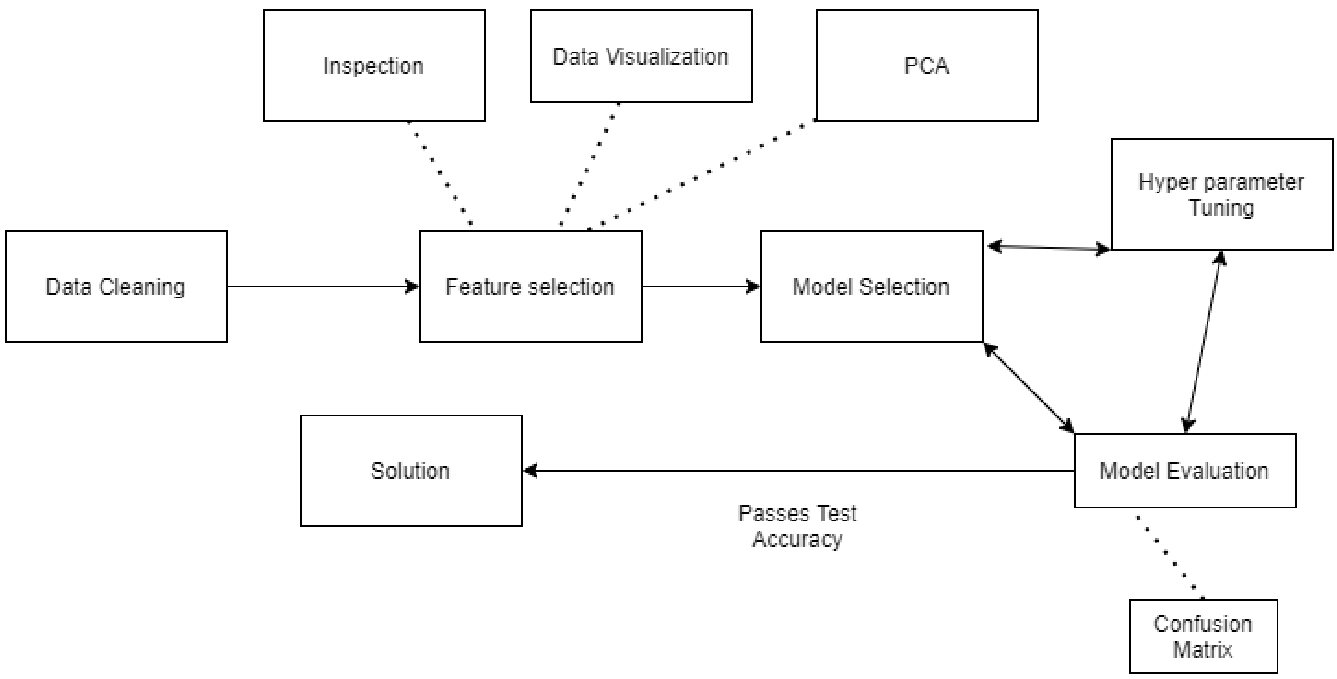
SVM

Methodology

- ###### **Data Cleaning:** Checking for null values and based on their number either droping them or replacing with mean, median, mode based on the type and description of data. Droping decscrete and catagorical variables that have highly skewed histograms.
- ###### **Data Visualization:** This step helps understand the understand the data in a visually. We can understand normality of the data as well. This helps us to decide whether to normalize the data. In case of catagorical variables it also helps in feature selection.
- ###### **Feature Selection:** Based on the Pearson correlation between the labeled column and rest of the features. In general, a very great correlation should have an absolute value greater than 0.75. When the labeled column is depended on multiple columns, the correlation with one column may be less. But combined features may have higher effect.
- ###### **Train Test Split:** We split the data into 80:20 ratio for tarining testing respectively.
- ###### **Model Selection:** Based on the data visualization and data correlation, we need to select a model that would best suit. Here we need to use SVM.
- ###### **Evalution:** In this case we are using F1 Score to determine the accuracy of the predicting model.



In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]:

```
from google.colab import drive
drive.mount('/content/drive')
```

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

In [3]:

```
df = pd.read_excel("drive/My Drive/voice.xlsx")
```

In [4]:

```
df
```

Out[4]:

	meanfreq	sd	median	Q25	Q75	IQR	skew	kurt	sp.ent	sfm	mode	cen
0	0.059781	0.064241	0.032027	0.015071	0.090193	0.075122	12.863462	274.402906	0.893369	0.491918	0.000000	0.05
1	0.066009	0.067310	0.040229	0.019414	0.092666	0.073252	22.423285	634.613855	0.892193	0.513724	0.000000	0.06
2	0.077316	0.083829	0.036718	0.008701	0.131908	0.123207	30.757155	1024.927705	0.846389	0.478905	0.000000	0.07
3	0.151228	0.072111	0.158011	0.096582	0.207955	0.111374	1.232831	4.177296	0.963322	0.727232	0.083878	0.15
4	0.135120	0.079146	0.124656	0.078720	0.206045	0.127325	1.101174	4.333713	0.971955	0.783568	0.104261	0.13
...	...	...	...	...	...	...	...	...	...	...	...	
3163	0.131884	0.084734	0.153707	0.049285	0.201144	0.151859	1.762129	6.630383	0.962934	0.763182	0.200836	0.13
3164	0.116221	0.089221	0.076758	0.042718	0.204911	0.162193	0.693730	2.503954	0.960716	0.709570	0.013683	0.11
3165	0.142056	0.095798	0.183731	0.033424	0.224360	0.190936	1.876502	6.604509	0.946854	0.654196	0.008006	0.14
3166	0.143659	0.090628	0.184976	0.043508	0.219943	0.176435	1.591065	5.388298	0.950436	0.675470	0.212202	0.14
3167	0.165509	0.092884	0.183044	0.070072	0.250827	0.180756	1.705029	5.769115	0.938829	0.601529	0.267702	0.16

3168 rows × 21 columns

In [5]:

```
df.isna().sum()
```

Out[5]:

```
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
```

NO Null values

In [7]:

```
df.dtypes
```

Out[7]:

```
meanfreq    float64
sd          float64
median      float64
Q25         float64
Q75         float64
IQR         float64
skew        float64
kurt        float64
sp.ent      float64
sfm         float64
```

```
mode          float64
centroid      float64
meanfun       float64
minfun        float64
maxfun        float64
meandom       float64
mindom        float64
maxdom        float64
dfrange       float64
modindx       float64
label          object
dtype: object
```

In [8]:

```
df["label"]=df["label"].replace('male',1)
df["label"]=df["label"].replace('female',2)
df["label"].unique()
```

Out[8]:

```
array([1, 2])
```

In [9]:

```
df.dtypes
```

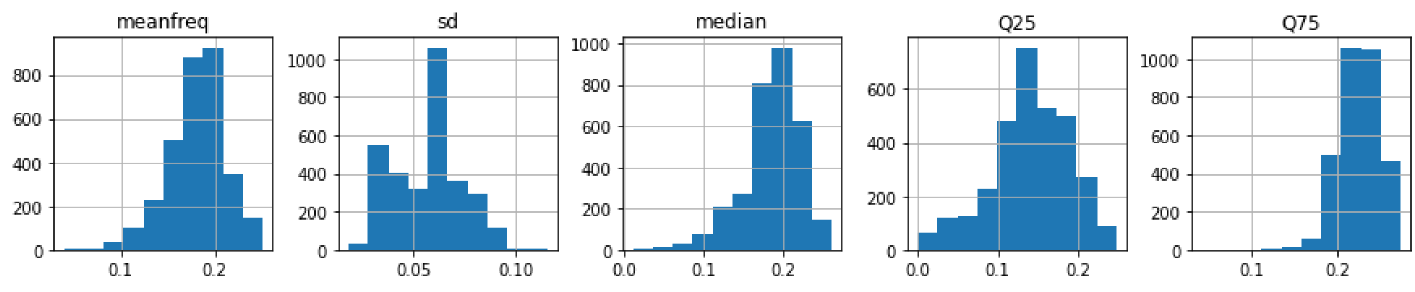
Out[9]:

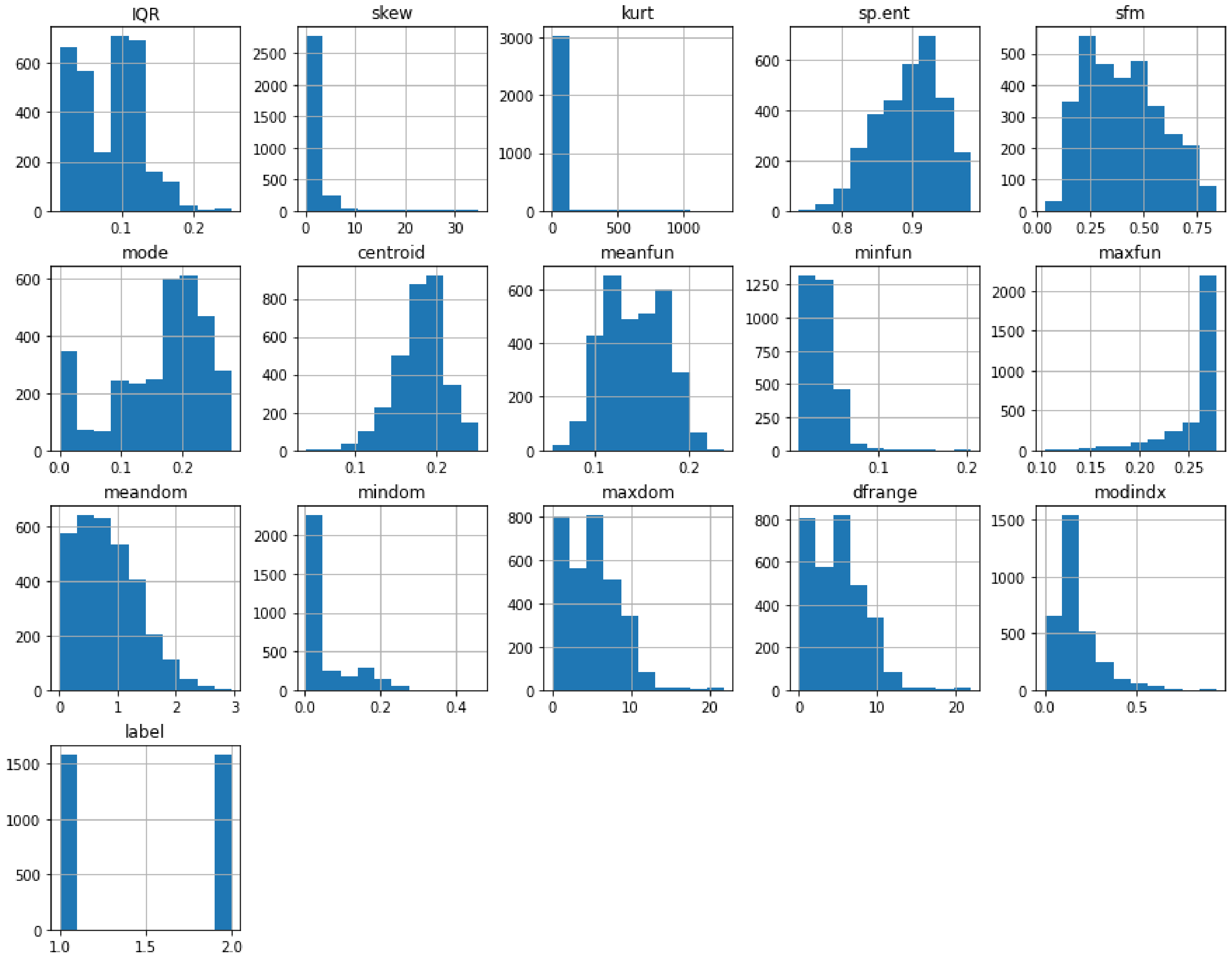
```
meanfreq      float64
sd            float64
median        float64
Q25           float64
Q75           float64
IQR           float64
skew          float64
kurt          float64
sp.ent        float64
sfm           float64
mode          float64
centroid      float64
meanfun       float64
minfun        float64
maxfun        float64
meandom       float64
mindom        float64
maxdom        float64
dfrange       float64
modindx       float64
label           int64
dtype: object
```

In [12]:

```
c=list(df)
fig=plt.figure(figsize=(15,15))
ax=fig.gca()
df[c].hist(ax=ax)
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:4: UserWarning: To output mu
ltiple subplots, the figure containing the passed axes is being cleared
  after removing the cwd from sys.path.
```





Kurtand skew has most of the values as only one value so removing it will not make any difference in decision making.

The label data is balanced, so no need for sampling.

In [13]:

```
df=df.drop(["kurt","skew"],axis=1)
df
```

Out[13]:

	meanfreq	sd	median	Q25	Q75	IQR	sp.ent	sfm	mode	centroid	meanfun	minfun
0	0.059781	0.064241	0.032027	0.015071	0.090193	0.075122	0.893369	0.491918	0.000000	0.059781	0.084279	0.015702
1	0.066009	0.067310	0.040229	0.019414	0.092666	0.073252	0.892193	0.513724	0.000000	0.066009	0.107937	0.015826
2	0.077316	0.083829	0.036718	0.008701	0.131908	0.123207	0.846389	0.478905	0.000000	0.077316	0.098706	0.015656
3	0.151228	0.072111	0.158011	0.096582	0.207955	0.111374	0.963322	0.727232	0.083878	0.151228	0.088965	0.017798
4	0.135120	0.079146	0.124656	0.078720	0.206045	0.127325	0.971955	0.783568	0.104261	0.135120	0.106398	0.016931
...	...	...	...	...	...	...	...	...	...	...	...	...
3163	0.131884	0.084734	0.153707	0.049285	0.201144	0.151859	0.962934	0.763182	0.200836	0.131884	0.182790	0.083770
3164	0.116221	0.089221	0.076758	0.042718	0.204911	0.162193	0.960716	0.709570	0.013683	0.116221	0.188980	0.034409
3165	0.142056	0.095798	0.183731	0.033424	0.224360	0.190936	0.946854	0.654196	0.008006	0.142056	0.209918	0.039506
3166	0.143659	0.090628	0.184976	0.043508	0.219943	0.176435	0.950436	0.675470	0.212202	0.143659	0.172375	0.034483
3167	0.165509	0.092884	0.183044	0.070072	0.250827	0.180756	0.938829	0.601529	0.267702	0.165509	0.185607	0.062257

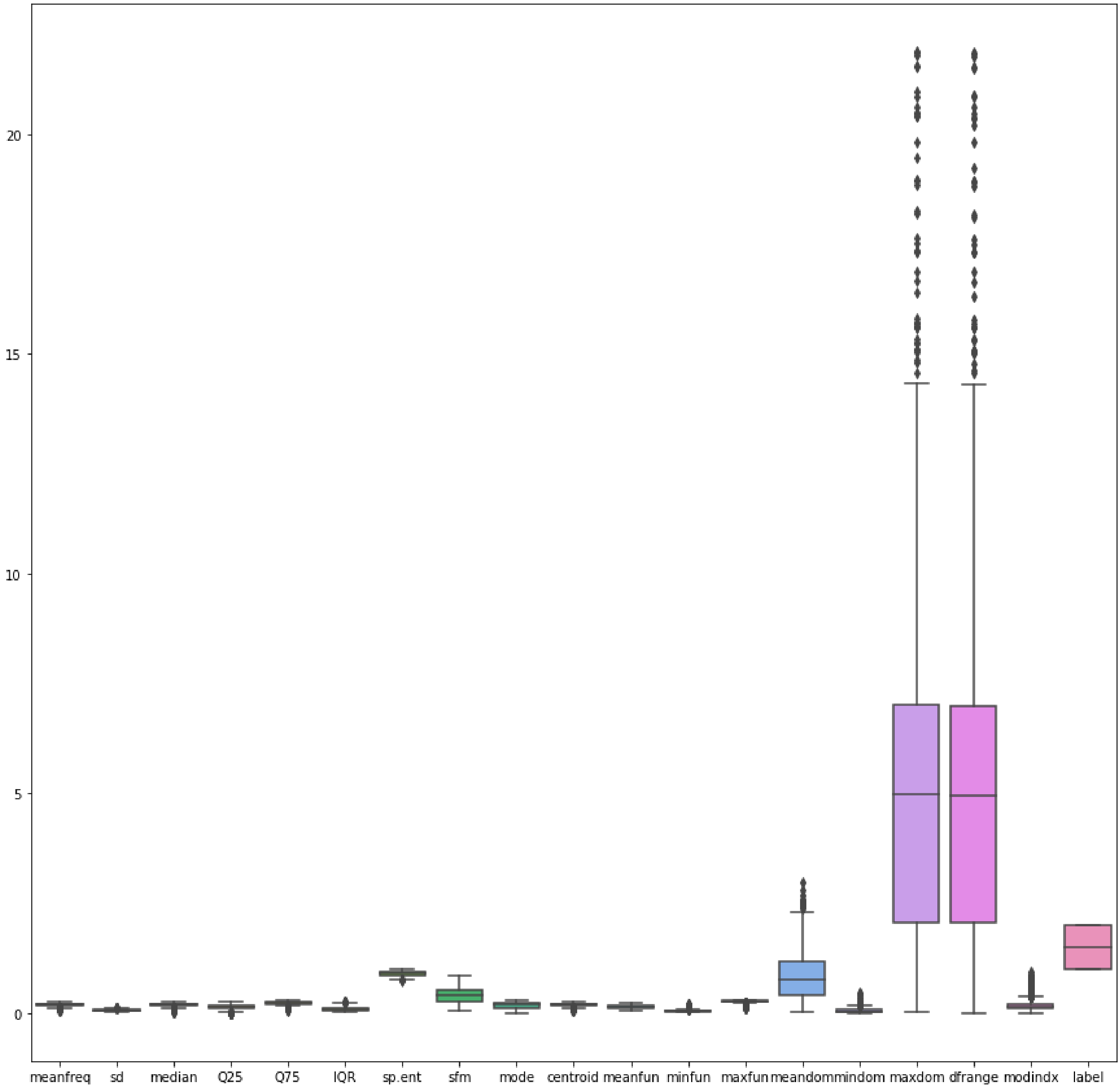
3168 rows × 19 columns

In [20]:

```python
import seaborn as sns
ax=plt.figure(figsize=(15,15))
sns.boxplot(data=df)
```

Out[20]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f36455f20b8>

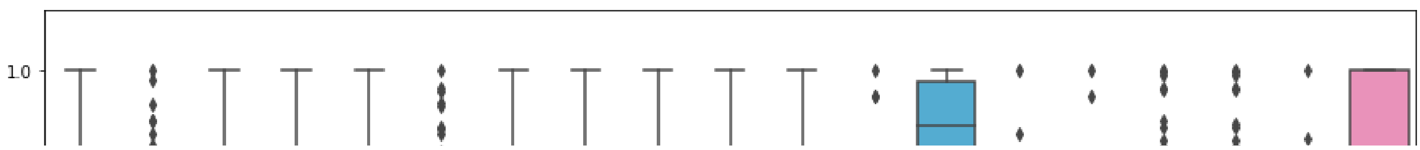


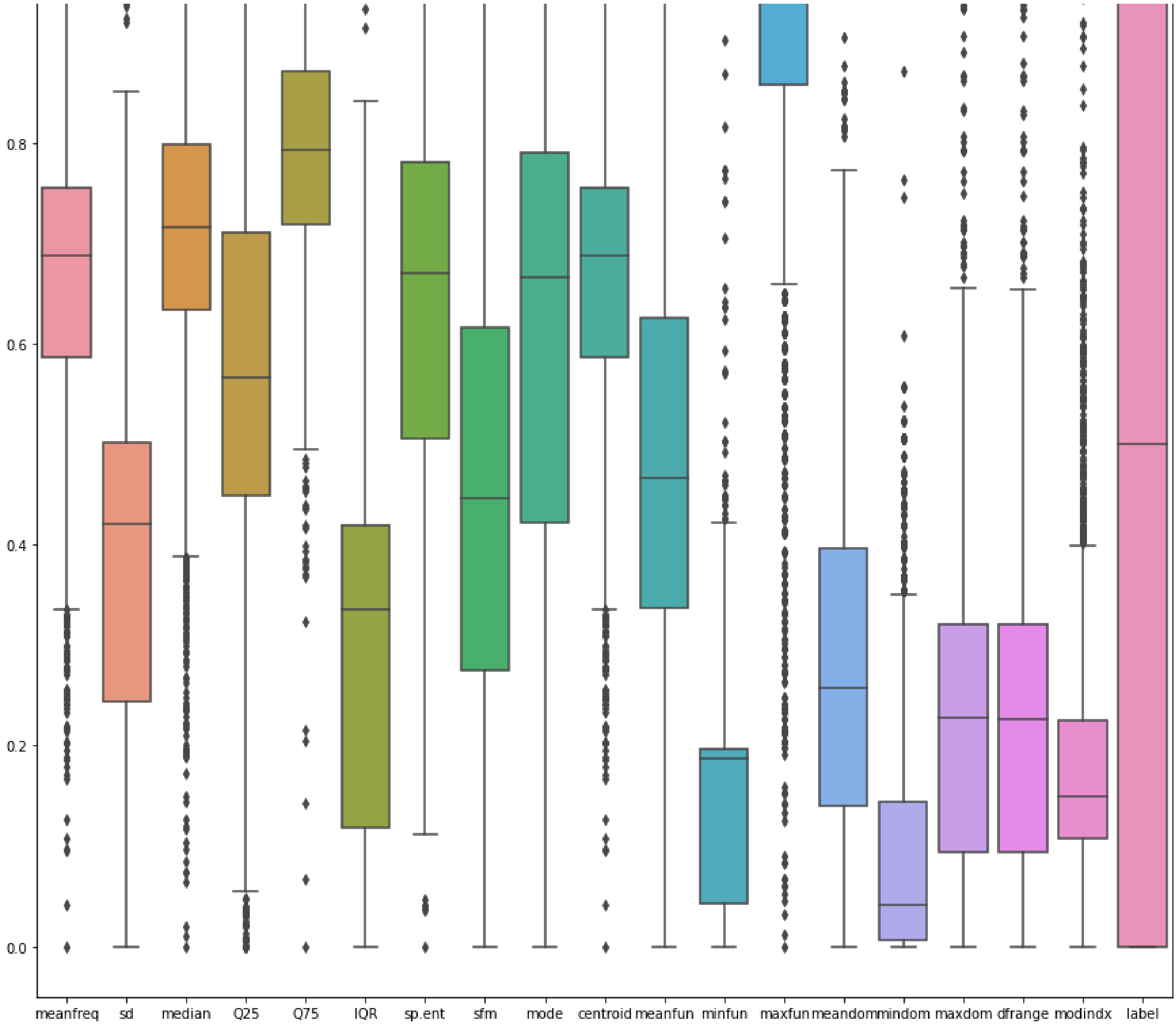
In [21]:

```python
df_norm = (df - df.min()) / (df.max() - df.min())
ax=plt.figure(figsize=(15,15))
sns.boxplot(data=df_norm) # boxplot for normalized data
```

Out[21]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f36457f9898>





In [22]:

```
cols = [col for col in df.columns if col not in ["label"]]
X = df[cols]
y = df["label"]
```

In [23]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

Logistic

In [24]:

```
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression(random_state=0).fit(X_train, y_train)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: Convergence
Warning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

In [25]:

```
from sklearn.metrics import classification_report
p_train = clf.predict(X_train)
p_test = clf.predict(X_test)
```

In [27]:

```
print(classification_report(y_train, p_train, target_names=["male","female"])) # report
on train data
```

```
              precision    recall  f1-score   support

        male       0.87      0.98      0.92      1279
      female       0.97      0.85      0.90      1255

    accuracy                           0.91      2534
   macro avg       0.92      0.91      0.91      2534
weighted avg       0.92      0.91      0.91      2534
```

In [28]:

```
print(classification_report(y_test, p_test, target_names=["male","female"])) # report on
test data
```

```
              precision    recall  f1-score   support

        male       0.83      0.98      0.90       305
      female       0.97      0.82      0.89       329

    accuracy                           0.90       634
   macro avg       0.90      0.90      0.90       634
weighted avg       0.91      0.90      0.90       634
```

In [31]:

```
from sklearn.metrics import confusion_matrix
confm=confusion_matrix(y_test, p_test, labels=[1,2]) # confusion matrix on test data
confm
```

Out[31]:

```
array([[298,   7],
       [ 59, 270]])
```

There is less variance in the model

SVM

In [33]:

```
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
param_grid = {'C' : [0.01, 0.1, 1, 10], 'kernel': ('rbf', 'linear')}
classifier = SVC()
grid_search = GridSearchCV(estimator=classifier, param_grid=param_grid, scoring='accurac
y', n_jobs=-1, verbose=42)
grid_search.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done   1 tasks      | elapsed:    1.7s
[Parallel(n_jobs=-1)]: Done   2 tasks      | elapsed:    1.7s
[Parallel(n_jobs=-1)]: Done   3 tasks      | elapsed:    2.2s
[Parallel(n_jobs=-1)]: Done   4 tasks      | elapsed:    2.2s
[Parallel(n_jobs=-1)]: Done   5 tasks      | elapsed:    2.4s
[Parallel(n_jobs=-1)]: Done   6 tasks      | elapsed:    2.6s
[Parallel(n_jobs=-1)]: Done   7 tasks      | elapsed:    2.6s
[Parallel(n_jobs=-1)]: Done   8 tasks      | elapsed:    2.8s
```

```
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:    2.9s
[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:    3.0s
[Parallel(n_jobs=-1)]: Done  11 tasks      | elapsed:    3.3s
[Parallel(n_jobs=-1)]: Done  12 tasks      | elapsed:    3.4s
[Parallel(n_jobs=-1)]: Done  13 tasks      | elapsed:    3.6s
[Parallel(n_jobs=-1)]: Done  14 tasks      | elapsed:    3.8s
[Parallel(n_jobs=-1)]: Done  15 tasks      | elapsed:    4.0s
[Parallel(n_jobs=-1)]: Done  16 tasks      | elapsed:    4.1s
[Parallel(n_jobs=-1)]: Done  17 tasks      | elapsed:    4.3s
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:    4.4s
[Parallel(n_jobs=-1)]: Done  19 tasks      | elapsed:    4.6s
[Parallel(n_jobs=-1)]: Done  20 tasks      | elapsed:    4.6s
[Parallel(n_jobs=-1)]: Done  21 tasks      | elapsed:    4.9s
[Parallel(n_jobs=-1)]: Done  22 tasks      | elapsed:    5.0s
[Parallel(n_jobs=-1)]: Done  23 tasks      | elapsed:    5.3s
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:    5.4s
[Parallel(n_jobs=-1)]: Done  25 tasks      | elapsed:    5.7s
[Parallel(n_jobs=-1)]: Done  26 tasks      | elapsed:    5.8s
[Parallel(n_jobs=-1)]: Done  27 tasks      | elapsed:    6.1s
[Parallel(n_jobs=-1)]: Done  28 tasks      | elapsed:    6.3s
[Parallel(n_jobs=-1)]: Done  29 tasks      | elapsed:    6.5s
[Parallel(n_jobs=-1)]: Done  30 tasks      | elapsed:    6.8s
[Parallel(n_jobs=-1)]: Done  31 tasks      | elapsed:    6.9s
[Parallel(n_jobs=-1)]: Done  32 tasks      | elapsed:    7.1s
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:    7.2s
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    7.5s
[Parallel(n_jobs=-1)]: Done  35 tasks      | elapsed:    7.6s
[Parallel(n_jobs=-1)]: Done  36 tasks      | elapsed:    8.2s
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed:    8.2s
[Parallel(n_jobs=-1)]: Done  38 out of  40 | elapsed:    8.9s remaining:    0.5s
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:    9.3s remaining:    0.0s
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:    9.3s finished
```

Out[33]:

```
GridSearchCV(cv=None, error_score=nan,
             estimator=SVC(C=1.0, break_ties=False, cache_size=200,
                           class_weight=None, coef0=0.0,
                           decision_function_shape='ovr', degree=3,
                           gamma='scale', kernel='rbf', max_iter=-1,
                           probability=False, random_state=None, shrinking=True,
                           tol=0.001, verbose=False),
             iid='deprecated', n_jobs=-1,
             param_grid={'C': [0.01, 0.1, 1, 10], 'kernel': ('rbf', 'linear')},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='accuracy', verbose=42)
```

In [34]:

```
p_train = grid_search.predict(X_train)
p_test = grid_search.predict(X_test)
```

In [35]:

```
print(classification_report(y_train, p_train, target_names=["male","female"])) # report on train data
```

```
              precision    recall  f1-score   support

        male       0.96      0.98      0.97      1279
      female       0.98      0.96      0.97      1255

    accuracy                           0.97      2534
   macro avg       0.97      0.97      0.97      2534
weighted avg       0.97      0.97      0.97      2534
```

In [36]:

```
print(classification_report(y_test, p_test, target_names=["male","female"])) # report on test data
```

```
              precision    recall  f1-score   support

        male       0.96      0.96      0.96       305
      female       0.97      0.97      0.97       329

    accuracy                           0.97       634
   macro avg       0.97      0.97      0.97       634
weighted avg       0.97      0.97      0.97       634
```

In [37]:

```
from sklearn.metrics import confusion_matrix
confm=confusion_matrix(y_test, p_test, labels=[1,2]) # confusion matrix on test data
confm
```

Out[37]:

```
array([[294,  11],
       [ 11, 318]])
```

The error has redused and the accuracy increased in both classes. The model has better bias and variance scores than Logistic regression.

In [ ]: