ASSIGNMENT 7

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Title:- Implement KNN Classifier or Regression for any dataset and Calculate the performance matric and compare the error rate with K value(K value range).

Objectives:-

1. To learn KNN algorithm 2. To implement KNN classifier

Theory:

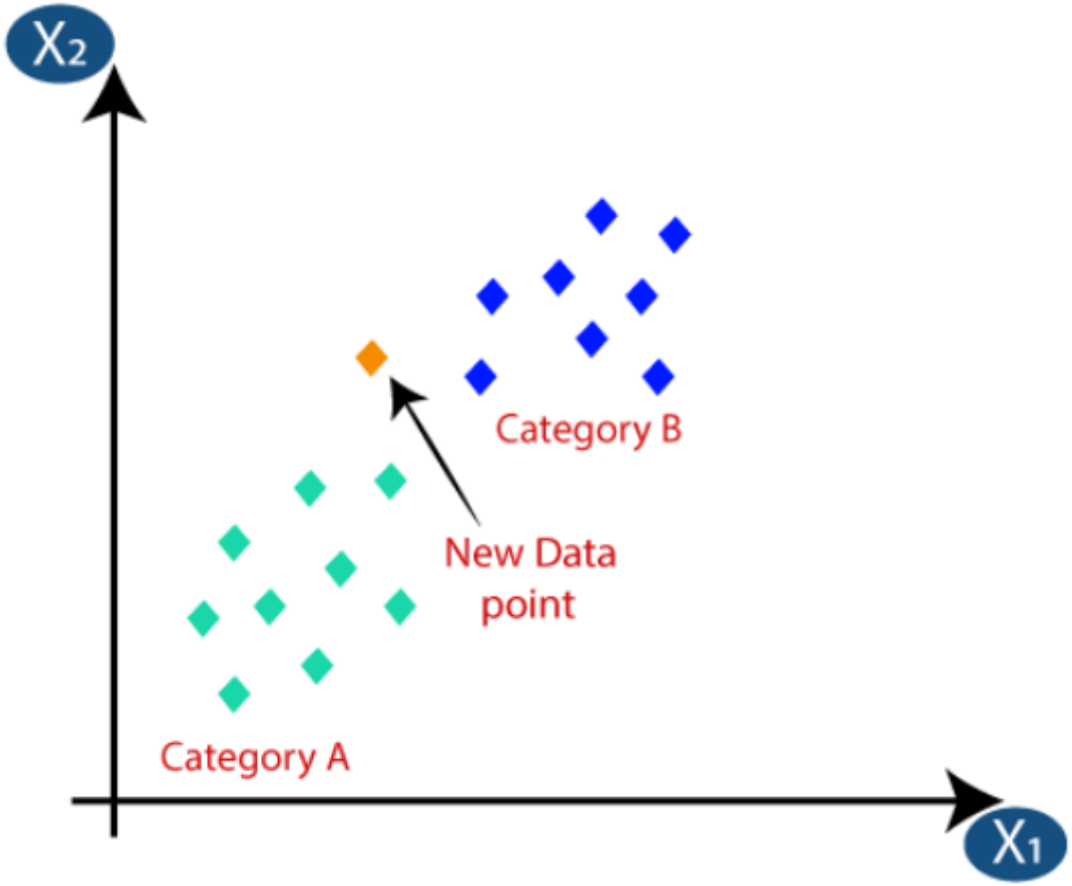
K-NN algorithm

- Knn is a Supervised machine learning algorithm that can be used for Regression as well as for Classification but mostly it is used for the Classification problems.
- K-NN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories.
- K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.
- K-NN is a non-parametric algorithm, which means it does not make any assumption on underlying data.
- It is also called a lazy learner algorithm because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset.
- KNN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much similar to the new data.

Algorithm

The K-NN working can be explained on the basis of the below algorithm:

- Step-1: Select the number K of the neighbors
- Step-2: Calculate the Euclidean distance of K number of neighbors
- Step-3: Take the K nearest neighbors as per the calculated Euclidean distance.
- Step-4: Among these k neighbors, count the number of the data points in each category.
- Step-5: Assign the new data points to that category for which the number of the neighbor is maximum.
- Step-6: Our model is ready.



- Firstly, we will choose the number of neighbors, so we will choose the k=5.

- Next, we will calculate the Euclidean distance between the data points. The Euclidean distance is the distance between two points, which we have already studied in geometry. It can be calculated as:

$$\text{Euclidean Distance between } A_1 \text{ and } B_2 = \sqrt{(X_2-X_1)^2+(Y_2-Y_1)^2}$$

-

Rules to Select K Value

- here is no particular way to determine the best value for "K", so we need to try some values to find the best out of them. The most preferred value for K is 5.
- A very low value for K such as K=1 or K=2, can be noisy and lead to the effects of outliers in the model.
- Large values for K are good, but it may find some difficulties.

Problem Statement - Gender Recognition by Voice.
Dataset Name - Gender Recognition by Voice Dataset.Kaggle
Dataset Link - https://www.kaggle.com/datasets/primaryobjects/voicegender
Dataset Information :
Gender Recognition by Voice and Speech Analysis

This database was created to identify a voice as male or female, based upon acoustic properties of the voice and speech. The dataset consists of 3,168 recorded voice samples, collected from male and female speakers..
Features Explanations:

- meanfreq: mean frequency (in kHz)
- sd: standard deviation of frequency
- median: median frequency (in kHz)
- Q25: first quantile (in kHz)
- Q75: third quantile (in kHz)
- IQR: interquantile range (in kHz)
- skew: skewness (see note in specprop description)
- kurt: kurtosis (see note in specprop description)
- sp.ent: spectral entropy
- sfm: spectral flatness

- mode: mode frequency
- centroid: frequency centroid (see specprop)
- peakf: peak frequency (frequency with highest energy)
- meanfun: average of fundamental frequency measured across acoustic signal
- minfun: minimum fundamental frequency measured across acoustic signal
- maxfun: maximum fundamental frequency measured across acoustic signal
- meandom: average of dominant frequency measured across acoustic signal
- mindom: minimum of dominant frequency measured across acoustic signal
- maxdom: maximum of dominant frequency measured across acoustic signal
- dfrange: range of dominant frequency measured across acoustic signal
- modindx: modulation index. Calculated as the accumulated absolute difference between adjacent measurements of fundamental frequencies divided by the frequency range
- label: male or female

Import Necessary Libraries

In [1]:
```
import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

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

In [2]:
```
from scipy.stats import norm
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report,confusion_matrix
from sklearn.metrics import roc_curve, auc, confusion_matrix, classification_report, accuracy_score,roc_auc_score
from sklearn import metrics
```

In [59]:
```
from scipy import stats
from sklearn.neighbors import KNeighborsClassifier
```

```
from sklearn.preprocessing import LabelEncoder
from matplotlib.colors import ListedColormap
```

Read Dataset

In [4]:
```
df =pd.read_csv('voice.csv')
```

View Top 5 Rows

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

Out[5]:

	meanfreq	sd	median	Q25	Q75	IQR	skew	kurt	sp.ent	sfm	...	centroid	meanfun	minfun	maxfun	me
0	0.059781	0.064241	0.032027	0.015071	0.090193	0.075122	12.863462	274.402906	0.893369	0.491918	...	0.059781	0.084279	0.015702	0.275862	0
1	0.066009	0.067310	0.040229	0.019414	0.092666	0.073252	22.423285	634.613855	0.892193	0.513724	...	0.066009	0.107937	0.015826	0.250000	0
2	0.077316	0.083829	0.036718	0.008701	0.131908	0.123207	30.757155	1024.927705	0.846389	0.478905	...	0.077316	0.098706	0.015656	0.271186	0
3	0.151228	0.072111	0.158011	0.096582	0.207955	0.111374	1.232831	4.177296	0.963322	0.727232	...	0.151228	0.088965	0.017798	0.250000	0
4	0.135120	0.079146	0.124656	0.078720	0.206045	0.127325	1.101174	4.333713	0.971955	0.783568	...	0.135120	0.106398	0.016931	0.266667	0

5 rows × 21 columns

View Last 5 rows

In [6]:
```
df.head()
```

Out[6]:

	meanfreq	sd	median	Q25	Q75	IQR	skew	kurt	sp.ent	sfm	...	centroid	meanfun	minfun	maxfun	me
0	0.059781	0.064241	0.032027	0.015071	0.090193	0.075122	12.863462	274.402906	0.893369	0.491918	...	0.059781	0.084279	0.015702	0.275862	0
1	0.066009	0.067310	0.040229	0.019414	0.092666	0.073252	22.423285	634.613855	0.892193	0.513724	...	0.066009	0.107937	0.015826	0.250000	0
2	0.077316	0.083829	0.036718	0.008701	0.131908	0.123207	30.757155	1024.927705	0.846389	0.478905	...	0.077316	0.098706	0.015656	0.271186	0

	meanfreq	sd	median	Q25	Q75	IQR	skew	kurt	sp.ent	sfm	...	centroid	meanfun	minfun	maxfun	me
3	0.151228	0.072111	0.158011	0.096582	0.207955	0.111374	1.232831	4.177296	0.963322	0.727232	...	0.151228	0.088965	0.017798	0.250000	0
4	0.135120	0.079146	0.124656	0.078720	0.206045	0.127325	1.101174	4.333713	0.971955	0.783568	...	0.135120	0.106398	0.016931	0.266667	0

5 rows × 21 columns

Dimensions of the Dataset

In [7]:
```
df.shape
```

Out[7]:
```
(3168, 21)
```

This dataset contains 3168 rows and 21 columns target feature

Columns in dataset

In [8]:
```
df.columns
```

Out[8]:
```
Index(['meanfreq', 'sd', 'median', 'Q25', 'Q75', 'IQR', 'skew', 'kurt',
       'sp.ent', 'sfm', 'mode', 'centroid', 'meanfun', 'minfun', 'maxfun',
       'meandom', 'mindom', 'maxdom', 'dfrange', 'modindx', 'label'],
      dtype='object')
```

Concise Summary

In [9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3168 entries, 0 to 3167
Data columns (total 21 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   meanfreq  3168 non-null   float64
 1   sd        3168 non-null   float64
 2   median    3168 non-null   float64
 3   Q25       3168 non-null   float64
```

```
 4   Q75       3168 non-null   float64
 5   IQR       3168 non-null   float64
 6   skew      3168 non-null   float64
 7   kurt      3168 non-null   float64
 8   sp.ent    3168 non-null   float64
 9   sfm       3168 non-null   float64
 10  mode      3168 non-null   float64
 11  centroid  3168 non-null   float64
 12  meanfun   3168 non-null   float64
 13  minfun    3168 non-null   float64
 14  maxfun    3168 non-null   float64
 15  meandom   3168 non-null   float64
 16  mindom    3168 non-null   float64
 17  maxdom    3168 non-null   float64
 18  dfrange   3168 non-null   float64
 19  modindx   3168 non-null   float64
 20  label     3168 non-null   object
dtypes: float64(20), object(1)
memory usage: 519.9+ KB
```

From above observation we can say that no null values in the dataset ,but lets varify by using pandas functions

Check Missing values

In [10]:
```
df.isnull().sum()
```

Out[10]:
```
meanfreq    0
sd          0
median      0
Q25         0
Q75         0
IQR         0
skew        0
kurt        0
sp.ent      0
sfm         0
mode        0
centroid    0
meanfun     0
minfun      0
maxfun      0
meandom     0
mindom      0
maxdom      0
dfrange     0
```

```
modindx     0
label       0
dtype: int64
```

Dataset does not contain any null values

Check Duplicate Value

In [11]:
```
df[df.duplicated()]
```

Out[11]:

	meanfreq	sd	median	Q25	Q75	IQR	skew	kurt	sp.ent	sfm	...	centroid	meanfun	minfun	maxfun	mea
298	0.213732	0.057705	0.242573	0.141701	0.257984	0.116283	2.113598	7.890927	0.859712	0.084934	...	0.213732	0.133667	0.028319	0.253968	0.8
2403	0.212190	0.043190	0.215153	0.188957	0.245644	0.056687	1.862573	6.109790	0.877669	0.314398	...	0.212190	0.139942	0.047198	0.279070	1.9

2 rows × 21 columns

two duplicate row ,Just Drop That duplicate row

In [12]:
```
df.drop(df[df.duplicated()].index,axis=0,inplace=True)
```

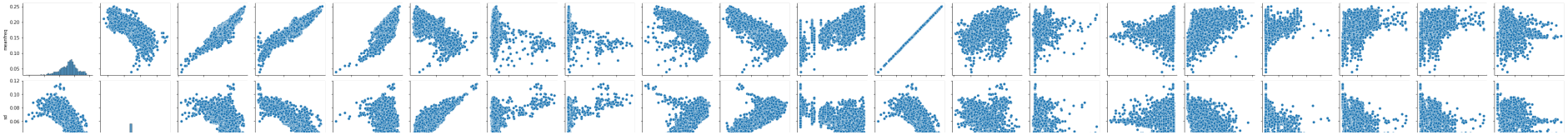
In [13]:
```
df.shape
```

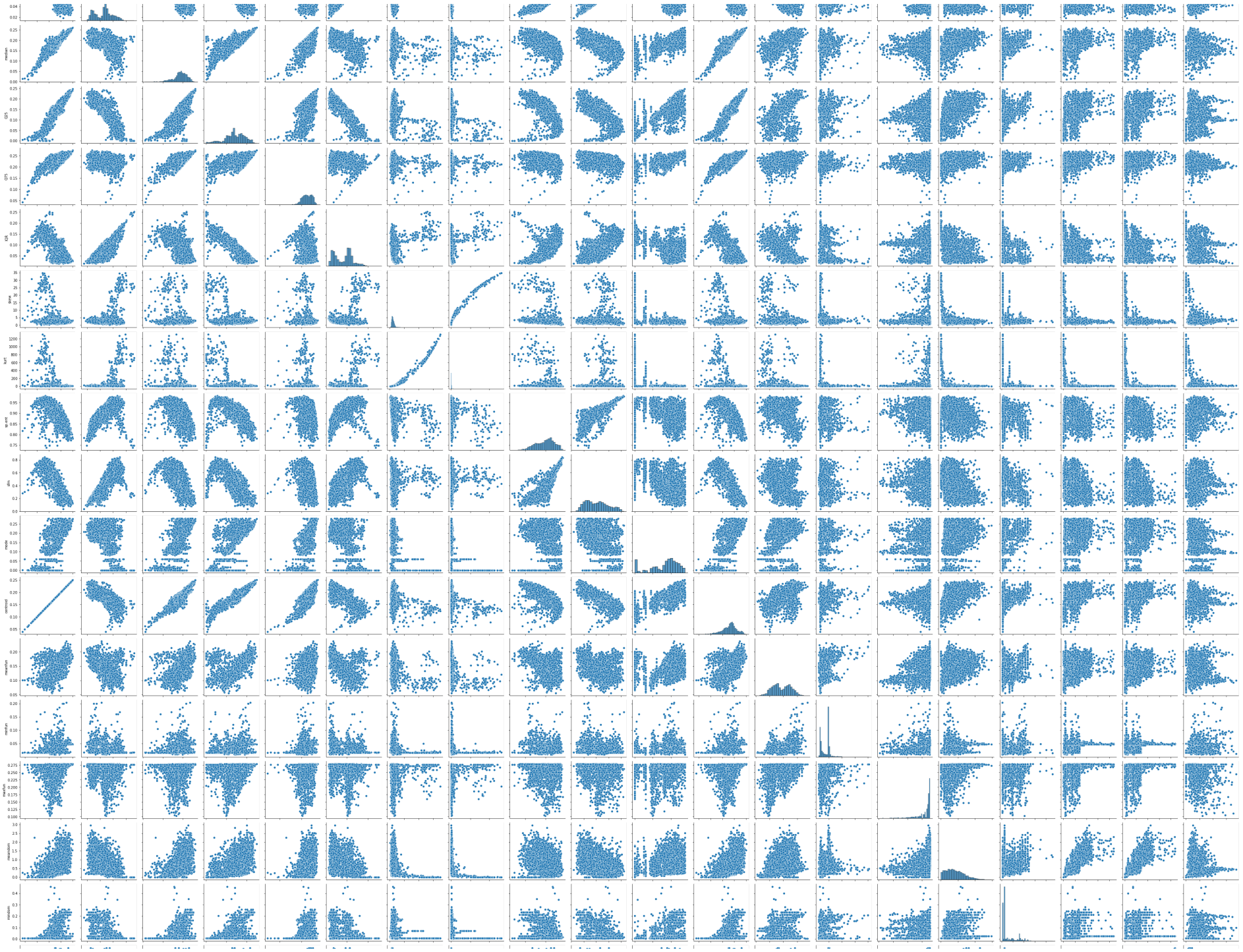
Out[13]:
```
(3166, 21)
```

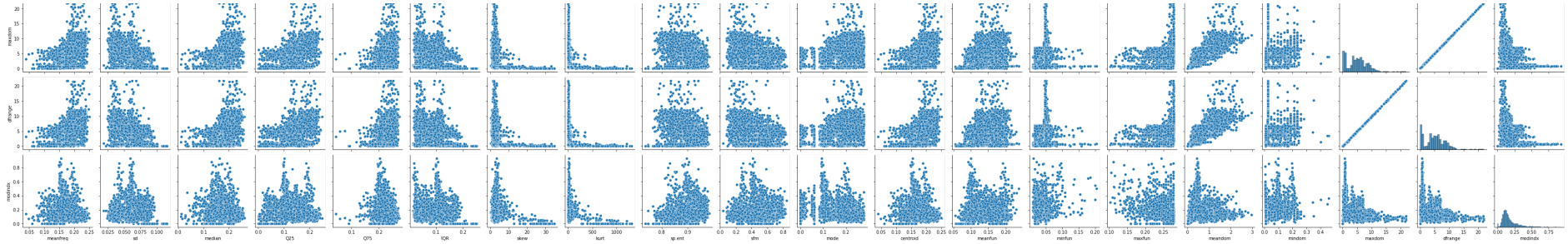
View Relationship between Data point in dataset

In [14]:
```
sns.pairplot(data= df)
```

Out[14]:
```
<seaborn.axisgrid.PairGrid at 0x2f390c6dc10>
```




median
Q25
Q75
IQR
skew
kurt
prcnt
dfm
mode
centroid
meanfun
minfun
maxfun
meandom
mindom



From above figure we can say that most of datapoints are not linearly co- related with each other

Statistical Summary of data

In [15]:
```
df.describe()
```

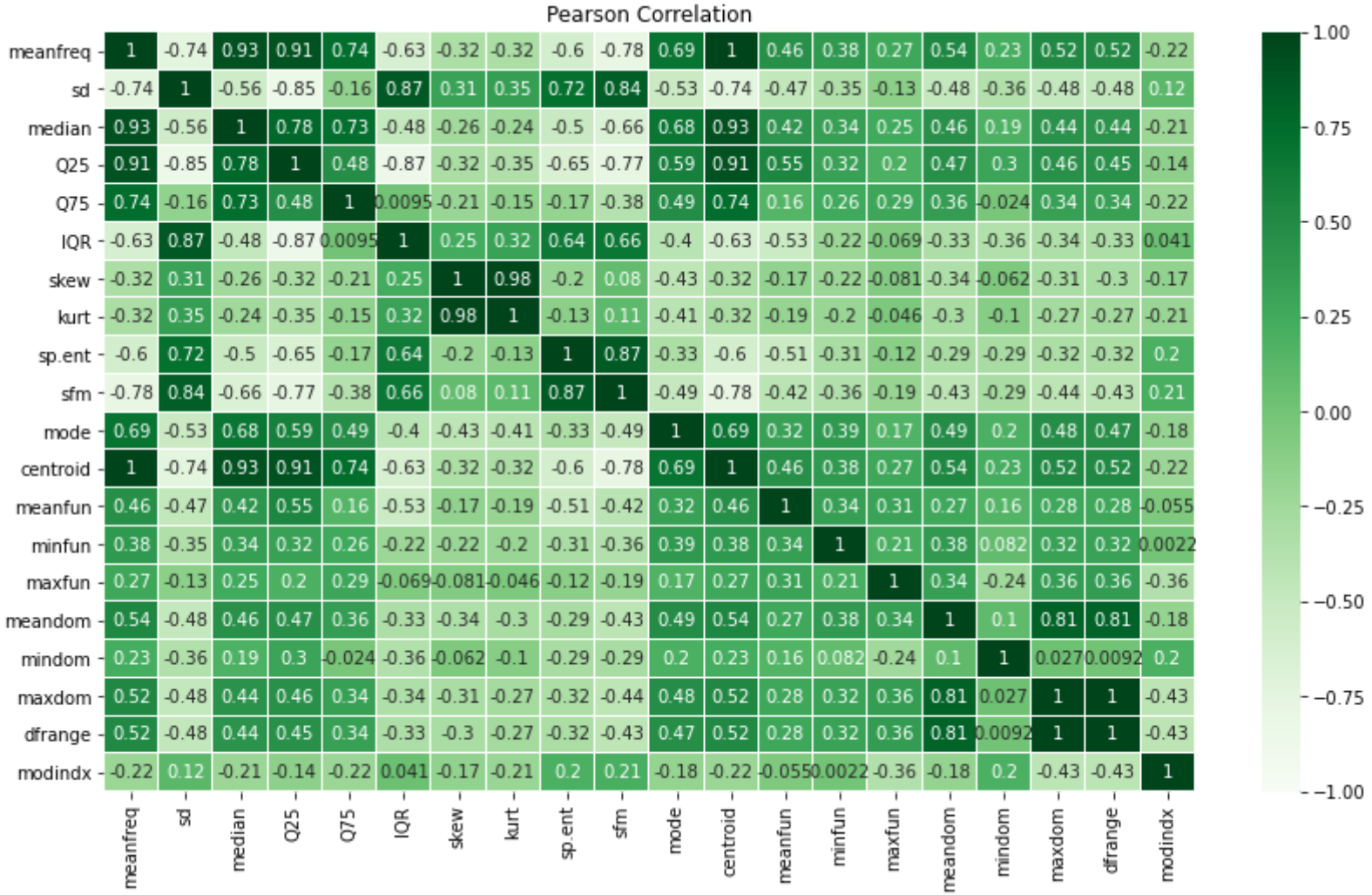
Out[15]:

	meanfreq	sd	median	Q25	Q75	IQR	skew	kurt	sp.ent	sfm	mode	
count	3166.000000	3166.000000	3166.000000	3166.000000	3166.000000	3166.000000	3166.000000	3166.000000	3166.000000	3166.000000	3166.000000	3
mean	0.180886	0.057130	0.185593	0.140440	0.224748	0.084308	3.140895	36.587139	0.895144	0.408348	0.165248	
std	0.029916	0.016656	0.036354	0.048687	0.023636	0.042790	4.241768	134.969236	0.044988	0.177476	0.077212	
min	0.039363	0.018363	0.010975	0.000229	0.042946	0.014558	0.141735	2.068455	0.738651	0.036876	0.000000	
25%	0.163649	0.041942	0.169578	0.111086	0.208740	0.042538	1.649353	5.666817	0.861823	0.258126	0.118008	
50%	0.184814	0.059162	0.190016	0.140255	0.225668	0.094280	2.197623	8.327893	0.901823	0.396472	0.186530	
75%	0.199118	0.067023	0.210588	0.175931	0.243640	0.114168	2.932527	13.649803	0.928717	0.533795	0.221070	
max	0.251124	0.115273	0.261224	0.247347	0.273469	0.252225	34.725453	1309.612887	0.981997	0.842936	0.280000	

Finding the correlation between variables

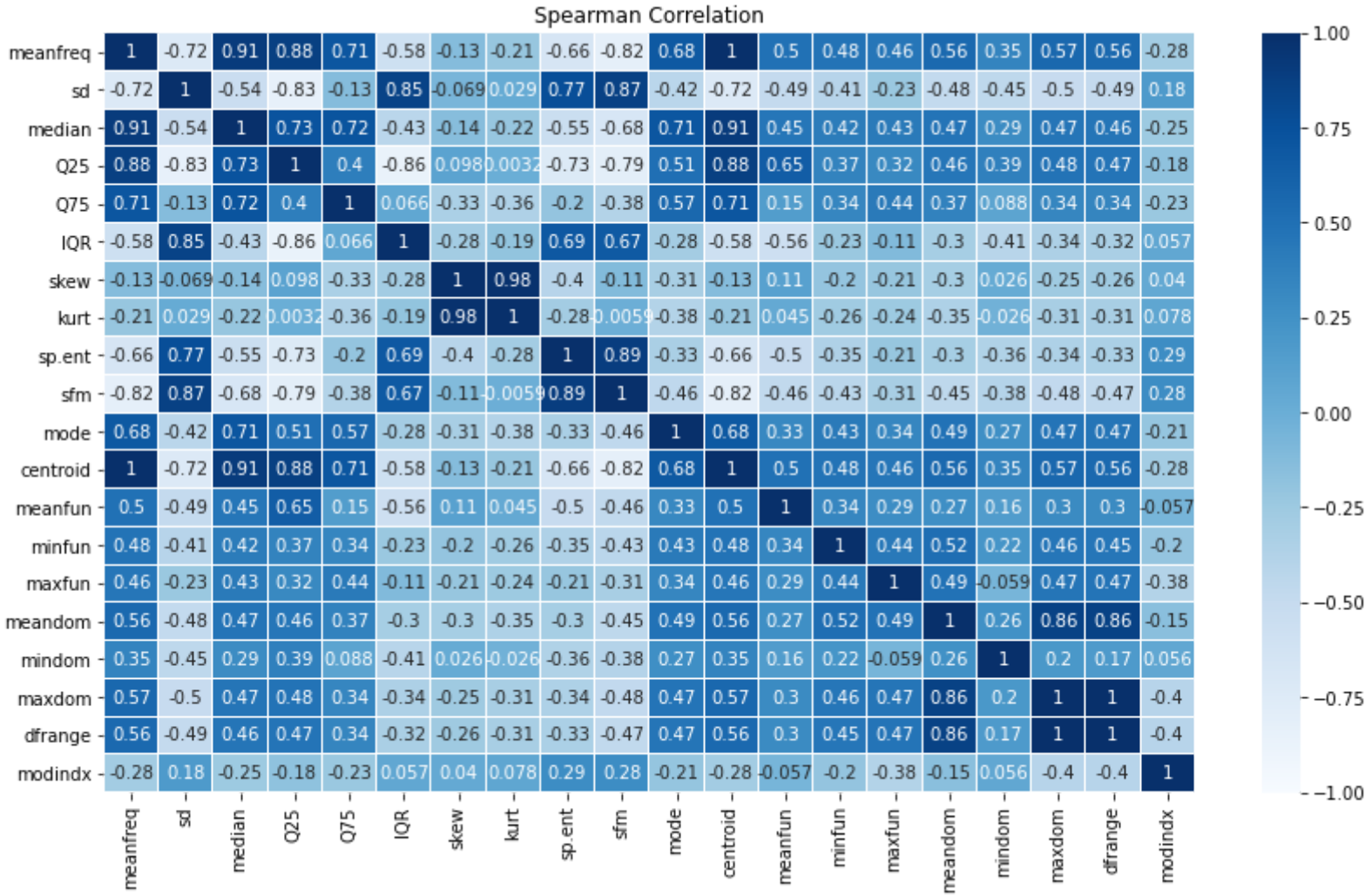
In [16]:
```
pearsonCorr = df.corr(method='pearson')
spearmanCorr = df.corr(method='spearman')
fig = plt.subplots(figsize=(14,8))
sns.heatmap(pearsonCorr, vmin=-1,vmax=1, cmap = "Greens", annot=True, linewidth=0.1)
plt.title("Pearson Correlation")
```

Out[16]: Text(0.5, 1.0, 'Pearson Correlation')



In [17]:
```
fig = plt.subplots(figsize=(14,8))
sns.heatmap(spearmanCorr, vmin=-1,vmax=1, cmap = "Blues", annot=True, linewidth=0.1)
plt.title("Spearman Correlation")
```

Out[17]: Text(0.5, 1.0, 'Spearman Correlation')



In [18]:
```
df.label.unique()
```

Out[18]:
```
array(['male', 'female'], dtype=object)
```

Value count of target variable

In [19]:
```
df.label.value_counts()
```

Out[19]:
```
female    1583
male      1583
Name: label, dtype: int64
```

Thus we can see there are equal number of male and female labels

Label Encoding

In [20]:
```
le = LabelEncoder()
df['label'] =le.fit_transform(df['label'])
```

In [21]:
```
df.label.unique()
```

Out[21]:
```
array([1, 0])
```

Model Building

In [22]:
```
X =df.drop(['label'], axis =1)
Y = df['label']
```

Data Standardisation

In [23]:
```
scaler = StandardScaler()
```

In [24]:
```
X = scaler.fit_transform(X)
```

In [25]:
```
X =pd.DataFrame(X,columns=df.columns[:-1])
X.head()
```

Out[25]:

	meanfreq	sd	median	Q25	Q75	IQR	skew	kurt	sp.ent	sfm	mode	centroid	meanfun	minfun	r
0	-4.048763	0.427014	-4.224894	-2.575370	-5.693565	-0.214711	2.292464	1.762278	-0.039446	0.470952	-2.140524	-4.048763	-1.811609	-1.097704	0.

	meanfreq	sd	median	Q25	Q75	IQR	skew	kurt	sp.ent	sfm	mode	centroid	meanfun	minfun	r
1	-3.840558	0.611291	-3.999247	-2.486167	-5.588933	-0.258411	4.546556	4.431537	-0.065595	0.593839	-2.140524	-3.840558	-1.079386	-1.091241	-0.
2	-3.462553	1.603266	-4.095821	-2.706234	-3.928446	0.909211	6.511582	7.323867	-1.083891	0.397619	-2.140524	-3.462553	-1.365073	-1.100102	0.
3	-0.991527	0.899560	-0.758836	-0.900952	-0.710567	0.632620	-0.449899	-0.240166	1.515717	1.797051	-1.054015	-0.991527	-1.666580	-0.988666	-0.
4	-1.530036	1.322037	-1.676492	-1.267871	-0.791400	1.005458	-0.480942	-0.239006	1.707634	2.114531	-0.789983	-1.530036	-1.127011	-1.033737	0.

In [26]:
```
X_train,X_test,y_train,y_test = train_test_split(X,Y,test_size=0.2,random_state=42)
```

In [27]:
```
X_train.shape,X_test.shape,y_train.shape,y_test.shape
```

Out[27]:
```
((2532, 20), (634, 20), (2532,), (634,))
```

In [38]:
```
for k in range(2,11):
    neigh = KNeighborsClassifier(n_neighbors = k).fit(X_train,y_train)
    print("K = ",k)
    print('Trainig Accuracy Score: ', neigh.score(X_train,y_train))
    print('Testing Accuracy Score: ', neigh.score(X_test,y_test))
    print('*'*35)
```

```
K =  2
Trainig Accuracy Score:  0.9861769352290679
Testing Accuracy Score:  0.9763406940063092
***********************************
K =  3
Trainig Accuracy Score:  0.9881516587677726
Testing Accuracy Score:  0.9794952681388013
***********************************
K =  4
Trainig Accuracy Score:  0.9865718799368088
Testing Accuracy Score:  0.9794952681388013
***********************************
K =  5
Trainig Accuracy Score:  0.9838072669826224
Testing Accuracy Score:  0.9794952681388013
***********************************
K =  6
```

```
Trainig Accuracy Score:  0.9830173775671406
Testing Accuracy Score:  0.9779179810725552
**********************************
K =  7
Trainig Accuracy Score:  0.9806477093206951
Testing Accuracy Score:  0.9716088328075709
**********************************
K =  8
Trainig Accuracy Score:  0.9806477093206951
Testing Accuracy Score:  0.9763406940063092
**********************************
K =  9
Trainig Accuracy Score:  0.9774881516587678
Testing Accuracy Score:  0.9747634069400631
**********************************
K =  10
Trainig Accuracy Score:  0.976303317535545
Testing Accuracy Score:  0.9716088328075709
**********************************
```

for K = 3 Trainig Accuracy Score: 0.9881516587677726 and Testing Accuracy Score: 0.9794952681388013 is highest Accuracy

In [44]:
```
KNN = KNeighborsClassifier(n_neighbors=3).fit(X_train,y_train)
```

In [47]:
```
ypred_test = KNN.predict(X_test)
ypred[0:5]
```

Out[47]:
```
array([1, 1, 1, 0, 0])
```

In [48]:
```
ypred_train = KNN.predict(X_train)
ypred[0:5]
```

Out[48]:
```
array([1, 1, 1, 0, 0])
```

Predict of Train Dataset

In [49]:
```
Accuracy_train=metrics.accuracy_score(y_train,ypred_train )
precision_train=metrics.precision_score(y_train,ypred_train)
recall_train=metrics.recall_score(y_train,ypred_train)
```

```
f1_score_train=metrics.f1_score(y_train,ypred_train)
roc_auc_train=metrics.roc_auc_score(y_train,ypred_train)
```

In [50]:

```
print("Model Name = KNN")
print("Accuracy is =",Accuracy_train)
print("Precision score is =",precision_train)
print("Recall score = ",recall_train)
print("f1 SCore score is = ",f1_score_train)
print("Roc_Auc score is= ",roc_auc_train)
```

```
Model Name = KNN
Accuracy is = 0.9881516587677726
Precision score is = 0.988791032826261
Recall score =  0.9872102318145484
f1 SCore score is =  0.988
Roc_Auc score is=  0.9881406350329572
```

Predict on X_test

In [51]:

```
Accuracy_test=metrics.accuracy_score(y_test,ypred_test)
precision_test=metrics.precision_score(y_test,ypred_test)
recall_test=metrics.recall_score(y_test,ypred_test)
f1_score_test=metrics.f1_score(y_test,ypred_test)
roc_auc_test=metrics.roc_auc_score(y_test,ypred_test)
```

In [52]:

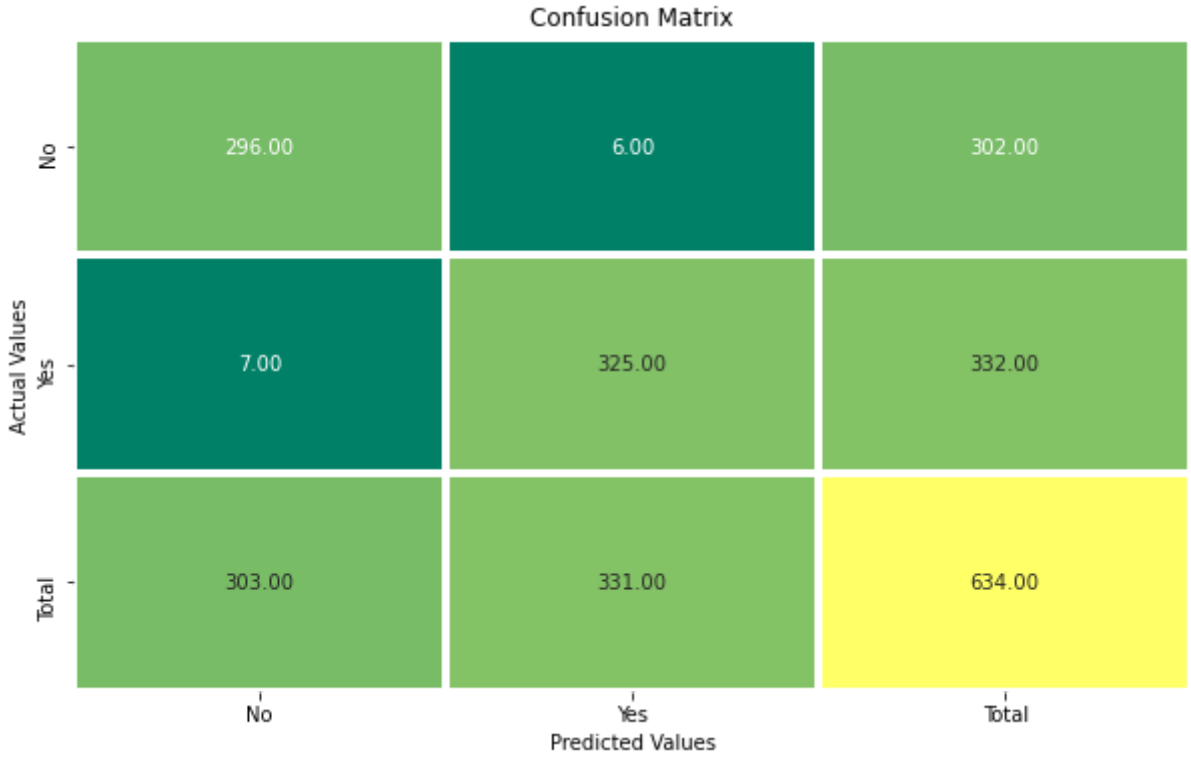
```
print("Model Name = KNN")
print("Accuracy is ",Accuracy_test)
print("Precision score is ",precision_test)
print("Recall _score is",recall_test)
print("f1 SCore score is ",f1_score_test)
print("Roc_Auc score is",roc_auc_test)
```

```
Model Name = KNN
Accuracy is  0.9794952681388013
Precision score is  0.9818731117824774
Recall _score is 0.9789156626506024
f1 SCore score is  0.9803921568627451
Roc_Auc score is 0.9795240564908642
```

Confusion Matrix

In [53]:
```
label=['No','Yes']
```

In [55]:
```
# confusion matrix
cm = confusion_matrix(y_test,ypred_test)
row_sum = cm.sum(axis=0)
cm = np.append(cm,row_sum.reshape(1,-1),axis=0)
col_sum = cm.sum(axis=1)
cm = np.append(cm,col_sum.reshape(-1,1),axis=1)
labels = label+['Total']
plt.figure(figsize=(10,6))
sns.heatmap(cm,annot=True,cmap='summer',fmt='0.2f',xticklabels=labels,
yticklabels=labels,linewidths=3,cbar=None,)
plt.xlabel('Predicted Values')
plt.ylabel('Actual Values')
plt.title('Confusion Matrix')
plt.show()
```



Classification Report

In [57]:
```
print('*'*30+'Classifcation Report'+'*'*30+'\n\n')
cr = classification_report(y_test,ypred_test)
print(cr)
```

```
******************************Classifcation Report******************************


              precision    recall  f1-score   support

           0       0.98      0.98      0.98       302
           1       0.98      0.98      0.98       332

    accuracy                           0.98       634
   macro avg       0.98      0.98      0.98       634
weighted avg       0.98      0.98      0.98       634
```

Conclusion

Thus we have successfully completed the implementation of KNN Classifier on Voice dataset with 97% accuracy

In [ ]: