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

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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.


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].

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.
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

<table>
<thead>
<tr>
<th>Clinical features</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Instance age in years</td>
</tr>
<tr>
<td>Sex</td>
<td>Instance gender</td>
</tr>
<tr>
<td>Cp</td>
<td>Chest pain type</td>
</tr>
<tr>
<td>Trestbps (mmHg)</td>
<td>Resting blood pressure</td>
</tr>
<tr>
<td>Chol (mg/dl)</td>
<td>Serum cholesterol</td>
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<tr>
<td>Fbs</td>
<td>Fasting blood sugar</td>
</tr>
<tr>
<td>Restecg</td>
<td>Resting electrocardiographic results</td>
</tr>
<tr>
<td>Thalach</td>
<td>Maximum heart rate achieved</td>
</tr>
<tr>
<td>Exang</td>
<td>Exercise induced angina</td>
</tr>
<tr>
<td>Oldpeak</td>
<td>ST depression induced by exercise relative to rest</td>
</tr>
<tr>
<td>Slope</td>
<td>The slope of the peak exercise ST segment</td>
</tr>
<tr>
<td>Ca</td>
<td>Number of major vessels (0-3) colored by fluoroscopy</td>
</tr>
<tr>
<td>Thal</td>
<td>3 = normal; 6 = fixed defect; 7 = reversible defect</td>
</tr>
<tr>
<td>Num</td>
<td>Diagnosis of heart disease</td>
</tr>
</tbody>
</table>
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](image1)

![Fig 3: Graph showing the accuracy of the machine learning techniques for the database II.](image2)

![Fig 4: Graph showing the accuracy of the machine learning techniques for the database III.](image3)
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.](image)

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.](image)
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.

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.
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%.

![Graph showing sensitivity values of all classes with respective to NN technique using the different supportive attributes along with common attributes](image)

**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

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%.

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### References

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