Epilepsy seizure determination combination Brain heart signal analysis and training

Mrs. ANU.K, M.E. Assistant Professor,

Department of Computer Science and Engineering

Ms. A.SUMITHRA, B.E, Student of Computer Science Engineering

Ms. P.BAKKIYA, B.E, Student of Computer science and Engineering

St. Joseph College of Engineering, Sriperumbudur, Chennai.

ABSTRACT

Epilepsy is a serious chronic neurological disorder, can be detected by analyzing the brain signals produced by brain neurons. Neurons are connected to each other in a complex way to communicate with human organs and generate signals. The monitoring of these brain signals is commonly done using Electroencephalogram (EEG) and Electrocorticography (ECOG) media. These signals are complex, noisy, non-linear, non-stationary and produce a high volume of data. Globally, epilepsy affects approximately 50 million people, with 100 million being affected at least once in their lifetime.

Overall, it accounts for 1% of the world's burden of diseases, and the prevalence rate is reported at 0.5–1%. The main symptom of epilepsy is to experience more than one seizure by a patient. It causes a sudden breakdown or unusual activity in the brain that impulses an involuntary alteration in a patient's behaviour, sensation, and loss of momentary consciousness. Hence, the detection of seizures and discovery of the brain-related knowledge is a challenging task. Therefore, the proposed system provides an effective solution to predict the detection of epilepsy seizure of combining brain heart signal in a more efficient way.

In this project, we will be using Machine Learning algorithm as Ensemble Model such as Random Forest, SVM and Logistic Regression to determine the presence of seizure at an early stage. The datasets will be collected from physio net

dataset and these datasets will be trained using machine learning algorithm and the model file will be generated. When an input data is given for seizure and to promote effectively determine the presence of epilepsy seizure and to promote effective treatment .Thus, this project helps in effective diagnosis of the seizure determination of combining brain heart signal with higher accuracy than the existing models.

LIST OF SYMBOLS AND ABBREVIATIONS

EEG	Electro Encephalo Gram
ECOG	Eastern Cooperative Oncology Group
SVM	support vector machine
ASS	Anterior superior spine
PRES	Posterior reversible encephalopathy syndrome
ACS	Acute coronary syndrome
ML	Machine Learning
BHI	Brain-heart Infusion

1.INTRODUCTION:

Malignant diseases of the hematopoietic system, despite their relatively low prevalence in the population, remain a socially significant group of diseases. Neurological complications in this cohort of patients occur in correlation with disease or with ongoing treatment.

These complications may affect patient survival and may determine whether a therapy protocol can be fully implemented. Acute symptomatic seizure (ASS) is one of the most significant neurological complications because of its high incidence and impact on survival. A number of studies have evaluated the risk of ASS in this cohort of patients, while assessment of the risks of epilepsy is virtually unreported in the research to date.Posterior reversible encephalopathy syndrome (PRES) is a brain disease associated with hypertension, which may determine the risk of epilepsy by indirect (in relation to arterial hypertension itself) mechanisms. In the general population of patients with PRES syndrome, ACS occurs in 77% of cases. In the cohort of oncohematological patients, the development of PRES syndrome may be accompanied by ASS in 97% of cases. In the general population, arterial hypertension is the main etiological factor in the development of PRES syndrome (72%) [13].

Approximately 60 million people worldwide have experienced epileptic seizure, which is a neurological disorder represented by brief and unpredictably occurring electrical disturbances in the brain. In neurology, epilepsy is defined as a collection of neurological dysfunctions with a permanent predisposition, which results in recurrent seizure

2.LITERATURE SURVEY

BHI-Net:Brain-HeartInteraction-Based Deep Architectures for Epileptic Seizures and Firing Location Detection Author: Nabi Sabor in 2022, proposed a new method based on the brain heart interaction(BHI)for detecting the seizure onset and its firing Location in the brain with lower complexity and better performance.

Acute Seizure Control Efficacy of Multi-site Closed loop Stimulation in a Temporal Lobe Seizure Model Authors: Yongte Zheng, Fang Zhang, Yueming Wang. Year in 2019, evaluated the acute seizure control efficacy of multi-site closed-loop simulation (MSCLS) in a rodent model with a custom designed closed-loop neurostimulator.

EpilepsyGAN: Synthetic Epileptic Brain Activities with Privacy Preservation Authors: D. Pascual and R. Wattenhofer Year in 2020, generated synthetic seizure like brain electrical activities . Alleviating the need for sensitive recorded data

3.SYSTEM ARCHITECTURE:

In this project, we will be using Machine Learning algorithms as Ensemble Model such as Random Forest, SVM and Logistic Regression to determine the presence of seizure at an early stage. So, the first step in the project will be collecting the dataset from PhysioNet dataset and then we will be separating these datasets into training as well as testing dataset where the testing dataset will be kept separate and the training dataset will be used to train the model.

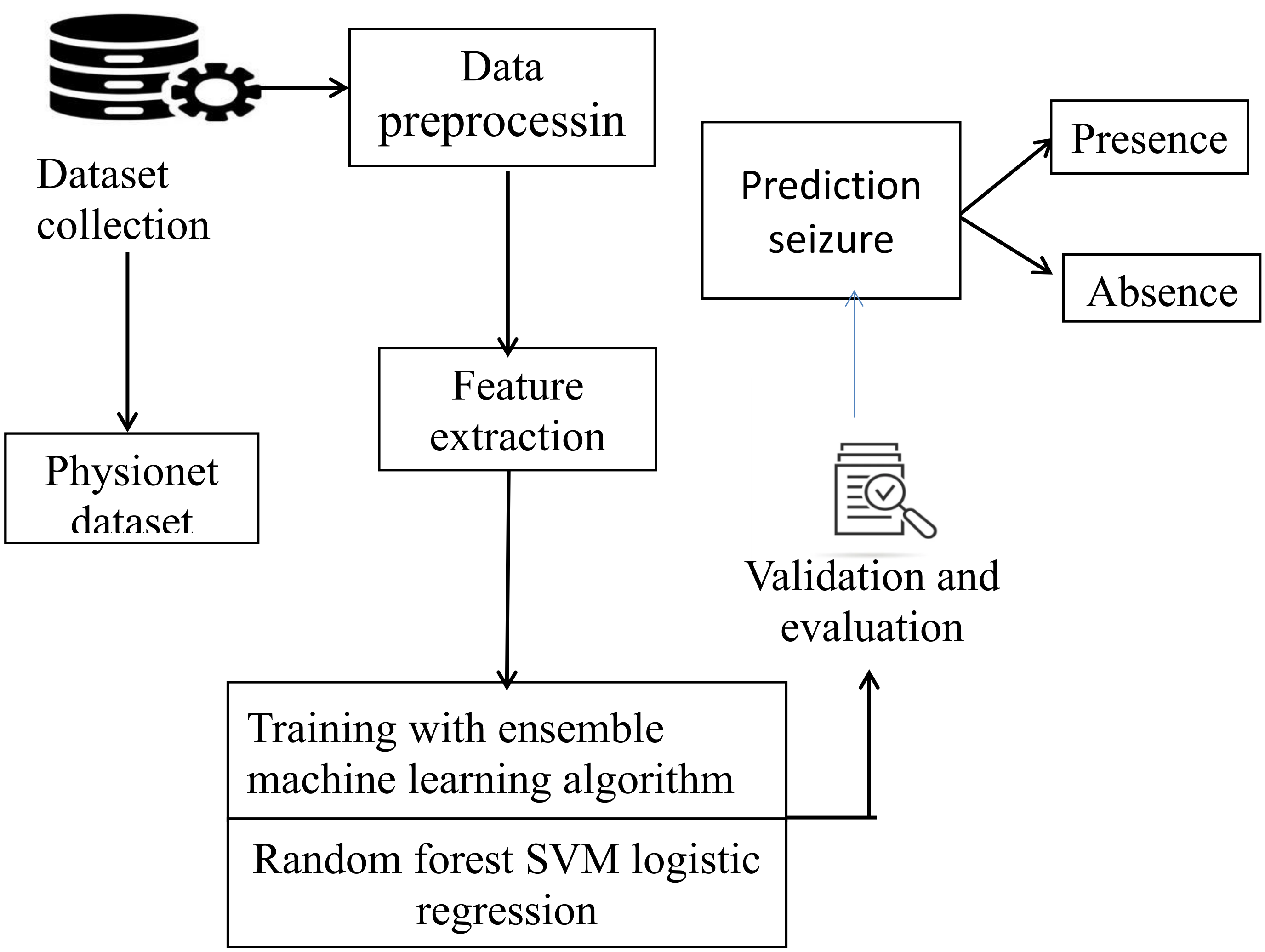


Figure 3.1 Proposed System architecture

Then, the preprocessing technique is used to preprocess the datasets. After datasets collected and preprocessing, the datasets have been used to extract the features and the model file will be generated. Then, we will be ready for training with the architecture. Now, we will be using various machine learning algorithms are used to train the model. The ensemble algorithms such as Random Forest, SVM and Logistic Regression are used to determine the seizure. After applying the multiple machine learning algorithms, it will validate and evaluate the datasets. When an input data is given for seizure prediction, it can effectively determine the presence of epilepsy seizure and to promote effective treatment. Thus, this project helps in effective diagnosis of the seizure determination of combining brain heart signal with higher accuracy than the existing models.

4.IMPLEMENTATION:

Dataset collection involves the process of collecting CHBMIT dataset.

The dataset has been collected for the project and the below figure can be seen as follows.

```
import os
import pywt
import math

import numpy as np
import pandas as pd

from scipy.signal import welch

from scipy.integrate import simps

from scipy.stats import skew, kurtosis, variation

from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score, classification_report, ␣
  ↪confusion_matrix
from sklearn import svm

from sklearn.tree import DecisionTreeClassifier
```

```
from pathlib import Path

from tqdm.notebook import tqdm

from os import chdir, getcwd, listdir, mkdir, path

from decimal import *

import matplotlib.pyplot as plt

import numpy.matlib
import types

import pickle

from sklearn.metrics.pairwise import cosine_similarity

from sklearn.metrics import (precision_score, recall_score,f1_score,␣
    ↪accuracy_score,mean_squared_error,mean_absolute_error)
from scipy.stats import kurtosis, skew

from sklearn.ensemble import RandomForestClassifier, VotingClassifier,␣
    ↪BaggingClassifier, ExtraTreesClassifier
from sklearn.ensemble import BaggingRegressor, RandomForestRegressor,␣
    ↪ExtraTreesRegressor
from sklearn.linear_model import LogisticRegression

from sklearn.svm import SVC

from os import chdir, getcwd, mkdir, path

# from wget import download

from tqdm.notebook import tqdm

from os import chdir, getcwd, listdir, mkdir, path

from decimal import *

import matplotlib.pyplot as plt

import numpy.matlib
import types

import pickle

from sklearn.metrics.pairwise import cosine_similarity

from sklearn.metrics import (precision_score, recall_score,f1_score,␣
```

```
↪accuracy_score,mean_squared_error,mean_absolute_error)
from scipy.stats import kurtosis, skew

from sklearn.ensemble import RandomForestClassifier, VotingClassifier,␣
↪BaggingClassifier, ExtraTreesClassifier
from sklearn.ensemble import BaggingRegressor, RandomForestRegressor,␣
↪ExtraTreesRegressor
from sklearn.linear_model import LogisticRegression

from sklearn.svm import SVC

from os import chdir, getcwd, mkdir, path

# from wget import download
```

List of numpy array, each position contains a patient's array of data

```
def read_and_store_data (dataset_folder, sample_rate, channels)
    :initial_path = getcwd()
    chdir(dataset_folder)


    patients = [d for d in listdir() if path.isdir(d) and
    d.startswith('chb')] patients.sort()
    arr = np.array([], dtype=np.float64).reshape(0, len(channels)
    for p in patients:chdir(p)

channels = ['FP1-F7', 'F7-T7','T7-P7', 'P7-O1', 'FP1-F3', 'F3-C3', 'C3-P3',␣
↪'P3-O1', 'FP2-F4', 'F4-C4', 'C4-P4', 'P4-O2', 'FP2-F8', 'F8-T8', 'T8-P8',␣
↪'P8-O2', 'FZ-CZ', 'CZ-PZ', 'seizure']


df=read_and_store_data("/content/gdrive/MyDrive/
↪seizure_classification",256,channels)
train_balance_df = pd.read_csv("/content/gdrive/MyDrive/
↪seizure_classfify_dataset/train_df.csv")

train_balance_df.head()
```

```
4    0.19536   0.195360   0.195360  0.195360  0.195360   0.195360  0.195360

          P3-O1      FP2-F4    F4-C4      C4-P4       P4-O2      FP2-F8       F8-T8  \
0    14.652015 -14.261294  0.19536 -10.744811   28.717949  35.360195  -24.810745
1     0.195360   0.195360  0.19536   0.195360    0.195360   0.195360    0.195360
2     0.195360   0.195360  0.19536   0.195360    0.195360   0.195360    0.195360
3     0.195360   0.195360  0.19536   0.195360    0.195360   0.195360    0.195360
```

5.SNAPSHOTS:

Figure 5.1 Dataset Collection

The below figure shows the preprocessing is applied for eeg signal convert into data frame format for feature extraction.

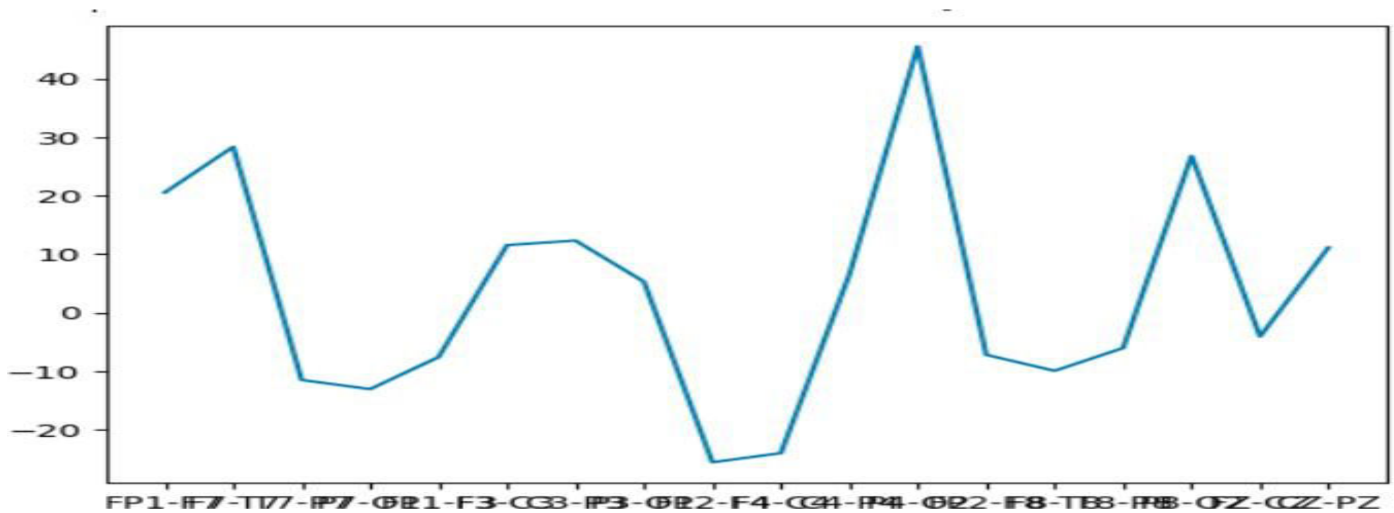
	FP1-F7	F7-T7	T7-P7	P7-01	FP1-F3	F3-C3	C3-P3	P3-01	FP2-F4	F4-C4	C4-P4	P4-02	FP2-F8	F8-T8	T8-P8	P8-02	FZ-CZ	CZ-PZ
0	-50.598291	118.192918	161.953602	42.783883	133.040293	-213.919414	311.990232	41.221001	56.849817	-2.148962	23.247863	45.909646	76.776557	-15.433455	-31.062271	93.577534	15.824176	28.327228
1	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360
2	0.195360	0.195360	0.195360	0.195360	0.195360	0.586081	-0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.195360	0.586081	0.195360	0.195360	0.195360
3	0.195360	0.195360	0.195360	0.195360	0.195360	0.976801	-0.976801	0.195360	0.195360	0.195360	0.195360	0.976801	0.195360	0.195360	0.976801	0.195360	0.195360	0.195360
4	0.195360	0.195360	-0.195360	0.195360	0.586081	-2.539683	2.148962	-0.195360	0.976801	-0.976801	0.195360	-2.148962	0.195360	0.976801	-3.711844	0.195360	-0.586081	-3.321123

Figure 5.2 EEG signal preprocessing

The below figure shows the time time domain feature is extracted from eeg signal.

Hurst_Coefficient	Mean	Standrd_Deviation	Petrosian_Fractal_Dimension	Hjorth_Mobility	Hjorth_complexcity	Correlation_Dimension	kurtosis_feature	skew_feature
0.590048	-4.493284	2.224706e+01	0.642332	0.331171	4.943547	5.266570e-01	-0.961199	0.042955
0.541133	0.195360	2.775558e-17	1.000000	0.055556	18.000000	6.433118e-18	-3.000000	0.000000
0.541133	0.195360	2.775558e-17	1.000000	0.055556	18.000000	6.433118e-18	-3.000000	0.000000
0.541133	0.195360	2.775558e-17	1.000000	0.055556	18.000000	6.433118e-18	-3.000000	0.000000
0.541133	0.238774	1.789979e-01	0.895727	0.208928	8.206025	2.314527e-18	13.058824	3.880570

Figure 5.3 Time domain feature extraction



The below figure shows the changes in the signal.

Figure 5.4 Changing Waves Frequency1

The below figure shows the changes in the signal.

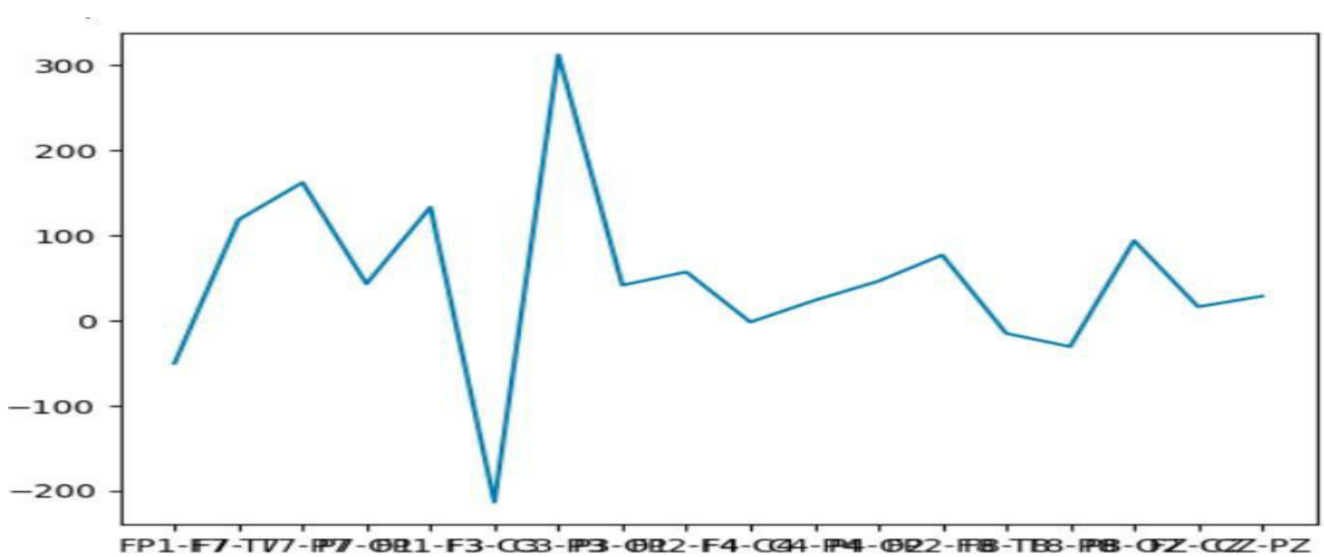


Figure 5.5 Changing Waves Frequency2

The below figure shows the Classification Report.

	precision	recall	f1-score	support
0.0	0.62	0.93	0.75	1000
1.0	0.87	0.43	0.57	1000
accuracy			0.68	2000
macro avg	0.74	0.68	0.66	2000
weighted avg	0.74	0.68	0.66	2000

Figure 5.6 Classification Report

The below figure shows the Confusion Matrix.

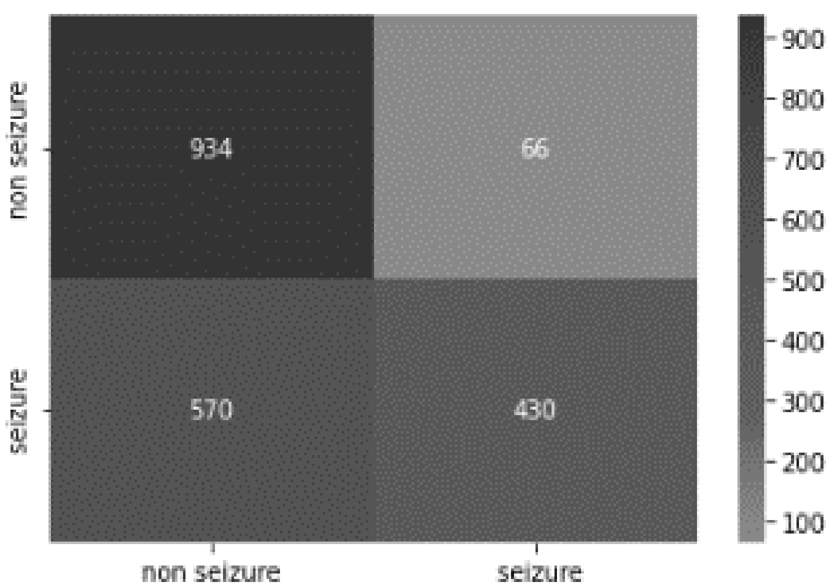


Figure 5.7 Confusion Matrix

The below figure shows the Prediction of sample data.

Input Data

```
[0.590047960040721,-4.493284493284492,22.24705773165208,0.6423320028298052,0.331171178116748,4.943546947945027,0.5266569916383048,-0.961198847178896,0.0429553398444255]
```

Output Data

```
predicted class is:  seizure
```

Figure 5.8 Prediction

6.CONCLUSION & FUTURE WORK

6.1 CONCLUSION:

The project has been successfully implemented to provide a solution for predict the presence of seizure at an early stage using multiple machine learning algorithms. The algorithm such as Random Forest, SVM and Logistic Regression to predict the seizure in a more efficient way. The machine learning algorithm is the finest technique which ensures accuracy in the achieved output and algorithm has a highest quality guesswork. There is lot of scope to improve the technology as seizure determination of combining brain heart signal can be done in several means.

6.2 FUTURE WORK:

In the coming future, we review the application of the detection of epilepsy seizure to determine technology in the healthcare field and it can promote for determine the all types of seizure with more accuracy. In this field they have more chance to develop or convert this project in many ways. Thus, this project has an efficient scope in coming future where manual predicting can be converted to computerized production in a cheap way.

7.REFERENCES

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8.BIOGRAPHY

AUTHOR 1

Mrs.ANU.K,M.E Assistant professor of Computer Science and Engineering Department in St. Joseph College of Engineering, Sriperumbudur, Chennai, Tamil Nadu. She has completed B.E and M.E in the Anna University Chennai.

AUTHOR 2

Ms.A.SUMITHRA,B.E Student of Computer Science and Engineering at St.Joseph College of Engineering, Sriperumbudur, Chennai, TamilNadu. I had attended many Workshops, Seminars in Python, Machine Learning. I got placed in Yaazh tech.

AUTHOR 3

Ms. P.BAKKIYA,B.E Student of Computer Science and Engineering at St.Joseph College of Engineering, Sriperumbudur, Chennai, TamilNadu. I had attended many Workshops, Data analysis course completed.