© 2018 IJSRSET | Volume 4 | Issue 4 | Print ISSN: 2395-1990 | Online ISSN : 2394-4099
Themed Section : Engineering and Technology

Meta-Heuristic Approaches for the Classification of Medical Datasets

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ABSTRACT

In the health care systems, the decision support system and the analysis of clinical data requires an interdisciplinary field of data mining, which guides the automated knowledge discovery process to apply the complex task of clinical data analysis. The wide spread of electronic data collection in medical environments leads to an exponential growth of clinical data extracted from heterogeneous patient samples. Rule-based classification is a typical data mining task that is being used in several medical diagnosis and decision support systems. The rules stored in the rule base have an impact on classification efficiency. Rule sets that are extracted with data mining tools and techniques are optimized using heuristic or meta-heuristic approaches inorder to improve the quality of the rule base. In the existing system a meta-heuristic approach called Wind-driven Swarm Optimization (WSO) is used based on the rule based classifier evaluation metric (Jval) in which the rules are extracted from decision trees. The WSO is used to obtain different permutations and combinations of rules whereby the optimal ruleset that satisfies the requirement of the developer is used for predicting the test data. The multimodal optimization is achieved in two stages in health care data mining applications in the proposed architecture. The formed solution of the wind driven optimization is reorganized to model the elimination of the old set solution by using the multimodal optimization. Second, to accelerate convergence, a differential evolution mutation operator is alternatively utilized to build base vectors for ants to construct new solutions. The results are validated for both heart and liver data set and the proposed solution achieves the significance performance interms of sensitivity, specificity, accuracy, precision and miss rate compared to the wind driven optimization.

Keywords : Data Mining, Optimization, Swarm Optimization, Rule based Classification

I. INTRODUCTION

Data mining predicts the future of modeling. Predictive modelling is a process by which a model is created to predict an outcome. If the outcome is categorical it is called categorical and if the outcome is numerical it is called regression. Data mining techniques, designed to extract useful information from large databases or data warehouses, have started to demonstrate their huge potentials in solving the aforementioned challenges and could be the next technical innovation that enables biologists and medical researchers to gain insightful observations and make groundbreaking. Coined in the mid-1990s, the term data mining has today become a synonym for ‘Knowledge Discovery in Databases’ emphasized the data analysis process rather than the use of specific analysis methods. Clinical decision making is the process by which we determine who needs what, when. While not exactly arbitrary, this exercise can be quite subjective. The strength of their case will depend on the way in which they gather and assemble information.

Data mining tasks can, in general, be classified to tasks of description and prediction. The main distinction between them is that prediction requires the data to include a special response variable. The response may be categorical or numerical, thus further classifying predictive data mining as, respectively, classification and regression. In this review we address classification problems in particular: while the difference between the two lies mainly in the set of methods used, the data mining process applied to regression and classification problems is quite similar.

In healthcare, data mining is becoming progressively more admired. Several factors have annoyed the use of data mining applications in healthcare. The major factor is that the massive amounts of data generated by healthcare connections are too intricate and capacious to be processed and analyzed by habitual methods.

Data mining can recover decision-making by discovering patterns and trends in large amounts of complex data. The modeling stage is the tangible data analysis. Most data mining software include online analytical processing; traditional statistical methods, such as cluster analysis, discriminant analysis and regression analysis; and non-traditional statistical analysis, such as neural networks, decision trees, link analysis and association analysis.

Database management, statistics, and computer science, including artificial intelligence and machine learning were considered to the parent of the data mining. The evaluation stage enables the similarity of models and outcome from any data mining model. Finally, actual implementation and operationalization of the data mining models were related by the deployment stage. The classification of data mining techniques was based on what they can do, namely description and visualization; association and clustering; and classification and estimation, which is predictive modeling.

Multiple optimal solutions, representing various designs with the same or very similar performance, are in demand in many practical applications, so that decision makers can have multiple choices. To obtain multiple optima of a problem, practitioners turn their attention to population-based evolutionary algorithms (EAs), which possess potential to locate and preserve multiple optima simultaneously.

Even though different kinds of EAs, such as particle swarm optimization (PSO), differential evolution (DE), ant colony optimization (ACO), and estimation of distribution algorithms (EDAs), have been successfully applied to solve various problems, most of them focus on single optimization, rather than multimodal optimization. Owing to the global learning and updating schemes used, these EAs usually drive the whole population toward only one global optimum. Therefore, these EAs cannot be directly applied to deal with multimodal optimization. To solve multimodal problems efficiently, some special tactics should be designed to cooperate with classical EAs.

In spite of the effectiveness of existing multimodal algorithms on tested problems, they are known to suffer from various drawbacks, such as inferior performance on irregular multimodal surfaces, the serious reliance on particular landscapes and the sensitive parameter settings, etc. In particular, most existing multimodal algorithms would lose efficiency when the dimensionality of multimodal problems increases. Such inferior performance may be attributed to the exponentially increasing number of optima resulted from the growth of dimensionality. Under this environment, high diversity preservation is especially important for EAs to deal with multimodal optimization.

Machine learning is the scientific field dealing with the ways in which machines learn from experience. For many scientists, the term “machine learning” is identical to the term “artificial intelligence”, given that the possibility of learning is the main characteristic of an entity called intelligent in the broadest sense of the word. The purpose of machine learning is the construction of computer systems that can adapt and learn from their experience. A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

In supervised learning, the system must "learn" inductively a function called target function, which is an expression of a model describing the data. The objective function is used to predict the value of a variable, called dependent variable or output variable, from a set of variables, called independent variables or input variables or characteristics or features. The set of possible input values of the function, i.e. its domain, are called instances. Each case is described by a set of characteristics (attributes or features). A subset of all cases, for which the output variable value is known, is called training data or examples. In order to infer the best target function, the learning system, given a training set, takes into consideration alternative functions, called hypothesis and denoted by h.

In supervised learning, there are two kinds of learning tasks: classification and regression. Classification models try to predict distinct classes, such as e.g. blood groups, while regression models predict numerical values. In unsupervised learning, the system tries to discover the hidden structure of data or associations between variables. In that case, training data consists of instances without any corresponding labels.

II. XISTING SYSTEM

Particle Swarm Optimization is an advance to troubles whose solutions can be represented as a point in an n-dimensional elucidation space. A number of particles are randomly set into motion through this space. At each iteration, they observe the "fitness" of themselves and their neighbours and "emulate" successful neighbours (those whose current position represents a better solution to the problem than theirs) by moving towards them. WSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value(global best) called gbest. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest.

The gain in distance while resting has to be related to the gain in distance by wind assistance, when moving on. The effect of wind on the expected flight range can therefore be expressed as the expected gain in flight distance when the bird is flying. The Wind-driven Swarm Optimization algorithm is inspired from the above biological models. WSO is designed and developed to optimize the overall performance of a classifier. The Jval is a novel evaluation metric for rule based classifier. The accuracy of a classification model is not the only factor that is to be considered for building a classifier but the size of the ruleset is also important for the design of an efficient rule-based classifier. Both the factors are considered in Jval's evaluation with user defined weights.

The health of an individual, h(S . xi), is the Jval value associated with that individual. It is interesting to observe that the biological model-based approach for position-update ensures that the gain in distance G(S.xi), increases faster initially but slower in latter iterations though Jval may increase linearly. This allows the search to explore the search-space during the initial iterations and exploit during the latter iterations. Furthermore, average wind support is a non-increasing positive integer variable, initially set to high values and gradually decreased in steps of two. It is used to balance between the exploration and exploitation trade-off.

DRAWBACKS

The existing system utilizes the meta heuristic approach called Wind-Driven Swarm Optimization to apply the clinical data mining process. It mainly uses the rule based classifier which generates the rule set from the decision trees. WSO is used to obtain different permutations and combinations of rules whereby the optimal rule set that satisfies the requirement of the developer is used for predicting the test data.

1. It does not have the capacity to process the multi-constraints to evaluate the training and testing data set.
2. Since the WSO is population based meta-heuristic stochastic optimization approach, it still lacks proper performance measures for evaluations such as running time and Accuracy.
3. It generates more number of rule set which leads to the complex execution and comparison operations.
4. The efficiency of a decision support system relies on the content of the rule base and classification accuracy.
5. The trade-off between the prediction accuracy and the size of the rule base is optimized during the design and development of rule-based clinical decision support system.

III. PROPOSED WORK

The proposed system applies the WSO optimization with the multimodal constraints to preserve the high diversity. In multimodal optimization, user has obtained more knowledge about optimal solutions in search space and it helps to use other solutions when the current solution is not possible. Obtaining the best possible outcome of a question is called optimization according to governing conditions. In optimization issues of real world, sometimes only one optimal solution is not sufficient.

Multimodal optimization deals with optimization tasks that involve finding all or most of the multiple solutions of a problem, as opposed to a single best solution. The techniques for multimodal optimization are usually borrowed as diversity maintenance techniques to other problems.

Evolutionary algorithms due to their population based approach, provide a natural advantage over classical optimization techniques. They maintain a population of possible solutions, which are processed every generation, and if the multiple solutions can be preserved over all these generations, then at termination of the algorithm we will have multiple good solutions, rather than only the best solution. Note that this is against the natural tendency of classical optimization techniques, which will always converge to the best solution, or a sub-optimal solution. Finding and maintenance of multiple solutions is wherein lies the challenge of using EAs for multi-modal optimization. Niching is a generic term referred to as the technique of finding and preserving multiple stable niches, or favorable parts of the solution space possibly around multiple solutions, so as to prevent convergence to a single solution.

A major goal of multimodal optimization is to find such alternatives by searching for multiple peaks in the landscape. However, as claimed and demonstrated here with respect to that goal, the notion of multi-modal optimization is problematic on a fundamental level.

IV. SYSTEM IMPLEMENTATION

The system has the following modules while implementing the creation of the knowledge mining model for Medical diagnosis and decision support systems and to use the multi model optimization to increase the prediction ratio of the decision system.

1. Data Collection and Preprocessing.
2. Exploring the Attributes (Feature Extraction).
3. Develop multimodal constraints and Testing process.

a) DATA COLLECTION AND PREPROCESSING

Data collection is a process of collecting information from all the relevant sources to find solutions for the research problem. The input data set and its relevancy parameters with its significance are collected in RAW format. The fields in the data set are disjointly organized as unique fields. The Character set fields are converted into numeric field based on its relevancy. It is the process of gathering and measuring data, information or any variables of interest in a standardized and established manner that enables the collector to answer or test hypothesis and evaluate outcomes of the particular collection. Data collection is concerned with the accurate acquisition of data; although methods may differ depending on the field, the emphasis on ensuring accuracy remains the same. The primary goal of any data collection endeavor is to capture quality data or evidence that easily translates to rich data analysis that may lead to credible and conclusive answers to questions that have been posed.

The input data set is in the form of CSV which contains the fields and entries as row and colums arranged by sepreating comma. In computing, a comma-separated values (CSV) file stores tabular data (numbers and text) in plain text. Each line of the file is a data record, where it consists of one or more fields, separated by commas. The use of the comma as a field separator is the source of the name for this file format.

In the preprocessing stage, the input data set is read and displayed in the raw form to reduce the storage overhead. By replacing the comma into tab spaces the input data is differentiated in the preprocessed initial stage. And the CSV data is organized into table format as rows and column with the column heading representation. The data is sampled as string to identify the unique field values in the numeric form. In the data cleaning process, the input data is removed with respect to the CSV vector.

b) EXPLORING THE ATTRIBUTES (FEATURE EXTRACTION)

For each fields the significance and the relevancy are computed as the weighting parameter. Based on the similarity of the fields, the field group set is created as the combinations of the input fields. From the created groups and its field weights, the feature set is developed in the form of ruleset. Data preprocessing is a data mining technique that involves transforming raw data into an understandable format. Data preprocessing is a proven method of resolving real world data issues. Data preprocessing prepares raw data for further processing. After the preprocessing stage, the feature extraction gets started from the measured data. Feature extraction is related to dimensionality reduction.

c) DEVELOP MULTIMODAL CONSTRAINTS AND TESTING PROCESS

Multi-Modal Optimization (MMO), which is commonly associated with single-objective optimization, primarily aims to present Decision-Makers (DMs) with multiple global and local optima. The rational is that selecting a solution may depend not just on the global performance in the optimized objective, but on other considerations. In biology the term species refers to the most basic biological classification. It is comprised of individuals that are able to breed with each other but not with others. In nature, a niche can be viewed as a subspace in the environment with finite resources that must be shared among the population of that niche, while competing to survive.

In EAs the term speciation (or "niching") commonly refers to an automatic technique to overcome the tendency of the population to cluster around one optimal solution in a multi-modal function optimization. Speciation techniques help maintaining diversity to prevent premature convergence, while dealing with multimodality. Speciation, in its original sense, could be viewed as a process that gradually divides the population into subpopulations (species). Common speciation is also a niching process as it finds the niches (optimums), while dividing the population into the niches. The notion of a conceptual solution, or in short a design concept, as understood in engineering design, is associated with abstractive ideas, which are generated by humans, describing a generic solution to a problem.

Here, however, the term concept is used to describe any meaningful subset of the searched set of all feasible solutions. In order to define a significant search for alternative solutions to be presented to the DMs, it is insufficient to divide the searched set based only on performance. This is true because when selecting a solution DMs consider their tacit knowledge about the searched space (s), along with the obtained performance in the optimization objective(s). It is claimed that, for a given problem, only the DMs are able to divide the searched set into meaningful subsets (concepts). Such a partition can serve the DMs in defining a meaningful search for alternative solutions. This claim should be viewed with respect to the idea of niching/speciation, which is done by the computer during MMO.

Different problems may require different partitions in order for the partition to be meaningful for the DMs. To clarify the above ideas, we discuss three different optimization problems. The first, concerns a single objective problem of planning the shortest path from a start point to a goal point in an environment containing obstacles. By itself, partitioning is insufficient for the search to be meaningful. To understand the notion of meaningful concepts/meaningful partition, consider the following tacit knowledge. The DMs are concerned about the possibility that when the path is to be executed, an adversary party will try to block paths between obstacle "A" and obstacle "B."

It is therefore that a meaningful partition in this case would be to divide the solutions between two concepts. The first, is a concept that contains all paths that pass between this obstacles and the second is a concept containing all other paths. On the other hand, if the DMs are concerned about the possibility that the adversary party will block any of the alternative ways to reach the goal, then they may decide to partition the set of feasible solutions into four subsets, and try to find and compare the best solution (shortest path) within each such subset. This would constitute a significant search problem as it will provide alternative solutions, which can be examined not only by their length but also in view of incoming information about the plans of the adversary party.

The second problem to be examined is that of a multiobjective design of a truss structure that should support a force at its tip. The objectives are to minimize the deflection at the tip of the truss, while minimizing its weight. These are contradicting objectives. In this case, one may claim that using the Pareto-optimality principle will result in a set of alternative solutions (the Pareto-optimal set) to choose from. It should be noted that the search spaces of such concepts are not the same. The genotype of an individual that belongs to the upper concept of the figure is much shorter than that of an individual of the other concept. This lead to a conclusion that crossover between individuals of different concepts should be either treated with cautious or avoided.

Among different niche (Constraints) an adaptive parameter adjustment is developed, which takes the difference. The convergence acceleration is achieved by the differential evolution, mutation operator is alternatively utilized to build base vectors for particles to construct new solutions. Then, to enhance the exploitation, a local search scheme based on Gaussian distribution is self-adaptively performed around the seeds of niches. In the testing process, Classification technique used to predict group membership for data instances. Classification predicts categorical labels and prediction models continuous valued functions. It generalizes known structure to apply to new data.

On one hand, it should be noticed that when locating multiple global optima simultaneously, it is highly possible that one niche may be responsible for locating a small number of global optima not just one, especially when the number of global optima is larger than that of niches. This indicates that solutions with the same or very similar fitness values in each niche should have nearly equal possibilities to be selected for ants. On the other hand, not all solutions in one niche are beneficial and usually the worst one should be less biased. This tells us that σ should not be too large, because the larger the value of σ, the more uniform the probability distribution. In addition, the solution quality of different niches may be different, and the proportion of the best solutions within each niche may be different as well. This indicates that σ should be different for different niches. Therefore, taking the above into consideration, we propose an adaptive adjusting strategy for σ, which is formulated as,

$$\sigma_i = 0.1 + 0.3e^{-\frac{FS^i_{\max} - FS^i_{\max}}{FS_{\max} - FS_{\min + \eta}}}$$

Where σ_i is the σ for the jth niche; $FS^i_{\max}$ and $FS^i_{\min}$ are the maximum and minimum fitness values of the jth niche, respectively; $FS_{\max}$ and $FS_{\min}$ are the maximum and minimum fitness values of the whole archive, respectively and η is a very small value used to avoid the denominator being zero.

Observing the equation, we find that for each niche, σ_i is ranging within (0.1, 0.4]. Then, from the observation that can conclude with a significant difference in solution quality exists in one niche, which is indicated by a large value of $FS^i_{\max} - FS^i_{\min}$, σ_i tends to 0.1, leading to bias to the better solutions. This is beneficial for exploitation. On the contrary, when the fitness values of solutions in one niche are very close to each other, suggested by a small value of $FS^i_{\max} - FS^i_{\min}$, σ_i has a tendency to 0.4, resulting in that each solution is nearly unbiased. This is profitable for exploration. Therefore, taking both the difference in solution quality of niches and that of solutions within each niche into consideration, this adaptive adjusting strategy for σ can potentially afford proper selections of solutions for ants to construct new ones.

Through this, a good balance between exploration and exploitation can also be achieved. Instead of selecting one solution for each dimension in ACOR we use all dimensions of the selected solution as the solution. Such operation can not only reduce the time complexity, but also potentially take the correlation among variables into consideration, which is beneficial for preserving useful information together.

V. RESULTS AND DISCUSSION

The comparative analysis illustrates the experimental evaluation of the existing WSO and proposed multimodal optimization in terms of various evaluation metrics defined follows. The results are taken for both heart and liver disease data set by changing the data items.

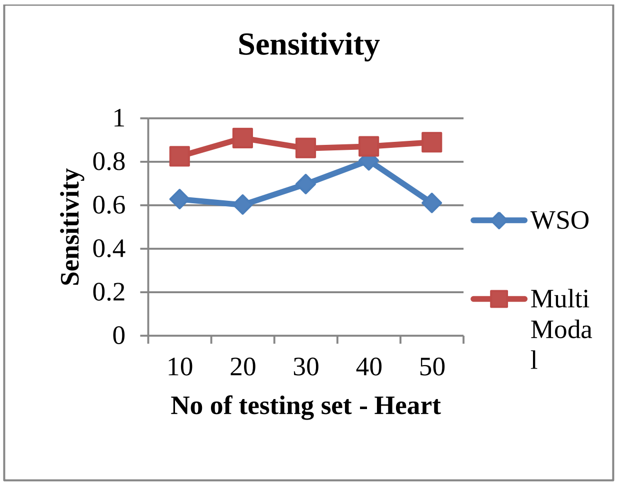

Fig 5.1 Sensitivity in heart data

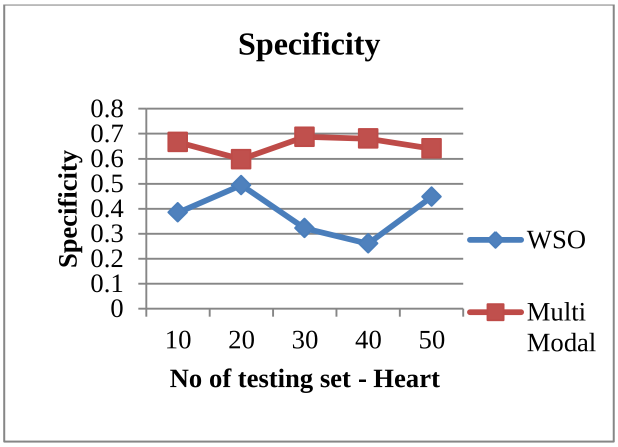

Fig 5.2 Specificity in heart data

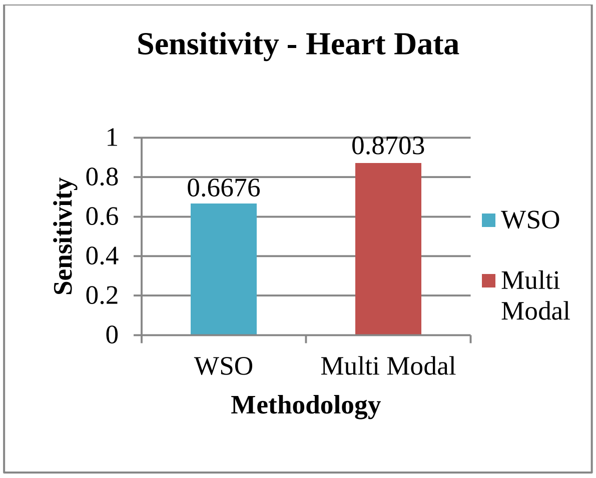

Fig 5.3 Average Sensitivity in heart data

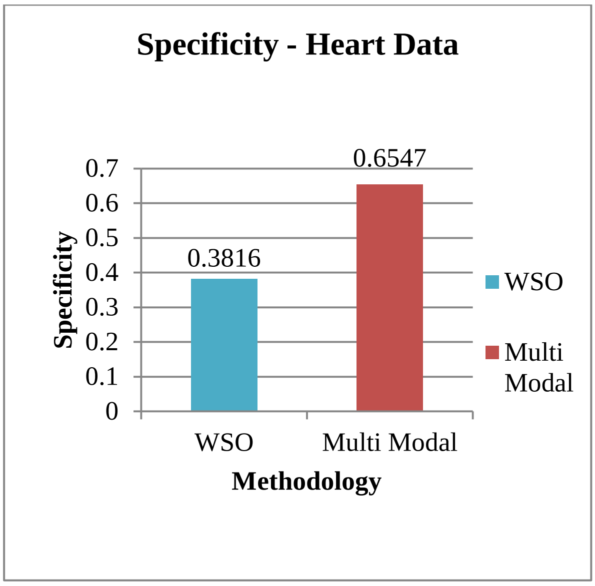

Fig 5.4 Average Specificity in heart data

By increasing the number of testing data items from 10 to 50 with the increment level of 10 the existing WSO obtains sensitivity ranged between 0.372671 and 0.6627329. The proposed Multimodal WSO attains 0.824 to 0.907 compared to the existing system. By increasing the number of testing data items from 10 to 50 with the increment level of 10 the existing WSO obtains specificity values ranged between 0.26052 and 0.4943. The proposed Multimodal WSO attains 0.59599 to 0.6876 compared to the existing system are represented in Fig 9.1 and Fig 9.2. The average results are displayed in Fig 9.3 and Fig 9.4.

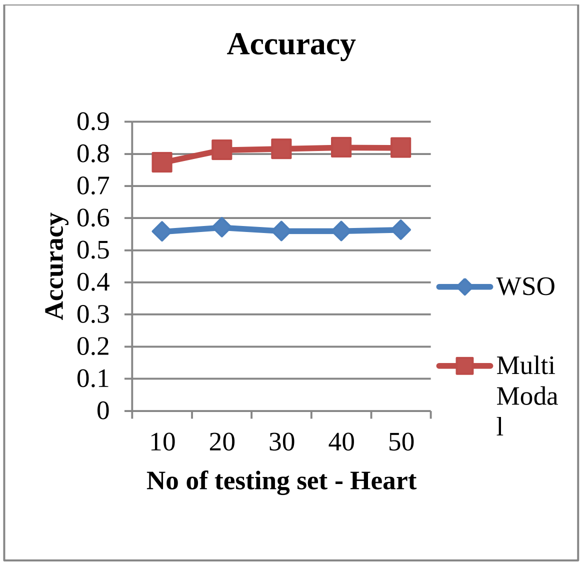

Fig 5.5 Accuracy in heart data

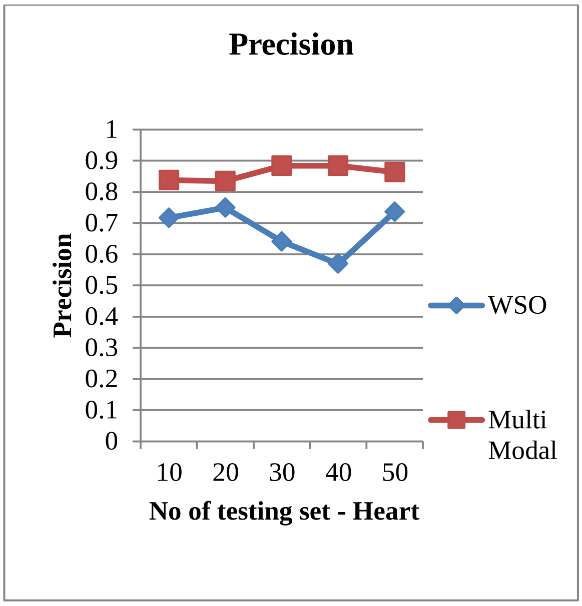

Fig 5.6 Precision in heart data

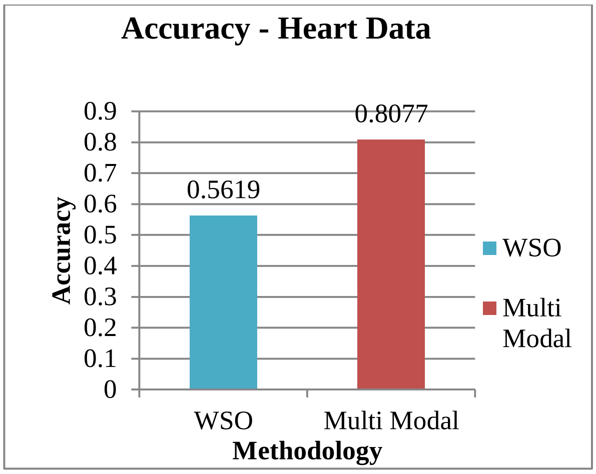

Fig 5.7 Average Accuracy in heart data

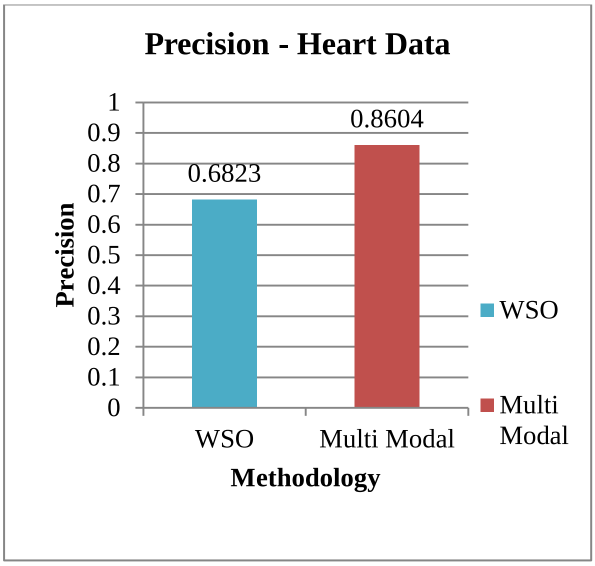

Fig 5.8 Average Precision in heart data

By increasing the number of testing data items from 10 to 50 with the increment level of 10 the existing WSO obtains accuracy ranged between 0.5589 and 0.5708. The proposed Multimodal WSO attains 0.7729 to 0.8198 compared to the existing system. By increasing the number of testing data items from 10 to 50 with the increment level of 10 the existing WSO obtains precision values ranged between 0.5691 and 0.7495. The proposed Multimodal WSO attains 0.8343 to 0.8836 compared to the existing system are represented in Fig 9.5 and Fig 9.6. The average results are displayed in Fig 9.7 and Fig 9.8.

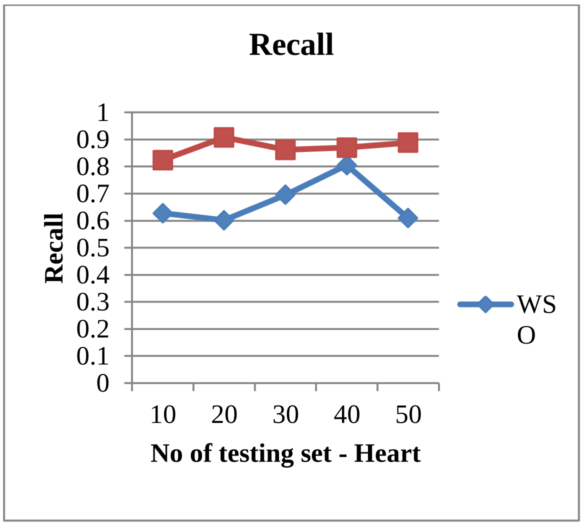

Fig 5.9 Recall in heart data

Fig 5.10 Miss rate in heart data

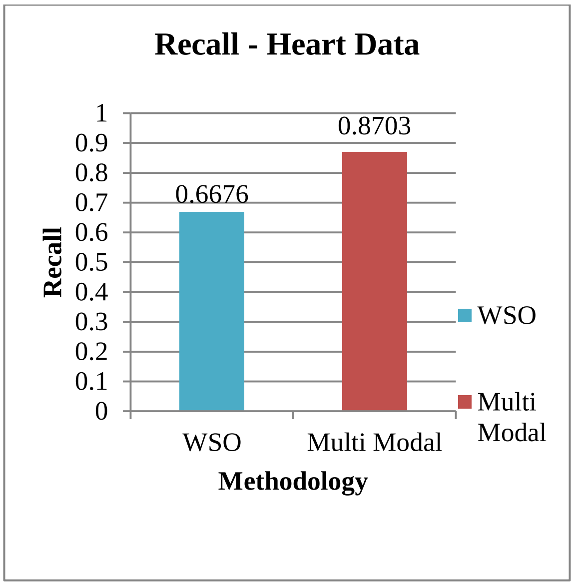

Fig 5.11 Average Recall in heart data

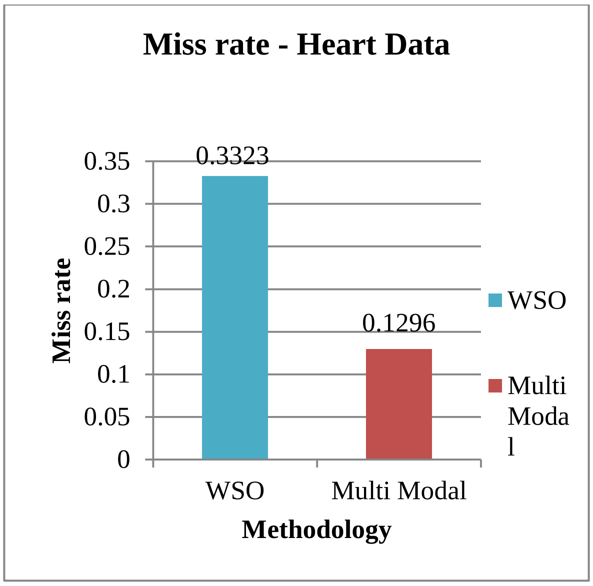

Fig 5.12 Average Miss rate in heart data

By increasing the number of testing data items from 10 to 50 with the increment level of 10 the existing

WSO obtains recall ranged between 0.1950 and 0.3988. The proposed Multimodal WSO attains 0.0923 to 0.1383 compared to the existing system. By increasing the number of testing data items from 10 to 50 with the increment level of 10 the existing WSO obtains miss rate values ranged between 0.6011 and 0.8049. The proposed Multimodal WSO attains 0.824 to 0.9076 compared to the existing system are represented in Fig 9.9 and Fig 9.10. The average results are displayed in Fig 9.11 and Fig 9.12.

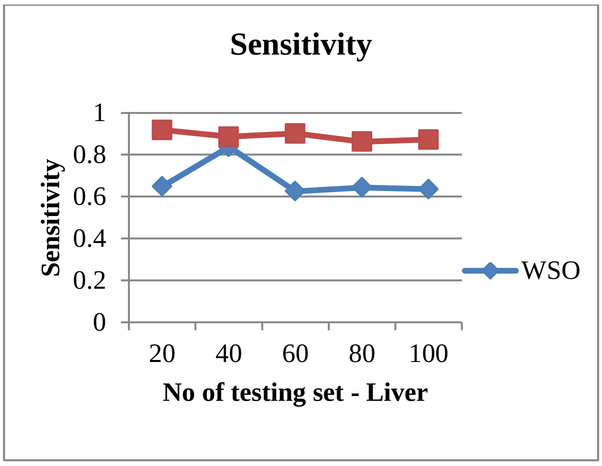

Fig 5.13 Sensitivity in Liver data

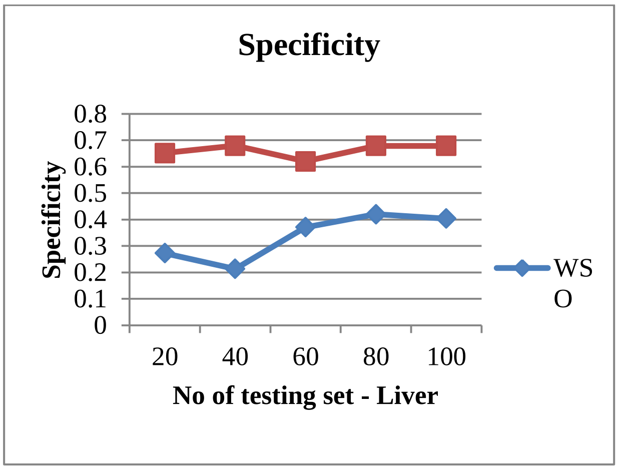

Fig 5.14 Specificity in Liver data

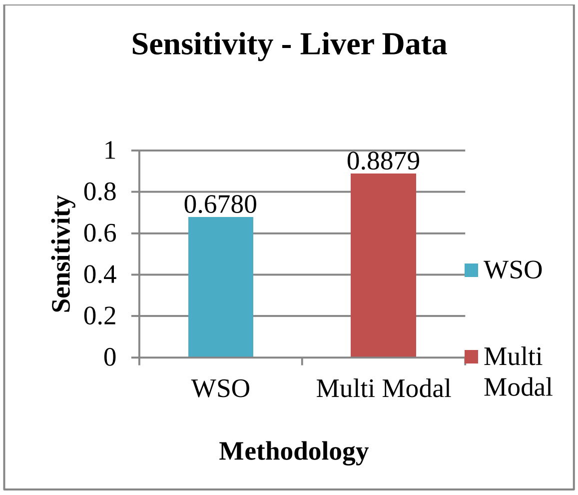

Fig 5.15 Average Sensitivity in Liver data

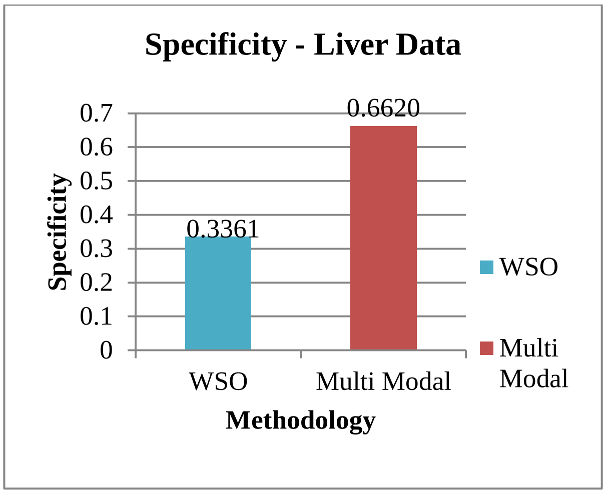

Fig 5.16 Average Specificity in Liver data

By increasing the number of testing data items from 20 to 100 with the increment level of 20 the existing WSO obtains sensitivity ranged between 0.6252 and 0.8369. The proposed Multimodal WSO attains 0.8624 to 0.9179 compared to the existing system. By increasing the number of testing data items from 20 to 100 with the increment level of 20 the existing WSO obtains specificity values ranged between 0.2134 and 0.4039. The proposed Multimodal WSO attains 0.6204 to 0.6795 compared to the existing system are represented in Fig 9.13 and Fig 9.14. The average results are displayed in Fig 9.15 and Fig 9.16

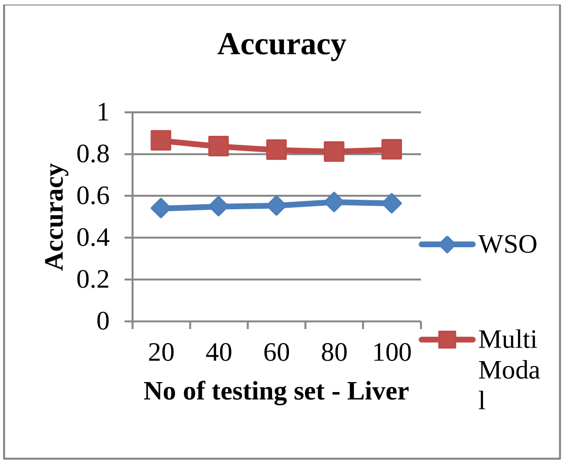

Fig 5.17 Accuracy in Liver data

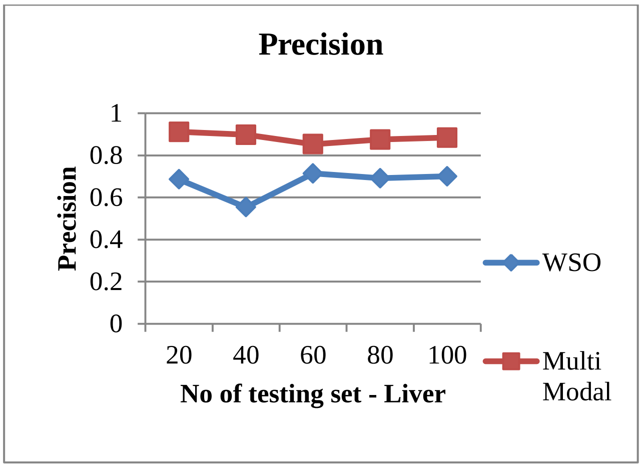

Fig 5.18 Precision in Liver data

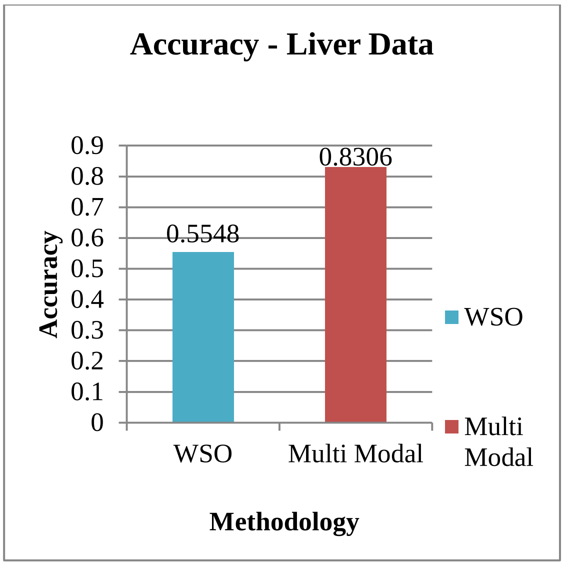

Fig 5.19 Average Accuracy in Liver data

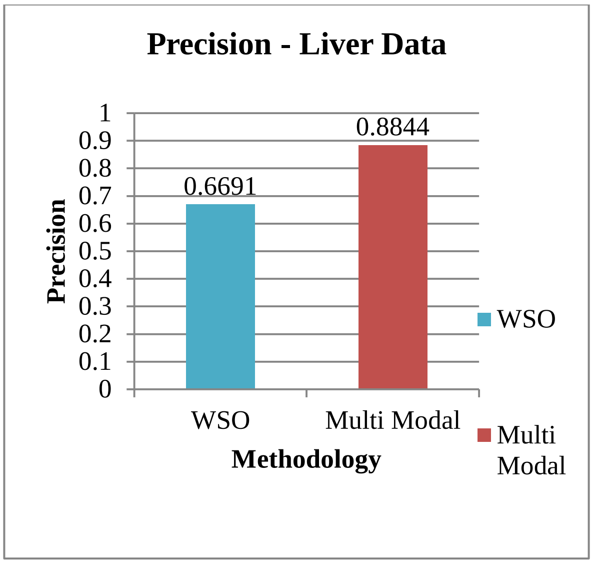

Fig 5.20 Average Precision in Liver data

By increasing the number of testing data items from 20 to 100 with the increment level of 20 the existing WSO obtains sensitivity ranged between 0.5395 and 0.5696. The proposed Multimodal WSO attains 0.8117 to 0.8638 compared to the existing system. By increasing the number of testing data items from 20 to 100 with the increment level of 20 the existing WSO obtains specificity values ranged between 0.5539 and 0.7139. The proposed Multimodal WSO attains 0.8533 to 0.9117compared to the existing system are represented in Fig 9.17 and Fig 9.18. The average results are displayed in Fig 9.19 and Fig 9.20.

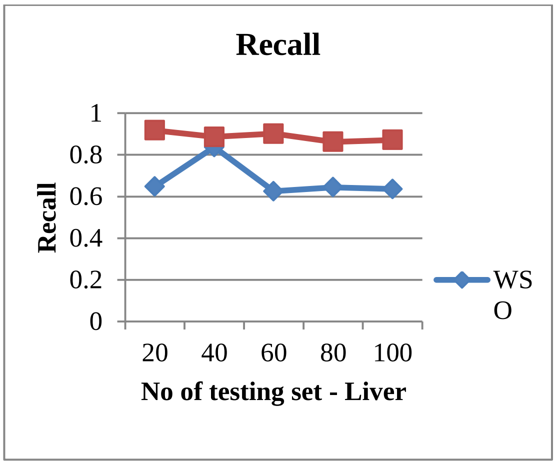

Fig 5.21 Recall in Liver data

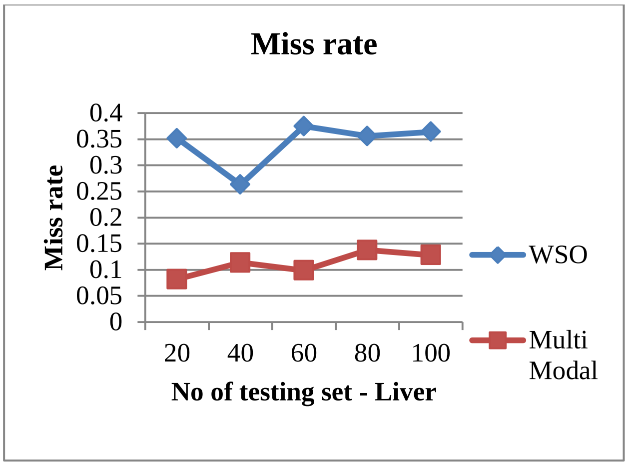

Fig 5.22 Miss rate in Liver data

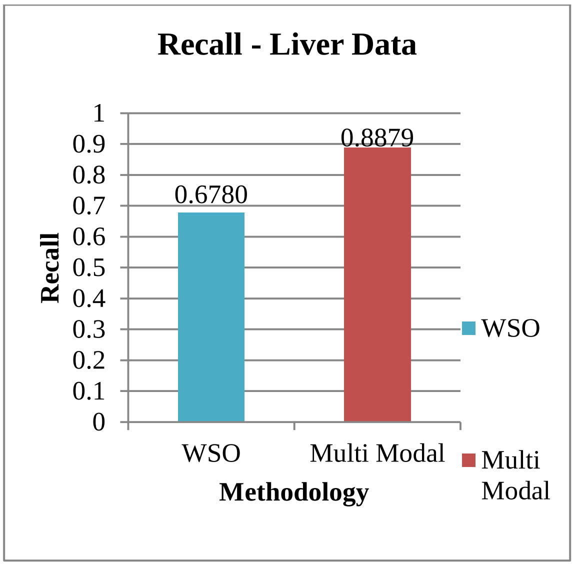

Fig 5.23 Average Recall in Liver data

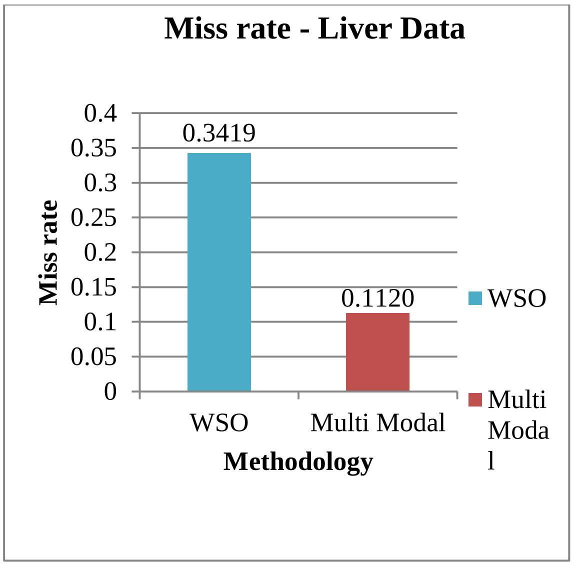

Fig 5.24 Average Miss rate in Liver data

By increasing the number of testing data items from 20 to 100 with the increment level of 20 the existing WSO obtains sensitivity ranged between 0.2630 and 0.3747. The proposed Multimodal WSO attains 0.0820 to 0.1375 compared to the existing system. By increasing the number of testing data items from 20 to 100 with the increment level of 20 the existing WSO obtains specificity values ranged between 0.6252 and 0.8369. The proposed Multimodal WSO attains 0.8624 to 0.9179 compared to the existing system are represented in Fig 9.21 and Fig 9.22. The average results are displayed in Fig 9.23 and Fig 9.24.

VI. CONCLUSION

The decision making in clinical data mining provides the enhanced optimization while using the knowledge discovery process in large Electronic Health Records. It leads to significant production and processing of data while using the machine learning and data mining methods. In the health care systems, the decision support system and the analysis of clinical data requires an interdisciplinary field of data mining, which guides the automated knowledge discovery process to apply the complex task of clinical data analysis. In the existing system the Wind-driven Swarm Optimization (WSO) is used to perform the classification process from the decision trees. By using the different permutations and optimal ruleset with multimodal optimization, the prediction of test data is improved significantly with the accelerated convergence. It is achieved by employing the differential evolution mutation operator with multi constraints and the performance evaluation showed that the proposed multimodal algorithm achieved the better results competed to existing WSO optimization in terms of sensitivity, specificity, accuracy, precision and miss rate.

VII. REFERENCES

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