484578e-01, -1.52148770e-02, ...,
         7.41245718e-05,  5.58820374e-05,  9.34508112e-05],
       [ 5.35372127e-05, -5.53091262e-03,  1.35371709e-02, ...,
         3.87838214e-03,  1.41788419e-02, -5.82796889e-03],
       ...,
       [-3.88395017e-05,  1.12232968e-04, -1.40543871e-03, ...,
         3.68522925e-01,  3.75361381e-01, -2.92472624e-01],
       [-7.85665562e-05,  4.22719070e-05, -3.33119538e-03, ...,
         1.43153772e-02,  3.86644752e-02, -2.58845884e-01],
       [-1.95401290e-04, -1.98217218e-05,  9.55309887e-03, ...,
         3.88068380e-02,  6.43857288e-02,  4.79739804e-02]])
```

```
[15]: #Transform the data
Features_reduced = np.dot(eigenvector_subset.transpose(),Features_meaned.
    ↪transpose()).transpose()
Features_reduced
```

```
[15]: array([[ -1.41343472e+03,  4.70134580e+02,  2.84244658e+01, ...,
         4.15078967e-01,  9.06630922e-01, -2.25026432e-01],
       [ -1.37755124e+03,  1.08605023e+02,  5.95305431e+01, ...,
        -4.15074824e-02, -4.22331452e-02,  1.84028598e-01],
       [ -1.15241176e+03,  1.31088223e+02,  6.10420703e+01, ...,
         4.02103965e-02, -1.72973592e-01,  1.41992917e-01],
       ...,
       [  1.12739797e+03, -1.14737308e+02, -2.45558023e+01, ...,
         3.12989095e-01, -3.28107836e-03, -1.13333542e-01],
       [  1.45447463e+03, -4.27942448e+02, -3.29994207e+01, ...,
         3.70680658e-01, -4.59279370e-02, -8.61247641e-02],
       [  2.56282951e+03,  2.00210681e+02, -4.24806990e+01, ...,
        -5.89768074e-02, -8.03310712e-02, -2.10165288e-02]])
```

```
[16]: PCA_df = pd.DataFrame(Features_reduced)
PCA_df
```

```
[16]:
```

	0	1	2	3	4	5	\
0	-1413.434724	470.134580	28.424466	13.879196	40.820047	-46.972007	
1	-1377.551238	108.605023	59.530543	25.883117	-29.940244	28.647525	
2	-1152.411762	131.088223	61.042070	25.135022	-29.413593	28.519969	

3	-692.298332	14.835719	53.288634	22.533661	-9.411187	36.527373
4	-640.389127	133.974232	54.899883	22.053800	-12.337565	38.486316
...
2121	1657.277161	47.326853	-55.520818	-10.339265	-29.489633	-20.718990
2122	1323.070040	-302.087589	-29.906180	0.127539	-21.426965	-5.432812
2123	1127.397969	-114.737308	-24.555802	0.747021	-25.360678	-6.057273
2124	1454.474628	-427.942448	-32.999421	-0.257821	-19.233663	-7.715140
2125	2562.829512	200.210681	-42.480699	-12.576243	-14.140811	-11.918309

	6	7	8	9	...	20	21	\
0	-34.539355	-31.888888	-24.626308	8.053120	...	0.093018	-0.810424	
1	6.920000	4.199390	26.167438	0.827025	...	0.922525	0.144430	
2	6.723026	3.926497	26.920672	-1.677391	...	1.043045	0.109449	
3	2.915169	-15.857135	8.636404	-10.282103	...	0.228416	-0.304752	
4	0.657737	-14.152976	8.526533	-6.546051	...	-0.246582	-0.227238	
...	
2121	-17.590565	22.660287	2.243139	3.793377	...	-0.016704	-0.093432	
2122	-24.794924	8.820563	-7.776421	1.622849	...	-0.054152	-0.235634	
2123	-26.694728	12.285514	-9.679601	3.296160	...	-0.014438	-0.190680	
2124	-25.851610	5.120339	-4.884823	1.412911	...	-0.044336	-0.258925	
2125	-35.517205	7.239103	0.122317	0.780335	...	0.273635	0.255655	

	22	23	24	25	26	27	28	\
0	-0.721120	0.299470	-0.078584	-0.709594	0.296404	0.415079	0.906631	
1	-0.304961	-0.209206	0.042727	-0.135705	0.117000	-0.041507	-0.042233	
2	-0.288802	-0.171645	0.007562	-0.168075	0.059803	0.040210	-0.172974	
3	-0.283725	-0.168691	-0.076990	-0.273580	0.210667	0.035501	-0.375974	
4	0.363436	0.132460	-0.147433	-0.122192	0.279740	0.220051	-0.021162	
...	
2121	-0.921338	0.694898	0.318349	1.329368	0.459549	0.166742	-0.134555	
2122	-0.874839	0.691758	0.068500	1.378358	0.377367	0.364705	-0.015705	
2123	-0.853806	0.710446	0.062186	1.426263	0.441196	0.312989	-0.003281	
2124	-0.911995	0.655145	0.062835	1.390439	0.316014	0.370681	-0.045928	
2125	0.158093	-0.197516	0.316936	0.094122	-0.071173	-0.058977	-0.080331	

	29
0	-0.225026
1	0.184029
2	0.141993
3	0.123455
4	-0.088130
...	...
2121	-0.086301
2122	-0.105195
2123	-0.113334
2124	-0.086125
2125	-0.021017

[2126 rows x 30 columns]

```
[17]: from sklearn.model_selection import train_test_split # Import train_test_split
      ↪ function
      from sklearn import metrics
```

```
[18]: # Split dataset into training set and test set
      X_train, X_test, y_train, y_test = train_test_split(PCA_df, Label, test_size=0.
      ↪ 3, random_state=1)
```

DECISION TREE

```
[19]: # Import Decision Tree Classifier
      from sklearn.tree import DecisionTreeClassifier
      # Create Decision Tree classifier object
      clf = DecisionTreeClassifier()

      # Train Decision Tree Classifier
      clf = clf.fit(X_train,y_train)

      #Predict the response for test dataset
      y_pred_train = clf.predict(X_train)
```

```
[20]: print("Decision Tree Model Accuracy with training data (in %):",metrics.
      ↪ accuracy_score(y_train, y_pred_train)*100)
```

Decision Tree Model Accuracy with training data (in %): 99.93279569892472

```
[21]: # Create Decision Tree classifier object
      clf = DecisionTreeClassifier(criterion="entropy", max_depth=8)

      # Train Decision Tree Classifier
      clf = clf.fit(X_train,y_train)

      #Predict the response for test dataset
      y_pred = clf.predict(X_test)
```

```
[22]: print("Decision Tree model accuracy(in %):",metrics.accuracy_score(y_test,
      ↪ y_pred)*100)
```

Decision Tree model accuracy(in %): 95.7680250783699

Naive Bayes

```
[23]: from sklearn.naive_bayes import GaussianNB
      gnb = GaussianNB()
      gnb.fit(X_train, y_train)
```

```

y_pred_train = gnb.predict(X_train)

print('Gaussian Naive Bayes Training-set accuracy(in %):', metrics.
      ↪accuracy_score(y_train, y_pred_train)*100)

```

Gaussian Naive Bayes Training-set accuracy(in %): 95.83333333333334

```

[24]: # making predictions on the testing set
y_pred = gnb.predict(X_test)

# comparing actual response values (y_test) with predicted response values
print("Gaussian Naive Bayes model accuracy(in %):", metrics.
      ↪accuracy_score(y_test, y_pred)*100)

```

Gaussian Naive Bayes model accuracy(in %): 95.61128526645768

Random Forest

```

[25]: # importing random forest classifier from assemble module
from sklearn.ensemble import RandomForestClassifier

```

```

[26]: # creating a RF classifier
rfclf = RandomForestClassifier(n_estimators = 100)

# Training the model on the training dataset
rfclf.fit(X_train, y_train)
y_pred_train = rfclf.predict(X_train)

print('Training-set accuracy(in %):', metrics.accuracy_score(y_train,
      ↪y_pred_train)*100)

```

Training-set accuracy(in %): 99.93279569892472

```

[27]: # performing predictions on the test dataset
y_pred = rfclf.predict(X_test)

# using metrics module for accuracy calculation
print("Random Forest model accuracy(in %): ", metrics.accuracy_score(y_test,
      ↪y_pred)*100)

```

Random Forest model accuracy(in %): 98.43260188087774

SVM

```

[28]: #Import svm model
from sklearn import svm

#Create a svm Classifier

```

```
svmclf = svm.SVC(kernel='linear') # Linear Kernel

#Train the model using the training sets
svmclf.fit(X_train, y_train)

y_pred_train = svmclf.predict(X_train)

print('Training-set accuracy(in %):', metrics.accuracy_score(y_train,
↪y_pred_train)*100)
```

Training-set accuracy(in %): 99.32795698924731

```
[29]: #Predict the response for test dataset
y_pred = svmclf.predict(X_test)

# using metrics module for accuracy calculation
print("SVM model accuracy(in %): ", metrics.accuracy_score(y_test, y_pred)*100)
```

SVM model accuracy(in %): 98.90282131661442

[]: