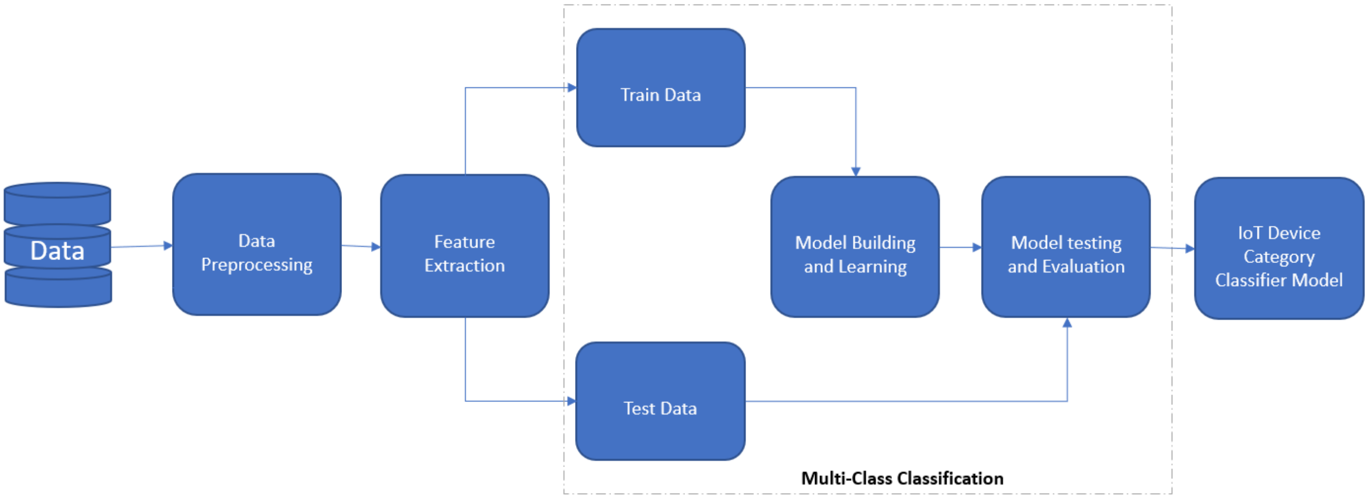
IoT Device Category Classification System using Advanced Deep Learning Techniques

Here in this notebook, we have implemented the Machine Learnig models that we will be comparing with the Deep Neural Network models which we have implemented in a different notebook.

The flow of our model pipeline for MultiClass IoT device classification task is as follows.



Importing required Libraries

```
# Import the libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
from sklearn.model_selection import train_test_split
from sklearn import metrics
```

```
# Getting the data into the dataframe
data = pd.read_csv('iot_data.csv')
```

```
# Let's look at the shape of the data
data.shape
```

```
    (1900, 299)
```

```
# Let's take a look of the names of the feature colums in the data set
data.columns
```

```
    Index(['Unnamed: 0', 'ack', 'ack_A', 'ack_B', 'bytes', 'bytes_A',
           'bytes_A_B_ratio', 'bytes_B', 'ds_field_A', 'ds_field_B',
           ...
           'suffix_is_co.il', 'suffix_is_com', 'suffix_is_com.sg',
           'suffix_is_else', 'suffix_is_empty_char_value',
           'suffix_is_googleapis.com', 'suffix_is_net', 'suffix_is_org',
           'suffix_is_unresolved', 'device_category'],
          dtype='object', length=299)
```

```
# Let's take a look into the first five rows from the data
data.head()
```

	Unnamed: 0	ack	ack_A	ack_B	bytes	bytes_A	bytes_A_B_ratio	bytes_B	ds_field_A	ds_field_B	...	suffix_is_co.il
0	0	9	5	5	1213	743	0.713924	668	0	0	...	0
1	1	9	5	5	1213	743	1.806874	668	0	0	...	0
2	2	9	5	5	1213	743	0.103124	668	0	0	...	0

```
# Removing the first column from the dataset
data = data.drop('Unnamed: 0', axis = 1)


# The updated data
data.head()
```

	ack	ack_A	ack_B	bytes	bytes_A	bytes_A_B_ratio	bytes_B	ds_field_A	ds_field_B	duration	...	suffix_is_co.il
0	9	5	5	1213	743	0.713924	668	0	0	1.5756	...	0
1	9	5	5	1213	743	1.806874	668	0	0	0.6890	...	0
2	9	5	5	1213	743	0.103124	668	0	0	0.9852	...	0
3	9	5	5	1213	743	1.806874	668	0	0	1.5756	...	0
4	9	5	5	1213	743	1.806874	668	0	0	1.5756	...	0

5 rows × 298 columns

```
# Getting the total count, mean, standard deviations, minimum, maxium and values at 25th, 50th and 75th quartile
data.describe()
```

	ack	ack_A	ack_B	bytes	bytes_A	bytes_A_B_ratio	bytes_B	ds_field_A	ds_f
count	1900.000000	1900.000000	1900.000000	1.900000e+03	1.900000e+03	1900.000000	1.900000e+03	1900.0	1900
mean	227.773158	81.211579	146.878947	1.498682e+05	1.421069e+05	1.181570	7.824499e+03	0.0	16
std	4461.164912	1125.546944	3415.513067	4.937287e+06	4.870776e+06	3.477177	7.768975e+04	0.0	28
min	0.000000	0.000000	0.000000	6.000000e+01	0.000000e+00	0.000000	6.000000e+01	0.0	0
25%	0.000000	0.000000	0.000000	2.400000e+02	0.000000e+00	0.000000	2.400000e+02	0.0	0
50%	9.000000	5.000000	5.000000	1.213000e+03	7.430000e+02	0.622177	6.680000e+02	0.0	0
75%	15.000000	7.000000	8.000000	2.411000e+03	1.160000e+03	1.201825	1.096000e+03	0.0	64
max	184378.000000	39265.000000	145113.000000	2.137146e+08	2.108638e+08	73.967293	2.850771e+06	0.0	64

8 rows × 297 columns

Data Cleaning

```
# As we can see some columns have only one value throughout the entire dataset.
# Because such columns will not be able to do better in learning process, we remove them.
for column in data.columns:
  if len(data[column].unique()) == 1:
    print(column, "has only one unique value")
    data = data.drop(column, axis = 1)
```

```
ds_field_A has only one unique value
http_cookie_values_entropy has only one unique value
http_cookie_values_stdev has only one unique value
http_cookie_values_var has only one unique value
http_req_bytes_entropy has only one unique value
http_req_bytes_stdev has only one unique value
http_req_bytes_var has only one unique value
packet_size_B_min has only one unique value
packet_size_min has only one unique value
ssl_handshake_duration_entropy has only one unique value
ssl_handshake_duration_stdev has only one unique value
ssl_handshake_duration_var has only one unique value
ttl_A_entropy has only one unique value
ttl_A_stdev has only one unique value
ttl_A_var has only one unique value
is_g_http has only one unique value
is_cdn_http has only one unique value
is_img_http has only one unique value
```

```
is_ad_http has only one unique value
B_port_is_5222 has only one unique value
B_port_is_5223 has only one unique value
B_port_is_54975 has only one unique value
B_port_is_8280 has only one unique value
B_port_is_9543 has only one unique value
subdomain_is_99sets has only one unique value
subdomain_is_ccc has only one unique value
subdomain_is_feeds has only one unique value
subdomain_is_h10141.www1 has only one unique value
subdomain_is_img has only one unique value
subdomain_is_whp.aus1.cold.extweb has only one unique value
subdomain_is_whp.hou9.cold.extweb has only one unique value
domain_is_epicurious has only one unique value
domain_is_hp has only one unique value
domain_is_hpeprint has only one unique value
domain_is_livecdn has only one unique value
domain_is_mako has only one unique value
domain_is_samsung has only one unique value
suffix_is_biz has only one unique value
suffix_is_cloudfront.net has only one unique value
suffix_is_co.il has only one unique value
suffix_is_com.sg has only one unique value
suffix_is_googleapis.com has only one unique value
suffix_is_net has only one unique value
suffix_is_org has only one unique value
```

```
# The shape of the data after getting rid of feature columns that has only one value throughout
data.shape
```

```
(1900, 254)
```

Let's try to look how many unique categories are there in the data so that we can get a sense of how many categories are there for the classification task of IOT devices.

```
# Let's explore how many unique category of iot devices we have
data['device_category'].unique()
```

```
array(['security_camera', 'TV', 'smoke_detector', 'thermostat',
       'water_sensor', 'watch', 'baby_monitor', 'motion_sensor', 'lights',
       'socket'], dtype=object)
```

We obtained 10 categories/classes of IOT devices that we will be classifying them into based on the learning task.

The 10 categories of IOT devices are:

1. Security Camera
2. TV
3. Smoke Detector
4. Thermostat
5. Water Sensor
6. Watch
7. Baby Monitor
8. Motion Sensor
9. Lights
10. Socket

We will create the Machine learning models that carry out the tasks of learning from the feature columns and help in predicting the correct target category of the IOT devices without any human participation.

Firstly, we seperate the data into features and target variables.

- X is the feature variable containing all the columns.
- y is the target variable containing the corresponding target values for the features.

```
# Splitting the data into features and target variables
X = data.drop('device_category', axis = 1)
y = data.device_category
```

Further, we divide the data into train and test set

- For the train set we have used 80% of the data
- For the test set we have used 20% of the data

```
# Splitting the data into train set (80% of the data) and test set (20% of the data)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Getting the total count, mean, standard deviations, minimum, maxium and values at 25th, 50th and 75th quartile for the X_train.

```
X_train.describe()
```

	ack	ack_A	ack_B	bytes	bytes_A	bytes_A_B_ratio	bytes_B	ds_field_B	du
count	1520.000000	1520.000000	1520.000000	1.520000e+03	1.520000e+03	1520.000000	1520.000000	1520.000000	1520.
mean	138.757895	63.402632	75.673026	4.372133e+04	3.716353e+04	1.137870	6620.691447	17.184211	280.
std	1459.197068	684.681461	798.799471	6.565083e+05	6.412107e+05	3.128233	42824.051349	28.317168	3185.
min	0.000000	0.000000	0.000000	6.000000e+01	0.000000e+00	0.000000	60.000000	0.000000	0.
25%	0.000000	0.000000	0.000000	2.400000e+02	0.000000e+00	0.000000	240.000000	0.000000	1.
50%	9.000000	5.000000	5.000000	1.213000e+03	7.430000e+02	0.622177	668.000000	0.000000	1.
75%	15.250000	7.000000	8.000000	2.411000e+03	1.150250e+03	1.201825	1096.000000	64.000000	1.
max	24718.000000	12359.000000	15898.000000	2.338507e+07	2.302210e+07	63.428067	741540.000000	64.000000	58432.

8 rows × 253 columns

Applying Scaling

As we can see that the minimum values and the maximum values for the fearures are very different in range we will scale them so that model learns better representations from the data.

```
scaler = sklearn.preprocessing.StandardScaler()
```

```
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
X_train
```

```
array([[-0.06770189, -0.06341185, -0.06971881, ...,  0.89138604,
        -0.67729846, -0.20965697],
       [-0.06084655, -0.05464576, -0.06470965, ..., -1.1218484 ,
         1.47645397, -0.20965697],
       [-0.09032451, -0.08386604, -0.09351233, ..., -1.1218484 ,
         1.47645397, -0.20965697],
       ...,
       [-0.09512325, -0.09263212, -0.09476462, ...,  0.89138604,
        -0.67729846, -0.20965697],
       [-0.08552577, -0.08240503, -0.08599859, ..., -1.1218484 ,
         1.47645397, -0.20965697],
       [-0.09512325, -0.09263212, -0.09476462, ..., -1.1218484 ,
         1.47645397, -0.20965697]])
```

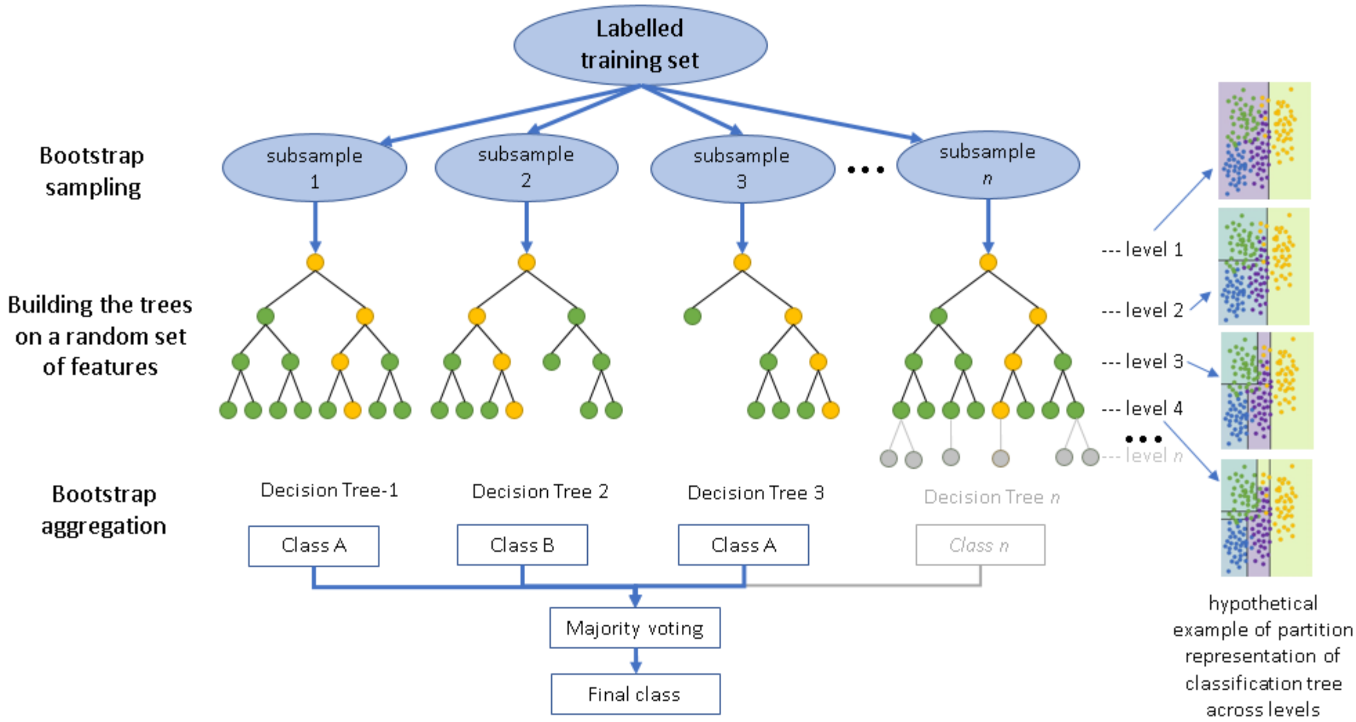
We have defined a utility function that helps to get the total number of misclassified examples by the Machine Learning models.

```
# A utility function
def misclassified_total(cm):
  sum = 0
  for i in range(0, cm.shape[0]):
    for j in range(0, cm.shape[1]):
      if i == j:
        continue
      else:
        sum = sum + cm[i][j]

  return sum
```

Random Forest Classifier

We will use Random Forest Classifier as our first model to learn the features and classify them into 10 IOT device categories.

- We have performed RandomizedSearchCV that will help in finding the best set of Hyperparameters values from the different set of values we provide for experimentation of different hyperparameters.
- This is helpful in returing the best combination of hyperparameters.
- The RandomizedSearchCV doesn't perform the exhaustive search on all the possible comibination of hyperparameters but random select different hyperparameter values and test them.
- This helps in faster execution compared to GridSearchCV.



[Image Reference : https://catalyst.earth/catalyst-system-files/help/COMMON/references/images/RT_schematic.png]

Model 1 (a) : Random Forest Classifier Hyperparameter tuning with Randomized Search CV

```
# Initializing the model
from sklearn.ensemble import RandomForestClassifier
randomForestClassifier = RandomForestClassifier()
```

We have used the 7 hyperparamters that we will experiment on tuning with the help of RandomizedSearchCV.

- n_estimators
- criterion
- min_samples_split
- min_samples_leaf
- max_depth
- max_features
- ccp_alpha

```
# We will try to perform Random Search CV on these set of Hyperparamter values
params = {'n_estimators': [10,30,50,100],
          'criterion': ['gini','entropy'],
          'min_samples_split':[0.1,2],
          'min_samples_leaf': [2,3],
          'max_depth': [2,3,5,10,20,30],
          'max_features': ['sqrt','log2'],
          'ccp_alpha': [0.0,0.001, 0.01,0.1]}
```

```
# Importing RandomizedSerachCV from scikit learn
from sklearn.model_selection import RandomizedSearchCV
```

```
# We initialise the model
```

```
rs_rf_model = RandomizedSearchCV(randomForestClassifier,param_distributions=params,cv=5,n_iter=20,n_jobs=1,verbose=0)

# We will also keep the track of the time that helps in getting the convergence time for each model
import time
```

Now, we will train the Random Forest Classifier model with the help of RandomizedSearchCV.

We will obtain the best set of hyperparameter values and the accuracy that corresponds to those hyperparameter values.

```
# Training the Random Forest Classifier model and getting best set of hyperparameters through RandomizedSearchCV
start_rs_rf_model = time.time()
rs_rf_model.fit(X_train,y_train)
end_rs_rf_model = time.time()

total_time_rs_rf_model = end_rs_rf_model - start_rs_rf_model


print(f"Total time required for Random Forest Classifier model to train with the help of RandomizedSearchCV : {total_time
```

```
Total time required for Random Forest Classifier model to train with the help of RandomizedSearchCV : 11.71s
```

Let's take a look of the accuracy obtained in correctly classifying the trained set with the help of `rs_rf_model`.

```
# Accuracy obtained on train set
rs_rf_accuracy_train = rs_rf_model.score(X_train, y_train)


# Accuracy obtained on the test set
rs_rf_accuracy_test = rs_rf_model.score(X_test, y_test)


# Printing the train and test set accuracy for RandomizedSearchCV Random Forest Classifier model
print(f'The train set accuracy of RandomizedSearchCV Random Forest Classifier model is {rs_rf_accuracy_train*100:.2f}%')
print(f'The test set accuracy of RandomizedSearchCV Random Forest Classifier model is {rs_rf_accuracy_test*100:.2f}%')
```

```
The train set accuracy of RandomizedSearchCV Random Forest Classifier model is 96.25%
The test set accuracy of RandomizedSearchCV Random Forest Classifier model is 85.26%
```

Let's take a look at the hyperparameters that provided the above accuracy for the Random Forest Classifier model which we obtained using the RandomizedSearchCV.

```
# The best hyperparameter values
rs_rf_model.best_params_
```

```
{'ccp_alpha': 0.0,
 'criterion': 'gini',
 'max_depth': 30,
 'max_features': 'log2',
 'min_samples_leaf': 2,
 'min_samples_split': 2,
 'n_estimators': 50}
```

Now, we will try to obtain the predictions for the test set `X_test` data and create a confusion matrix.

The diagonal elements of the confusion matrix are correctly classified categories whereas the other elements are the number of misclassified categories from the predictions on Test set.

```
# Getting predictions for the test set
Y_pred_rs_rf = rs_rf_model.predict(X_test)


# Confusion matrix for RandomizedSearchCV Random Forest Classifier model
cm1_rs_rf_model = metrics.confusion_matrix(y_test, Y_pred_rs_rf)
print(cm1_rs_rf_model)
cm1_rs_rf_model.shape
```

```
[[35  0  0  1  0  0  0  0  0  0]
 [ 1 27  0  0  0  0  0  0  0  0]
 [ 0  0 21  0  0  0 10  0  0  0]
 [ 1  0  0 35  0  0  0  0  0  0]
 [ 0  0  0  0 41  0  0  0  0  0]
 [ 0  0  0  1  0 46  0  0  0  0]
 [ 0  0 18  0  0  0 20  0  0  3]
 [ 0  0  0  0  0  0  0 50  0  0]
 [ 3  0  0  0  0  0  0  0 44  0]
```

```
[ 0  0  7  0  0  0 11  0  0  5]]
(10, 10)
```

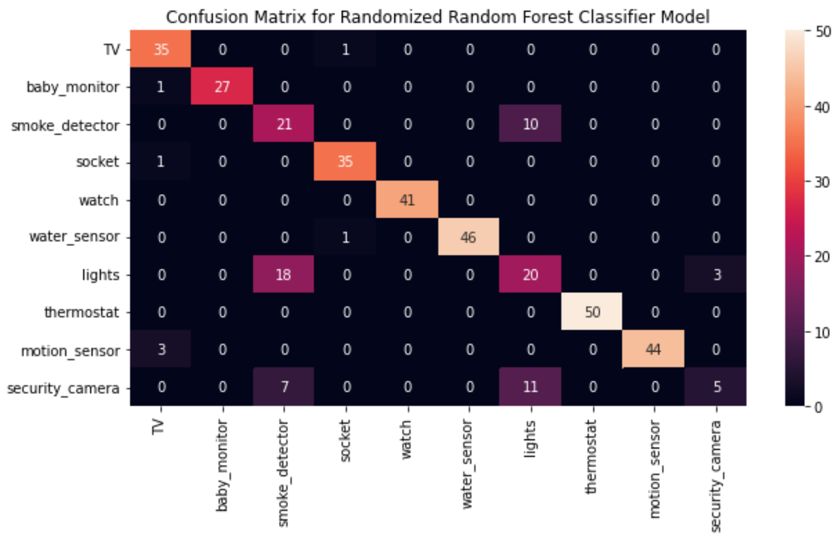
Now, we will get the count of misclassified categories in the predicted targets for the test set.

```
# Getting the count of misclassified categories in the test set prediction
misclassified_rs_rf_model = misclassified_total(cm1_rs_rf_model)
print(f'Number of Misclassified categories by the Randomized Forest Classifier : {misclassified_rs_rf_model}')
```

```
Number of Misclassified categories by the Randomized Forest Classifier : 56
```

Let's create a HeatMap for the Random Forest Classifier Model with the best set of Hyperparameters tuned by RandomizedSearchCV.

```
class_names = ['TV', 'baby_monitor', 'smoke_detector','socket',
              'watch',
              'water_sensor',
              'lights',
              'thermostat',
              'motion_sensor',
              'security_camera']

plt.figure(figsize= (10,5))
hm_rs_rf_model = sns.heatmap(cm1_rs_rf_model, annot=True, fmt="d",  xticklabels=class_names, yticklabels=class_names)
hm_rs_rf_model = hm_rs_rf_model.set_title("Confusion Matrix for Randomized Random Forest Classifier Model")
```



We will perform the Hyperparameter tuning with the help of evolutionary algorithms like genetic algorithm and try to compare the accuracy obtained on the Random Forest Classifier tuned with Genetic Algorithm with the one obtained above.

Model 1 (b) : Random Forest Classifier Hyperparameter Tuning with Genetic Algorithm

```
# Installing the required library for carrying out hyperparameter tuning using Genetic Algorithm
!pip install sklearn-genetic-opt
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting sklearn-genetic-opt
  Downloading sklearn_genetic_opt-0.9.0-py3-none-any.whl (31 kB)
Collecting deap>=1.3.1
  Downloading deap-1.3.3-cp37-cp37m-manylinux_2_5_x86_64.manylinux1_x86_64.manylinux_2_17_x86_64.manylinux2014_x86_6
     |████████████████████████████████| 139 kB 13.1 MB/s
Requirement already satisfied: numpy>=1.14.5 in /usr/local/lib/python3.7/dist-packages (from sklearn-genetic-opt) (1
Requirement already satisfied: tqdm>=4.61.1 in /usr/local/lib/python3.7/dist-packages (from sklearn-genetic-opt) (4.
Requirement already satisfied: scikit-learn>=0.21.3 in /usr/local/lib/python3.7/dist-packages (from sklearn-genetic-
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.21.3->sk
Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.21.3->sk
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.
Installing collected packages: deap, sklearn-genetic-opt
Successfully installed deap-1.3.3 sklearn-genetic-opt-0.9.0
```

```
# Importing required packages for Genetic Hyperparameter Tuning (GASearchCV)
from sklearn_genetic import GASearchCV
from sklearn_genetic.space import Continuous, Categorical, Integer
from sklearn_genetic.plots import plot_fitness_evolution, plot_search_space
from sklearn.model_selection import StratifiedKFold
```

We have used the 7 hyperparamters that we will experiment on tuning with the help of RandomizedSearchCV.

- min_weight_fraction_leaf
- bootstrap
- max_depth
- max_leaf_nodes
- n_estimators

```
# Here we have taken the different hyperparameters and set of values that the GASearchCV will try to optimise
params_grid = {
              'min_weight_fraction_leaf': Continuous(0.01, 0.5, distribution='log-uniform'),
              'bootstrap': Categorical([True, False]),
              'max_depth': Integer(2, 30),
              'max_leaf_nodes': Integer(2, 35),
              'n_estimators': Integer(100, 300)
              }


clf = RandomForestClassifier()

# For the cross validation purpose we have used StratifiedKFold
cv = StratifiedKFold(n_splits=3, shuffle=True)

evolved_estimator = GASearchCV(estimator=clf,
                               cv=cv,
                               scoring='accuracy',
                               population_size=10,
                               generations=10,
                               tournament_size=3,
                               elitism=True,
                               crossover_probability=0.8,
                               mutation_probability=0.1,
                               param_grid=params_grid,
                               criteria='max',
                               algorithm='eaMuPlusLambda',
                               n_jobs=-1,
                               verbose=True,
                               keep_top_k=4)


# We will try to find best set of hyperparameters using GASearchCV
from sklearn.metrics import accuracy_score

start_ga_rf_model = time.time()
evolved_estimator.fit(X_train,y_train)
end_ga_rf_model = time.time()


total_time_ga_rf_model = end_ga_rf_model - start_ga_rf_model
```

```
gen     nevals  fitness         fitness_std     fitness_max     fitness_min
0       10      0.725927        0.0823145       0.832241        0.537555
1       19      0.781506        0.047615        0.824338        0.663806
2       18      0.815063        0.0137147       0.828304        0.788132
3       17      0.829934        0.00628689      0.841449        0.822364
4       20      0.839085        0.00725978      0.848037        0.822358
5       18      0.84619         0.00466777      0.850664        0.835541
6       18      0.846387        0.00420551      0.850664        0.839464
7       20      0.847039        0.0038022       0.850664        0.840769
8       18      0.847568        0.00427775      0.852639        0.840131
9       18      0.848228        0.00375567      0.853299        0.842106
10      17      0.850464        0.000300489     0.850664        0.850005
```

Now, we use the Random Forest Classifier with the best values of Hyperparameters obtained using the GASearchCV to find the predictions of the target values on the features ie. `X_test`.

We then use the function `accuracy_score` from scikit-learn in order to determine the accuracy of the model.

```
print(f'Time taken by the GASearch Random Forest Classifier to find the best set of Hyperparameters is : {total_time_ga_r
```

```
Time taken by the GASearch Random Forest Classifier to find the best set of Hyperparameters is : 272.54s
```

```
Y_pred_ga_rf_model_test = evolved_estimator.predict(X_test)


accuracy_ga_rf_model_test = accuracy_score(y_test, Y_pred_ga_rf_model_test)
```

```
Y_pred_ga_rf_model_train = evolved_estimator.predict(X_train)


accuracy_ga_rf_model_train = accuracy_score(y_train, Y_pred_ga_rf_model_train)


print(f'The train set accuracy of the Random Forest Classifier using GASearch CV is : {accuracy_ga_rf_model_train*100:.2f
print(f'The test set accuracy of the Random Forest Classifier using GASearch CV is : {accuracy_ga_rf_model_test*100:.2f}%
```

```
The train set accuracy of the Random Forest Classifier using GASearch CV is : 87.70%
The test set accuracy of the Random Forest Classifier using GASearch CV is : 83.68%
```

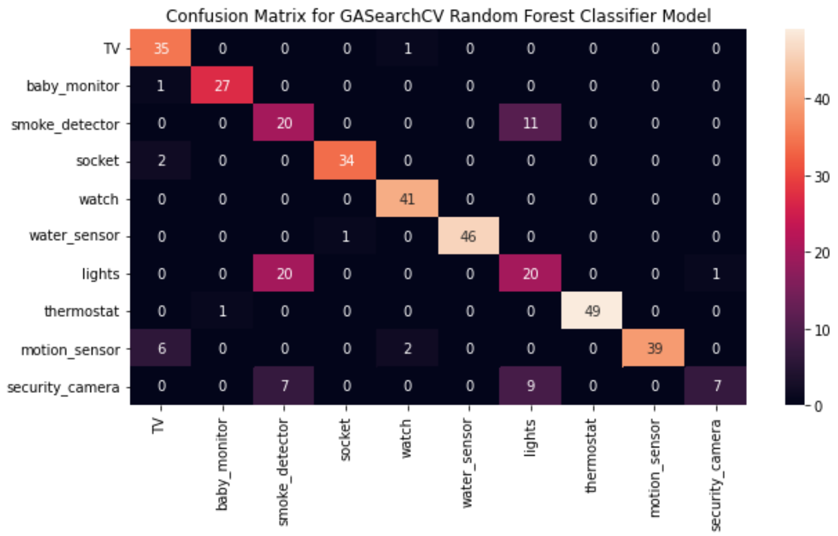
```
cm_ga_rf_model = metrics.confusion_matrix(y_test, Y_pred_ga_rf_model_test)
print(cm_ga_rf_model)
```

```
[[35  0  0  0  1  0  0  0  0  0]
 [ 1 27  0  0  0  0  0  0  0  0]
 [ 0  0 20  0  0  0 11  0  0  0]
 [ 2  0  0 34  0  0  0  0  0  0]
 [ 0  0  0  0 41  0  0  0  0  0]
 [ 0  0  0  1  0 46  0  0  0  0]
 [ 0  0 20  0  0  0 20  0  0  1]
 [ 0  1  0  0  0  0  0 49  0  0]
 [ 6  0  0  0  2  0  0  0 39  0]
 [ 0  0  7  0  0  0  9  0  0  7]]
```

```
misclassified_ga_rf_model = misclassified_total(cm_ga_rf_model)
print(f'Number of Misclassified categories by the GASearchCV Random Forest Classifier : {misclassified_ga_rf_model}')
```

```
Number of Misclassified categories by the GASearchCV Random Forest Classifier : 62
```

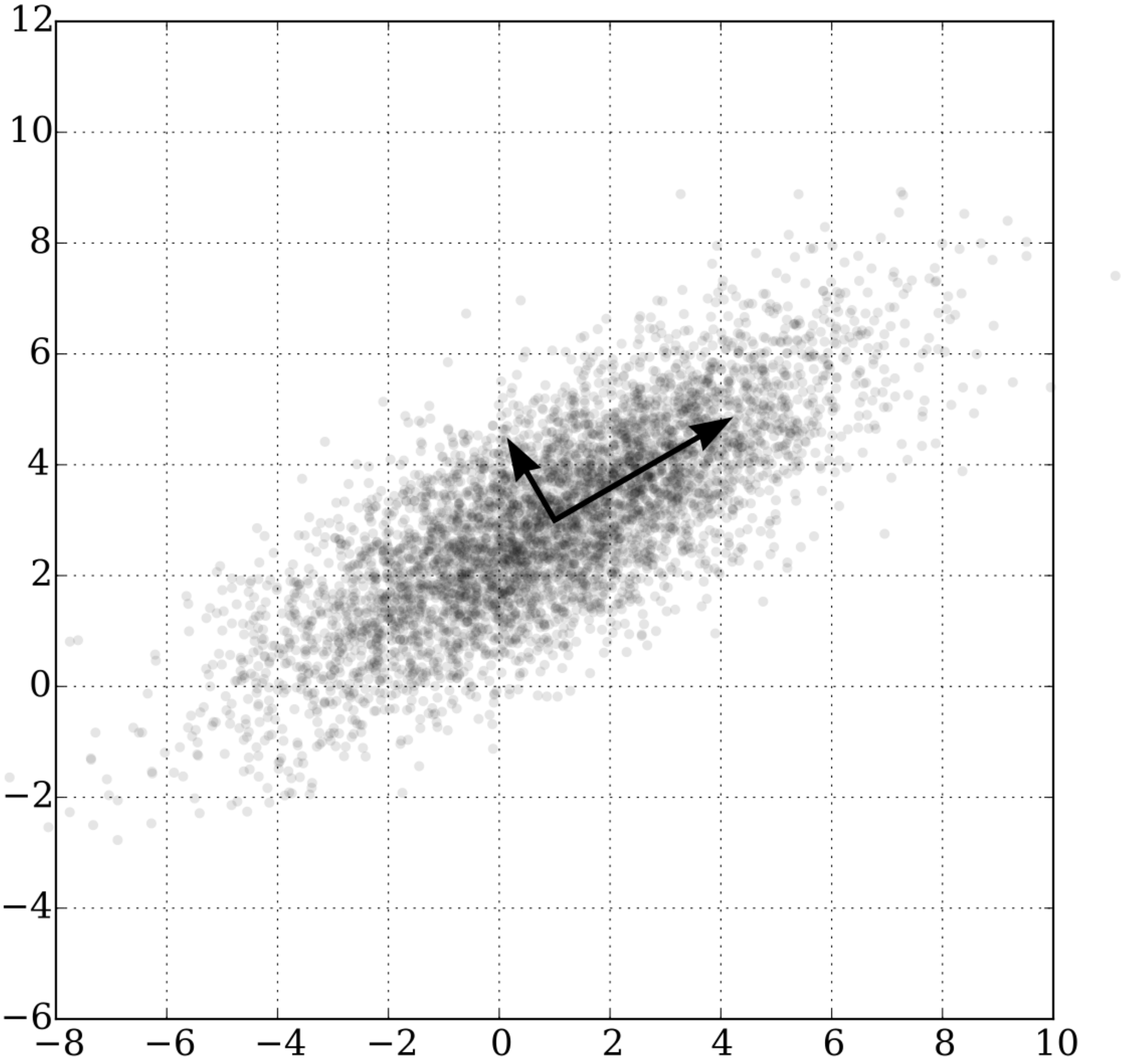
```
plt.figure(figsize= (10,5))
hm_ga_rf_model = sns.heatmap(cm_ga_rf_model, annot=True, fmt="d",  xticklabels=class_names, yticklabels=class_names)
hm_ga_rf_model = hm_ga_rf_model.set_title("Confusion Matrix for GASearchCV Random Forest Classifier Model")
```



Principal Component Analysis for Feature Extraction and Dimensionality Reduction

We will do feature extraction using Principal Component Analysis and select small set of transformed features that explain the variance well rather than taking all the features including ones that doesn't contribute much in the learning process.

This helps in dimensionality reduction and helps in bringing the data set from a large feature space to smaller feature space.



[Image Reference : https://upload.wikimedia.org/wikipedia/commons/thumb/f/f5/GaussianScatterPCA.svg/1280px-GaussianScatterPCA.svg.png]

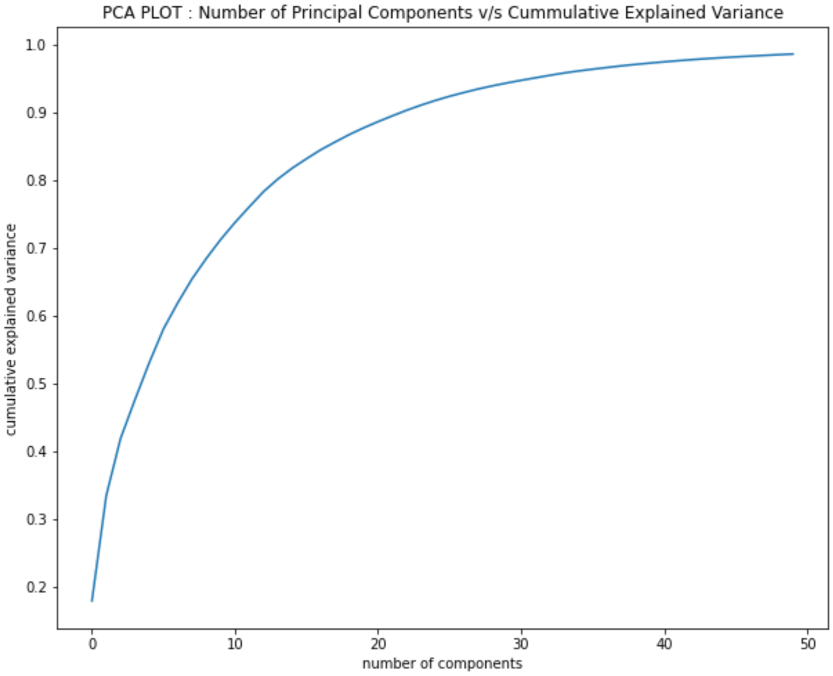
```
# PCA on data
from sklearn.decomposition import PCA


# We have tried to use top 50 features that explain the variance in the data well
pca = PCA(n_components=50)
X_train_pca = pca.fit_transform(X_train)


# Let's take a look at the cummulative explained variance by the 50 features selected through PCA.
variance_explained = sorted(pca.explained_variance_ratio_.cumsum())


variance_explained
```

```
[0.17979554345997342,
 0.33495469028352,
 0.41925683054470875,
 0.4762153089342385,
 0.5307759333780705,
 0.5809257186644189,
 0.6194709985105824,
```

```
0.6548418392046205,
0.6850792460020559,
0.7129162309611485,
0.7379576983166531,
0.761124278971427,
0.7836153842721327,
0.802158572459773,
0.8181716890640927,
0.8320588987555153,
0.8453233176108308,
0.8567512553167824,
0.8678089448434738,
0.8776928656374904,
0.8867935307702279,
0.8953220132276416,
0.9035846976555593,
0.9111041054290525,
0.9179970327345424,
0.924204259095669,
0.9297481357548616,
0.9350326828203522,
0.9395893771347167,
0.9438155569184248,
0.9477489898747219,
0.951455610267926,
0.9550979528580725,
0.958566775959078,
0.9615210452522813,
0.9641719588684488,
0.9666662985488165,
0.9690853531816248,
0.9712146527970615,
0.9731653585347373,
0.9750249640432475,
0.976744070620301,
0.9783559174498064,
0.9798123431745874,
0.9810797515043281,
0.9823201424808283,
0.9834492906860554,
0.9845593188987026,
0.9855841633225763,
0.9865487483643917]
```

We can see that the reduced set of features capture and explain about 98.65% variance in the dataset.

```
plt.figure(figsize= (10,8))
plt.plot(variance_explained)
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance');
plt.title('PCA PLOT : Number of Principal Components v/s Cummulative Explained Variance');
```



```
X_test_pca = pca.transform(X_test)
```

Random Forest Classifier on top features obtained using PCA

```
# We initialise the model
rs_rf_model_pca = RandomForestClassifier()
rs_rf_model_pca = RandomizedSearchCV(randomForestClassifier,param_distributions=params,cv=5,n_iter=20,n_jobs=1,verbose=0)
```

```
# Training the RF model on PCA data

start_rs_rf_model_pca = time.time()
rs_rf_model_pca.fit(X_train_pca, y_train)
end_rs_rf_model_pca = time.time()
```

```
total_time_rs_rf_model_pca = end_rs_rf_model_pca - start_rs_rf_model_pca
print(f'Time taken for Random Forest Classifier using Randomized Search CV model on PCA data to train is : {total_time_rs
```

```
Time taken for Random Forest Classifier using Randomized Search CV model on PCA data to train is : 41.54s
```

```
rs_rf_accuracy_train_pca = rs_rf_model_pca.score(X_train_pca, y_train)
```

```
rs_rf_accuracy_test_pca = rs_rf_model_pca.score(X_test_pca, y_test)
```

```
# Printing the train and test set accuracy for RandomizedSearchCV Random Forest Classifier (PCA) model
print(f'The train set accuracy of RandomizedSearchCV Random Forest Classifier (PCA) model is {rs_rf_accuracy_train_pca*10
print(f'The test set accuracy of RandomizedSearchCV Random Forest Classifier (PCA) model is {rs_rf_accuracy_test_pca*100:
```

```
The train set accuracy of RandomizedSearchCV Random Forest Classifier (PCA) model is 96.32%
The test set accuracy of RandomizedSearchCV Random Forest Classifier (PCA) model is 85.26%
```

```
rs_rf_model_pca.best_params_
```

```
{'ccp_alpha': 0.0,
 'criterion': 'gini',
 'max_depth': 30,
 'max_features': 'log2',
 'min_samples_leaf': 3,
 'min_samples_split': 2,
 'n_estimators': 30}
```

```
Y_pred_rs_rf_pca = rs_rf_model_pca.predict(X_test_pca)
```

```
cm_rs_rf_model_pca = metrics.confusion_matrix(y_test, Y_pred_rs_rf_pca)
print(cm_rs_rf_model_pca)
cm_rs_rf_model_pca.shape
```

```
[[32  0  0  2  1  0  0  0  1  0]
 [ 0 28  0  0  0  0  0  0  0  0]
 [ 0  0 18  0  0  0 12  0  0  1]
 [ 1  0  0 34  0  0  0  0  1  0]
 [ 0  0  0  0 41  0  0  0  0  0]
 [ 0  0  0  1  0 46  0  0  0  0]
 [ 0  0 17  0  0  0 17  0  0  7]
 [ 0  0  0  0  0  0  0 49  1  0]
 [ 1  0  0  1  0  0  0  0 45  0]
 [ 0  0  3  0  0  0  6  0  0 14]]
(10, 10)
```

```
misclassified_rs_rf_model_pca = misclassified_total(cm_rs_rf_model_pca)
misclassified_rs_rf_model_pca
```

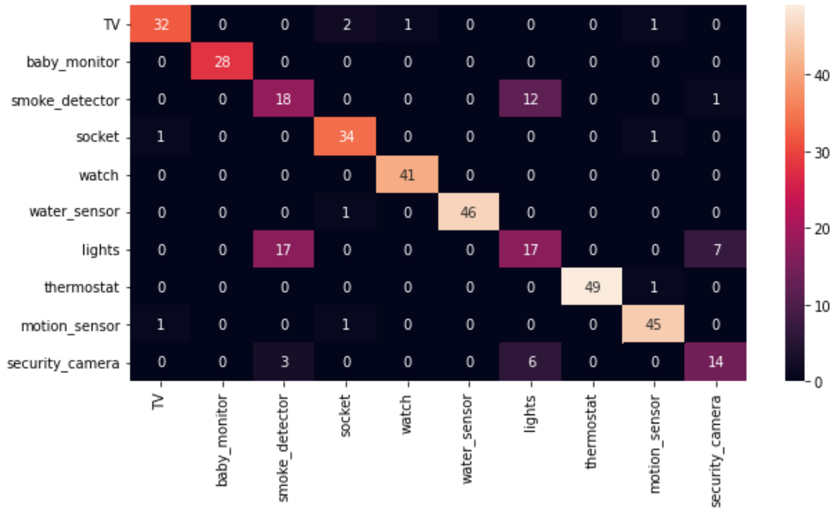
```
56
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test, Y_pred_rs_rf_pca))
```

```
                     precision    recall  f1-score   support
```

```
              TV       0.94      0.89      0.91        36
    baby_monitor       1.00      1.00      1.00        28
          lights       0.47      0.58      0.52        31
   motion_sensor       0.89      0.94      0.92        36
 security_camera       0.98      1.00      0.99        41
  smoke_detector       1.00      0.98      0.99        47
          socket       0.49      0.41      0.45        41
      thermostat       1.00      0.98      0.99        50
           watch       0.94      0.96      0.95        47
    water_sensor       0.64      0.61      0.62        23

        accuracy                           0.85       380
       macro avg       0.83      0.84      0.83       380
    weighted avg       0.85      0.85      0.85       380
```

```
plt.figure(figsize= (10,5))
hm_rs_rf_model_pca = sns.heatmap(cm_rs_rf_model_pca, annot=True, fmt="d",  xticklabels=class_names, yticklabels=class_nam
hm_rs_rf_model_pca = hm_rs_rf_model_pca.set_title("Confusion Matrix for Randomized Random Forest Classifier (PCA) Model")
```



Genetic Algorithm for finding out best parameters on extracted features using PCA

```
start_ga_rf_model_pca = time.time()
evolved_estimator.fit(X_train_pca,y_train)
end_ga_rf_model_pca = time.time()

total_time_ga_rf_model_pca = -(start_ga_rf_model_pca - end_ga_rf_model_pca)
```

```
gen     nevals  fitness         fitness_std     fitness_max     fitness_min
0       10      0.769481        0.044199        0.833556        0.6954
1       19      0.814079        0.0193844       0.833556        0.776317
2       17      0.824079        0.00587451      0.8342          0.815132
3       17      0.829012        0.00475209      0.8342          0.817118
4       18      0.83138         0.0021616       0.8342          0.828939
5       18      0.833288        0.00452674      0.840128        0.825674
6       18      0.836968        0.0033009       0.840128        0.83222
7       17      0.835986        0.00418015      0.840793        0.828951
8       20      0.836183        0.00489024      0.840797        0.824986
9       19      0.839872        0.00212531      0.840797        0.833559
10      18      0.839677        0.00238855      0.840797        0.832912
```

```
print(f'Time taken by the GASearch Random Forest Classifier (PCA) to find the best set of Hyperparameters is : {total_tim
```

```
Time taken by the GASearch Random Forest Classifier (PCA) to find the best set of Hyperparameters is : 513.71s
```

```
Y_pred_ga_rf_model_test_pca = evolved_estimator.predict(X_test_pca)
```

```
accuracy_ga_rf_model_test_pca = accuracy_score(y_test, Y_pred_ga_rf_model_test_pca)
```

```
Y_pred_ga_rf_model_train_pca = evolved_estimator.predict(X_train_pca)
```

```
accuracy_ga_rf_model_train_pca = accuracy_score(y_train, Y_pred_ga_rf_model_train_pca)
```

```
print(f'The train set accuracy of the Random Forest Classifier (PCA) using GASearch CV is : {accuracy_ga_rf_model_train_p
print(f'The test set accuracy of the Random Forest Classifier (PCA) using GASearch CV is : {accuracy_ga_rf_model_test_pca
```

```
The train set accuracy of the Random Forest Classifier (PCA) using GASearch CV is : 88.68%
The test set accuracy of the Random Forest Classifier (PCA) using GASearch CV is : 83.95%
```

```
cm_ga_rf_model_pca = metrics.confusion_matrix(y_test, Y_pred_ga_rf_model_test_pca)
print(cm_ga_rf_model_pca)
# cm_ga_rf_model_pca.shape
```

```
[[33  0  0  1  1  0  0  0  1  0]
 [ 0 26  0  0  2  0  0  0  0  0]
 [ 0  0 18  0  0  0 13  0  0  0]
 [ 3  0  0 32  0  0  0  0  1  0]
 [ 0  0  0  0 41  0  0  0  0  0]
 [ 0  0  0  1  0 46  0  0  0  0]
 [ 0  0 17  0  0  0 19  0  0  5]
 [ 0  0  0  0  0  0  0 49  1  0]
 [ 3  0  0  1  0  0  0  0 43  0]
 [ 0  0  3  0  0  0  8  0  0 12]]
```

```
misclassified_ga_rf_model_pca = misclassified_total(cm_ga_rf_model_pca)
misclassified_ga_rf_model_pca
```

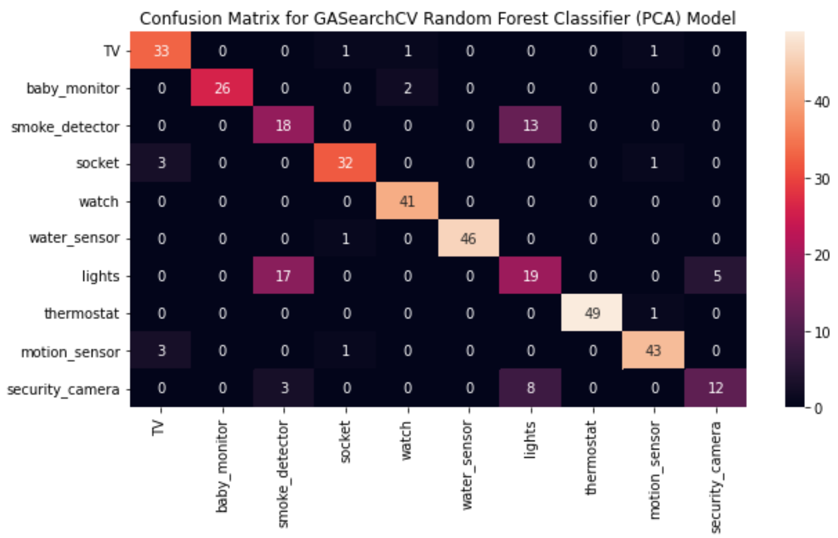
```
61
```

```
print(classification_report(y_test, Y_pred_ga_rf_model_test_pca))
```

```
                 precision    recall  f1-score   support

             TV       0.85      0.92      0.88        36
   baby_monitor       1.00      0.93      0.96        28
         lights       0.47      0.58      0.52        31
  motion_sensor       0.91      0.89      0.90        36
security_camera       0.93      1.00      0.96        41
 smoke_detector       1.00      0.98      0.99        47
         socket       0.47      0.46      0.47        41
     thermostat       1.00      0.98      0.99        50
          watch       0.93      0.91      0.92        47
   water_sensor       0.71      0.52      0.60        23

       accuracy                           0.84       380
      macro avg       0.83      0.82      0.82       380
   weighted avg       0.84      0.84      0.84       380
```

Heatmap of GASearchCV on PCA data that shows how many examples from the test set were correctly classified and how many were incorrectly classified.

```
plt.figure(figsize= (10,5))
hm_ga_rf_model_pca = sns.heatmap(cm_ga_rf_model_pca, annot=True, fmt="d",  xticklabels=class_names, yticklabels=class_nam
hm_ga_rf_model_pca = hm_ga_rf_model_pca.set_title("Confusion Matrix for GASearchCV Random Forest Classifier (PCA) Model")
```




```
import warnings
```

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

Model 2 : Logistic Regression

Logistic regression is a classification algorithm, used for prediction of an occurence of a particular event based on the probability.

A logistic curve with logit function is used on which the data is fitted and model is trained.

The model learns to predict a categorical output based on the features which may be discrete or continuous or a combination of both.

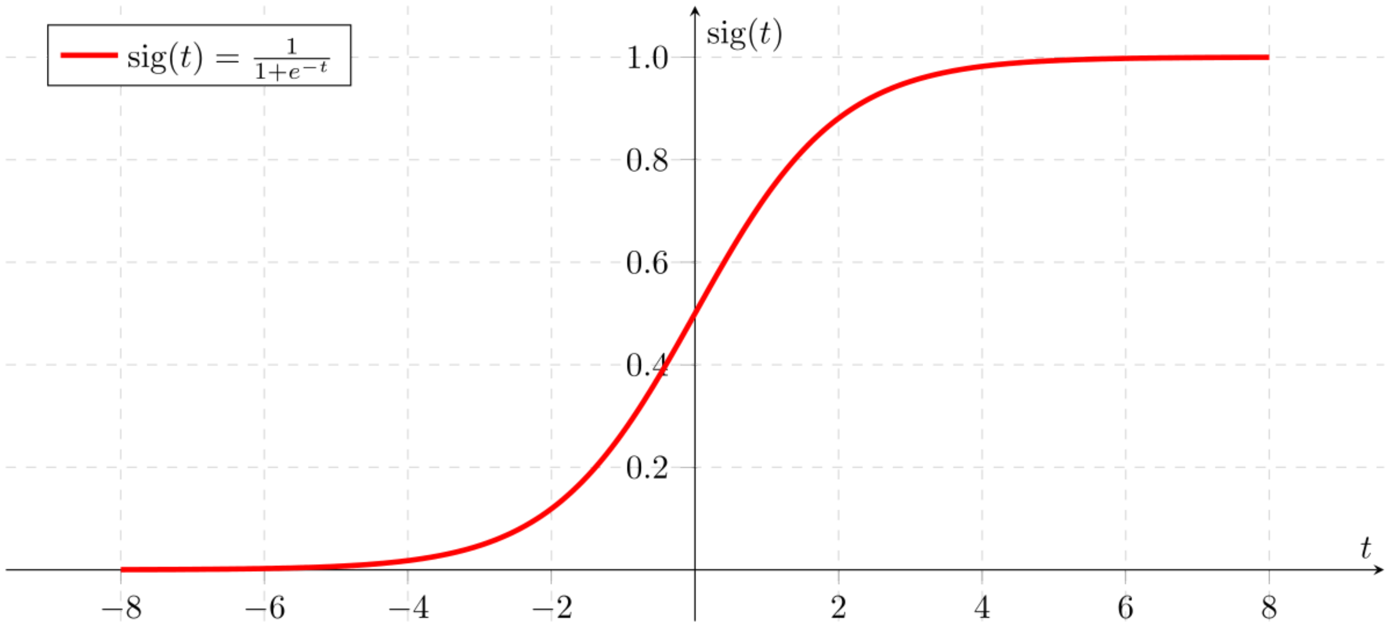
The algorithm works by taking the linear combination of input values with weights or coefficients in order to make a prediction of an output value.

- ln(y) = b0 + b1 * X

where X = Input Variable, y = Output target, b0 = Bias, b1 = Weight.

The right side calculation is linear whereas the left side ratio is known as log-odds ratio of the default class ie. ratio of probability of the event over the probability of not of the event.

The below figure shows the logistic regression curve that seperates different classes/categories.



[Image Reference : https://miro.medium.com/max/1838/1*RqXFpiNGwdiKBWyLJc_E7g.png]

```
from sklearn.linear_model import LogisticRegression

lr_model = LogisticRegression(penalty='l1', tol=0.001, solver ='saga')


start_lr_model = time.time()
lr_model = lr_model.fit(X_train, y_train)
end_lr_model = time.time()

total_time_lr_model = end_lr_model - start_lr_model


print(f'Time taken by the Logistic Regressor to learn the classification of the IOT devices is : {total_time_lr_model:.2f
```

```
    Time taken by the Logistic Regressor to learn the classification of the IOT devices is : 3.68s
```

```
accuracy_lr_model_train = lr_model.score(X_train, y_train)


accuracy_lr_model_test = lr_model.score(X_test, y_test)


Y_pred_lr_model = lr_model.predict(X_test)


print(f'The train set accuracy of the Logistic Regressor is : {accuracy_lr_model_train*100:.2f}%')
print(f'The test set accuracy of the Logistic Regressor is : {accuracy_lr_model_test*100:.2f}%')
```

```
    The train set accuracy of the Logistic Regressor is : 80.72%
```

```
The test set accuracy of the Logistic Regressor is : 79.47%
```

```
cm_lr_model = metrics.confusion_matrix(y_test, Y_pred_lr_model)
print(cm_lr_model)
```

```
[[27  0  0  1  1  0  0  5  2  0]
 [ 0 24  0  0  4  0  0  0  0  0]
 [ 0  0 29  0  0  0  2  0  0  0]
 [ 3  0  0 32  0  1  0  0  0  0]
 [ 0  0  0  0 41  0  0  0  0  0]
 [ 0  0  0  1  0 46  0  0  0  0]
 [ 0  0 29  0  0  0 12  0  0  0]
 [ 0  0  0  0  0  0  0 49  1  0]
 [ 9  0  0  0  1  0  0  0 37  0]
 [ 0  0 13  0  0  0  5  0  0  5]]
```

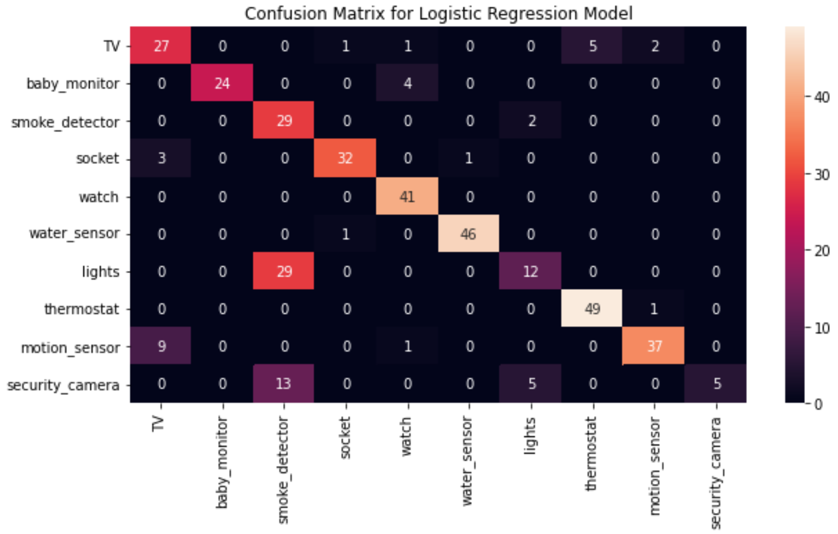
```
misclassified_lr_model = misclassified_total(cm_lr_model)
misclassified_lr_model
```

```
78
```

```
print(classification_report(y_test, Y_pred_lr_model))
```

```
                 precision    recall  f1-score   support

             TV       0.69      0.75      0.72        36
   baby_monitor       1.00      0.86      0.92        28
         lights       0.41      0.94      0.57        31
  motion_sensor       0.94      0.89      0.91        36
security_camera       0.87      1.00      0.93        41
 smoke_detector       0.98      0.98      0.98        47
         socket       0.63      0.29      0.40        41
     thermostat       0.91      0.98      0.94        50
          watch       0.93      0.79      0.85        47
   water_sensor       1.00      0.22      0.36        23

       accuracy                           0.79       380
      macro avg       0.84      0.77      0.76       380
   weighted avg       0.84      0.79      0.78       380
```

```
plt.figure(figsize= (10,5))
hm_lr_model = sns.heatmap(cm_lr_model, annot=True, fmt="d",  xticklabels=class_names, yticklabels=class_names)
hm_lr_model = hm_lr_model.set_title("Confusion Matrix for Logistic Regression Model")
```




```
from sklearn.model_selection import GridSearchCV
```

```
params_grid_lr = {
              'penalty':['l2','l1'],
              'solver':[ 'newton-cg','lbfgs', 'liblinear'],
              'tol' : [0.01,0.005]
            }
```

```
gs_lr_model = LogisticRegression()
gs_lr_model = GridSearchCV(gs_lr_model,param_grid=params_grid_lr,cv=5,n_jobs=1,verbose=0)

start_gs_lr_model = time.time()
gs_lr_model.fit(X_train,y_train)
end_gs_lr_model = time.time()

total_time_gs_lr_model = end_gs_lr_model - start_gs_lr_model
```

```
print(f'Time taken by the Grid Search CV to find best hyperparameter settings on Logistic Regression Classifier is : {tot
```

```
Time taken by the Grid Search CV to find best hyperparameter settings on Logistic Regression Classifier is : 40.62s
```

```
accuracy_gs_lr_model_train = gs_lr_model.score(X_train, y_train)

accuracy_gs_lr_model_test = gs_lr_model.score(X_test, y_test)
```

```
Y_pred_gs_lr_model = gs_lr_model.predict(X_test)
```

```
print(f'The train set accuracy of the Grid Search CV Logistic Regressor is : {accuracy_gs_lr_model_train*100:.2f}%')
print(f'The test set accuracy of the Grid Search CV Logistic Regressor is : {accuracy_gs_lr_model_test*100:.2f}%')
```

```
The train set accuracy of the Grid Search CV Logistic Regressor is : 87.70%
The test set accuracy of the Grid Search CV Logistic Regressor is : 85.00%
```

```
gs_lr_model.best_params_
```

```
{'penalty': 'l2', 'solver': 'newton-cg', 'tol': 0.01}
```

```
cm_gs_lr_model = metrics.confusion_matrix(y_test, Y_pred_gs_lr_model)
print(cm_gs_lr_model)
```

```
[[34  0  0  0  1  0  0  1  0  0]
 [ 0 27  0  0  1  0  0  0  0  0]
 [ 0  0 25  0  0  0  6  0  0  0]
 [ 1  0  0 35  0  0  0  0  0  0]
 [ 0  0  0  0 41  0  0  0  0  0]
 [ 0  0  0  1  0 46  0  0  0  0]
 [ 0  0 25  0  0  0 15  0  0  1]
 [ 0  0  0  0  0  0  0 49  1  0]
 [ 3  0  0  0  1  0  0  0 43  0]
 [ 0  0  9  0  0  0  6  0  0  8]]
```

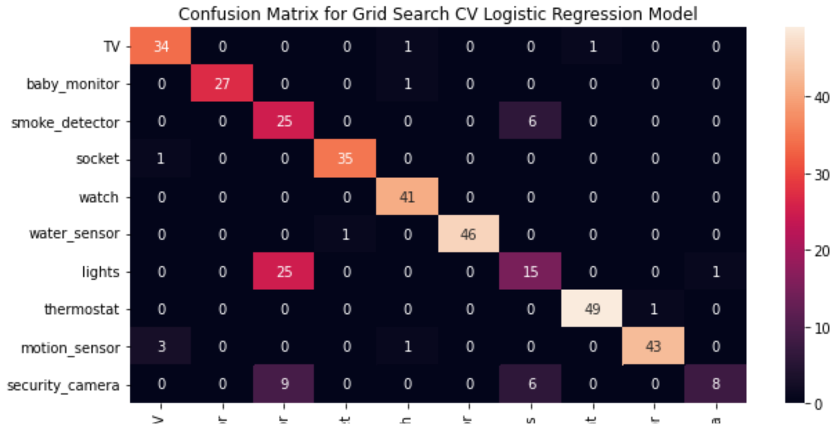
```
misclassified_gs_lr_model = misclassified_total(cm_gs_lr_model)
misclassified_gs_lr_model
```

```
57
```

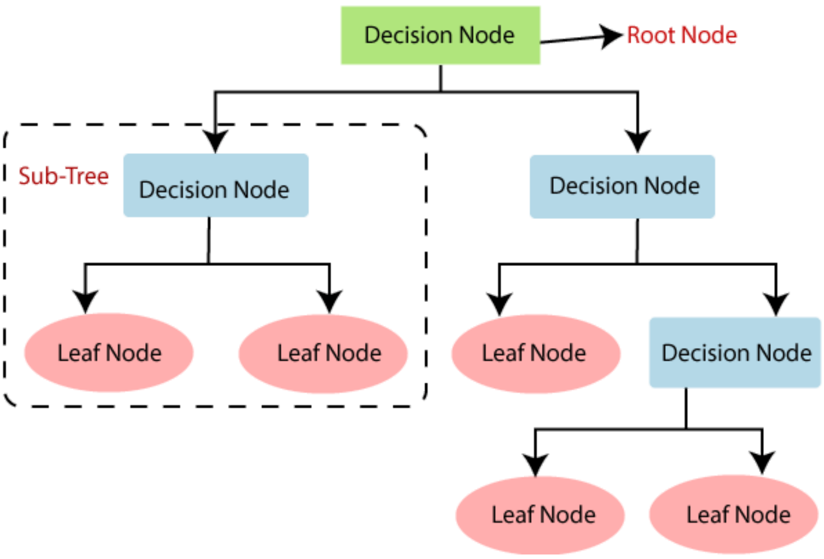
```
print(classification_report(y_test, Y_pred_gs_lr_model))
```

```
                 precision    recall  f1-score   support

             TV       0.89      0.94      0.92        36
   baby_monitor       1.00      0.96      0.98        28
         lights       0.42      0.81      0.56        31
  motion_sensor       0.97      0.97      0.97        36
security_camera       0.93      1.00      0.96        41
 smoke_detector       1.00      0.98      0.99        47
         socket       0.56      0.37      0.44        41
     thermostat       0.98      0.98      0.98        50
          watch       0.98      0.91      0.95        47
   water_sensor       0.89      0.35      0.50        23

       accuracy                           0.85       380
      macro avg       0.86      0.83      0.82       380
   weighted avg       0.87      0.85      0.85       380
```

```
plt.figure(figsize= (10,5))
hm_gs_lr_model = sns.heatmap(cm_gs_lr_model, annot=True, fmt="d",  xticklabels=class_names, yticklabels=class_names)
hm_gs_lr_model = hm_gs_lr_model.set_title("Confusion Matrix for Grid Search CV Logistic Regression Model")
```



Model 3 : Decision Tree Classifier



A comprehensible classification approach that may be accurate in a variety of application situations, including energy-based applications, is offered by decision tree classifiers.

By constructing a decision tree, the decision tree classifier develops the classification model.

A test on an attribute is specified by each node in the tree, and each branch descending from that node represents one of the possible values for that property.

Each leaf is a representation of the class labels connected to the instance.

According to the results of the tests along the path, instances in the training set are categorised by moving them from the tree's root to a leaf.Beginning with the root node, each node divides the instance space into two or more sub-spaces in accordance with an attribute test condition. The next step is to construct a new node by going down the tree branch that corresponds to the attribute's value.

Following that, the same procedure is performed for the subtree rooted at the new node, and so on, until all records in the training set have been assigned a classification.

By selecting an attribute test condition at each stage that optimally separates the data, the decision tree construction process typically operates top-down.

To decide how to partition the records most effectively, a variety of metrics might be employed. There is a lot of exploitation of the Gini index impurity-based criterion for building the tree.

It calculates the probability that a randomly selected instance from the set would be erroneously identified if it were randomly assigned a label based on how those labels are distributed in the subset.

```
from sklearn.tree import DecisionTreeClassifier


params_grid_dt = {
                'criterion':['gini','entropy'],
                'max_leaf_nodes': [2,5,10,20,50,100],
                'min_samples_split':[0.1,2],
                'min_samples_leaf': [2,3,4],
```

```
              'max_depth': [2,3,5,10,20,30],
            }
dt_model = DecisionTreeClassifier()
gs_dt_model = GridSearchCV(dt_model,param_grid=params_grid_dt,cv=5,n_jobs=1,verbose=0)
```

```
start_gs_dt_model = time.time()
gs_dt_model.fit(X_train,y_train)
end_gs_dt_model = time.time()

total_time_gs_dt_model = end_gs_dt_model - start_gs_dt_model
```

```
print(f'Time taken by the Grid Search CV to find best hyperparameter settings on Decision Tree Classifier is : {total_tim
```

```
    Time taken by the Grid Search CV to find best hyperparameter settings on Decision Tree Classifier is : 157.41s
```

```
accuracy_gs_dt_model_train = gs_dt_model.score(X_train, y_train)

accuracy_gs_dt_model_test = gs_dt_model.score(X_test, y_test)
```

```
Y_pred_gs_dt_model = gs_dt_model.predict(X_test)
```

```
print(f'The train set accuracy of the Grid Search CV Decision Tree Classifier is : {accuracy_gs_dt_model_train*100:.2f}%'
print(f'The test set accuracy of the Grid Search CV Decision Tree Classifier is : {accuracy_gs_dt_model_test*100:.2f}%')
```

```
    The train set accuracy of the Grid Search CV Decision Tree Classifier is : 95.07%
    The test set accuracy of the Grid Search CV Decision Tree Classifier is : 82.63%
```

```
gs_dt_model.best_params_
```

```
    {'criterion': 'entropy',
     'max_depth': 20,
     'max_leaf_nodes': 100,
     'min_samples_leaf': 3,
     'min_samples_split': 2}
```

```
cm_gs_dt_model = metrics.confusion_matrix(y_test, Y_pred_gs_dt_model)
print(cm_gs_dt_model)
```

```
    [[33  0  0  1  1  0  0  1  0  0]
     [ 1 26  0  1  0  0  0  0  0  0]
     [ 0  0 20  0  0  0 10  0  0  1]
     [ 3  0  0 33  0  0  0  0  0  0]
     [ 0  0  0  0 41  0  0  0  0  0]
     [ 0  0  0  0  0 47  0  0  0  0]
     [ 0  0 19  0  0  0 17  0  0  5]
     [ 0  0  0  0  0  0  0 50  0  0]
     [ 7  2  0  1  0  0  0  2 35  0]
     [ 0  0  5  1  0  0  5  0  0 12]]
```

```
misclassified_gs_dt_model = misclassified_total(cm_gs_dt_model)
misclassified_gs_dt_model
```

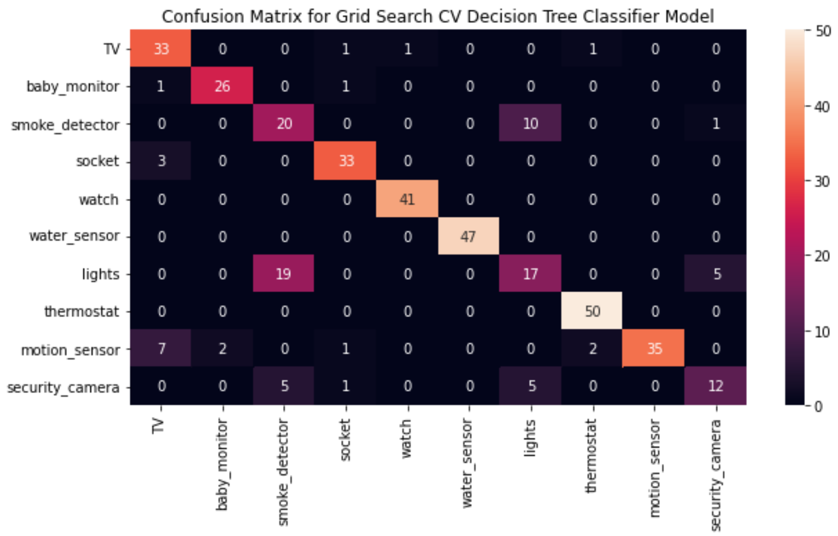
```
    66
```

```
print(classification_report(y_test, Y_pred_gs_dt_model))
```

```
                     precision    recall  f1-score   support

                 TV       0.75      0.92      0.83        36
       baby_monitor       0.93      0.93      0.93        28
             lights       0.45      0.65      0.53        31
      motion_sensor       0.89      0.92      0.90        36
    security_camera       0.98      1.00      0.99        41
     smoke_detector       1.00      1.00      1.00        47
             socket       0.53      0.41      0.47        41
         thermostat       0.94      1.00      0.97        50
              watch       1.00      0.74      0.85        47
       water_sensor       0.67      0.52      0.59        23

           accuracy                           0.83       380
          macro avg       0.81      0.81      0.81       380
       weighted avg       0.84      0.83      0.83       380
```

```
plt.figure(figsize= (10,5))
hm_gs_dt_model = sns.heatmap(cm_gs_dt_model, annot=True, fmt="d",  xticklabels=class_names, yticklabels=class_names)
```

```
hm_gs_dt_model = hm_gs_dt_model.set_title("Confusion Matrix for Grid Search CV Decision Tree Classifier Model")
```



Model 4 : XGBClassifier

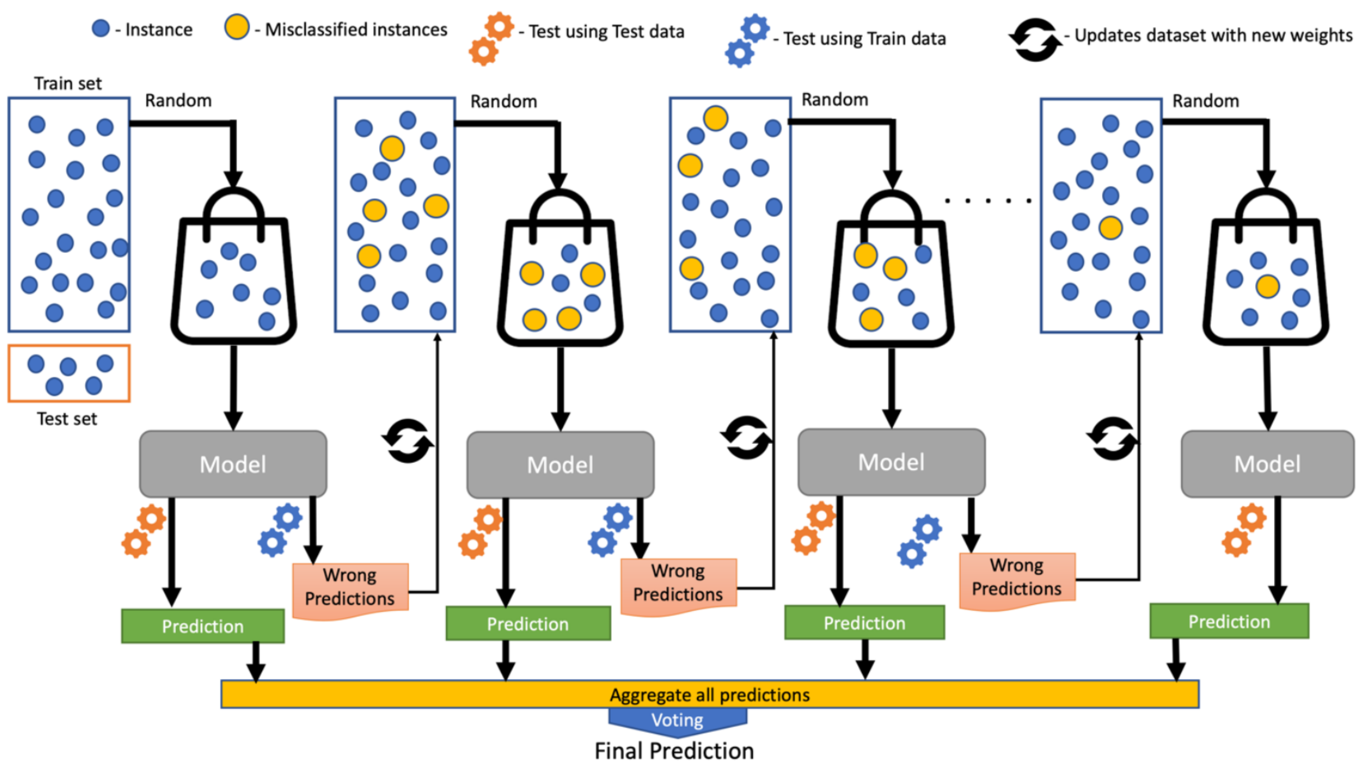
XGBoost is a distributed gradient boosting library that has been developed to be very effective, adaptable, and portable.

It uses the Gradient Boosting framework to construct machine learning algorithms. Many data science issues are quickly and accurately solved using a parallel tree boosting method offered by XGBoost.

The same code operates on the most popular distributed environments (Hadoop, SGE, and MPI) and can tackle issues involving a much larger number of samples.

Below is a representation of how the XGBoost classification algorithm works in general.

[Image Reference : https://miro.medium.com/max/1750/1*etquzYCBh3v58rcsXjDsyw.png]




```
from xgboost import XGBClassifier
```

```python
xgb_model = XGBClassifier()

start_xgb_model = time.time()
xgb_model.fit(X_train_pca, y_train)
end_xgb_model = time.time()

total_time_xgb_model = end_xgb_model - start_xgb_model
```

```python
print(f'Time taken by the XGBoost Classifier to learn the classification of the IOT devices is : {total_time_xgb_model:.2
```

```
Time taken by the XGBoost Classifier to learn the classification of the IOT devices is : 5.34s
```

```python
accuracy_xgb_model_train = xgb_model.score(X_train_pca, y_train)

accuracy_xgb_model_test = xgb_model.score(X_test_pca, y_test)
```

```python
Y_pred_xgb_model = xgb_model.predict(X_test_pca)
```

```python
print(f'The train set accuracy of the XGBoost Classifier is : {accuracy_xgb_model_train*100:.2f}%')
print(f'The test set accuracy of the XGBoost Classifier is : {accuracy_xgb_model_test*100:.2f}%')
```

```
The train set accuracy of the XGBoost Classifier is : 96.38%
The test set accuracy of the XGBoost Classifier is : 84.21%
```

```python
cm_xgb_model = metrics.confusion_matrix(y_test, Y_pred_xgb_model)
print(cm_xgb_model)
```

```
[[34  0  0  0  0  0  0  1  1  0]
 [ 1 27  0  0  0  0  0  0  0  0]
 [ 0  0 19  0  0  0 11  0  0  1]
 [ 0  0  0 36  0  0  0  0  0  0]
 [ 0  0  0  0 41  0  0  0  0  0]
 [ 0  0  0  1  0 46  0  0  0  0]
 [ 0  0 20  0  0  0 16  0  0  5]
 [ 0  0  0  0  0  0  0 48  2  0]
 [ 3  1  0  0  0  0  0  0 43  0]
 [ 0  0  3  0  0  0 10  0  0 10]]
```

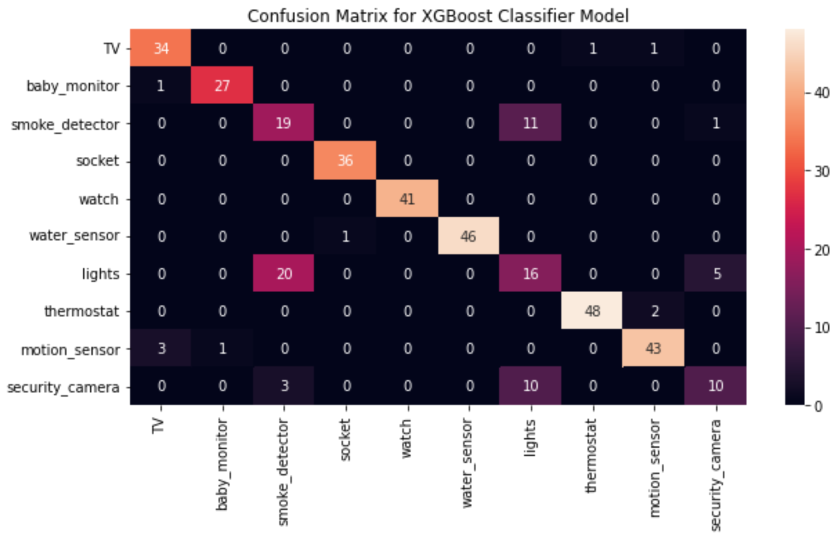
```python
misclassified_xgb_model = misclassified_total(cm_xgb_model)
misclassified_xgb_model
```

```
60
```

```python
print(classification_report(y_test, Y_pred_xgb_model))
```

```
                 precision    recall  f1-score   support

             TV       0.89      0.94      0.92        36
   baby_monitor       0.96      0.96      0.96        28
         lights       0.45      0.61      0.52        31
  motion_sensor       0.97      1.00      0.99        36
security_camera       1.00      1.00      1.00        41
 smoke_detector       1.00      0.98      0.99        47
         socket       0.43      0.39      0.41        41
     thermostat       0.98      0.96      0.97        50
          watch       0.93      0.91      0.92        47
   water_sensor       0.62      0.43      0.51        23

       accuracy                           0.84       380
      macro avg       0.83      0.82      0.82       380
   weighted avg       0.85      0.84      0.84       380
```

```python
plt.figure(figsize= (10,5))
hm_xgb_model = sns.heatmap(cm_xgb_model, annot=True, fmt="d",  xticklabels=class_names, yticklabels=class_names)
hm_xgb_model = hm_xgb_model.set_title("Confusion Matrix for XGBoost Classifier Model")
```


Confusion Matrix for XGBoost Classifier Model
TV
baby_monitor
smoke_detector
socket
watch
water_sensor
lights
thermostat
motion_sensor
security_camera
34 0 0 0 0 0 0 1 1 0
1 27 0 0 0 0 0 0 0 0
0 0 19 0 0 0 11 0 0 1
0 0 0 36 0 0 0 0 0 0
0 0 0 0 41 0 0 0 0 0
0 0 0 1 0 46 0 0 0 0
0 0 20 0 0 0 16 0 0 5
0 0 0 0 0 0 0 48 2 0
3 1 0 0 0 0 0 0 43 0
0 0 3 0 0 0 10 0 0 10
40
30
20
10
0