APPLYING MACHINE LEARNING TECHNIQUES TO FIND IMPORTANT ATTRIBUTES FOR HEART FAILURE SEVERITY ASSESSMENT

Puram Surya Prudvi [1] and Ershad Sharifahmadian [2]

[1]Department of Computer Engineering, Masters in Computer Engineering, University of Houston Clear Lake, Houston, Texas, USA
[2]Department of Computer Engineering, Visiting Asst Professor, University of Houston Clear Lake, Houston, Texas, USA

ABSTRACT

The diagnosis of heart disease depends mostly on the combination of clinical and pathological data. It leads to the quality of medical care provided for the patient. In this paper, three machine learning (ML) techniques −Classification and Regression tree (CART), Neural Networks (NN), and Support vector machine (SVM)− are utilized to find the best attributes for estimating the severity of heart failure. The data is collected from three different resources, then each input attribute used for assessing the severity of heart failure is analyzed individually after implementing the machine learning techniques. Finally, the most important supportive attributes are presented in this paper by which medical staffs can identify heart failure severity fast and more accurately. In fact, by screening important attributes, clinicians can make better decision about right treatment procedures or preventive actions that reduce risk of heart attacks.

KEYWORDS

Congestive Heart Failure (CHF), Decision support system, Heart failure severity, Machine learning, Risk classification

1. INTRODUCTION

Heart failure (HF) occurs due to an insufficient supply of blood from the heart. To meet the general body needs a certain amount of blood is necessary. Breathlessness, insufficient sleep, excessive tiredness, swelling of legs are some of the symptoms of the heart failure. Heart failure is not same as a heart attack which is caused due to damage of the heart muscle. Some of the common causes of heart failure are heart attack, high blood pressure, excess alcohol consumption, drugs consumption, cigarette smoking, atrial fibrillation etc. High output of blood also causes heart failure. When the amount of blood pumped by the heart is greater than the typical amount of blood and the heart is not able to keep up, and then high-output heart failure will occur, which can be termed as Congestive heart failure (CHF). Person affected with CHF usually has substantial symptoms such as shortness of breath and chest pain.

Heart failure management includes the perpetuation of life, reduction of symptoms and being more activity. The maintenance of heart failure is very important for the person affected with HF. The Heart failure severity assessment and type prediction are important when the patient condition is analyzed [1]. Thus, for the severity assessment, several symptoms from patients should be observed. The main goal of this study is to find important attributes by which the severity assessment of heart failure is better identified. This goal can be achieved based on classification of data using the machine learning techniques. The data with different attributes in different experiments are given to ML techniques. Then, based on the results of classification (i.e.

output of ML techniques) important attributes are selected. The severity assessment is exceptionally helpful, for instance, in remote healthcare monitoring. In this paper, the severity assessment is done using three machine learning techniques including CART (classification and regression tree), SVM (support vector machine), and NN (neural networks). Then, the performance of ML techniques is evaluated for each attribute (i.e. symptom) separately. In this study, the results are evaluated such that the attribute which helps to assess the HF severity more accurately is considered as one of the important supportive attributes.

2. RELATED WORK

In the previous works several approaches for assessing severity of Heart Failure, other diseases and various Machine learning approaches for classification are proposed.

Gabriele Guidi, Maria Chiara Pettenati, Paolo Melillo et.al. [1] proposed a clinical decision support system for assessing the severity. In the support system, a management interface is built for the heart failure type prediction and severity assessment. To implement the smart functions machine learning techniques are implemented. P. Melillo, N. De Luca, M. Bracale, and L. Pecchia et.al. [5] proposed Classification tree based risk assessment for separating higher risk patients from lower risk patients using of long term heart rate variability measures. T.John Peter, K. Somasundaram et.al. [9] used Naïve Bayes, K-Nearest Neighbour, Decision Tree for prediction of risk in heart failure patients. Kavetha.BV, Venu Gopala Krishnan.J, et.al [10] used CVPartition method for classifying, deciding and detecting Maligant and Benign in mammorgams. Amiya Halder, Oyendrila Dobe et.al [17] explained about Fuzzy feature selection and support vector machine for detecting Tumor in Brain MRI.

The present work describes about three machine learning approaches for assessing the severity of heart failure and the important attributes for assessing severity are concluded by several insights into the data.

3. METHOD

To analyze the importance of supportive attributes in estimating the severity of heart failure, the outcome of ML techniques is considered. The ML techniques classify patients based on the severity level of the heart failure as i) mild, ii) moderate and iii) severe. The general block diagram of HF severity assessment is given in the figure 1.

Classification and Regression Trees is an order strategy which utilizes chronicled information to build purported decision trees. Decision trees are then used to group additional information. To utilize CART, we need to know number of classes from the earlier [2], [3].

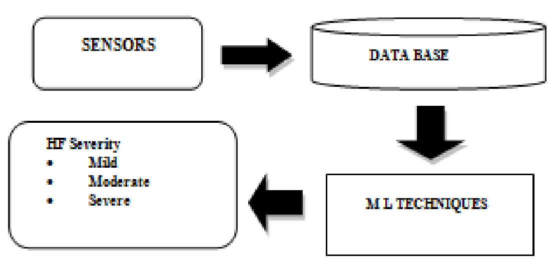

Fig. 1. General block diagram of HF severity assessment

we are going to discuss the three machine learning techniques and their role in classification:

a. ***Decision trees*** arrange occurrence by sorting them down the tree from the root to some leaf node, which gives the arrangement of the occurrence. Every node in the tree determines a trial of some trait of the occurrence and each branch downward from that node relates to one of the conceivable qualities for the given attribute. An occurrence is ordered by beginning at the root node of the tree, testing the property determined by this node, and then moving down the tree limb comparing to the estimation of the characteristic. This procedure is then continual for the sub- tree rooted at the new node [4].
b. ***Support vector machine*** (SVM) forms a model that allocates new examples to Classification or regression analysis for a given set of training data sets [5]. The SVM model is an illustration of the training examples with space as a plane and the data as points and are cleverly mapped, separated by a clear gap to project that they belong to two distinct categories
c. ***Neural networks*** learning method is a computational approach based on a rough analogy of artificial neural networks which are an enormous collection of neural units exhibiting the exact same way the brain solves problems with the help of large clusters of biological neurons [4]. The feed-forward neural network is also implemented. By varying the hidden neurons from 2 to 8. The best configuration is 8 neurons for the severity assessment.

4. RESULTS

In this paper, we used the heart disease data from three resources. The database I is an anonymized database of HF patients, with varying severity degrees, all treated by the Cardiology Department at the St. Maria Nuova Hospital, Florence, Italy, in the period 2001–2008 [1]. This database consists of 136 records from 90 patients, including baseline and follow-up data (when available). At the time of the data collection, the specialist physician provided the mentioned HF severity assessment in the desired three levels: i) mild, ii) moderate, and iii) severe, which was stored in the database. 12 variables (i.e. attributes) in this database that are used as input for the machine learning techniques are the following:

1) Anamnestic data: age, gender, and New York Heart Association (NYHA) class.

2) Instrumental data: weight, systolic blood pressure, diastolic blood pressure, EF (Ejection Fraction), BNP (Brain natriuretic peptide), heart rate, ECG parameters (atrial fibrillation true/false, left bundle branch block true/false, and ventricular tachycardia true/false).

The database II is machine learning repository of UCI [6] which was collected from the Cleveland Clinic Foundation.

We have 303 instances of which 164 instances belonged to the healthy cases and 139 instances belonged to the heart disease. 14 clinical features have been recorded for each instance. The table I shows the 14 clinical features and their description.

Table I- Clinical features and their description

Clinical features	**Description**
Age	Instance age in years
Sex	Instance gender
Cp	Chest pain type
Trestbps (mmHg)	Resting blood pressure
Chol (mg/dl)	Serum cholesterol
Fbs	Fasting blood sugar
Restecg	Resting electrocardiographic results
Thalach	Maximum heart rate achieved
Exang	Exercise induced angina
Oldpeak	ST depression induced by exercise relative to rest
Slope	The slope of the peak exercise ST segment
Ca	Number of major vessels (0-3) colored by flourosopy
Thal	3 = normal; 6 = fixed defect; 7 = reversible defect
Num	Diagnosis of heart disease

The database III is anonymized data collected from 246 patients with 14 attributes such as age, sex, Dyspnea, smoking, dust, Respiratory frequency, Inhale and exhale time, ECG ST segmentation, Heart rate, peripheral capillary oxygen saturation (spo2), systolic and diastolic blood pressures. The data is collected from Siddhartha government medical hospital, Vijayawada, India. The data provides an overview of prevalence of Chronic Obstructive Pulmonary Disease (COPD) in Vijayawada, India. It provides insights into the mortality, morbidity and etiological determination of COPD and emphasis in understanding the multidimensional nature of problem. All the data is normalized eliminating redundant data (for example, storing the same data in more than one table) and ensuring data dependencies make sense.

Using the machine learning techniques, we evaluate the performance of each attribute in assessing the severity of HF. First, input data is considered from three resources and then the common attributes in the three datasets are considered. Each attribute is used for the ML techniques along with the common attributes, and the performance in assessing the HF severity is observed.

Three machine learning techniques are applied and the corresponding results are as presented:
We extract the common attributes from the three datasets. The common attributes are age, sex, Heart rate, blood pressure. Then, we examine the performance of each method in assessing the severity of heart failure based on each supportive attribute. First, Classification and regression tree (CART) is examined with the common attributes. Then each supportive attribute from each

dataset is added to the common attributes and results are studied separately. Later the support vector machine (SVM), and NN are inspected in the same way. The accuracy, precision, and sensitivity are calculated for each method individually. Each test is done using MATLAB R2016b.

The accuracy of the three ML techniques using the three datasets are shown in Figures 2, 3,4. For database I, common attributes are considered and their role is evaluated in assessing the severity of the heart failure. Then, supportive attributes such as BNP, ECG parameters, NYHA class, EF rate, Weight are used with the common attributes. Then, the accuracy of each ML techniques is calculated. Among all the supportive attributes from the database I, BNP, NYHA class, ECG parameters provide higher accuracy comparing other input attributes as shown in the figure 2.

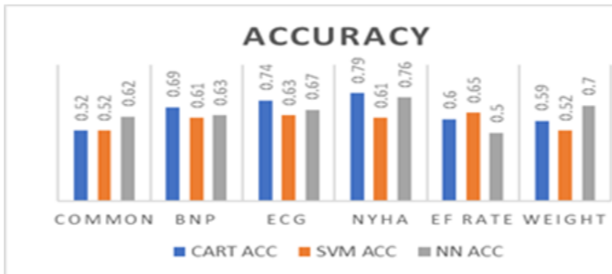

Fig 2: Graph showing the accuracy of the machine learning techniques for the database I

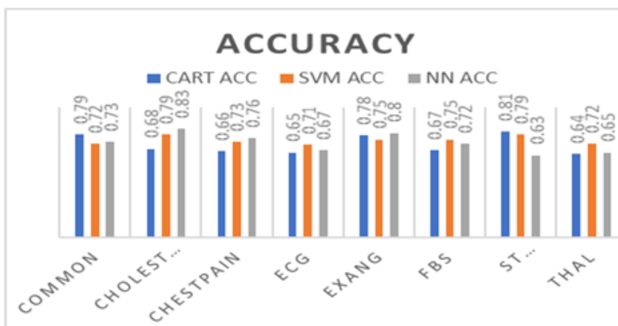

Fig 3: Graph showing the accuracy of the machine learning techniques for the database II.

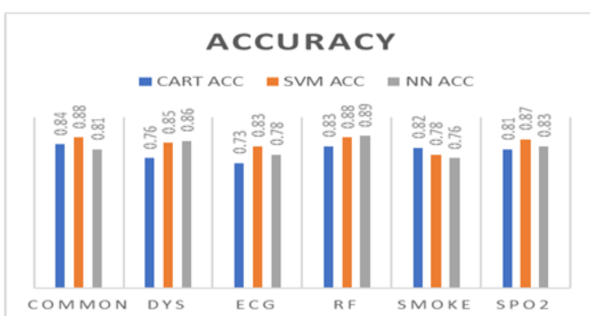

Fig 4: Graph showing the accuracy of the machine learning techniques for the database III.

Next, the common attributes from the database II are considered, then the supportive attributes such as Cholesterol, Chest pain, ECG parameters, Exercise induced angina, fasting blood sugar, ST segment, Thalassemia are considered. Among all the supportive attributes, Cholesterol, Chest pain, ECG parameters and ST segment provide higher accuracy as shown in the figure 3. Last, ML techniques are applied on the database III collected from Siddhartha government medical hospital, Vijayawada, India. After that, the supportive attributes are identified and the role of each attribute in assessing the severity of the heart failure is observed. Of all the supportive attributes, the Respiratory Frequency (RF), spo2, ECG parameters, and Dyspnea provide higher accuracy as shown in the figure 4.

5. DISCUSSION

The selection of the important supportive attributes among all attributes in the heart failure severity assessment is done not only based on the accuracy but also based on the precision and sensitivity. The rate of precision is observed for each method and evaluated for each level of severity (i.e. Mild, Moderate and Severe). The precision for each level is tested with different supportive attributes along with the common attributes. The figure 5 demonstrates the variation in precision for each class (i.e. Mild, Moderate and Severe) when the CART is implemented for different supportive attributes.

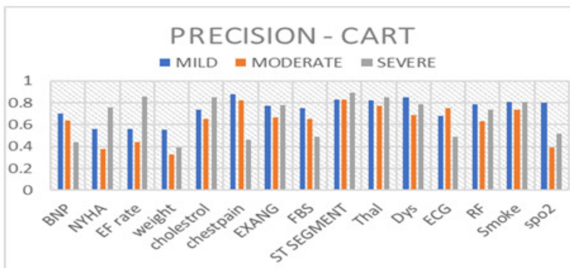

Fig 5: Graph showing precision values of all classes with respective to CART technique using the different supportive attributes along with common attributes.

The figure 6 explains the sensitivity of each class when the CART is implemented for different supportive attributes. In medical diagnosis, test sensitivity is the ability of a test to correctly identify those with the disease. In other words, sensitivity is the extent to which the true positives are not overlooked. When we observe the accuracy, precision and sensitivity rates of different supportive attributes while implementing CART we noticed that BNP, chest pain, smoking, ECG parameters, and dyspnea exhibited the better results. Therefore, we can select those as important attributes in severity assessment of heart failure during the CART implementation.

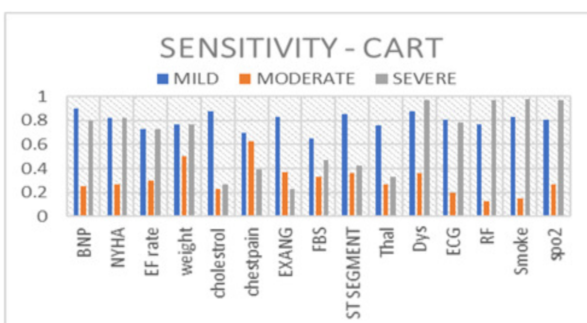

Fig 6: Graph showing sensitivity values of all classes with respective to CART technique using the different supportive attributes along with common attributes.

In the same way, SVM and NN are used. The supportive attributes and the common attributes are evaluated. Figures 7, and 8 show the precision, sensitivity for each level of severity (i.e. class) when the SVM is implemented. After implementing the SVM, we find out that BNP, smoking, ECG parameters, cholesterol, chest pain, dyspnea are important supportive attributes.

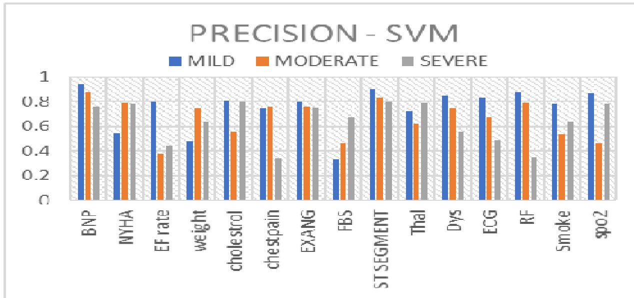

Fig 7: Graph showing precision values of all classes with respective to SVM technique using the different supportive attributes along with common attributes

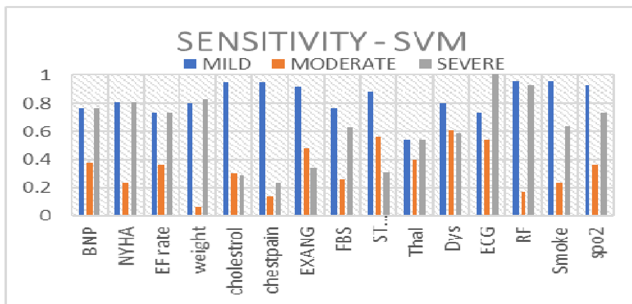

Fig 8: Graph showing sensitivity values of all classes with respective to SVM technique using the different supportive attributes along with common attributes

Figures 9 and 10 demonstrate the precision, and sensitivity for each class when the NN is implemented. After NN implementation, we conclude that ECG parameters, cholesterol, Chest pain, smoking, dyspnea are the important supportive attributes as those performed well comparing to other attributes. CART produced satisfactory results in severity assessment if compared with other studies that assess HF severity such as [1] that classify HF patients in three groups mild, moderate, and severe. As shown in the graphs, the accuracy, precision, and sensitivity are calculated for each supportive attribute individually.

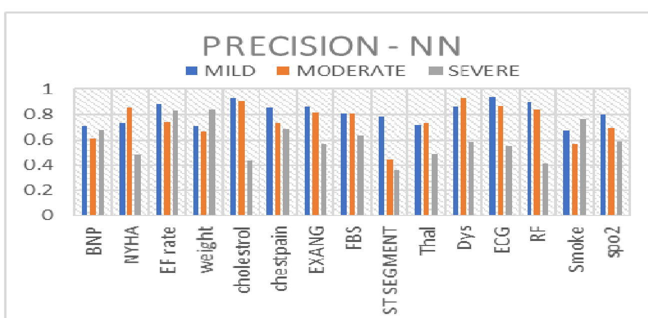

Fig 9: Graph showing precision values of all classes with respective to NN technique using the different supportive attributes along with common attributes

Based on results, CART outperforms well with the accuracy of 84.4%. For different machine learning techniques, different supportive attributes are considered. the SVM has the average accuracy of 76%. The neural network has the average accuracy of 78%.

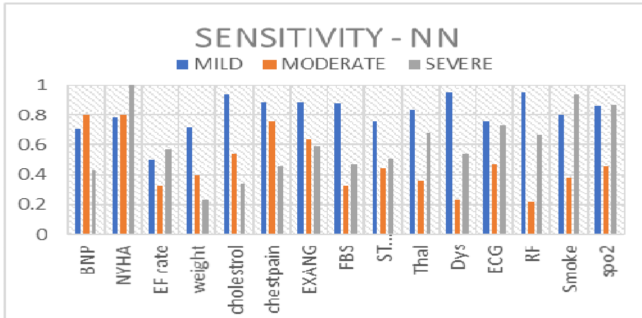

Fig 10: Graph showing sensitivity values of all classes with respective to NN technique using the different supportive attributes along with common attributes

5. CONCLUSION

T This work identifies main attributes for fast and more accurate assessment of the heart failure severity in patients and the status of the disease. After evaluating selected clinical observations from patients (i.e. Main attributes), physicians and other health professionals can better choose right treatment procedures or preventive actions that reduce risk of heart attacks. First, we selected the common clinical attributes such as age, sex, heart rate etc. Three datasets were used. Those databases were selected to comprehensively evaluate broad ranges of clinical parameters which influence the heart failure severity assessment. The three machine learning techniques were implemented to identify the main supportive attributes. Different ml techniques were used to show that identified main attributes are independent from ml techniques, in other words, the changing classification method (i.e. ML technique) will not significantly affect the main supportive attributes. Later we evaluated the performance of each technique by adding different clinical attributes individually to the common attributes. After examining the performance of the ml techniques, main clinical attributes were identified as important supportive attribute for each technique. After cart implementation, we notice that BNP, chest pain, smoking, ECG parameters, and dyspnea exhibited the better results. After implementing the SVM, we find out that BNP, smoking, ECG parameters, cholesterol, chest pain, dyspnea are important supportive attributes. After NN implementation, we conclude that ECG parameters, cholesterol, chest pain, smoking, dyspnea are the important supportive attributes. Cart outperforms well with the accuracy of 84.4%. The SVM has the average accuracy of 76%. The neural network has the average accuracy of 78%. Among all the methods, cart technique provided the better results in severity assessment of heart failure with the accuracy of 84.4%.

ACKNOWLEDMENT

The authors would like to thank Dr. Gabriele Guidi, Robert Detrano, Dr. M.P.P. Bala Narasimhulu for their support and providing database for this project.

REFERENCES

[1] Gabriele Guidi, Maria Chiara Pettenati, Paolo Melillo, "A Machine Learning System to Improve Heart Failure Patient Assistance," IEEE J. biomedical and health informatics, vol. 18, no. 6, pp. 1750-1756, Nov 2014

[2] Priyanka Pandey,Amita Jain, “A Comparative study of Classification techniques: Support vector Machine & Decision Tress”, . International Conference on Computing for Sustainable Global Development, pp.3620-3624, 2016.

[3] Roman Timofeev, “Classification and Regression Tress. Theory and Applications”, Cent. Of Appl. Statis. And Econ., Humboldt Univ., Berlin, Dec.20,2004.

[4] s [Online].

[5] P. Melillo, N. De Luca, M. Bracale, and L. Pecchia, “Classification tree for risk assessment in patients suffering from congestive heart failure via long-term heart rate variability,” IEEE J. Biomed. Health Inform., vol. 17, pp. 727–733, May 2013.

[6] UCI Machine Learning Repository [homepage on the Internet]. Arlington: The Association; 2006 [updated 1996 Dec 3;cited 2011 Feb 2].Available from: http://archive.ics.uci.edu/ml/datasets/Heart+Disease.

[7] M. Sokolova and G. Lapalme, “A systematic analysis of performance measures for classification tasks,” Inf. Process. Manage., vol. 45, no. 4, pp. 427–437, Jul. 2009.

[8] Chun-Fu Lin and Sheng-De Wang, “Fuzzy Support Vector Machines”, IEEE Transactions on Neural Networks, Vol.2, No.2, March 2002.

[9] T.John Peter, K. Somasundaram, “An empirical study on prediction of heart disease using classification data mining techniques”, IEEE-International Conference On Advances In Engineering, Science And Management (ICAESM -2012) March 30, pp.514-518, 2012.

[10] Kavetha.BV, Venu Gopala Krishnan.J, “Decide,Detect And Classify Benign And Maligant in Mammorgams using CV-Partitioning Method”, ARPN Journal of Engineering and Applied Sciences.Vol.10,No.10, June 2015.

[11] AH Chen, SY Huang, PS Cheng, EJ Lin, “HDPS: Heart Disease Prediction System. Computing in Cardiology”, Vol.38, pp. 557-560, 2011.

[12] Ryusuke Hata, Kazuyuki Muras, “Multi-valued Autoencoders for Multi-Valued Neural Networks”, IEEE Trans. International Joint Conference on Neural Networks, pp.4412-4417, 2016.

[13] Atul Kumar Pandey, Prabhat Pandey, K.L. Jaiswal, Ashish Kumar Sen, “A Heart Disease Prediction Model using Decision Tree. IOSR Journal of Computer Engineering”, Vol.12, Issue 6, pp. 83-86, Aug 2013.

[14] Seyed Saleh Mohaseni Matiar Mohamadyrai, “Heart Arrhythmias Classification via a Sequential Classifier Using Neural Network, Principal Component Analysis and Heart Rate Variation”, IEEE Trans.8th International Conference on Intelligent Systems, pp.715-722, 2016.

[15] Udaya Sampath K. Perara Miriya Thanthrige, Jagath Samarabandu Xianbin Wang, “Machine Learning Techniques for Intrusion Detection on Public Dataset”, IEEE Trans. Canadian Conference on Electrical and Computer Engineering, 2016.

[16] Fabricio Aparecido Breve, Daniel Carlos Guimaraes Pedronette, “Combined Unsupervised and Semi-Supervised Learning for Data Classification”, IEEE Trans. International WorkShop on Machine Learning for Signal Procession, sep.2016.

[17] Amiya Halder, Oyendrila Dobe, “Detection of Tumor in Brain MRI Using Fuzzy Feature Selection and Support Vector Machine”, International Conference on Advances in Computing, Communications and Informatics, pp.21-24, sep.2016.

[18] B.Venkatalakshmi, M.V Shivsankar, “Heart Disease Diagnosis Using Predictive Data mining”, ICIET’14, Volume 3, Issue 3, March 2014.