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Cardiac disorders detection approach based on local transfer function classifier

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Abstract—**Truly, heart is successor to the brain in being the most significant vital organ in the body of a human. Heart, being a magnificent pump, has his performance orchestrated via a group of valves and highly sophisticated neural control. While the kinetics of the heart is accompanied by sound production, sound waves produced, by the heart, are reliable diagnostic tools to check heart activity. Chronologically, several data sets have been put forward to sneak on the heart performance and lead to medical intervention whenever necessary. The heart sounds data set, utilized in this paper, provides researchers with abundance of sound signals that was classified using different classification algorithms; decision tree, rotation forest, random forest are few to mention. This paper proposes an approach based on local transfer function classifier as a new model of neural networks for heart valve diseases detection. In order to achieve this objective, and to increase the efficiency of the predication model, boolean reasoning discretization algorithm is introduced to discretion the heart signal data set, then the rough set reduction technique is applied to find all reducts of the data which contains the minimal subset of attributes that are associated with a class label for classification. Then, the rough sets dependency rules are generated directly from all generated reducts. Rough confusion matrix is used to evaluate the performance of the predicted reducts and classes. Finally, a local transfer function classifier was employed to evaluate the ability of the selected descriptors for discrimination whether they represent healthy or unhealthy. The experimental results obtained, show that the overall accuracy offered by the employed local transfer function classifier was high compared with other techniques including decision table, rotation forest, random forest, and NBtree.**

Index Terms—**Cardiac disorders, LTF-C, machine learning, feature selection**

I. Introduction

HEART sounds automated diagnosis in recent years became very important to determine condition of the patient (healthy or unhealthy) and determine type of the disease (valvular disease or not), since heart diseases are identified by sounds produced by the heart [1], [9]. Most of heart valve diseases have an effect on the heart sound of patients [2]. Operation of auscultation of heart sounds by the Stethoscope require a professional person to recognize the sounds then detect whether the subject is patient or not and also can detect the type of the heart disease in patients [3], [5]. Junior physicians can't easy detect type of heart disease from the it sound. Using artificial intelligent tools for remote classification of heart sound signal is a useful technique to avoid the needing to the experience physician and expensive equipments such as Echocardiography (ECG), Magnetic Resonance Imaging, (MRI), etc., which used to recognize heart diseases in accurate manner than heart auscultation. In [1] a different classification algorithms using support vector machine (SVM) with different parameters have been applied to find the best classification accuracy. But due to the high number of features, $100 features$, the classification accuracy could be enhanced if irrelevant and noisy features are removed. Discretization or feature selection or both should be prior the classification operation by most of the classification techniques which could lowers the classification performance and accuracy under many conditions [4]. The discretization method should be a supervised manner to satisfy nature of the classification problem, then feature selection method should be applied after the discretization, that demonstrates the dependence on such method for producing an appropriate results, the successful performance of the two pre-processing steps mean successful classification results. Finally a classification technique should be applied to perform the class label, disease type, prediction. Every classification technique has its own strong and weak points [5]. The most important preprocessing step is the feature reduction of the input data set. The data set contain features that are considered as noisy or irrelevant features, these features could have a negative impact on the classification accuracy of the instances, patients. Feature reduction methods are either feature extraction or feature selection method. Feature extraction method applies operation on the original features and extracts a lower number of features that carries the same characteristics. Feature selection methods has two advantages, the first advantage is rank and select the most important features, where if only a subset of features with the highest rank are used in classification, high classification accuracy could be achieved. The extracted heart sound data are three different data sets, each of 100 features where they are slitted into six different parts. The first data set is required to classify whether the heart of the patients are normal or not. The second and third data set are required for the detection of the heart valve disease. The heart valve diseases under investigation in this paper are aortic stenosis *AS*, aortic regurgitation *AR*, mitral stenosis *MS* and mitral regurgitation *MR*. This disease classification is performed in two steps where the first step is applied on the second data set for determining the type of the systolic murmur which means *AS* or *MR*, and the second step is applied on the third data set of a diastolic murmur diseases which means *AR* or *MS*. The second advantage of feature selection method is to determine which stage of the heart sound could have the greatest indication to heart valve disease in the case of each murmur type. The four stages of a heart sound are the first heart signal $S1$, the systolic period, the second heart signal and the diastolic period [1].

This paper proposes an approach based on local transfer function classifier as a new model of neural networks for heart valve diseases detection. In order to achieve a good detection, and to increase the efficiency of the predication model, boolean reasoning discretization algorithm is introduced to discretion the heart signal data set, then the rough set reduction technique is applied to find all reducts of the data which contains the minimal subset of attributes that are associated with a class label for classification. Then, the rough sets dependency rules are generated directly from all generated reducts. Rough confusion matrix is used to evaluate the performance of the predicted reducts and classes. Finally, a local transfer function classifier was employed to evaluate the ability of the selected descriptors for discrimination whether they represent healthy or unhealthy.

The rest of this paper is structured as follows: Section II gives a brief introduction of the heart signals data collection and its characteristics. Section III shows an overview of rough set approach to features selection and reduction methods. The proposed approach is given in section IV. The experimental results and conclusions are presented in Section V and VI respectively.

II. Heart sound signals Data Set and its features

A lot of researches have been applied on heart sound for the detection of heart valve disease. Features are extracted from the heart sound signal into a data set that is composed of 100 features. Then, a classification algorithm is applied on such data set for detection of heart valve disease. Features are extracted in three phases, segmentation [6] [7], transformation and extraction. These extracted features represent the four stages of a heart signal which are $S1$ signal, systolic period, $S2$ signal and diastolic period as shown in figure 1. These features are divided into six groups as follows: (1) **att0:att3** are the standard deviation of all heart sounds, $S1$, $S2$ and average heart rate; (2) **att4:att11** represents signal $S1$; (3) **att12:att35** represents the systolic period; (4) **att36:att43** represents signal $S2$; (5) **att44:att91** represents the diastolic period, and (6) **att92:att99** the four stages of a heart signals are passed from four band-pass frequency filters. The energy of each output is calculated to form these last 8 features.

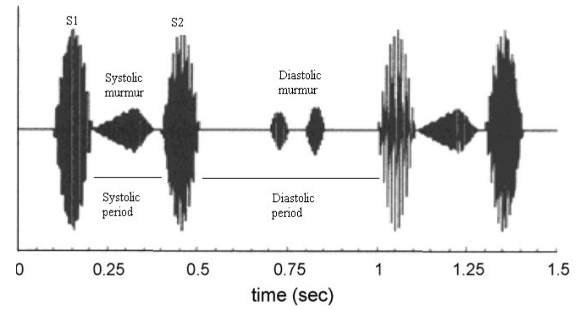

Fig. 1. Heart signal: systolic period and diastolic period [1]

III. Preliminaries

This section provides a brief explanation of the basic framework of rough sets and local transfer function neural network classifier, along with some of the key basic concepts.

A. Rough sets

Rough set theory [17], [16], [15], [14] is a fairly new intelligent technique for managing uncertainty that has can be used for the discovery of data dependencies, evaluation of the importance of attributes, discovery of patterns in data, reduction of attributes, and the extraction of rules from databases. Such rules have the potential to reveal new patterns in the data and can also collectively function as a classifier for unseen data sets. Unlike other computational intelligence techniques, rough set analysis requires no external parameters and uses only the information present in the given data. One of the interesting features of rough sets theory is that it can tell whether the data is complete or not based on the data itself. If the data is incomplete, it suggests more information about the objects to be collected in order to build a good classification model. On the other hand, if the data is complete, rough sets can determine the minimum data needed for classification. This property of rough sets is important for applications where domain knowledge is limited or data collection is very expensive/laborious because it makes sure the data collected is just good enough to build a good classification model without sacrificing the accuracy of the classification model or wasting time and effort to gather extra information about the objects [17], [16], [15], [14].

In rough set theory, data is collected in a table, called a decision table (DT). Rows of the decision table correspond to objects, and columns correspond to attributes. In the data set, we assume that the set of examples with a class label to indicate the class to which each example belongs are given. We call the class label the decision attributes, and the rest of the attributes the condition attributes. Rough sets theory defines three regions based on the equivalent classes induced by the attribute values: *lower approximation*, *upper approximation* and *boundary*. Lower approximation contains all the objects, which are classified surely based on the data collected, and upper approximation contains all the objects which can be classified probably, while the boundary is the difference between the upper approximation and the lower approximation. So, we can define a rough set as any set defined through its lower and upper approximations. On the other hand, indiscernibility notion is fundamental to rough sets theory. Informally, two objects in a decision table are indiscernible if one cannot distinguish between them on the basis of a given set of attributes. Hence, indiscernibility is a function of the set of attributes under consideration. For each set of attributes we can thus define a binary indiscernibility relation, which is a collection of pairs of objects that are indiscernible to each other. An indiscernibility relation partitions the set of cases or objects into a number of equivalence classes. An equivalence class of a particular object is simply the collection of objects that are indiscernible to the object in question.

B. *Local transfer function neural network classifier*

A new model based on artificial neural network, called Local transfer function classifier produces encouraging results for many data sets, it is virtually the same architecture as Radial Basis Function Neural Network (RBFNN), its used in supervised learning [13].

Let the training set be composed of N pairs of the form: $(X^{(i)}, c^{(i)})$, where $X^{(i)} = \left[x_1^{(i)}, x_2^{(i)}, ..., x_n^{(i)}\right]$ is the i-th input pattern belonging to the $c^{(i)}$-th class $(c^{(i)} = 1, 2, ..., k)$. Vectors $X^{(i)}$ can be treated as points in the n-dimensional space X. Close neighborhood of the point $X^{(i)}$ should belong to the same class as $X^{(i)}$, therefore the space X can be divided into finite number of *decision regions*-areas of the same value of classification.

IV. THE PROPOSED HEART VALVE DISEASES ANALYSIS

One way to construct a simple model computed from data, easier to understand and having good predictive power, is to create a set of minimal number of rules. Some condition values may be unnecessary in a decision rule produced directly from the data set. Such values can then be eliminated to create a more comprehensible minimal rule preserving essential information. The proposed heart valve diseases detection approach is comprised of the following three fundamental building phases: (1) Pre-processing including a Discretiztion of the attributes; (2) Generate the reducts with minimal number of attributes along with significant of the attributes; (3) Rule generation for the classification: generate a list of rules, compute the overall accuracy of the generated rules; this phase utilizes the rules generated from the previous phase to predict the classification accuracy. These three phases are described in detail in the following section along with the steps involved and the characteristic features for each process. Fig. 2 illustrates the general architecture of the proposed of heart valve disease analysis.

A. *Pre-processing phase: Rough Discretization process*

When dealing with attributes in concept image classification, it is obvious that they may have varying degree of importance in the problem being considered, importance can be pre-assumed using auxiliary knowledge about the problem,

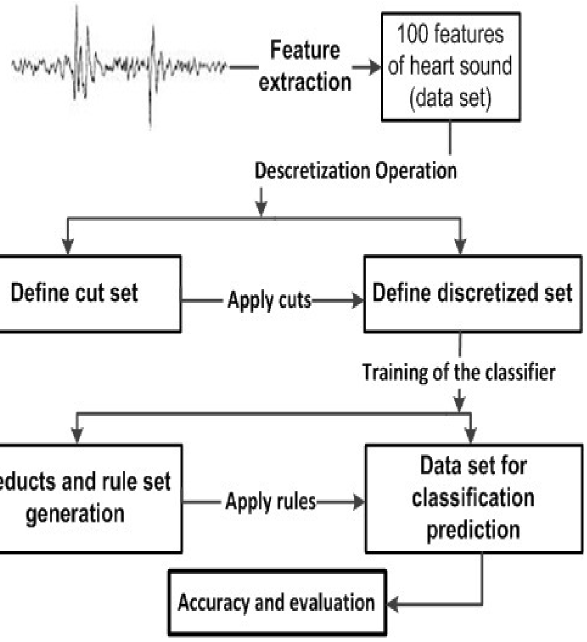

Fig. 2. The general architecture of the proposed of heart valve disease analysis

properly chosen weights. However, in the case of using the rough set approach to concept classification, it avoids any additional information aside from what is included in the information table itself. Basically, the rough set approach tries to determine from the data available in the information table whether all the attributes are of the same strength and, if not, how they differ in respect of the classifier power. Therefore, some strategies for discretization of real valued features must be used when we need to apply learning strategies for data classification (*e.g.*, equal width and equal frequency intervals). It has been shown that the quality of learning algorithm is dependent on this strategy, which has been used for real-valued data discritization [10].

Many classification algorithms such as rough set theory, require that training data contain only discretized feature values. Otherwise, too many equivalent classes will be produced and the algorithms will be over sensitive to noise. To use such an algorithm when there are numeric-valued features, all numeric values must first be converted into discrete values - a process called discretization[11]. This process is performed by dividing the values of a continuous attributes into a small number of intervals, where each interval is mapped to a discrete categorical, nominal, symbolic symbol. Discretization can significantly influence the effectiveness of a classification algorithm.

Medical data sets contains continues and discrete valued data in real world data set. The discretization process divides the attributes value into intervals[12]. The discretization based on RS and Boolean Reasoning (RSBR) shows the best results in the case of heart valve disease data set. In the discretization of a decision table $S = (U, A \bigcap \{d\})$, where U is a non-empty finite set of objects and A is a non-empty finite set of attributes. And V_a = $[x_a, x_a)$ is an interval of real values x_a, w_a in attribute a. The required is to a partition P_a of V_a for any $a \in A$. Any partition of V_a is defined by a sequence of the so-called cuts $x_1 < x_2 < .. < x_k$ from V_a. The main steps of the RSBR discretization algorithm are provided in algorithm 1.

Algorithm 1 RSBR discretization algorithm

Input: Information system table (S) with real valued attribute A_{ij} and n is the number of intervales for each attribute.

Output: Information table (ST) with discretized real valued attribute

1: **for** $A_{ij} \in S$ **do**
2: Define a set of boolean variables as follows:

$$B = \{\sum_{i=1}^{n} C_{ai}, \sum_{i=1}^{n} C_{bi} \sum_{i=1}^{n} C_{ci}, ..., \sum_{i=1}^{n} C_{ni}\} \tag{1}$$

3: **end for**
Where $\sum_{i=1}^{n} C_{ai}$ correspond to a set of interval defined on the variables of attributes a
4: Create a new information table S_{new} by using the set of intervals C_{ai}
5: Find the minimal subset of C_{ai} that discerns all the objects in the decision class D using the following formula:

$$\Upsilon^u = \wedge\{\Phi(i,j) : d(x_i \neq d(x_j))\} \tag{2}$$

Where $\Phi(i,j)$ is the number of minimal cuts that must be used to discern two different instances x_i and x_j in the information table.

B. Reducts with minimal number of attributes process

Reduct is an important concept in rough sets theory and data reduction is a main application of rough set theory in pattern recognition and data mining. As it has been proven that finding the minimal reduct of an information system is a NP hard problem [10].

The computation of the reducts from a decision table is a way of selecting relevant features [18]. It is a global method in the sense that the resultant reducts represent the minimal sets of features which are necessary to maintain the same classification accuracy given by the original and complete set of attributes. A straight manner for selecting relevant features is to assign a measure of relevance to each attribute and choose the attributes with higher values. Based on the reduct system, we generate the list of rules that will be used for building the classifier model for the new objects. In decision tables, there often exist conditional attributes that do not provide any additional information about the objects. So, we should remove those attributes since it reduces complexity and cost of decision process [18]. A decision table may have more than one reduct. Anyone of them can be used to replace the original table. Finding all the reducts from a decision table is NP-complete. Fortunately, in applications, it is usually not necessary to find all of them. Few of them are sufficient. A natural question is, which reducts are the best. The selection depends on the optimality criterion associated with the attribute. If it is possible to assign a cost function to attributes, then the selection can be naturally based on the combined minimum cost criteria. In the absence of an attribute cost function, the only source of information to select the reduct is the content of the table.

We present a reduct algorithm based on the entropy information measure introduced in [18]. Algorithm-2 shows the main steps of the reduct algorithm.

Algorithm 2 Reduct-based on entropy algorithm

Input: Rough Sets Decision System (RSDS)

Output: One reduct of RSDS

1: $\forall a \in A$ compute the equivalence relation
2: $\phi \leftharpoondown reduct$;
3: **for** $a_i \in A - reduct$ **do**
4: Compute $H_i = H(a_i \mid reduct)$ {Where H_i is the information quantity of the attribute set, R is a equivalence relation matrix}

$$H = -\frac{1}{n}\sum_{i=1}^{n} log\lambda_i \tag{3}$$

$$\lambda_i = \frac{|[x_i]R|}{n} \tag{4}$$

5: **end for**
6: Compute the significance of attribute a (SIG) in attribute set A using the following equations:

$$SIG(a,A) = H(A) - H(A-a) \tag{5}$$

$$H(a|reduct) = \max(SIG(a_i, reduct)) \tag{6}$$

7: Select attribute which satisfies Equation(20)
8: **if** $H(a|reduct) > 0$ **then**
9: $reduct \cup a \longrightarrow reduct$
10: **end if**
11: Go to Step 3

C. Rule generation for the classification process

The generated reducts are used to generate decision rules. The decision rule, at its left side, is a combination of values of attributes such that the set of (almost) all objects matching this combination have the decision value given at the rule's rough side. The rule derived from reducts can be used to classify the data. The set of rules is referred to as a classifier and can be used to classify new and unseen data. The main steps of the rule generation and classification algorithm are provided in Algorithm 3 (cf. [18]).

V. Experimental results and discussions

A. The heart sound signals data set characteristics

Cardiac disorders of heart diseases in the proposed approach were applied on three different data set of cardiac disorders

Algorithm 3 Rule generation for the classification

Input: reduct sets $R_{final} = \{r_1 \cup r_2 \cup .... \cup r_n\}$
Output: Set of rules

```
for each reduct r do
  for each correspondence object x do
    Contract the decision rule (c1 = v1 ∧ c2 = v2 ∧ .... ∧ cn = vn) ⟶ d = u
    Scan the reduct r over an object x
    Construct (ci, 1 ≤ i ≤ n)
    for every c ∈ C do
      Assign the value v to the correspondence attribute a
    end for
    Construct a decision attribute d
    Assign the value u to the correspondence decision attribute d
  end for
end for
```

with different number of instances in every class. The first data set is healthy and unhealthy persons "$HS-H-U$" contains 70 instances, where 38 instances represent healthy persons and the other 32 instances represents unhealthy patients. The second data set represents 84 instances systolic diseases such that 41 instances aortic stenosis and 43 instances mitral regurgitation "$HS-AS-MR$". Finally the third data "$HS-AR-MS$" set represents 76 instances diastolic diseases, it consists of 38 instances aortic regurgitation and 38 instances mitral stenosis.

TABLE I
MINIMAL REDUCT SETS OF THE THREE DATA SETS

Data type	Reduct sets
$HS-H-U$	att0, att2, att33, att87, att93, att96
$HS-AS-MR$	att0, att2, att31, att87, att89, att99
$HS-AR-MS$	att1, att4, att12, att35, att37

Table I shows the generated reducts that contains minimal number of attributes. While Table II, III, and IV show the generated rules set of the three data sets of heart valve disease signals. As an explanation for some of rules, should be first clearing some terms, "att3" is feature of standard deviation of all heart sounds, S1, S2 and average heart rate, "att36" is feature of signal S2, "att92 and att96" are represent the four stage of the heart signal. If att36= 0.15405 and att92=0.06865 and att3=0.32355 then this patient is normal, about 16 cases match this rule. If att96=0.04485 and att3=0.32355 and att92=0.06865 then this patient is up normal, about 8 cases match this rule.

B. Results analysis and discussion

In this approach, local transfer function neural network classifier (LTF-C) has been applied on three types of heart valve murmurs data sets. It shows the highest classification results as shown by figures 3,4 and 5. The best classification in the three data sets is achieved by LTF-C classifier, comes

TABLE II
GENERATED RULES FOR THE $HS-H-U$ DATA SET

Matches	Decision rules	Class
16	(att36="(0.15405,Inf)") & (att92="(-Inf,0.06865)") & (att3="(0.32355,Inf)")	1
6	(att96="(-Inf,0.04485)") & (att0="(-Inf,0.05875)") & (att3="(-Inf,0.32355)")	1
3	(att96="(-Inf,0.04485)") & (att92="(0.06865,Inf)") & (att36="(0.15405,Inf)") & (att0="(0.05875,Inf)") & (att3="(-Inf,0.32355)")	1
2	(att3="(0.32355,Inf)") & (att36="(-Inf,0.15405)") & (att0="(-Inf,0.05875)") & (att96="(-Inf,0.04485)") & (att92="(-Inf,0.06865)")	1
2	(att0="(0.05875,Inf)") & (att36="(-Inf,0.15405)") & (att92="(-Inf,0.06865)") & (att3="(-Inf,0.32355)")	1
3	(att3="(0.32355,Inf)") & (att92="(0.06865,Inf)") & (att94="(0.2325,Inf)") & (att96="(-Inf,0.04485)")	1
9	(att96="(0.04485,Inf)") & (att36="(0.15405,Inf)") & (att0="(0.05875,Inf)") & (att92="(0.06865,Inf)")	2
3	(att96="(0.04485,Inf)") & (att3="(-Inf,0.32355)") & (att0="(-Inf,0.05875)") & (att36="(0.15405,Inf)") & (att92="(-Inf,0.06865)") & (att94="(-Inf,0.2325)")	2
8	(att96="(0.04485,Inf)") & (att3="(-Inf,0.32355)") & (att92="(0.06865,Inf)")	2
2	(att94="(-Inf,0.2325)") & (att3="(0.32355,Inf)") & (att36="(-Inf,0.15405)") & (att0="(-Inf,0.05875)") & (att92="(-Inf,0.06865)") & (att96="(0.04485,Inf)")	2
3	(att0="(0.05875,Inf)") & (att96="(0.04485,Inf)") & (att92="(-Inf,0.06865)") & (att3="(-Inf,0.32355)") & (att36="(0.15405,Inf)")	2
1	(att3="(0.32355,Inf)") & (att0="(0.05875,Inf)") & (att36="(-Inf,0.15405)") & (att96="(0.04485,Inf)") & (att92="(-Inf,0.06865)") & (att94="(-Inf,0.2325)")	2

TABLE III
GENERATED RULES FOR THE $HS-AR-MS$ DATA SET

Matches	Decision rules	Class
28	(att12="(-Inf,5.0E-5)")&(att35="(-Inf,0.19665)")&(att4="(0.22775,Inf)")	2
22	(att35="(0.19665,Inf)")&(att37="(0.01215,Inf)")	1
15	(att1="(-Inf,0.23755)")&(att4="(-Inf,0.22775)")&(att37="(0.01215,Inf)")&(att12="(5.0E-5,Inf)")	1
7	(att12="(5.0E-5,Inf)")&(att37="(-Inf,0.01215)")	1
5	(att37="(-Inf,0.01215)")&(att1="(-Inf,0.23755)")&(att4="(-Inf,0.22775)")&(att35="(-Inf,0.19665)")	1
4	(att12="(-Inf,5.0E-5)")&(att4="(-Inf,0.22775)")&(att35="(-Inf,0.19665)")&(att37="(0.01215,Inf)")	2
2	(att12="(-Inf,5.0E-5)")&(att37="(-Inf,0.01215)")&(att4="(-Inf,0.22775)")&(att1="(0.23755,Inf)")	2

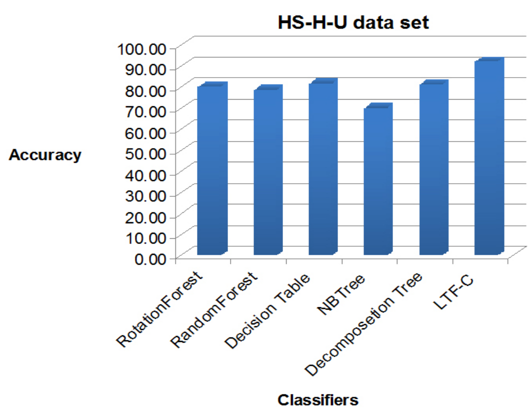

Fig. 3. Classification results for Healthy Unhealthy Data Set

TABLE IV
GENERATED RULES FOR THE $HS-AS-MR$ DATA SET

Matches	Decision rules	Class
23	(att31=”(0.01485,Inf)”)&(att0=”(0.0279,Inf)”) &(att99=”(-Inf,67.9889)”)	2
20	(att2=”(-Inf,0.58995)”)&(att87=”(-Inf,0.00105)”) &(att31=”(-Inf,0.01485)”)	1
8	(att87=”(-Inf,0.00105)”)&(att99=”(67.9889,Inf)”) &(att31=”(0.01485,Inf)”)	1
6	(att0=”(0.0279,Inf)”)&(att31=”(-Inf,0.01485)”) &(att87=”(0.00105,Inf)”)&(att89=”(0.00895,Inf)”)	1
6	(att99=”(67.9889,Inf)”)&(att87=”(0.00105,Inf)”) &(att0=”(0.0279,Inf)”)&(att31=”(0.01485,Inf)”) &(att89=”(0.00895,Inf)”)	2
5	(att31=”(0.01485,Inf)”)&(att2=”(-Inf,0.58995)”) &(att0=”(-Inf,0.0279)”)&(att87=”(-Inf,0.00105)”) &(att89=”(-Inf,0.00895)”)&(att99=”(-Inf,67.9889)”)	2
4	(att0=”(0.0279,Inf)”)&(att31=”(-Inf,0.01485)”) &(att2=”(0.58995,Inf)”)&(att87=”(-Inf,0.00105)”)	1
4	(att87=”(0.00105,Inf)”)&(att0=”(0.0279,Inf)”) &(att2=”(0.58995,Inf)”)&(att31=”(-Inf,0.01485)”) &(att89=”(-Inf,0.00895)”)&(att99=”(-Inf,67.9889)”)	2

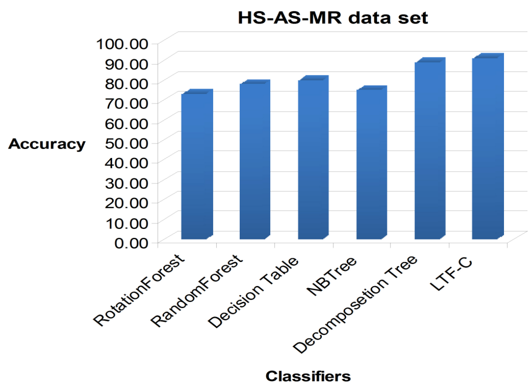

Fig. 4. Classification results for AS-MR Data Set

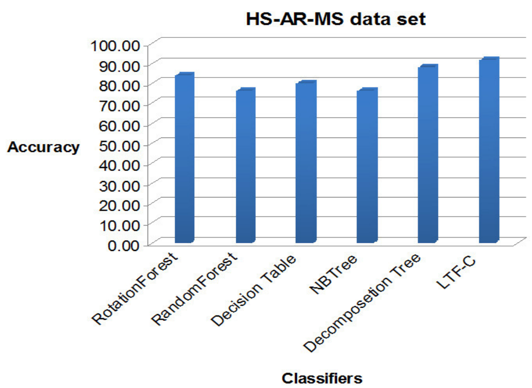

Fig. 5. Classification results for AR-MS Data Set

after it in the order Decision Table regarding the healthy unhealthy data set “$HS-H-U$” and Decomposition Tree classifier regarding both other data sets the systolic data set “$HS-AS-MR$” and the diastolic data set “$HS-AR-MS$”. The following table V shows the collection results of the three data sets.

Table V illustrates the overall local transfer function neural network classifier accuracy in terms of sensitivity and specificity compared with decision table, rotation forest, random forest, and NBtree. Empirical results reveal that the proposed local transfer function neural network approach performs better than the other classifiers.

TABLE V
ACCURACY RESULTS FOR THREE HEART VALVE DISEASES DATA SETS

Classifier	$HS-H-U$	$HS-AS-MR$	$HS-AR-MS$
LTF-C	**92.00**	**91.00**	**91.70**
Decomposetion Tree	81.00	89.00	88.00
NBTree	70.00	75.00	76.00
Decision Table	81.43	80.00	80.00
RandomForest	78.57	78.00	76.00
RotationForest	80.00	73.00	84.00

VI. CONCLUSIONS AND FUTURE WORKS

The heart sounds data set, utilized in this paper, provides researchers with abundance of sound signals that was classified using different classification algorithms; decision tree, rotation forest, random forest are few to mention. Such algorithms were of disputable performance if compared with the classification algorithm adopted in this paper, i.e., the ”local transfer function neural network classifier (LTF-C)”. Discretization of analogue heart sounds was a preparatory step to apply LTF-C classification technique. Consequently, discretized data were classified into several domains and Rough Confusion Matrix was used to produce reducts out of them. The purpose of such data manipulation is to reach a state of subjecting features to discernability, so classes of distinct features can fuel proper decision for a cardiologist, to which class of cardiac disorder this patient belongs. Classes were meant to touch upon crucial cardiac diseases and to aid in diagnosis and prognosis as well. The LTF-C achieved a high accuracy classification compared with other machine learning techniques such as Decomposition Tree, NBTree, Decision Table, RandomForest in addition to RotationForest.

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