# A New Multilayer Perceptron Model to Detect Heart Disease Severity

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Abstract-With the recent outbound spread of chronicle heart diseases across the world, gender and age, the medical practitioners are focusing on preventive measures rather than curing methods. Thus the modern research trends are bound to provide the preventive extension to the medical science. Although the medical practices can generate gigantic amount of relevant data pertaining to the diseases, however the medical science fail to deploy any technique to mine the data for predictive models. Thus the data mining and predictive models are the most suitable way to provide the necessary tools for predictive analysis. Hence this work deploys a multilayer perceptron model for predictive detection of heart disease severity based on various parameters. The deployed multi-layered perception uses the backpropagation for optimal supervised learning. The work also deploys a novel principle attribute analysis to understand the orientation of the attributes affecting the results. The final outcome of this work is to analyse the Heart Disease Severity based on proposed multilayer perceptron model.

## *Keywords*— HMM, MLP, Rule Based Approach, Genetic Algorithm for Search, Optimal Feature Selection

## I. INTRODUCTION

The hearth or the cardiovascular diseases have a huge impact on the death rates[1] in the world especially in the developing countries. Celtia et al in the year of 2000 have proven that cardiovascular diseases cause 25% of the deaths. The work presented by World Bank Country groups in the year of 2001, had cited the health rate by heart diseases around 25%. However the work of Mathers et al presented in the year of 2004, had analyses the death rate as 46%, which is a notable increase in the span of 4 years. It is predicted that in the year of 2020 an approximated 2.5 million people from India are likely to be severely affected by heart diseases. In spite of the best clinical practices and available medications, the death rates are increasing and expected to be 55% in India by the end of 2020.

The focus of this work is to demonstrate a Novel Multilayer Perceptron Model to Detect Heart Disease Severity[2]. Henceforth this work analyses the recent research outcomes from the parallel works.

The present research trends are directing towards a more specific and focused study of predictive models for determining the severity of the heart diseases based on the clinical results and best possible computing techniques [3].

The outcomes from work of Huyan Wang at al had proposed a traditional model for Chinese medical practices based on a computing model to diagnosis based on the Bayesian model.

Also the works been carried out with the perspective of generic programming in order to produce expert systems are notable for prediction and diagnosis of heart diseases[4]. The work of Assanelli et al in the year of 1993 demonstrates the use of ECG data to predict the heart diseases. Meanwhile, Ng, G. and Ong, K has developed a chest pain expert system, which diagnoses the cause of chest pain leading towards the cardiac attacks.

Text classification techniques combined with a Naive Bayes classifier and relational learning algorithms are methods<sup>[5]</sup> used by Craven in the year of 1999. Hidden Markov Models are used in Craven in the year of 2001, but similarly to Rosario and Hearst produced in the year of 2004, the research focus was entity recognition. A context based approach using MeSH term co-occurrences are used by Srinivasan and Rindflesch for relationship discrimination between diseases and drugs[6]. A lot of work is focused on building rules used to extract relation. Feldman et al. use a rulebased system to extract relations that are focused on proteins, drugs, genes, and diseases and demonstrated in 2002. Friedman et al. go deeper into building a rule-based system by hand-crafting a semantic grammar and a set of semantic constraints

in order to recognize a range of biological and molecular relations[7].

In biomedical literature, rule-based approaches have been widely used for solving relation extraction tasks. The main sources of information used by this technique are either syntactic: part-ofspeech (POS) and syntactic structures; or semantic information in the form of fixed patterns that contain words that trigger a certain relation. One of the drawbacks of using methods based on rules is that they tend to require more human-expert effort than data-driven methods. The best rule-based systems are the ones that use rules constructed automatically-extracted manually or semi automatically and refined manually. A positive aspect of rule-based systems is the fact that they obtain good precision results, while the recall levels tend to be low. Syntactic rule-based relation extraction systems are complex systems based on additional tools used to assign POS tags or to extract syntactic parse trees. It is known that in the biomedical literature such tools are not yet at the state-of-the-art level as they are for general English texts, and therefore their performance on sentences is not always the best.

Henceforth this work can be visualized as the potential findings of work and guidelines for the performance of a framework that is capable to find relevant information about diseases and treatments in a medical domain repository. The results that obtained will show that it is a realistic scenario to use NLP and ML techniques to build a tool that capable to identify and disseminate textual information related to diseases and treatments.

Thus this work identifies the problems in the existing and parallel research outcomes as:

- Firstly, a lot of data pertaining to cardiac dieses are available, but the datasets are over populated with multiple parameters. The outcome of processing multiple parameters leads to high computational complexity and processing less parameter may lead to lower order of accuracy in prediction. Hence, there is a clear demand for a technique to identify most appropriate set of parameters to be processed during predictive analysis[8-12].
- Secondly, there are various computation techniques deployed to timely predict with

less computational complexity. However, the neural network based programming approaches are proven to be time efficient. Henceforth, there is also a demand for finding the optimal neural network setup for predictive analysis[13-19].

## II. PROPOSED FRAMEWORK FOR PRE-PROCESSING

The first step of this proposed work is the preprocessing framework for determining and extracting the influential parameters. The most appropriate algorithm for feature or attribute selection is a Genetic algorithm[20-22], where initially all the attributes are considered as individual subsets and the final combination of the attributes or features are noted as optimal best feature subset. The framework is been proposed here:

Step-1. Calculate and Collect the list of attributes to be ordered in terms of significance:

$$M[] \leftarrow \forall P \exists (\sum_{i=1}^{n} p_i) \tag{1}$$

Where, M denotes the initial set of attributes, P denotes the total available list of attributes.

Step-2. Assign the selection vector as S[L] where L is the size of the initial attribute list. Initially the vector is filled with zeros to denote no optimal subset is selected.

$$\forall \mathbf{S}, \mathbf{S}[\mathbf{i}] \leftarrow \mathbf{0} \tag{2}$$

Step-3. In this step of the algorithm, the fitness for all the attributes is been calculated so that the ranking can be provided for the features against all other attributes.

$$\begin{split} &Info_{Gain}(S_{i}) = \\ & \begin{cases} 1 + Info_{Gain}(Class_{i}, S_{i}), \\ & if \ Info_{Gain}(Class_{i}, S_{i}) \geq Info_{Gain}(Class_{i-1}, S_{i-1}) \\ & 1 + Info_{Gain}(Class_{i}, S_{i}), Else \end{cases} \end{split}$$

Step-4. Once the attributes are been ranked, the final selected subset is produced.

$$S[m] \leftarrow Highest(Info_{Gain}(M))$$
 (4)

The work analyses the data set provided by UCI machine learning. Each database has the same instance format. While the databases have 76 raw attributes. The descriptions of the dataset parameters are provided here [Table -1]:

TABLE I: UCI HEART DISEASE DATABASES

| Serial<br>Number | Parameter<br>Names | Parameter Descriptions  |  |  |  |  |
|------------------|--------------------|---|--|--|--|--|
| 1                | ID                 | Patient identification number   |  |  |  |  |
| 2                | CCF                | Social security number (I replaced this with a dummy value of 0)  |  |  |  |  |
| 3                | AGE                | Age in years  |  |  |  |  |
| 4                | SEX                | Sex $(1 = male; 0 = female)$  |  |  |  |  |
| 5                | PAINLOC            | Chest pain location (1 = substernal; 0 = otherwise)   |  |  |  |  |
| 6                | PAINEXER           | (1 = provoked by exertion; 0 = otherwise)   |  |  |  |  |
| 7                | RELREST            | (1 = relieved after rest; 0 = otherwise)  |  |  |  |  |
| 8                | PNCADEN            | (Sum of 5, 6, and 7)  |  |  |  |  |
| 9                | СР                 | Chest pain type<br>Value 1 typical angina<br>Value 2 atypical angina<br>Value 3 non-anginal pain<br>Value 4 asymptomatic  |  |  |  |  |
| 10               | TRESTBPS           | Resting blood pressure (in mm Hg on admission to the hospital   |  |  |  |  |
| 11               | HTN                | Not Defined   |  |  |  |  |
| 12               | CHOL               | Serum cholestoral in mg/dl  |  |  |  |  |
| 13               | SMOKE              | I believe this is 1 = yes; 0 = no (is or is<br>not a smoker)  |  |  |  |  |
| 14               | CIGS               | (Cigarettes per day)  |  |  |  |  |
| 15               | YEARS              | (Number of years as a smoker)   |  |  |  |  |
| 16               | FBS                | (Fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)   |  |  |  |  |
| 17               | DM                 | (1 = history of diabetes; 0 = no such<br>history)   |  |  |  |  |
| 18               | FAMHIST            | Family history of coronary artery disease $(1 = yes; 0 = no)$   |  |  |  |  |
| 19               | RESTECG            | Resting electrocardiographic results<br>Value 0 normal<br>Value 1 having ST-T wave<br>abnormality (T wave inversions and/or<br>ST<br>elevation or depression of ><br>0.05 mv)<br>Value 2 showing probable or<br>definite left ventricular hypertrophy<br>by Estes' criteria |  |  |  |  |
| 20               | EKGMO              | (month of exercise ECG reading)   |  |  |  |  |
| 21               | EKGDAY             | (day of exercise ECG reading)   |  |  |  |  |
| 22               | EKGYR              | (year of exercise ECG reading)  |  |  |  |  |
| 23               | DIG                | (digitalis used furing exercise ECG 1 = yes; 0 = no)  |  |  |  |  |
| 24               | PROP               | (Beta blocker used during exercise ECG $1 = yes; 0 = no$ )  |  |  |  |  |
| 25               | NITR               | (nitrates used during exercise ECG 1 = yes; 0 = no)   |  |  |  |  |
| 26               | PRO                | (calcium channel blocker used during<br>exercise ECG $1 = yes; 0 = no$ )  |  |  |  |  |
| 27               | DIURETIC           | (diuretic used used during exercise ECG $1 = yes; 0 = no$ )   |  |  |  |  |
| 28               | PROTO              | Exercise protocol<br>1 = Bruce<br>2 = Kottus<br>3 = mchenry<br>4 = fast Balke   |  |  |  |  |

|  |   | 5 = Balke   |
|--|---|---|
|  |   | 6 = Noughton  |
|  |   | 7 = bike 150 kpa min/min  |
|  |   | 8 = bike 125 kpa min/min  |
|  |   | 9 = bike 100 kpa min/min  |
|  |   | 10 = bike 75 kpa min/min  |
|  |   | 11 = bike 50  kpa min/min   |
|  |   | 12 = arm ergometer  |
| 29   | THALDUR   | Duration of exercise test in minutes  |
| 30   | THALTIME  | Time when ST measure depression was   |
|  |   | noted   |
| 31   | MET   | Mets achieved   |
| 32   | THALACH   | Maximum heart rate achieved   |
| 33   | THALREST  | Resting heart rate  |
| 34   | TPEAKBPS  | Peak exercise blood pressure (first of 2 parts)   |
| 35   | PEAKBPD   | Peak exercise blood pressure (second of 2 parts)  |
| 36   | DUMMY   |   |
| 37   | TRESTBPD  | Resting blood pressure  |
| 38   | EXANG   | Exercise induced angina (1 = yes; 0 = no)   |
| 39   | ХНҮРО   | (1 = yes; 0 = no)   |
| 40   | OLDPEAK   | ST depression induced by exercise   |
|  | OLDI LIM  | relative to rest  |
|  |   | The slope of the peak exercise ST segment   |
| 41   | SLOPE   | 8   |
| 41   | SLOPE   | Value 1 upsloping<br>Value 2 flat   |
|  |   | Value 2 That<br>Value 3 downsloping   |
| 42   | RLDV5   | Height at rest  |
| 42   | RLDV5   | Height at peak exercise   |
| 43   | KLDVJE  | Number of major vessels (0-3) colored   |
| 44   | CA  | by flourosopy   |
| 45   | RESTCKM   | Irrelevant  |
|  |   |   |
|  | EXERCKM   |   |
| 46   | EXERCKM<br>RESTEF   | Irrelevant  |
| 46   |   | Irrelevant<br>Rest raidonuclid Ejection fraction  |
| 46   |   | Irrelevant  |
| 46   |   | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality  |
| 46 47  | RESTEF  | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none  |
| 46 47  | RESTEF  | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate  |
| 46 47  | RESTEF  | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe  |
| 46<br>47<br>48   | RESTEF  | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe<br>3 = akinesis or dyskmem   |
| 46<br>47<br>48<br>48<br>49<br>50   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM  | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe<br>3 = akinesis or dyskmem<br>Exercise radinalid Ejection fraction   |
| 46<br>47<br>48<br>48   | RESTEF<br>RESTWM<br>EXEREF  | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe<br>3 = akinesis or dyskmem<br>Exercise radinalid Ejection fraction<br>Exercise wall Motion<br>3 = normal; 6 = fixed defect; 7 =<br>reversable defect   |
| 46<br>47<br>48<br>48<br>49<br>50   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM  | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe<br>3 = akinesis or dyskmem<br>Exercise radinalid Ejection fraction<br>Exercise wall Motion<br>3 = normal; 6 = fixed defect; 7 =<br>reversable defect<br>Not used   |
| 46<br>47<br>48<br>48<br>50<br>51   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL  | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe<br>3 = akinesis or dyskmem<br>Exercise radinalid Ejection fraction<br>Exercise wall Motion<br>3 = normal; 6 = fixed defect; 7 =<br>reversable defect<br>Not used<br>Not used   |
| 46<br>47<br>48<br>48<br>50<br>51<br>52   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE                                     | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe<br>3 = akinesis or dyskmem<br>Exercise radinalid Ejection fraction<br>Exercise wall Motion<br>3 = normal; 6 = fixed defect; 7 =<br>reversable defect<br>Not used<br>Not used<br>Not used   |
| 46<br>47<br>48<br>49<br>50<br>51<br>51<br>52<br>53   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL  | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe<br>3 = akinesis or dyskmem<br>Exercise radinalid Ejection fraction<br>Exercise wall Motion<br>3 = normal; 6 = fixed defect; 7 =<br>reversable defect<br>Not used<br>Not used<br>Month of cardiac cath (perhaps "call")   |
| 46<br>47<br>48<br>49<br>50<br>51<br>52<br>53<br>54   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE                                     | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe<br>3 = akinesis or dyskmem<br>Exercise radinalid Ejection fraction<br>Exercise wall Motion<br>3 = normal; 6 = fixed defect; 7 =<br>reversable defect<br>Not used<br>Not used<br>Not used<br>Month of cardiac cath (perhaps "call")<br>Day of cardiac cath  |
| $ \begin{array}{c}     46 \\     47 \\     48 \\     49 \\     50 \\     51 \\     52 \\     53 \\     54 \\     55 \\   \end{array} $   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO                              | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe<br>3 = akinesis or dyskmem<br>Exercise radinalid Ejection fraction<br>Exercise wall Motion<br>3 = normal; 6 = fixed defect; 7 =<br>reversable defect<br>Not used<br>Not used<br>Month of cardiac cath (perhaps "call")   |
| $ \begin{array}{c}     46 \\     47 \\     48 \\     49 \\     50 \\     51 \\     52 \\     53 \\     54 \\     55 \\     56 \\   \end{array} $   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY                      | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe<br>3 = akinesis or dyskmem<br>Exercise radinalid Ejection fraction<br>Exercise wall Motion<br>3 = normal; 6 = fixed defect; 7 =<br>reversable defect<br>Not used<br>Not used<br>Not used<br>Month of cardiac cath (perhaps "call")<br>Day of cardiac cath  |
| $ \begin{array}{c}     46 \\     47 \\     48 \\     49 \\     50 \\     51 \\     52 \\     53 \\     54 \\     55 \\     56 \\   \end{array} $   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY                      | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe<br>3 = akinesis or dyskmem<br>Exercise radinalid Ejection fraction<br>Exercise wall Motion<br>3 = normal; 6 = fixed defect; 7 =<br>reversable defect<br>Not used<br>Not used<br>Not used<br>Month of cardiac cath (perhaps "call")<br>Day of cardiac cath  |
| $ \begin{array}{c}     46 \\     47 \\     48 \\     49 \\     50 \\     51 \\     52 \\     53 \\     54 \\     55 \\     56 \\   \end{array} $   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY                      | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe<br>3 = akinesis or dyskmem<br>Exercise radinalid Ejection fraction<br>Exercise wall Motion<br>3 = normal; 6 = fixed defect; 7 =<br>reversable defect<br>Not used<br>Not used<br>Not used<br>Month of cardiac cath (perhaps "call")<br>Day of cardiac cath<br>Year of cardiac cath<br>Diagnosis of heart disease (angiographic  |
| 46<br>47<br>48<br>48<br>50<br>51<br>51<br>52<br>53<br>54<br>55<br>56<br>57   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY<br>CYR               | Irrelevant<br>Rest raidonuclid Ejection fraction<br>Rest wall Motion abnormality<br>0 = none<br>1 = mild or moderate<br>2 = moderate or severe<br>3 = akinesis or dyskmem<br>Exercise radinalid Ejection fraction<br>Exercise radinalid Ejection fraction<br>a = normal; 6 = fixed defect; 7 =<br>reversable defect<br>Not used<br>Not used<br>Not used<br>Month of cardiac cath (perhaps "call")<br>Day of cardiac cath<br>Year of cardiac cath<br>Diagnosis of heart disease (angiographic<br>disease status)   |
| $ \begin{array}{c}     46 \\     47 \\     48 \\     49 \\     50 \\     51 \\     52 \\     53 \\     54 \\     55 \\     56 \\   \end{array} $   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY                      | Irrelevant         Rest raidonuclid Ejection fraction         Rest wall Motion abnormality         0 = none         1 = mild or moderate         2 = moderate or severe         3 = akinesis or dyskmem         Exercise radinalid Ejection fraction         Exercise radinalid Ejection fraction         Exercise radinalid Ejection fraction         3 = normal; 6 = fixed defect; 7 =         reversable defect         Not used         Not used         Month of cardiac cath (perhaps "call")         Day of cardiac cath         Year of cardiac cath         Diagnosis of heart disease (angiographic disease status)         Value 0 < 50% diameter              |
| 46<br>47<br>48<br>48<br>50<br>51<br>51<br>52<br>53<br>54<br>55<br>56<br>57   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY<br>CYR               | Irrelevant         Rest raidonuclid Ejection fraction         Rest vall Motion abnormality         0 = none         1 = mild or moderate         2 = moderate or severe         3 = akinesis or dyskmem         Exercise radinalid Ejection fraction         Exercise vall Motion         3 = normal; 6 = fixed defect; 7 =         reversable defect         Not used         Not used         Month of cardiac cath (perhaps "call")         Day of cardiac cath         Year of cardiac cath         Diagnosis of heart disease (angiographic disease status)         Value 0 < 50% diameter   |
| 46<br>47<br>48<br>48<br>50<br>51<br>51<br>52<br>53<br>54<br>55<br>56<br>57   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY<br>CYR               | Irrelevant         Rest raidonuclid Ejection fraction         Rest vall Motion abnormality         0 = none         1 = mild or moderate         2 = moderate or severe         3 = akinesis or dyskmem         Exercise radinalid Ejection fraction         Exercise vall Motion         3 = normal; 6 = fixed defect; 7 =         reversable defect         Not used         Not used         Month of cardiac cath (perhaps "call")         Day of cardiac cath         Year of cardiac cath         Diagnosis of heart disease (angiographic disease status)         Value 0 < 50% diameter   |
| 46           47           48           49           50           51           52           53           54           55           56           57           58   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY<br>CYR<br>NUM        | Irrelevant         Rest raidonuclid Ejection fraction         Rest vall Motion abnormality         0 = none         1 = mild or moderate         2 = moderate or severe         3 = akinesis or dyskmem         Exercise radinalid Ejection fraction         Exercise radinalid Ejection fraction         Exercise vall Motion         3 = normal; 6 = fixed defect; 7 =         reversable defect         Not used         Not used         Month of cardiac cath (perhaps "call")         Day of cardiac cath         Vear of cardiac cath         Diagnosis of heart disease (angiographic disease status)         Value 0 < 50% diameter                              |
| 46           47           48           49           50           51           52           53           54           55           56           57           58           59  | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY<br>CVR<br>NUM        | Irrelevant         Rest raidonuclid Ejection fraction         Rest vall Motion abnormality         0 = none         1 = mild or moderate         2 = moderate or severe         3 = akinesis or dyskmem         Exercise radinalid Ejection fraction         Exercise radinalid Ejection fraction         Exercise radinalid Ejection fraction         a normal; 6 = fixed defect; 7 =         reversable defect         Not used         Not used         Month of cardiac cath (perhaps "call")         Day of cardiac cath         Year of cardiac cath         Diagnosis of heart disease (angiographic disease status)         Value 0 < 50% diameter                |
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| $ \begin{array}{c ccccccccccccccccccccccccccccccccccc$   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY<br>CYR<br>NUM        | Irrelevant         Rest raidonuclid Ejection fraction         Rest wall Motion abnormality         0 = none         1 = mild or moderate         2 = moderate or severe         3 = akinesis or dyskmem         Exercise radinalid Ejection fraction         Exercise radinalid Ejection fraction         Exercise radinalid Ejection fraction         a = normal; 6 = fixed defect; 7 =         reversable defect         Not used         Not used         Month of cardiac cath (perhaps "call")         Day of cardiac cath         Year of cardiac cath         Diagnosis of heart disease (angiographic disease status)         Value 0 < 50% diameter              |
| $ \begin{array}{c ccccccccccccccccccccccccccccccccccc$   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY<br>CYR<br>NUM        | Irrelevant         Rest raidonuclid Ejection fraction         Rest wall Motion abnormality         0 = none         1 = mild or moderate         2 = moderate or severe         3 = akinesis or dyskmem         Exercise radinalid Ejection fraction         Exercise radinalid Ejection fraction         Exercise vall Motion         3 = normal; 6 = fixed defect; 7 =         reversable defect         Not used         Not used         Month of cardiac cath (perhaps "call")         Day of cardiac cath         Year of cardiac cath         Diagnosis of heart disease (angiographic disease status)         Value 0 < 50% diameter                              |
| $ \begin{array}{c ccccccccccccccccccccccccccccccccccc$   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY<br>CYR<br>NUM<br>NUM | Irrelevant         Rest raidonuclid Ejection fraction         Rest wall Motion abnormality         0 = none         1 = mild or moderate         2 = moderate or severe         3 = akinesis or dyskmem         Exercise radinalid Ejection fraction         Exercise radinalid Ejection fraction         Exercise vall Motion         3 = normal; 6 = fixed defect; 7 =         reversable defect         Not used         Not used         Month of cardiac cath (perhaps "call")         Day of cardiac cath         Year of cardiac cath         Diagnosis of heart disease (angiographic disease status)         Value 0 < 50% diameter                              |
| $ \begin{array}{c ccccccccccccccccccccccccccccccccccc$   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY<br>CYR<br>NUM        | Irrelevant         Rest raidonuclid Ejection fraction         Rest vall Motion abnormality         0 = none         1 = mild or moderate         2 = moderate or severe         3 = akinesis or dyskmem         Exercise radinalid Ejection fraction         Exercise vall Motion         3 = normal; 6 = fixed defect; 7 =         reversable defect         Not used         Not used         Month of cardiac cath (perhaps "call")         Day of cardiac cath         Year of cardiac cath         Diagnosis of heart disease (angiographic disease status)         Value 0 < 50% diameter   |
| $ \begin{array}{c ccccccccccccccccccccccccccccccccccc$   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY<br>CYR<br>NUM<br>NUM | Irrelevant         Rest raidonuclid Ejection fraction         Rest wall Motion abnormality         0 = none         1 = mild or moderate         2 = moderate or severe         3 = akinesis or dyskmem         Exercise radinalid Ejection fraction         Exercise radinalid Ejection fraction         Exercise wall Motion         3 = normal; 6 = fixed defect; 7 =         reversable defect         Not used         Not used         Month of cardiac cath (perhaps "call")         Day of cardiac cath         Year of cardiac cath         Vear of cardiac cath         Diagnosis of heart disease (angiographic disease status)         Value 0 < 50% diameter |
| $ \begin{array}{c ccccccccccccccccccccccccccccccccccc$   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY<br>CYR<br>NUM<br>NUM | Irrelevant         Rest raidonuclid Ejection fraction         Rest wall Motion abnormality         0 = none         1 = mild or moderate         2 = moderate or severe         3 = akinesis or dyskmem         Exercise radinalid Ejection fraction         Exercise radinalid Ejection fraction         Exercise vall Motion         3 = normal; 6 = fixed defect; 7 =         reversable defect         Not used         Not used         Month of cardiac cath (perhaps "call")         Day of cardiac cath         Year of cardiac cath         Diagnosis of heart disease (angiographic disease status)         Value 0 < 50% diameter                              |
| $ \begin{array}{c ccccccccccccccccccccccccccccccccccc$   | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY<br>CYR<br>NUM        | Irrelevant         Rest raidonuclid Ejection fraction         Rest wall Motion abnormality         0 = none         1 = mild or moderate         2 = moderate or severe         3 = akinesis or dyskmem         Exercise radinalid Ejection fraction         Exercise radinalid Ejection fraction         Exercise vall Motion         3 = normal; 6 = fixed defect; 7 =         reversable defect         Not used         Not used         Month of cardiac cath (perhaps "call")         Day of cardiac cath         Year of cardiac cath         Diagnosis of heart disease (angiographic disease status)         Value 0 < 50% diameter                              |
| $ \begin{array}{c}             46 \\             47 \\             48 \\             49 \\             50 \\             51 \\             52 \\             53 \\             54 \\             55 \\           $ | RESTEF<br>RESTWM<br>EXEREF<br>EXERWM<br>THAL<br>THALSEV<br>THALPUL<br>EARLOBE<br>CMO<br>CDAY<br>CYR<br>NUM<br>NUM | Irrelevant         Rest raidonuclid Ejection fraction         Rest wall Motion abnormality         0 = none         1 = mild or moderate         2 = moderate or severe         3 = akinesis or dyskmem         Exercise radinalid Ejection fraction         Exercise radinalid Ejection fraction         Exercise vall Motion         3 = normal; 6 = fixed defect; 7 =         reversable defect         Not used         Not used         Month of cardiac cath (perhaps "call")         Day of cardiac cath         Year of cardiac cath         Diagnosis of heart disease (angiographic disease status)         Value 0 < 50% diameter                              |

| 69 | LVX1   | Not used             |
|----|--------|----------------------|
| 70 | LVX2   | Not used             |
| 71 | LVX3   | Not used             |
| 72 | LVX4   | Not used             |
| 73 | LVF    | Not used             |
| 74 | CATHEF | Not used             |
| 75 | JUNK   | Not used             |
| 76 | NAME   | Last name of patient |

Henceforth, the proposed framework constructs a correlation matrix to rank the attributes most likely to influence the results. Bayes net structure is presented here [Table - 2]:

| presentea | TABLE I | I: Bayes Net Structure  |
|-----------|---------|---|
| MERIT     | SCALED  | Parameter Subsets   |
|           |         | 4 7 13 14 19 22 24 25 26 27 29 30 31 32   |
| 0.61438   | 0.80802 | 36 39 40 41 42 44 48 53 55 57 59 60 61  |
|           |         | 63 65 66 68 70 72 73  |
|           |         | 2 4 5 6 7 11 13 19 27 29 30 31 32 40 41   |
| 0.56553   | 0.59578 | 43 44 45 48 49 51 52 54 55 57 59 60 61  |
|           |         | 62 63 64 65 66 67 70 71 72 73   |
|           |         | 4 7 13 14 17 19 22 24 25 26 27 29 30 31   |
| 0.61334   | 0.80347 | 32 36 39 40 41 42 44 48 53 55 57 59 60  |
|           |         | 61 63 65 66 68 70 72 73   |
|           |         | 4 7 13 14 15 19 20 22 24 25 26 27 29 30   |
| 0.57217   | 0.62464 | 31 32 36 39 40 41 42 44 48 53 55 57 59  |
|           |         | 60 61 63 66 68 70 72 73   |
|           |         | 2 6 7 8 9 11 14 20 22 24 25 26 27 29 30   |
| 0.54682   | 0.51454 | 33 36 38 39 40 41 42 43 44 48 51 53 59  |
|           |         | 60 62 63 64 65 67 68 70 72 73   |
|           |         | 2 4 5 7 9 11 13 17 19 27 29 30 31 32 39   |
| 0.55164   | 0.53548 | 40 41 42 44 47 51 53 54 55 57 59 60 61  |
|           |         | 63 65 66 68 70 72 73  |
|           |         | 4 7 13 14 19 22 24 25 26 27 30 31 32 36   |
| 0.57864   | 0.65273 | 39 40 41 43 44 45 48 49 51 52 54 55 57  |
|           |         | 59 60 61 62 63 64 65 66 67 70 72 73   |
|           |         | 2 3 5 6 7 11 12 13 18 19 22 23 29 30 31   |
| 0.42837   | 0       | 32 40 41 43 44 45 48 51 55 57 59 61 62  |
|           |         | 63 64 65 67 69 70 72 73   |
|           |         | 4 7 9 12 13 14 19 20 22 24 25 26 27 29  |
| 0.46084   | 0.14101 | 30 31 32 36 39 40 41 42 44 53 55 56 57  |
|           |         | 59 60 61 63 65 66 68 70 72 73   |
|           |         | 2 4 5 6 7 11 13 19 21 22 27 29 30 31 32   |
| 0.58916   | 0.69843 | 39 40 41 43 44 45 48 55 57 59 60 62 63  |
|           |         | 64 65 67 70 72  |
|           |         | 2 4 5 7 11 13 19 22 27 29 30 31 32 39 40  |
| 0.60163   | 0.75263 | 41 43 44 45 48 55 57 59 60 62 63 64 65  |
|           |         | 67 70 72 73   |
|           |         | 2 4 5 7 11 13 19 22 27 29 30 31 32 39 40  |
| 0.60201   | 0.75429 | 41 44 45 55 57 59 60 62 63 64 65 67 70  |
|           |         | 72 73   |
| 0.55005   | 0.50500 | 2 3 6 7 11 13 18 19 22 23 29 30 31 32 40  |
| 0.55207   | 0.53733 | 41 44 45 48 51 55 57 59 61 62 63 64 65  |
|           |         | 67 69 70 72   |
| 0.56005   | 0.58199 | 4 7 13 14 19 22 24 25 26 27 29 30 31 32   |
| 0.56235   |         | 36 39 40 41 42 44 47 48 51 52 53 54 55  |
|           |         | 57 59 60 61 63 65 66 68 70 72 73  |
| 0.5909    | 0.66212 | 4 13 14 19 22 24 25 26 27 29 30 31 32<br>36 39 40 41 42 44 48 53 55 57 60 61 63   |
| 0.5808    | 0.66213 |   |
|           |         | 66         68         70         72         73           2         5         7         11         13         19         22         27         29         30         31         32         38         39 |
| 0.6035    | 0.76075 | 40 41 43 44 45 48 55 57 59 60 62 63 64  |
| 0.0055    | 0.70075 | 40 41 43 44 43 48 55 57 59 60 62 65 64<br>65 67 70 72   |
|           |         | 65         67         70         72           2         4         5         7         11         13         19         21         22         27         29         30         31         32         34  |
| 0.47965   | 0.22275 | 2 4 5 7 11 13 19 21 22 27 29 30 31 32 34<br>39 40 41 43 44 45 48 55 57 59 60 62 63  |
| 0.47903   | 0.22213 | 64 65 67 70 72 73   |
|           |         | 2 4 5 7 11 13 19 27 29 30 31 32 39 40 41  |
| 0.56274   | 0.58368 | 43 44 45 48 49 51 52 54 55 57 59 60 61  |
| L         |         | TJ TT TJ TO TJ JI J2 J4 JJ J1 J7 00 01  |

|         |         | 62 63 64 65 66 67 70 72 73  |
|---------|---------|---|
| 0.44954 | 0.09193 | 4 7 12 13 14 19 22 24 25 26 27 29 30 31<br>32 35 36 37 39 40 41 42 44 48 53 55 57<br>59 60 62 63 64 67 70 72 76 |

Thus, finally the list of most appropriate attributes influencing the dieses is been listed here [Table -3]:

|  | TABLE III: ATTRIBUTES INFLUENCING THE DIESE | S |
|--|---|---|
|--|---|---|

| 4 SEX<br>7 RELREST |                  |  |  |  |  |  |
|--------------------|------------------|--|--|--|--|--|
| ,                  |                  |  |  |  |  |  |
| 12                 |                  |  |  |  |  |  |
| 12 CHOL            |                  |  |  |  |  |  |
| 13 SMOKE           |                  |  |  |  |  |  |
| 14 CIGS            |                  |  |  |  |  |  |
| 19 RESTECG         |                  |  |  |  |  |  |
| 22 EKGYR           |                  |  |  |  |  |  |
| 24 PROP            |                  |  |  |  |  |  |
| 25 NITR            |                  |  |  |  |  |  |
| 26 PRO             |                  |  |  |  |  |  |
| 27 DIURETIC        |                  |  |  |  |  |  |
| 29 THALDUR         |                  |  |  |  |  |  |
| 30 THALTIME        |                  |  |  |  |  |  |
| 31 MET             |                  |  |  |  |  |  |
| 32 THALACH         |                  |  |  |  |  |  |
| 36 DUMMY           |                  |  |  |  |  |  |
| 39 XHYPO           | OLDPEAK<br>SLOPE |  |  |  |  |  |
| 40 OLDPEAK         |                  |  |  |  |  |  |
| 41 SLOPE           |                  |  |  |  |  |  |
| 42 RLDV5           |                  |  |  |  |  |  |
| 44 CA              |                  |  |  |  |  |  |
| 48 RESTWM          |                  |  |  |  |  |  |
| 53 THALPUL         |                  |  |  |  |  |  |
| 55 CMO             |                  |  |  |  |  |  |
| 57 CYR             |                  |  |  |  |  |  |
| 59 LMT             |                  |  |  |  |  |  |
| 60 LADPROX         |                  |  |  |  |  |  |
| 61 LADDIST         |                  |  |  |  |  |  |
| 63 CXMAIN          |                  |  |  |  |  |  |
| 65 OM1             |                  |  |  |  |  |  |
| 66 OM2             |                  |  |  |  |  |  |
| 67 RCAPROX         |                  |  |  |  |  |  |
| 68 RCADIST         |                  |  |  |  |  |  |
| 70 LVX2            |                  |  |  |  |  |  |
| 72 LVX4            |                  |  |  |  |  |  |
| 73 LVF             |                  |  |  |  |  |  |

Hence, the rest of the work demonstrates the multilayer perceptron neural network model to predict the severity of the disease[23-26].

As this work is intended to predict the heart dieses severity, hence the following parameters are also been included with the consideration of redundant attributes. Henceforth the optimal set of attributes for further analysis is listed here [Table - 4]:

TABLE IV: ATTRIBUTES INFLUENCING THE DIESES

| Serial Number | Parameter Names |
|---------------|-----------------|
| 4             | SEX             |
| 7             | RELREST         |

| 12 | CHOL     |
|----|----------|
| 13 | SMOKE    |
| 14 | CIGS     |
| 19 | RESTECG  |
| 22 | EKGYR    |
| 24 | PROP     |
| 25 | NITR     |
| 26 | PRO      |
| 27 | DIURETIC |
| 29 | THALDUR  |
| 30 | THALTIME |
| 31 | MET      |
| 32 | THALACH  |
| 36 | DUMMY    |
| 39 | ХНҮРО    |
| 40 | OLDPEAK  |
| 41 | SLOPE    |
| 42 | RLDV5    |
| 44 | CA       |
| 48 | RESTWM   |
| 53 | THALPUL  |
| 55 | СМО      |
| 57 | CYR      |
| 59 | LMT      |
| 60 | LADPROX  |
| 61 | LADDIST  |
| 63 | CXMAIN   |
| 65 | OM1      |
| 66 | OM2      |
| 67 | RCAPROX  |
| 68 | RCADIST  |
| 70 | LVX2     |
| 72 | LVX4     |
| 73 | LVF      |

III. PROPOSED MULTILAYER PERCEPTRON MODEL

The proposed multilayer perceptron model[27] is made with the sole purpose to reduce the confusion matrix and increase the accuracy of the clustering for diseases based on severity. Henceforth here the work proposes the multilayer perceptron model [Figure -1].

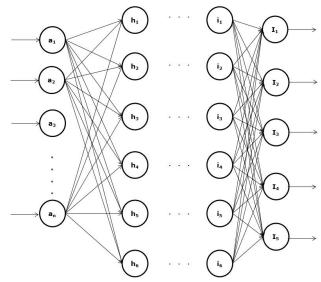


Figure 1: 8 Layer Proposed Multilayer Perceptron Model

The proposed MLP is arranged as the input layer is responsible for processing the inputs during the training, the hidden layers are available for considering the weight adjustment and finally the five output nodes are clustering the results in five distinguished categories. The detail of the MLP is discussed in this section of the work [Table - 5].

| TABLE V: MLP CHARACTERESTICS     |                            |  |  |  |  |  |
|----------------------------------|----------------------------|--|--|--|--|--|
| Attribute of MLP                 | Detail Description         |  |  |  |  |  |
| Back Propagation Learning Rule,  |                            |  |  |  |  |  |
| variable number of hidden layers | 1 to 5 Layers              |  |  |  |  |  |
| Random Number Seed               | 0                          |  |  |  |  |  |
| Learning Rate                    | 0.1                        |  |  |  |  |  |
| Learning Rate Function           | Static learning rate       |  |  |  |  |  |
| Constant Bias Input              | 1.0                        |  |  |  |  |  |
| Training Iterations              | 500                        |  |  |  |  |  |
|                                  | Batch Training -           |  |  |  |  |  |
|                                  | weight changes are applied |  |  |  |  |  |
|                                  | at the end of              |  |  |  |  |  |
| Training Mode                    | each epoch                 |  |  |  |  |  |
|                                  | Sigmoid (Logistic), S-     |  |  |  |  |  |
|                                  | shape function between +1  |  |  |  |  |  |
| Transfer Function                | and 0                      |  |  |  |  |  |
| Momentum                         | 0.2                        |  |  |  |  |  |
| Weight Decay                     | 0.1                        |  |  |  |  |  |
| Bias Input Value                 | 1.0                        |  |  |  |  |  |
| Inputs                           | 36                         |  |  |  |  |  |
| Output Layer                     | 5                          |  |  |  |  |  |
| Total Neurons                    | 5                          |  |  |  |  |  |
| Total Nodes                      | 226                        |  |  |  |  |  |

The mathematical model of the proposed method is explained here:

$$I_i = \sum_{i=1}^n a_i \bullet \sum_{j,k=1}^{n+1} w_{jk} \pm \theta \tag{5}$$

Here I denote the output layer of the MLP.

$$\theta = \frac{1}{2} \sum_{i=1\,j,k=1}^{n,n+1} \left( w_{jk} - a_i \right)^2 \tag{6}$$

Here  $\theta$  denotes the weight adjustments.

The auto-adjustable hidden layer depends on the number of active attributes in the dataset instance. From, Eq - 3,

$$j, k = MAX(S[i] \leftarrow Info_{Gain}(S_i))$$
(7)

The results are been discussed in further section of the work.

#### IV. RESULTS AND DISCUSSION

The objective of this work is to increase the accurately identify and cluster the dataset [25,28,30] for multiple levels of dieses severity. Thus firstly, the categories of the severity are identified [Table – 6].

TABLE VI: CLUSTERS INFORMATION

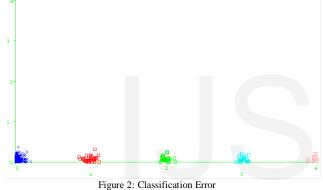
| Dieses Severity                 | Cluster Name |
|---------------------------------|--------------|
| No Disease                      | 0            |
| Disease – 1 Major Blood Vessel  |              |
| Blocked                         | 1            |
| Disease – 2 Major Blood Vessels |              |
| Blocked                         | 2            |
| Disease – 3 Major Blood Vessels |              |
| Blocked                         | 3            |
| Disease – 4 Major Blood Vessels |              |
| Blocked                         | 4            |

After the analysis of the dataset, the following clustering results are been obtained [Table – 7]:

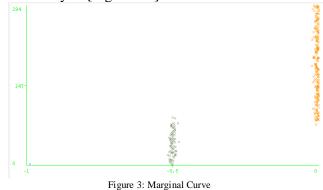
| - | <b>FABLE</b> | VII: | SEVER | ITY | BAS | SED | CL | USTE | RING |
|---|--------------|------|-------|-----|-----|-----|----|------|------|

| Cluster Names | 0   | 1  | 2  | 3  | 4  |
|---------------|-----|----|----|----|----|
| 0             | 188 | 0  | 0  | 0  | 0  |
| 1             | 0   | 37 | 0  | 0  | 0  |
| 2             | 0   | 0  | 26 | 0  | 0  |
| 3             | 0   | 0  | 0  | 28 | 0  |
| 4             | 0   | 0  | 0  | 0  | 15 |

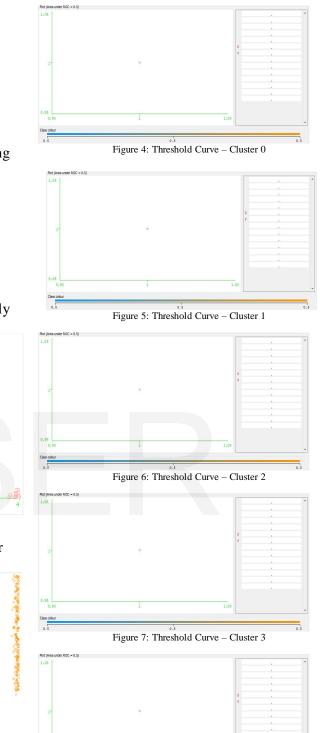
The Classification error are also been visually analyzed [Figure -2].



The margin curve of the analysis is presented for visual analysis [Figure -3].

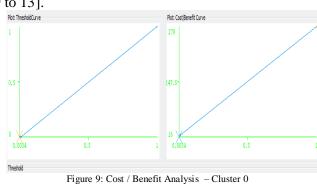


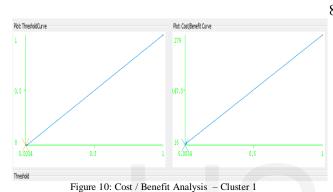
The threshold curve for cluster 0 to cluster 4 is presented here [Figure -4 to 8]:

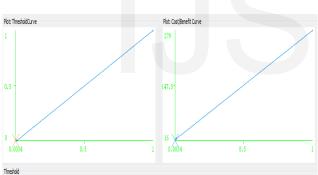


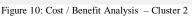


The cost benefit analysis for the proposed method on all clusters are been analysed visually [Figure – 9 to 13].









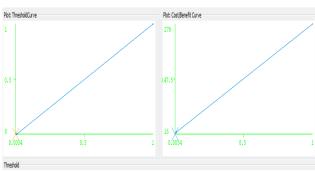
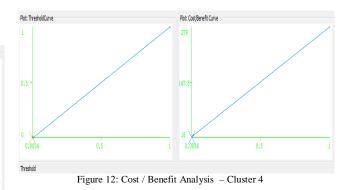


Figure 11: Cost / Benefit Analysis - Cluster 3



The work also analyses the Precision, Recall, F-Measure and ROC Area for each clusters [Table – 8].

TABLE VIII: PRECISION, RECALL, F-MEASURE AND ROC AREA

| ANALYSIS         |            |            |               |            |                   |             |  |  |  |  |
|------------------|------------|------------|---------------|------------|-------------------|-------------|--|--|--|--|
| Class            | TP<br>Rate | FP<br>Rate | Preci<br>sion | Recal<br>1 | F-<br>Meas<br>ure | ROC<br>Area |  |  |  |  |
| 0                | 1          | 1          | 0.639         | 1          | 0.78              | 0.5         |  |  |  |  |
| 1                | 0          | 0          | 0             | 0          | 0                 | 0.5         |  |  |  |  |
| 2                | 0          | 0          | 0             | 0          | 0                 | 0.5         |  |  |  |  |
| 3                | 0          | 0          | 0             | 0          | 0                 | 0.5         |  |  |  |  |
| 4                | 0          | 0          | 0             | 0          | 0                 | 0.493       |  |  |  |  |
| Weighted<br>Avg. | 0.639      | 0.639      | 0.409         | 0.639      | 0.499             | 0.5         |  |  |  |  |

## V. CONCLUSION

The work analyses the current advancements[29-31] in the space of cardiovascular disorders. The problems identified by the recent advancements as a clear demand for a technique to identify most appropriate set of parameters to be processed during predictive analysis and a demand for finding the optimal neural network setup for predictive analysis. The first part of the work demonstrates the optimal genetic algorithm based searching techniques to find the optimal set of attributes for better and timely prediction of the clustering techniques. The constructions of the most appropriate attributes set is been automated for any given dataset. Also the work results in to a MLP based auto adjustable 7 lavered algorithm for correct and accurate clustering of the data. The work demonstrates zero overlapping of the data during clustering data.

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