Autism Detection with Differential Diagnosis using Machine Learning

PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

Autism Spectrum Disorder (ASD), a neurological disorder, is usually followed by sensory problems such as excessive or lack of sensitivity to sounds, odors, or feelings. Although genetics is the root cause of the problem, early identification and therapy can assist in ameliorating the situation. Machine learning-based intelligent diagnosis has emerged in recent decades to supplement traditional clinical procedures, which may take a long time and be costly. The goal of this study is to identify the most important characteristics and to automate the diagnosis process by using current classification algorithms for better diagnosis using differential diagnosis technology. We looked at baby, child, teen, and adult ASD datasets. For these four ASD datasets, we examined province classification and feature selection strategies to establish the top-performing predictor and feature set. ASD may be recognized utilizing differential diagnosis technologies and machine learning algorithms by analyzing the symptoms of other illnesses and detecting it early on, which aids in correct treatment.

Keywords: Autism Spectrum Disorder, Machine Learning, Differential Diagnosis.

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

KNN	K-Nearest Neighbors
SVM	Support Vector Machine
RFC	Random Forest Classifier
LREG	Logistic Regression
GUI	Graphical User Interface
TE	Transfer Efficiency (Dataset)
MSR	Magnetic Sound Recorder (Dataset)
WWW	World Wide Web
HTTPS	Hyper Text Transfer Protocol
ASD	Autism Spectrum Disorder
ML	Machine Learning
LR	Linear regression

CHAPTER 1

INTRODUCTION

Autism spectrum disorder (ASD) is a neurological developmental condition that is characterized by a wide range of symptoms. It has an impact on how individuals communicate with one another, as well as how they act and learn. When a kid is extremely young, the symptoms and indications arise. It is a chronic illness that cannot be totally treated. According to one study, 33% of children with challenges other than ASD show some ASD symptoms but do not match all of the diagnostic requirements.

Because of the rise in the number of ASD cases globally, as well as the time and costs required in identifying a patient, ASD has a substantial economic effect. Early discovery of ASD can benefit both patients and healthcare providers by allowing adequate therapy and/or medication to be prescribed, lowering the long-term expense of misdiagnosis. On the other hand, traditional clinical methods, such as the Autism Diagnostic Interview Revised (ADIR) and the Autism Diagnostic Observation Schedule Revised (ADOS-R), on the other hand, are time-consuming and inconvenient. Because the verbal parts cannot be responded to appropriately for the patient, children who are premature and have delayed speech issues score around 25% of the total ADI-R questions. Furthermore, completing an interview with a caregiver by a professional examiner takes 90 to 150 minutes, which is time-consuming and frequently results in data being missed.

The identification of ASD by ADOS-R, on the other hand, is based on scoring measurements based on the responses supplied. Furthermore, one of the significant drawbacks of this technique is the potential for children with various clinical conditions to be overclassified. As a result, healthcare providers are in desperate need of a quick, simple, and accessible ASD screening tool that can effectively determine whether a patient with a specific measurable trait has ASD and advise them on whether or not to seek a formal clinical diagnosis. AGR, the National Database of Autism Research (NDAR), and the Boston Autism Consortium are among the few datasets now accessible, all of which are linked to clinical diagnoses that are largely genetic in origin (AC).

1. We examine the characteristics of the Newborn, Child, Adolescent, and Older ASD datasets and look for correlations among demographic information and ASD cases.

2. We look at standard subset of features techniques and find the one that fits best for all four ASD datasets in terms of identifying the most important characteristics for the greatest classification results. Our findings demonstrate that selecting the right features improves ASD classification accuracy substantially.

3. For each of the four ASD datasets, we evaluate state-of-the-art different classifiers and determine the highest performing model.

1.1 Supervised Learning:

Supervised learning is a type of machine learning method in which users provide sample labeled data to the machine learning system in order to train it, and on that basis, it predicts the output. The system creates a model using labeled data to understand the datasets and learn about each data, once the training and processing are done then users test the model by providing a sample data to check whether it is predicting the exact output or not.

1.2 Unsupervised Learning:

Unsupervised learning is a learning method in which a machine learns without any supervision. The training is provided to the machine with the set of data that has not been labeled, classified, or categorized, and the algorithm needs to act on that data without any supervision. The goal of unsupervised learning is to restructure the input data into new features or a group of objects with similar patterns.

1.3 Reinforcement Learning:

Reinforcement learning is a feedback-based learning method, in which a learning agent gets a reward for each right action and gets a penalty for each wrong action. The agent learns automatically with these feedbacks and improves its performance. In reinforcement learning, the agent interacts with the environment and explores it. The goal of an agent is to get the most reward points, and hence, itimproves its performance

1.4 Inefficient use of old technologies

Usage of old technologies / device which are not updated, it has some compatibility errors on showing accuracy on spot. The model in practice is using just 5-10 features of voice data which may affect the accuracy.

1.5 Efficiency of new one

This model uses more features to test and train, so the accuracy of the prediction increases by a large extent. This also can predict the disease at the earlier stages as it uses more features to train the model than the traditional ones. GUI has been developed to make the user check the prediction with ease.

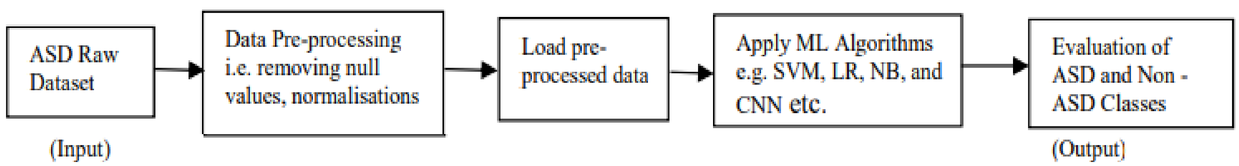
CHAPTER 2

LITERATURE SURVEY

Various researches have been done on Detection of Autism Spectrum Disorder Using Machine Learning Techniques. This research is done prior to taking up the project and understanding the various methods that were used previously. This study helped to identify the benefits and drawbacks of the existing system.

2.1 Suman Raj in "Analysis and Detection of Autism Spectrum Disorder Using Machine Learning Techniques"

In the proposed workflow which involves the pre-processing of data, training, and testing with specified models, evaluation of results and prediction of ASD. This work is implemented in Python 3.



2.2 Katherine Kuhl-Meltzoff Stavropoulos, Yasamine Bolourian and Jan Blacherin in "Differential Diagnosis of Autism Spectrum Disorder and Post Traumatic Stress Disorder: Two Clinical Cases

The patient had multiple pre-existing diagnoses (PTSD and ADHD), which further complicated her ability to find and receive an accurate diagnosis. Although she had received a previous diagnosis of ADHD, our clinic does not test for or diagnose ADHD, and the presenting question did not pertain to ADHD. Often, children with existing mental health diagnoses do not receive an appropriate further diagnosis due to diagnostic overshadowing. Diagnostic overshadowing occurs when professionals attribute a patient's symptoms to a particular condition while overlooking a co-occurring condition. When diagnostic overshadowing occurs, it is difficult for parents or school professionals who are concerned about a child's behavior to find providers who will conduct comprehensive diagnostic assessments. Although in this case the patient's symptoms and presentation did not warrant a further diagnosis of ASD, it is important for providers to be aware of diagnostic overshadowing in order to avoid missing an accurate comorbid diagnosis.

2.3 Eleni A. Demetriou and Shin H. Park in "Machine Learning for Differential Diagnosis Between Clinical Conditions With Social Difficulty: Autism Spectrum Disorder, Early Psychosis, and Social Anxiety Disorder"

Differential diagnosis in adult cohorts with social difficulty is confounded by comorbid mental health conditions, common etiologies, and shared phenotypes. Identifying shared and discriminating profiles can facilitate intervention and remediation strategies. The objective of the study was to identify salient features of a composite test battery of cognitive and mood measures using a machine learning paradigm in clinical cohorts with social interaction difficulties.

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

Autism spectrum disorder (ASD) is difficult to diagnose since there is no medical test for it, such as a blood test. To make a diagnosis, doctors look at the child's developmental history and behaviors. ASD can be discovered as early as 18 months of age. By the age of two, a professional diagnosis can be regarded quite trustworthy. Many youngsters, however, do not obtain a definite diagnosis until they are considerably older.

3.2 PROPOSED SYSTEM

To detect ASD early on, we gathered data from a large number of patients, converted them into a perfect dataset, then performed Data Pre-processing to remove null values and normalized the dataset. Apply several machine learning techniques to the preprocessed dataset to discover the value. And we do Differential diagnoses for rule out other disorders and determine whether the person has autism or not.

3.2.1 MODULES USED

- The speech dataset is gathered from several clinicians who are already conducting research on ASD, as well as some from parents of children with Autism, and it is cleaned to eliminate any distorted, duplicate, or missing data.
- Identification and extraction of the features from the speech dataset such as fundamental frequency and pitch. Verified the values of each data and make correction.
- Implementation of different machine learning algorithms such as SVM, KNN, LREG etc. are used in order to identify the pattern in the voice data and classify them.
- The features are extracted, the dataset is trained and tested using the machine learning model to predict the Autism spectrum disorder or not. And suggesting the treatment ,on the other hand the collected data can be used for research purpose.

3.2.2 FLOW CHART

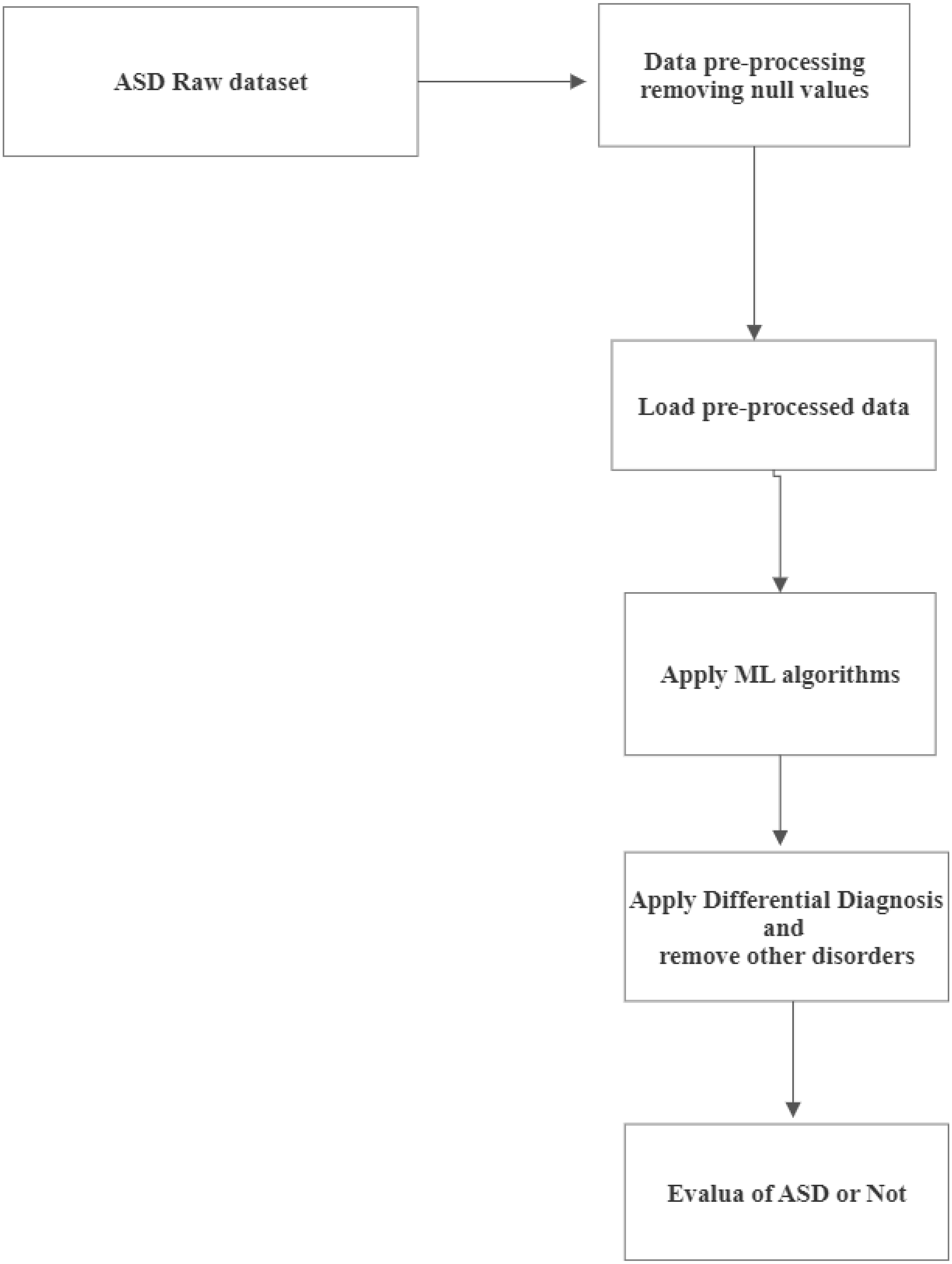


Fig 3.2.2 Overview of the system

CHAPTER 4

PROJECT DESCRIPTION

4.1 PROBLEM DEFINITION

Autism spectrum disorder is a condition related to brain development that impacts how a person perceives and socializes with others, causing problems in social interaction and communication. The disorder also includes limited and repetitive patterns of behavior. The term "spectrum" in autism spectrum disorder refers to the wide range of symptoms and severity.

Autism spectrum disorder includes conditions that were previously considered separate — autism, Asperger's syndrome, childhood disintegrative disorder and an unspecified form of pervasive developmental disorder. Some people still use the term "Asperger's syndrome," which is generally thought to be at the mild end of autism spectrum disorder.

4.2 OBJECTIVES

The main objectives of the project is to make a change human life by the early detection of Autism Disorder. The model is developed to process more accurate data in terms of diagnostic accuracy. Added with accuracy, it is also more scalable, less expensive. And therefore it is more accessible to people who might not have access to established medical facilities and professionals. It also helps the users to minimize considerable amount of degradation and can be treated at the earliest.

4.3 OVERVIEW OF THE PROJECT

1. We examine the characteristics of the Newborn, Child, Adolescent, and Older ASD datasets and look for correlations among demographic information and ASD cases.

2. We look at standard subset of features techniques and find the one that fits best for all four ASD datasets in terms of identifying the most important characteristics for the greatest classification results. Our findings demonstrate that selecting the right features improves ASD classification accuracy substantially.

3. For each of the four ASD datasets, we evaluate state-of-the-art different classifiers and determine the highest performing model.

4.4 BLOCK DIAGRAM

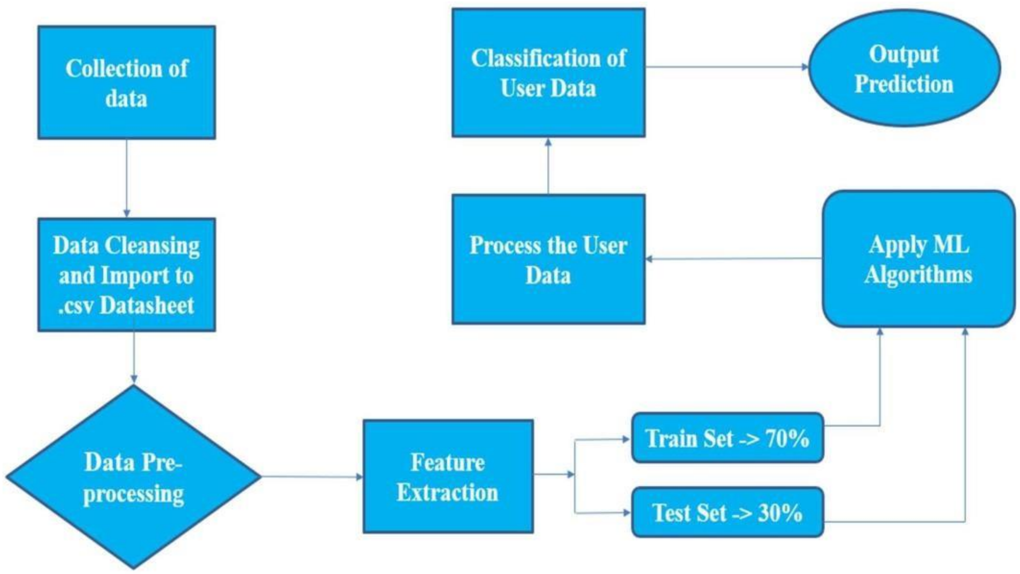


Fig 4.4 Model Schema

4.5 MODULE DESCRIPTION

Using Machine Learning algorithms, this system will identify the Autism Spectrum Disorder. This approach uses the below processes to detect the Autism Spectrum Disorder.

- Data collection and cleaning
- Feature Extraction
- Pattern Recognition and Training
- Apply Differential Diagnoses
- Testing and Prediction

4.5.1 DATA COLLECTION AND CLEANING

Firstly the datasets containing healthy and ASD affected people voices are collected from Kaggle and UCI Repository. Apart from the voice datasets, sample feature dataset (i.e csv file) have been downloaded a for reference and to understand and apply cleansing methods on the dataset. As the features are going to be extracted from the voices and going to be written into a csv file, the csv file should be regulated. The dataset should not contain a null, NaN (Not a Number) value, and the value should be corresponding to the float x64 format to be executed properly. So the feature’s headers and dummy values for the headers in the specified format to avoid the errors while feature extraction and the incoming data will be cleaned as the values will be written into the csv in the float x64 format.

4.5.2 FEATURE EXTRACTION

With this method of identifying it can be more time effectives to identifying Autism Spectrum Disorder to patents, and with help of Differential diagnosis to remove other disorder and easy to find it is whether it is ASD or not.

4.5.3 PATTERN RECOGNITION AND TRAINING

In this stage, with the csv file, the training of the machine learning model is been done to identify the patterns in the provided data. Once the pattern has been identified, the data field is classified by **1** (people having ASD)and **0**(people who do not have the disease). Once this process is done, then the data is trained and tested with various machine learning algorithms to see which algorithm yields highest accuracy. The algorithms used are Naïve Bayes, SVM, KNN, RFC and Logistic Regression. All these algorithms are also cross validated to obtain the highest possible accurate model. Here Logistic Regression has been used, since it has the highest average accuracy with and without Cross- Validation.

4.5.4 TESTING AND PREDICTION

The trained model is extracted into a .sav file to be used for prediction. To combine every features of this model, a GUI has been created. Then the trained model is being loaded onto the GUI and is ready for the prediction. With the help of the GUI, users can speak the mentioned text through the microphone of the device to check if he/she has the ASD in real-time.

4.6 Merits and Demerits

4.6.1 Merits

- ❖ Accuracy has been increased by training more features to provide optimum results.
- ❖ GUI (Graphical User Interface) has been created to increase usability of the app.

4.6.2 Demerits

- ❖ Every data is collected from the user or from their parents it may be get the wrong result if the data has any mistakes.
- ❖ The data collected only based on the appearance and from their actions from small tasks, it may be gets wrong result is the data is wrong.

4.7 Application

- ❖ Early detection of Autism Spectrum Disorder with Speech Pattern Recognition.
- ❖ This method of diagnosis doesn’t be expensive.
- ❖ Early detection of autism in at-risk children can open door to intensive training by therapists

4.8 WORKING

The Application get the data from the user, After the collection of huge data we apply normalization to remove all null values from the data set. Data will be stored in csv file for efficient usage in different codes and algorithms we use. There are nearly 10 variables will be present in the data set to be evaluated. The evaluation process contains various machine learning algorithms that will find the cluster, property and identify all the required vectors to be placed in the data table, we use KERAS library from python module that will efficiently apply all the algorithms that is required to be compared to find if the condition is accurately Autism so that it can be treated efficiently. The algorithms that we use are (SVM) Support Vector Machine , K Nearest Neighbor (KNN), K-Mean Clustering Algorithm, Naïve bayes, Linear Regression, Multiple Linear Regression, Logistic Regression, Decision Tree , Random Forest ,Hierarchical clustering, DBSCAN Clustering, et cetera . The reason to use these multiple algorithms is to find accurate results that could potentially increase the level of finding the severity of the ASD. A good working model for a problem may not be accurate of other cases.

The Assessment will be conducted to the patient's parents they can fill the questionnaire and information about the patient's activities which can be further evaluated by all the above stated algorithms. The assessment consists of social interaction, communication, repetitive behaviors, Response to questions are the main symptoms of ASD. After evaluation the results will be further compared to other disorders that have same symptoms or related to Autism Spectrum Disorder, ex: ADHD, Learning Disability, Social Communication Disorder.

By using Differential Diagnosis method, we can more efficiently identity if the patient is affected by Autism or any other disorder that has similar symptoms like ASD. After applying various algorithms in dataset, the most accurate algorithm is used for the application development. With the differential diagnosis eliminating other disorders identify whether the child has ASD or not.

CHAPTER 5
PERFORMANCE EVALUATION

5.1 RESULTS AND ANALYSIS

This study uses different types of performance evaluation metrics for the three pretrained models such as accuracy, sensitivity, and specificity and a confusion matrix. A confusion matrix is a type of measure of classification performance that represents a table of the true and false values of the testing results. In the confusion matrix of the Xception model, the True Positives were 132 autistic children out of 150 autistic children, the False Negatives were 18 children classified as autistic children, the True Negatives were 141 correctly classified children out of the 150 normal children, and the False Positives were 9 children.

$$\text{Accuracy} = \frac{TP + TN}{FP + FN + TP + TN} \times 100\%,$$

$$\text{Specificity} = \frac{TN}{TN + FN} \times 100\%,$$

$$\text{Sensitivity} = \frac{TP}{TP + FP} \times 100\%,$$

The equations for these metrics are as follows:

where TP is the True Positive, FP is the False Positive, TN is the True Negative, and FN is the False Negative. Specificity is the capacity of the model to correctly identify the normal children, and sensitivity is the capacity of the model to correctly identify autistic children.

5.1.1 PERFORMANCE TABLE

	precision	recall	f1-score	support
ADHD	1.00	1.00	1.00	30
ID	1.00	1.00	1.00	30
LD	1.00	1.00	1.00	30
Mild	1.00	1.00	1.00	6
Mild-Moderate	1.00	1.00	1.00	8
Moderate	1.00	0.67	0.80	3
Moderate-Severe	1.00	1.00	1.00	6
Normal	1.00	1.00	1.00	30
Normal-Mild	1.00	1.00	1.00	1
SCD	1.00	1.00	1.00	30
Severe	0.97	1.00	0.98	28

Fig 5.1.2 Performance on Accuracy

Table 5.1 Accuracy of the model with different algorithms

ALGORITHM	WITH CROSS VALIDATION	WITHOUT CROSS VALIDATION
SVM	84.7	67.8
RANDOM FOREST	85.4	65.7
LOGISTIC REGRESSION	89.9	81.3
KNN	83.3	68.2
NAÏVE BAYES	87.5	75.7

```
Numpy array of predictions

array([[0.    , 0.006 , 0.003 , 0.813 , 0.0347, 0.0022, 0.0151, 0.0594,
        0.0013, 0.    , 0.0651],
       [0.    , 0.    , 0.    , 0.0809, 0.1319, 0.0106, 0.7707, 0.0001,
        0.0006, 0.    , 0.0051],
       [0.0434, 0.    , 0.    , 0.0078, 0.4686, 0.0205, 0.411 , 0.0002,
        0.0484, 0.    , 0.    ],
       [0.    , 0.    , 0.    , 0.2689, 0.2654, 0.0711, 0.0967, 0.0244,
        0.265 , 0.    , 0.0086],
       [0.    , 0.    , 0.    , 0.0993, 0.0051, 0.0046, 0.0031, 0.    ,
        0.    , 0.    , 0.8879]], dtype=float32)

As percent probability
[ 0.0004  0.6039  0.3033 81.2991  3.4746  0.2245  1.5129  5.9433  0.1256
  0.0014  6.5109]
Log loss score: 0.08796859242771363
```

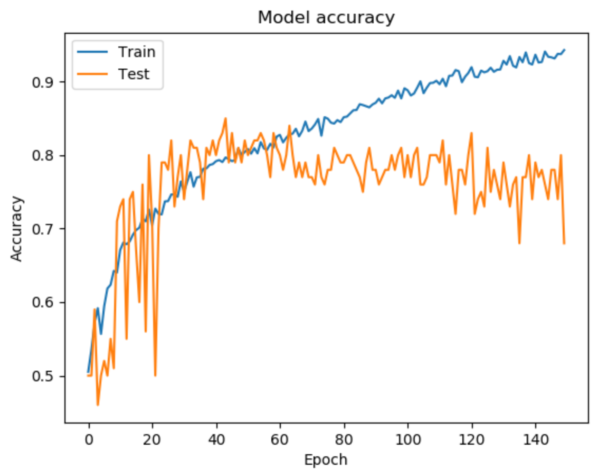


Fig 5.1.4 Accuracy Plot

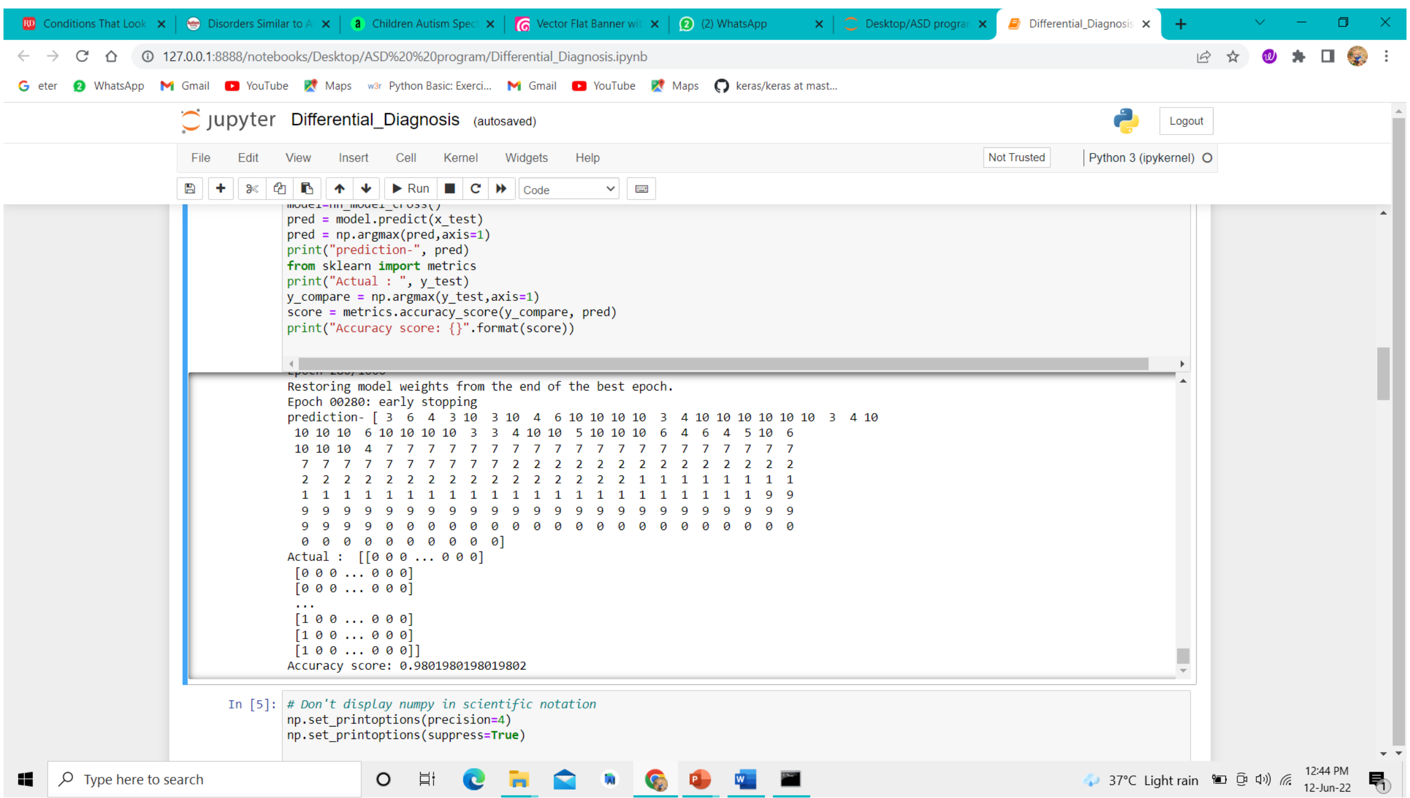


Fig 5.1.5 Accuracy of Predictions

CHAPTER 6

SOFTWARE SPECIFICATION

6.1 JUPYTER

Fig 6.1 Jupyter

Jupyter Notebook is a web-based interactive computational environment for creating notebook documents. A Jupyter Notebook document is a browser- based REPL containing an ordered list of input/output cells which can contain code, text (using Markdown), mathematics, plots and rich media. Underneath theinterface, a notebook is a JSON document, following a versioned schema, usuallyending with the ".ipynb" extension.

Jupyter notebooks can illustrate the analysis process step by step by arranging the stuff like code, images, text, output etc. in a step by step manner. It helps a data scientist to document the thought process while developing the analysis process.

6.2 LANGUAGE SUPPORTED BY JUPYTER

PYTHON

Fig 6.2 Python

Python is a general purpose, dynamic, high-level, and interpreted programming language. It supports Object Oriented programming approach to develop applications. It is simple and easy to learn and provides lots of high-level data structures. Python is designed to be highly readable. It uses English keywords frequently where as other languages use punctuation, and it has fewer syntactical constructions than other languages.

Characteristics of Python:

- It supports functional and structured programming methods as well as OOP.
- It can be used as a scripting language or can be compiled to byte-code for building large applications.
- It provides very high-level dynamic data types and supports dynamic type checking.
- It supports automatic garbage collection.

6.3 ANACONDA FRAMEWORK

Fig 6.3 Anaconda

Anaconda is the Open Source data science distribution for the Python and R programming languages scientific computing, such as data science, machine learning applications, predictive analysis, large-scale data processing, etc. The Anaconda can be used to simplify package management and deployment. It includes more than 300 data science packages that are suitable for Windows, Linux, and MacOS.

Anaconda will be available in three different editions, which are:

- **Individual Edition:** This edition was developed for Solo practitioners.
- **Team Edition:** The team edition has been developed to work with the team on the same page.
- **Enterprise Edition:** The Enterprise edition has been developed to use data science and machine learning to make a better decision.

CHAPTER 7

CONCLUSION

7.1 CONCLUSION:

We got to the conclusion that applying differential diagnosis to determine whether the child or individual has Autism Spectrum Disorder or anything else was the best way to diagnose the ASD by creating a more effective dataset using multiple machine learning techniques.

As we know, ASD cannot be cured, but we can give physical training to the child as early as possible to prevent disorder attacks. By identifying the child as early as possible, it can be turned into an advantage for the parents to train him or her according to their disability, giving them a better chance to cure and convert.

7.2 FUTURE SCOPE:

- Create a mobile application which would allow the user to record his/her voice, extract the necessary vocal features, and feed it into my machine learning model to diagnose ASD.

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APPENDICES

APPENDIX 1

SOFTWARE AND HARDWARE DESCRIPTION

SOFTWARE REQUIREMENTS

- ENVIRONMENT : Anaconda and Jupyter notebook
- CODING LANGUAGE : Python 3.9
- OPERATING SYSTEMS : Microsoft windows 11
- DOCUMENTATION : Microsoft word 2020

HARDWARE REQUIREMENTS

- PROCESSOR : Intel Core i5
- RAM : 8 GB

APPENDIX 2

SOURCE CODE

ASD.IPYNB

```
import numpy as np
from sklearn import svm, datasets
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt

def plot_confusion_matrix(cm, names, title='Confusion matrix', cmap=plt.cm.Blues):
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(names))
    plt.xticks(tick_marks, names, rotation=45)
    plt.yticks(tick_marks, names)
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

y_compare = np.argmax(y_test,axis=1)
# Compute confusion matrix
cm = confusion_matrix(y_compare, pred)
np.set_printoptions(precision=2)
print('Confusion matrix, without normalization')
print(cm)
plt.figure()
plot_confusion_matrix(cm, products)
```

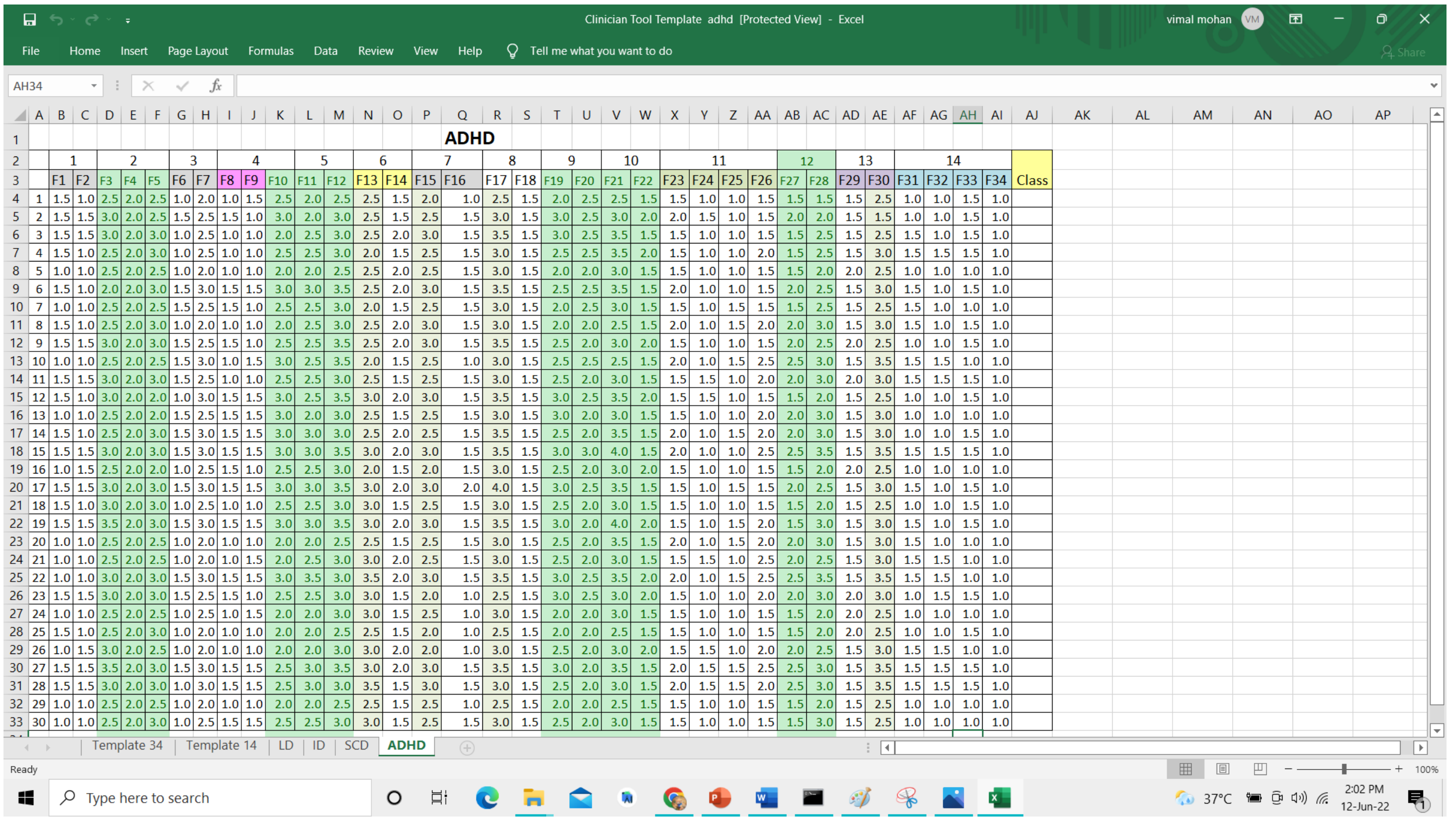
```
# Normalize the confusion matrix by row (i.e by the number of samples
# in each class)
cm_normalized = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
print('Normalized confusion matrix')
print(cm_normalized)
plt.figure()
plot_confusion_matrix(cm_normalized, products, title='Normalized confusion matrix')

plt.show()

import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
from sklearn.externals import joblib
import numpy as np

from sklearn.metrics import roc_curve, auc
import pandas as pd
import matplotlib.pyplot as plt
from pandas.plotting import scatter_matrix
from matplotlib import cm
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score, precision_recall_curve, precision_score
import seaborn as sns
from sklearn import metrics
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
import matplotlib.font_manager as fm
```

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC

cases = pd.read_csv('diffdiagnosis.csv',header=None)

#cases=shuffle(cases)
data=cases.values
X=data[:,0:34].astype(float)
y=data[:,34]

test_data = X[0:]
val_data = X[0:]
data = X[0:]

#X = cases[feature_names]
#y = cases['Class']
#print(X)
#X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.9)
#X_train, y_train= data.drop('Class', axis=1), y
X_train, y_train= X,y
y_test, X_test = y,X
#Multinomial Logistic Regression
logreg = LogisticRegression(random_state=0, solver='newton-cg', multi_class='multinomial')
logreg.fit(X_train, y_train)
#pr=loaded_model.predict(X_test)
result = logreg.score(X_test, y_test)
#print(result)

rfe = RFE(logreg, 20)
```

```
rfe = rfe.fit(X_train, y_train)
# summarize the selection of the attributes
print(rfe.support_)
print(rfe.ranking_)



print('Accuracy of Decision Tree classifier on training set: {:.2f}'
     .format(logreg.score(X_train, y_train)))
print('Accuracy of Decision Tree classifier on test set: {:.2f}'
     .format(logreg.score(X_test, y_test)))
pred = logreg.predict(X_test)
print(confusion_matrix(y_test, pred))
print(classification_report(y_test, pred))

from sklearn import metrics
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2

data = pd.read_csv("diffdiagnosis.csv")
X = data.iloc[:,0:34]  #independent columns
y = data.iloc[:,-1]
fsel=SelectKBest(chi2,k=20)
fs=chi2(X,y)

print(fs)
#print(fs[8])
#print(fs[8],fs[9],fs[10],fs[11],fs[14],fs[15],fs[21],fs[24],fs[28],fs[30])
fsel.fit(X,y)
Xnew=fsel.transform(X)
v=X.columns[fsel.get_support(indices=True)].tolist()
print(v)
```

APPENDIX 3

SCREEN SHOTS:



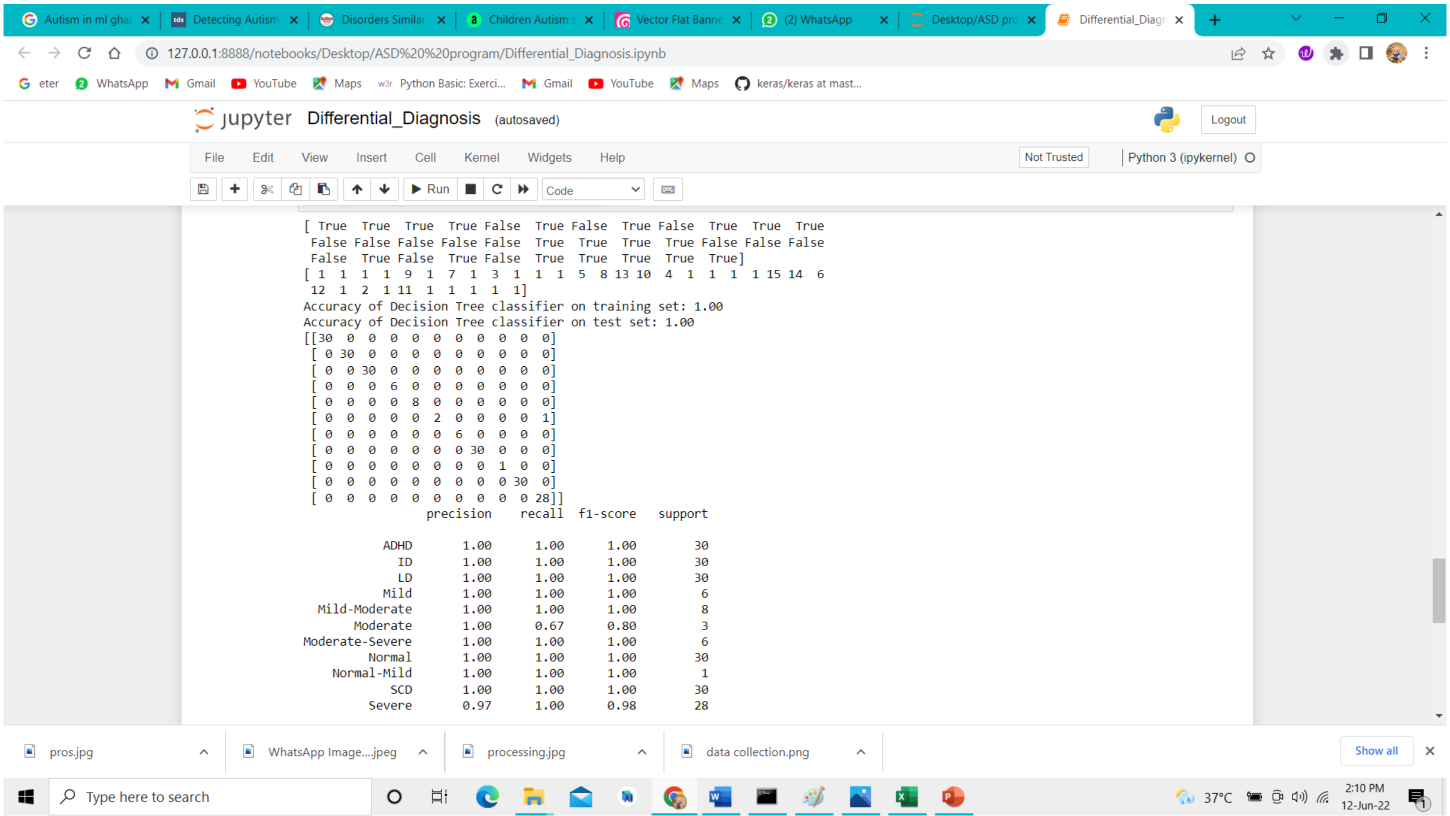
ADHD

	1		2			3		4			5		6		7		8		9		10		11				12		13		14				
	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23	F24	F25	F26	F27	F28	F29	F30	F31	F32	F33	F34	Class
1	1.5	1.0	2.5	2.0	2.5	1.0	2.0	1.0	1.5	2.5	2.0	2.5	2.5	1.5	2.0	1.0	2.5	1.5	2.0	2.5	2.5	1.5	1.5	1.0	1.0	1.5	1.5	1.5	1.5	2.5	1.0	1.0	1.5	1.0	
2	1.5	1.5	3.0	2.0	2.5	1.5	2.5	1.5	1.0	3.0	2.0	3.0	2.5	1.5	2.5	1.5	3.0	1.5	3.0	2.5	3.0	2.0	2.0	1.5	1.0	1.5	2.0	2.0	1.5	1.5	1.0	1.0	1.5	1.0	
3	1.5	1.5	3.0	2.0	3.0	1.0	2.5	1.0	1.0	2.0	2.5	3.0	2.5	2.0	3.0	1.5	3.5	1.5	3.0	2.5	3.5	1.5	1.5	1.0	1.0	1.5	1.5	2.5	1.5	2.5	1.5	1.0	1.5	1.0	
4	1.5	1.0	2.5	2.0	3.0	1.0	2.5	1.0	1.0	2.5	2.5	3.0	2.0	1.5	2.5	1.5	3.0	1.5	2.5	2.5	3.5	2.0	1.5	1.0	1.0	2.0	1.5	2.5	1.5	3.0	1.5	1.5	1.5	1.0	
5	1.0	1.0	2.5	2.0	2.5	1.0	2.0	1.0	1.0	2.0	2.0	2.5	2.5	2.0	2.5	1.5	3.0	1.5	2.0	2.0	3.0	1.5	1.5	1.0	1.0	1.5	1.5	2.0	2.0	2.5	1.0	1.0	1.0	1.0	
6	1.5	1.0	2.0	2.0	3.0	1.5	3.0	1.5	1.5	3.0	3.0	3.5	2.5	2.0	3.0	1.5	3.5	1.5	2.5	2.5	3.5	1.5	2.0	1.0	1.0	1.5	2.0	2.5	1.5	3.0	1.5	1.0	1.5	1.0	
7	1.0	1.0	2.5	2.0	2.5	1.5	2.5	1.5	1.0	2.5	2.5	3.0	2.0	1.5	2.5	1.5	3.0	1.5	2.0	2.5	3.0	1.5	1.5	1.0	1.5	1.5	1.5	2.5	1.5	2.5	1.5	1.0	1.0	1.0	
8	1.5	1.0	2.5	2.0	3.0	1.0	2.0	1.0	1.0	2.0	2.5	3.0	2.5	2.0	3.0	1.5	3.0	1.5	2.0	2.0	2.5	1.5	2.0	1.0	1.5	2.0	2.0	3.0	1.5	3.0	1.5	1.0	1.5	1.0	
9	1.5	1.5	3.0	2.0	3.0	1.5	2.5	1.5	1.0	2.5	2.5	3.5	2.5	2.0	3.0	1.5	3.5	1.5	2.5	2.0	3.0	2.0	1.5	1.0	1.0	1.5	2.0	2.5	2.0	2.5	1.0	1.0	1.5	1.0	
10	1.0	1.0	2.5	2.0	2.5	1.5	3.0	1.0	1.5	3.0	2.5	3.5	2.0	1.5	2.5	1.0	3.0	1.5	2.5	2.5	2.5	1.5	2.0	1.0	1.5	2.5	2.5	3.0	1.5	3.5	1.5	1.5	1.0	1.0	
11	1.5	1.5	3.0	2.0	3.0	1.5	2.5	1.0	1.0	2.5	2.5	3.0	2.5	1.5	2.5	1.5	3.0	1.5	2.5	2.0	3.0	1.5	1.5	1.5	1.0	2.0	2.0	3.0	2.0	3.0	1.5	1.5	1.5	1.0	
12	1.5	1.0	3.0	2.0	2.0	1.0	3.0	1.5	1.5	3.0	2.5	3.5	3.0	2.0	3.0	1.5	3.5	1.5	3.0	2.5	3.5	2.0	1.5	1.5	1.0	1.5	1.5	2.0	1.5	2.5	1.0	1.0	1.5	1.0	
13	1.0	1.0	2.5	2.0	2.0	1.5	2.5	1.5	1.5	3.0	2.0	3.0	2.5	1.5	2.5	1.5	3.0	1.5	3.0	2.0	3.0	1.5	1.5	1.0	1.0	2.0	2.0	3.0	1.5	3.0	1.0	1.0	1.0	1.0	
14	1.5	1.0	2.5	2.0	3.0	1.5	3.0	1.5	1.5	3.0	3.0	3.0	2.5	2.0	2.5	1.5	3.5	1.5	2.5	2.0	3.5	1.5	2.0	1.0	1.5	2.0	2.0	3.0	1.5	3.0	1.0	1.0	1.5	1.0	
15	1.5	1.5	3.0	2.0	3.0	1.5	3.0	1.5	1.5	3.0	3.0	3.5	3.0	2.0	3.0	1.5	3.5	1.5	3.0	3.0	4.0	1.5	2.0	1.0	1.0	2.5	2.5	3.5	1.5	3.5	1.5	1.5	1.5	1.0	
16	1.0	1.5	2.5	2.0	2.0	1.0	2.5	1.5	1.0	2.5	2.5	3.0	2.0	1.5	2.0	1.5	3.0	1.5	2.5	2.0	3.0	2.0	1.5	1.0	1.0	1.5	1.5	2.0	2.0	2.5	1.0	1.0	1.0	1.0	
17	1.5	1.5	3.0	2.0	3.0	1.5	3.0	1.5	1.5	3.0	3.0	3.5	3.0	2.0	3.0	2.0	4.0	1.5	3.0	2.5	3.5	1.5	1.5	1.0	1.5	1.5	2.0	2.5	1.5	3.0	1.5	1.0	1.5	1.0	
18	1.5	1.0	3.0	2.0	3.0	1.0	2.5	1.0	1.0	2.5	2.5	3.0	3.0	1.5	2.5	1.5	3.0	1.5	2.5	2.0	3.0	1.5	1.5	1.0	1.0	1.5	1.5	2.0	1.5	2.5	1.0	1.0	1.5	1.0	
19	1.5	1.5	3.5	2.0	3.0	1.5	3.0	1.5	1.5	3.0	3.0	3.5	3.0	2.0	3.0	1.5	3.5	1.5	3.0	2.0	4.0	2.0	1.5	1.0	1.5	2.0	1.5	3.0	1.5	3.0	1.5	1.0	1.5	1.0	
20	1.0	1.0	2.5	2.0	2.5	1.0	2.0	1.0	1.0	2.0	2.0	2.5	2.5	1.5	2.5	1.5	3.0	1.5	2.5	2.0	3.5	1.5	2.0	1.0	1.5	2.0	2.0	3.0	1.5	3.0	1.5	1.0	1.0	1.0	
21	1.0	1.0	2.5	2.0	2.5	1.0	2.0	1.0	1.5	2.0	2.5	3.0	3.0	2.0	2.5	1.5	3.0	1.5	2.5	2.0	3.0	1.5	1.5	1.5	1.0	2.5	2.0	2.5	1.5	3.0	1.5	1.5	1.0	1.0	
22	1.0	1.0	3.0	2.0	3.0	1.5	3.0	1.5	1.5	3.0	3.5	3.0	3.5	2.0	3.0	1.5	3.5	1.5	3.0	2.5	3.5	2.0	2.0	1.0	1.5	2.5	2.5	3.5	1.5	3.5	1.5	1.5	1.0	1.0	
23	1.5	1.5	3.0	2.0	3.0	1.5	2.5	1.5	1.0	2.5	2.5	3.0	3.0	1.5	2.0	1.0	2.5	1.5	3.0	2.5	3.0	2.0	1.5	1.0	1.0	2.0	2.0	3.0	2.0	3.0	1.0	1.5	1.5	1.0	
24	1.0	1.0	2.5	2.0	2.5	1.0	2.5	1.0	1.5	2.0	2.0	3.0	3.0	1.5	2.5	1.0	3.0	1.5	2.0	2.0	3.0	1.5	1.5	1.0	1.0	1.5	1.5	2.0	2.0	2.5	1.0	1.0	1.0	1.0	
25	1.5	1.0	2.5	2.0	3.0	1.0	2.0	1.0	1.0	2.0	2.0	2.5	2.5	1.5	2.0	1.0	2.5	1.5	2.0	2.0	2.5	1.5	1.5	1.0	1.0	1.5	1.5	2.0	2.0	2.5	1.0	1.0	1.5	1.0	
26	1.0	1.5	3.0	2.0	2.5	1.0	2.0	1.0	1.0	2.0	2.0	3.0	3.0	2.0	2.0	1.0	3.0	1.5	2.5	2.0	3.0	2.0	1.5	1.5	1.0	2.0	2.0	2.5	1.5	3.0	1.5	1.5	1.0	1.0	
27	1.5	1.5	3.5	2.0	3.0	1.5	3.0	1.5	1.5	2.5	3.0	3.5	3.0	2.0	3.0	1.5	3.5	1.5	3.0	2.0	3.5	1.5	2.0	1.5	1.5	2.5	2.5	3.0	1.5	3.5	1.5	1.5	1.5	1.0	
28	1.5	1.5	3.0	2.0	3.0	1.0	3.0	1.5	1.5	2.5	3.0	3.0	3.5	1.5	3.0	1.5	3.0	1.5	2.5	2.0	3.0	1.5	2.0	1.5	1.5	2.0	2.5	3.0	1.5	3.5	1.5	1.5	1.5	1.0	
29	1.0	1.0	2.5	2.0	2.5	1.0	2.0	1.0	1.0	2.0	2.0	2.5	2.5	1.5	2.5	1.0	2.5	1.5	2.0	2.0	2.5	1.5	1.5	1.0	1.0	1.5	1.5	2.0	1.5	2.5	1.0	1.0	1.0	1.0	
30	1.0	1.0	2.5	2.0	3.0	1.0	2.5	1.5	1.5	2.5	2.5	3.0	3.0	1.5	2.5	1.5	3.0	1.5	2.5	2.0	3.0	1.5	1.5	1.0	1.0	1.5	1.5	3.0	1.5	2.5	1.0	1.0	1.0	1.0	

Fig A3.1 Healthy Dataset

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ
1		1		2			3		4			5		6		7		8		9		10		11				12		13		14				
2		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23	F24	F25	F26	F27	F28	F29	F30	F31	F32	F33	F34	Class
3	1	2.00	2.50	1.50	2.00	1.50	2.00	1.50	2.00	2.00	1.50	2.00	2.00	2.00	2.00	2.00	1.50	2.00	2.00	1.50	1.50	1.50	1.00	1.00	1.50	1.00	1.50	1.00	1.50	1.50	2.00	1.50	1.50	2.00	1.00	mild
4	2	2.50	3.00	3.00	4.00	3.50	3.00	3.50	3.00	3.00	3.50	2.50	3.00	3.00	3.00	3.50	3.00	2.00	3.00	3.00	3.50	3.00	2.50	3.00	2.50	2.50	3.00	3.00	3.00	3.00	2.50	3.00	3.00	2.50	1.00	m-s
5	3	2.00	2.50	2.50	3.00	2.50	2.00	2.50	1.50	2.00	2.00	2.00	2.00	3.00	3.00	2.50	2.00	3.00	2.50	2.00	2.50	2.00	2.50	2.00	1.50	3.00	1.50	3.00	3.00	2.50	2.00	2.00	2.00	1.50	1.50	m-m
6	4	2.00	2.00	2.00	2.50	2.00	1.50	1.50	2.00	2.00	2.00	1.50	1.50	2.50	2.50	2.00	2.50	2.00	2.00	2.50	2.00	2.50	2.00	2.00	2.00	3.00	3.00	2.50	2.00	2.00	1.50	2.00	2.00	1.50	2.00	n-m
7	5	3.50	3.50	3.00	3.00	2.50	3.50	3.00	3.50	3.00	3.00	4.00	3.50	3.50	3.00	3.00	3.50	3.00	3.00	3.50	3.00	3.50	2.00	3.50	3.00	3.50	3.00	3.50	3.00	3.00	3.50	3.00	3.50	3.50	1.00	sev
8	6	2.50	2.00	2.50	3.00	1.50	2.00	1.50	2.00	2.00	1.50	2.00	2.00	1.50	1.50	2.00	2.00	2.00	2.00	1.50	1.50	1.50	2.50	2.50	2.00	1.50	3.00	2.00	1.50	2.00	1.50	2.00	2.00	1.50	2.50	mild
9	7	4.00	4.00	4.00	4.00	3.00	4.00	4.00	4.00	3.50	3.50	4.00	3.50	3.00	3.50	3.50	4.00	4.00	3.50	4.00	3.00	4.00	2.00	3.00	3.50	3.00	3.00	4.00	3.50	4.00	2.00	3.50	3.50	3.50	3.50	sev
10	8	2.50	3.00	2.00	2.00	2.00	1.50	2.00	2.50	3.00	2.50	2.00	2.00	3.00	3.50	2.00	2.50	3.00	3.00	3.00	2.50	2.50	2.50	3.50	3.00	3.00	2.50	3.00	2.50	3.00	1.50	3.00	2.50	2.50	2.50	m-m
11	9	3.00	3.00	3.00	2.50	3.00	2.50	2.00	3.50	3.50	3.00	3.00	3.00	3.00	3.00	3.00	3.50	3.50	3.00	3.00	3.00	2.00	3.00	2.50	2.50	2.50	2.00	3.00	3.00	2.00	2.50	3.00	2.50	2.00	1.00	m-s
12	10	3.50	3.50	4.00	3.50	3.50	4.00	4.00	3.50	3.50	3.50	3.00	3.00	4.00	3.50	3.50	4.00	3.00	3.00	3.50	3.00	3.00	3.00	4.00	4.00	3.50	3.50	3.50	3.50	3.50	3.50	3.50	3.50	3.50	4.00	sev
13	11	3.00	3.50	3.50	4.00	2.00	3.00	3.00	4.00	3.50	4.00	3.00	3.50	4.00	3.50	4.00	4.00	3.00	3.50	3.50	3.00	3.50	3.00	3.50	3.50	3.00	4.00	3.00	3.00	3.00	1.50	3.50	3.00	3.00	2.00	sev
14	12	3.00	3.00	3.00	2.50	3.00	3.50	3.00	3.50	3.50	3.00	4.00	3.50	3.50	3.50	4.00	4.00	3.50	3.50	3.50	3.50	3.50	3.00	3.50	3.50	3.00	3.00	3.50	3.00	2.00	3.00	3.50	3.50	3.00	3.50	sev
15	13	4.00	4.00	3.50	2.00	3.50	3.50	3.00	3.00	3.00	3.00	3.50	3.00	3.00	3.00	3.00	3.50	3.00	3.00	3.00	2.50	3.00	2.50	3.00	2.50	2.50	3.00	3.00	3.00	1.50	3.50	3.50	3.50	3.00	3.50	sev
16	14	2.50	2.50	2.00	2.00	2.00	2.00	2.00	2.50	2.00	2.00	2.00	2.00	2.00	2.00	2.50	2.50	2.00	1.50	2.50	2.00	3.00	1.50	2.50	2.00	1.50	2.00	1.50	1.50	2.00	2.00	1.50	1.50	2.00	1.00	mild
17	15	3.00	3.00	2.50	2.00	2.50	3.50	3.50	2.50	3.00	2.50	2.50	3.00	3.50	3.00	3.00	3.50	3.00	3.00	3.00	3.00	3.00	1.50	2.00	2.00	2.00	2.50	2.00	2.50	2.50	2.00	2.50	2.00	2.00	1.00	m-m
18	16	3.50	3.50	3.00	3.00	3.00	3.50	3.50	3.00	3.00	3.00	3.50	3.50	3.00	3.00	3.00	3.50	3.00	3.00	3.00	3.00	3.00	1.50	3.00	2.50	2.50	3.00	3.00	3.00	3.50	3.00	3.00	3.50	3.50	3.50	sev
19	17	3.00	3.00	3.00	2.50	3.00	3.00	3.00	3.50	3.00	3.00	2.50	2.00	3.00	3.50	2.00	2.50	3.00	2.50	3.00	3.50	3.00	1.50	2.00	2.50	2.00	2.50	3.00	2.50	2.50	2.50	3.00	2.50	2.50	3.50	sev
20	18	3.50	3.50	3.00	3.00	3.00	3.00	3.00	3.00	3.00	2.50	3.00	3.00	3.50	3.50	3.00	3.50	3.00	3.00	3.00	3.00	3.00	1.50	3.00	3.00	2.50	3.00	3.00	3.00	2.00	3.00	3.00	3.50	3.50	3.50	sev
21	19	4.00	3.50	3.00	3.50	3.00	2.50	3.00	3.00	3.00	3.00	3.00	3.00	3.50	3.00	3.00	3.00	3.00	3.00	3.50	3.50	3.00	3.00	2.50	2.00	2.00	2.50	2.50	2.50	3.00	2.00	3.00	3.50	3.50	3.50	sev
22	20	4.00	4.00	3.00	2.50	3.50	3.00	3.00	3.50	3.00	3.50	3.00	3.00	3.50	3.50	3.50	3.50	3.00	3.00	3.50	3.50	3.00	1.50	3.00	2.00	1.50	3.00	3.00	3.00	3.50	2.00	3.00	3.50	3.50	3.50	sev
23	21	3.50	3.50	3.00	2.50	3.00	4.00	3.50	3.50	3.50	3.00	3.00	3.00	3.00	3.00	3.50	3.50	3.00	3.00	3.00	3.00	3.50	3.50	3.00	3.00	2.50	3.00	3.50	3.50	3.00	3.00	3.00	3.00	3.00	3.50	sev
24	22	2.00	2.00	3.00	3.00	2.50	2.00	2.00	2.00	2.00	2.00	2.00	2.50	2.50	2.50	3.00	2.50	3.00	3.00	3.00	2.00	2.50	2.00	3.50	2.50	3.00	2.50	2.50	2.00	3.50	2.00	3.00	3.50	2.50	2.50	mild
25	23	3.00	3.50	3.00	3.50	3.00	2.00	2.50	3.00	3.00	3.00	2.00	2.00	3.00	3.00	2.50	3.00	3.00	3.00	3.00	3.50	3.50	3.00	3.00	2.00	3.00	3.00	3.00	3.00	3.00	2.00	3.00	2.00	2.00	2.00	mod

Fig A3.2 ASD Dataset



Output based on given dataset

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