Chapter 16
A Novel Machine Learning System to Improve Heart Failure Patients Support

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16.1 Medical Background

Heart failure affects 26 billion of people all over the world (Health Catalyst article entitled 2018). Heart Failure (HF) is an alteration of structure named vascular stiffening and functioning of heart that leads to an inadequate pumping function (Strait and Lakatta 2012). Inadequate pumping of heart leads to an insufficient amount of oxygen flow to the internal organs, tissues, and blood. Oxygen is essential for organs and tissues for performing metabolic activities. Because of slow function of heart, possibility of buildup of sodium and unwanted water in lungs and in other tissues called edema. The main indications of heart failure are shortness of breath, fatigue, edema, increased heart rate, etc. (American Heart Association 2017). Heart failure is a life-threatening stage (Elfadil and Ibrahim 2011) and it leads to death if it left unattended. The clinical course of heart failure is chronic and the patient is in steady condition and hospitalized with continuous observation. With the help of some therapies, the criticality will be reduced. The global occurrence of Heart Failure is accelerating because of the age of the population and extending survival of patients affected with coronary diseases. In this case to reduce the human risk, we need a medical support system that helps to assist the HF patients.

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16.2 Introduction

Medical decision support systems speedily growing as the important tools for medical practitioners since the quantity of available data increases along with the responsibility to provide effective care. Here we present a Medical Decision Support System (MDSS) that comes with a movable kit for getting hold of medical parameters which permits the support to telemonitoring functions. The MDSS system provides smart functions with the help of different machine learning methods which we matched to find the best method that performs better with the present data in our database and distinct for the HF field. The above system yields many outputs that can be viewed with the help of an interface tool called HF Administrator. This can have two choices like to bring about the demographics of the patient, the continuous check-ups and to train the artificial intelligent methods with the help of patient data. The device can be used to show the output of the system after the AI was trained adequately. The description and all the smart functions of this tool along with the comparison of different machine learning methods with the best method are explained in this paper.

16.2.1 Project Goals (Final Output)

The aim of this device is to provide the end-users like the physicians to give the necessary outputs like Criticality Assessment, Type Prediction, Short-range prediction, Sequential follow-up comparison, and Overall Prediction.

Criticality Assessment: It is a three-level assessment (mild, moderate, critical) of actual HF criticality.

Type Prediction: It predicts the type of HF of the patient and also the acute episodes that possibly

Short-Range Prediction: It shows the indication of the chances of occurrence of a serious problem. Since these cases are sensitive, it needs the data for training on daily basis.

Sequential follow-up comparison: It is a clear view of various parameters of the patient in treatment in different dates of follow-ups. Histograms and line charts are used for showing the follow-ups.

Guidelines of therapy: It is the outcome that shows the doctor, that all the targets are achieved based upon the guidelines. Some classes of drugs need some regular follow-ups to check whether to increase or decrease or whether the dose is tolerated by the patient.

From the above goals, some of them are achieved using machine learning algorithms using proper training which was explained in Chap. 4. The end users of this device may change based on the application needed and it may be heart

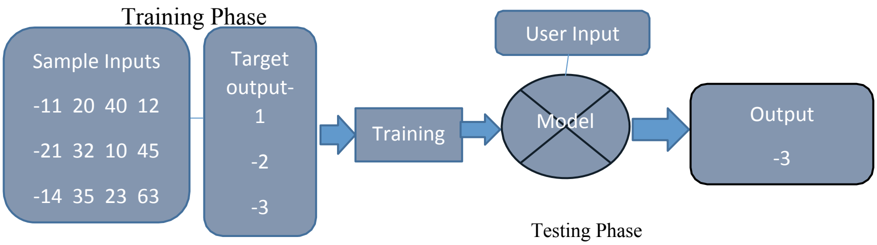

Fig. 16.1 Supervised learning representation

specialists or other non-technical. For the non-technical staff, criticality assessment output is much useful. For example, in a home-based monitoring setup, a nurse often goes to the home of the patient for taking some measurements and feed the results using a tablet device. The smart core device will answer with the criticality assessment which will be sent to the patient's doctor or to the heart specialist and he will sort his patient based on the severity. The more details based on this procedure are explained in the following literature (Guidi et al. in press, 2012a, b).

16.2.2 Supervised Training

One of the machine learning algorithms used is the supervised learning training method. Here the input will be given based on the observation and the desired output is also given. The training pair consists of one input value with the target value, which is explained in Fig. 16.1. The training is having training and testing phases. After the training phase, a reusable model is taken as the output and during testing phase, new inputs that the system never knows before are given to test how the system behaves for both the sets of inputs. It is not necessary to know the learning procedure because the system from the proof of the information given and it individually finds the required output.

16.3 The HF_ADMIN Device

16.3.1 Scope of Device

The device main goal is to get back the parametric data of actual patients at the time of outpatient visits appropriate for training a machine learning procedure. As given in Fig. 16.1, every follow-up should be assisted by a "Target output", i.e., the assessment of the HF by the heart specialist. The next aim is that the device acts as a special-purpose control panel for the treatment of HF patients, together with the main management and several other useful functions interconnected to the disease.

16.3.2 Device Design

This device has been constructed in deep cooperation with doctors for satisfying real time essentials in terms of both subjects and usability which are taken during outpatient visits. The necessity of usability which targets to diminish the device's impact on the casualty visits workflow. To confirm that the doctor can take actual and instant benefit from the use of the device in cardiology casualty visits, the device comprises of some practical structures such as the Alteration of Diet in Renal Disease calculation (ADRD), smart therapy unit which discovers the drug molecules to suggest based on dose and an instructor that confirms that the guideline of procedures are strictly followed. In this section, we will label in detail the device and its parts like parameter attainment, follow-up displays, criticality assessment based on AI methods, Smart Therapy unit, asynchronous compilation unit, short-range prediction, module for asynchronous compiling, etc. For patient demographics, all of these units work together by an HF_ADMIN_device.

16.3.3 Patient Management

Selection of a particular patient is possible in this section whether he is already included in the database or needs to be added as a new name. The complete information about the patient is present in the database and also we can visualize the updated data related to the patient's consultant. Figure 16.2 shows the personal

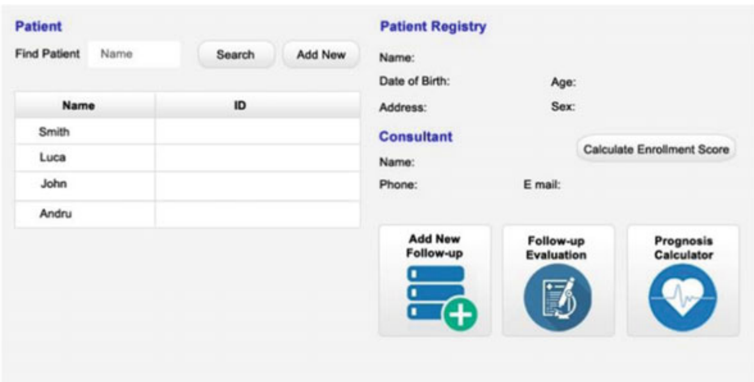

Fig. 16.2 Patient monitoring interface

information of the patient, consultant information, and prognosis details of the patient.

16.3.4 Enrollment Mark

This attribute is for the calculation of the risk of extending hospitalization based on the practical score. This device needs the contribution of some functional parameters such as the BNP (Brain Natriuretic Peptide) and Ejection Fraction of heart altogether with some other structural parameters such as the total number of hospitalization records of patient for HF complication or for other factors. This model delivers a possibility of risk score. If the HF patient seems to be at great risk of re-hospitalization then it is appropriate to be enrolled in the scheme and it may be helpful for the training of the Machine.

16.3.5 Parameters Attainment

This section is used by the heart specialist during his daily visits. In Fig. 16.3. It is shown that having five sections. The first section is noted with the personal details and enrollment details of the patient. The calculation of the prognosis score can be calculated in the second section. Frequent updates and daily measurements are

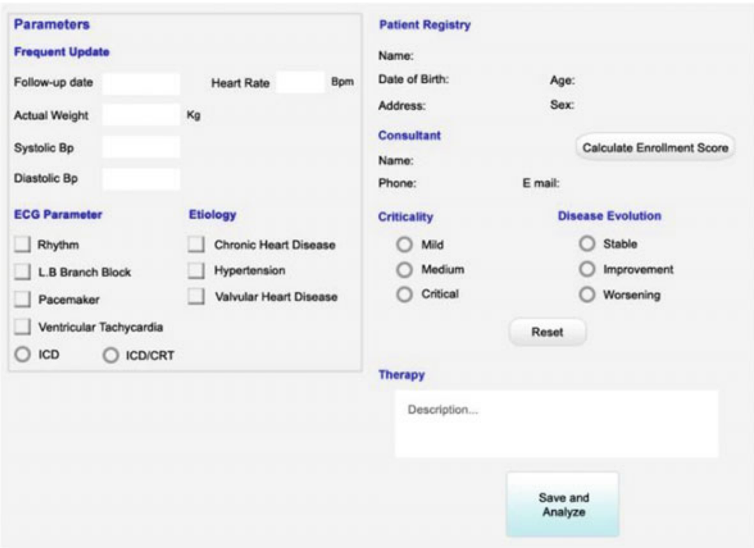

Fig. 16.3 Input mask

calculated in the third section. Therapy details and the follow-ups are given in the fourth section. Section 16.5??? is committed to exposing the progress and position of HF patients based on three classes by the doctor. This detail will be taken as the target output in the process of supervised learning techniques. Various input parameters given by this attainment mask will then bring together with all these target outputs that are mild-medium-critical and improvement-no change-worsening which will be useful for outputs as explained in the introduction section. Some buttons are given to save the details, view back and analyze. After pressing analyze button the user of the device When the "analyze" button is clicked, the user is supposed to select prompted to choose any one from artificial intelligence trained with the system's database or with a default database fixed in the system.

16.3.6 Follow-Ups Display

In this pane, the user can select a follow-up of the particular patient and see its number values and an overall summary report of various existing problems of the patients and details about the treatment. It is also having a graphical outlook of several patient's follow-up records and the option to select it needs to display or not some of the parameters and to choose one from the three different types of charts. This output is called the Chronological follow-up evaluation. A follow-up can be also examined by using AI techniques (Guidi et al. 2012) if it was not treated during the concerned outpatient visit.

16.3.7 Smart Therapy Unit

Smart particle discovering: In the parameter attainment mask, there is another one part that was given to therapy management, i.e., the doctor can enter the therapy suggested to the patient. For some specific drugs types like ACE inhibitors, angiotensin receptor blockers, beta-blockers by taking the amount in milligrams, the smart system which is on the basis of fixed thresholds, will automatically identify the active component and highlights if the dosage for that particular drug is considered as high, medium or short.

Therapy Guidelines Unit: The usage of this guidelines unit is explained in the introduction part. This unit helps the heart specialist to be sure that the recommended level of maximum tolerable dosage as mentioned in the guidelines is provided to the patient. In specific, with the help of details given as current in the method of Smart particle discovery unit, for the sets of drugs beta-blockers, angiotensin receptor blockers, ACE inhibitors, treatment is categorized as low-middle-high for that particular patient. Then it will be presented as a target for various follow-up dosages of these drugs. If treatment remains without change through numerous follow-ups without any increase in dos them an alarm make sound and the specialist is requested to evaluate whether this condition is desired one or not.

16.4 Core of Intelligence

With the help of the supervised training technique explained in the above sessions and our database, the system is trained to give outputs like criticality assessment and HF Type prediction. The outputs of short-term prediction and long- term prediction are not given because they need training. Short-term prediction needs the monitoring of the patent on a regular basis. The long term prediction is also not carried because it needs a continuous follow-up and for getting details it takes more time. The intelligent core system is having the output for the criticality assessment and HF prediction.

16.4.1 Database

The two functions are trained with an unknown database of HF patients, with different criticality degrees which are treated by the Cardiology Departments. The database totally consists of a full of 130 records from 90 patients, including starting and regular follow-up data. In the data collection phase, the cardiologist provided the given HF criticality assessment in the following three levels: Mild, Medium and critical, which was kept in the database. After a great collection of data, the condition of every patient in terms of HF type was calculated and combined with the concern record. This will help to train the system using a supervised method. Some of the ML input parameters are taken from previous literature related to HF. For an accurate analysis of the patient, the instrumental parameters should go together with various past medical parameters. Different variables in database which are utilized as input for the Machine Learning methods are the following:

Anamnestic data like patient_age, patient_gender,

Instrumental data like patient_weight, Ejection Fraction (EF), Heart Rate of the patient, ECG Parameters (atrial fibrillation true/false left bundle branch block true/false), ventricular tachycardia true/false), Brain Natriuretic Peptide (BNP), Systolic Blood Pressure, Diastolic Blood Pressure.

The following table shows the Criticality assessment and prediction type in the database (Table 16.1).

Table 16.1 Criticality assessment parameters

Criticality assessment	Mild	Medium	Critical
No. of patients	50	35	46
Prediction type	Constant	Rare	Frequent
No. of patients	109	12	10

Table 16.2 Varied parameters for better result

Method	Parameter investigated
Neural network	No. of hidden layers
SVM	Combination of two SVM
Neuro-Fuzzy Genetic method	No. of fuzzy rules and generations
CART	Pruning level
Random forest	No. of features for each tree

16.4.2 Details of Machine Learning Techniques

Neural Network (NN): NN is trained at regular intervals by changing the number of hidden neurons from 2 to 8. For HF criticality assessment 5 hidden layers are used and for prediction of HF type 8 hidden layers are specified.

SVM: SVM is a binary classifier and in trial and error method, all the we tried all the possibilities of permutations and good results were achieved with SVM tree and we obtained the best results with the grouping of critical Vs non- critical and then analysed the mild and medium criteria.

Neuro-Fuzzy Genetic Method: Using this method, the suitable and best results are reached with a population of 28 individuals, each composed by 45 fuzzy rules and the algorithm rounds for more than 550 generations.

CART: The CART was tested by the system itself with different levels of pruning. Best results in finding criticality are gained with a prune level of 2.

Random Forest: Various tests are performed to obtain a suitable performance with various features for each tree. Suitable parameters are set to stabilize the error rate. Various tests are made for generating better accuracy and it was done in the MatLab environment and finally integrated with the HF_Admin unit (Table 16.2).

16.5 Performance Evaluation

For comparing and evaluating the performance of the machine learning techniques. To make use of the available data, each record of the database is considered as the information of follow-ups. In the same manner, a database consists of 130 different heart patients each one is having a single follow-up. The follow-up details are collected over slightly longer period of time like 6–8 months and the parametric attainment and health condition of the surveyed patient was changed which helps to validate the approximation defined. Multiclass accuracy formula was used to calculate the performances of the three classifiers (Sokolova and Lapalme 2009).

$$\text{Accuracy} = \frac{\sum_{i=1}^{\text{No.ofclass}} \frac{\text{TP}_i + \text{TN}_i}{\text{TP}_i + \text{TN}_i + \text{FP}_i + \text{FN}_i}}{N} \tag{16.1}$$

TP: True Positive; TN: True Negative; FP: False Positive; FN: False Negative.

16.6 Discussion of Results

The validation results of several machine learning methods are given in Tables 16.3 and 16.4. Random Forest algorithms perform better in case of automatic criticality assessment. CART attained somewhat lesser performance than Random Forest and it had the benefit to deliver a clear and understandable model. CART (Pecchia et al. 2011) is using the If—Then rules. Different values of BNP and EF are measured and the theme was considered as CHF. In the case of criticality assessment, Random Forest and CART (Pecchia et al. 2011) formed better results when compared with various literatures that measure HF severity other studies that assess HF severity such as (Yang et al. 2010) which classifies HF related patients in three groups based on the levels of accuracy. In the above justification tables, the STD will be considered as very high in criticality assessment. The performance of the system is said to be fold-dependent since the developed system is not noticing the medium status. The various test that is done and the various accuracy levels are explained in the above tables. Random Forest algorithm is the best algorithm which is better combining accuracy levels and some errors are also committed (additional information about Random Forest algorithms are given in (Karpievitch et al. 2009)). Accuracy is not only considered as the most significant factor for measuring the performance of the system. The procedure of making decision in this kind of support systems should be understandable by the human. In this regard, CART

Table 16.3 Criticality assessment performance

ML method	Accuracy in %	STD	Errors
Neural network	76.8	7.2	0
SVM	79.3	9.2	3
Neuro-Fuzzy Genetic method	68.9	9.7	1
CART	80.8	8.7	2
Random forest	82.3	7.3	1

Table 16.4 RF type prediction performance

ML method	Accuracy in %	Accuracy in %	Errors
Neural network	83.62	10.7	0
SVM	84.1	11.5	7
Neuro-Fuzzy genetic method	84.4	11.3	5
CART	86.5	11.1	8
Random forest	84.5	11	4

method is considered to be best one and the accuracy of CART is somehow lower than Random Forest. CART is not using prior knowledge (Melillo et al. 2013) but the rule set of CART is considered to be consistent. CART algorithm selected the most applicable features for making the decisions which are easily understandable by technical and non-technical. Table 16.1 values for HF type prediction are said to be biased because of irregularity between various patients with stable HF values and also the dataset comprised of clustered data. Because of this condition, the most efficient methods to handle that data. An accurate HF prediction set must need a well-balanced database with greater number of independent events like patients.

16.7 Conclusion

A Decision Support System to enhance the support for patients affected by Heart Failure (HF) is proposed in this paper. The necessity for this medical system is mainly because of the continuously growing number of patients who are suffering from acute diseases because of numerous factors which include the aging of society. Specifically, HF is considered as a chronic and life-threatening disease with great prevalence and it can be managed by the usage of various remote monitoring systems. For a heart failure patient, for monitoring the progress of parameters and complete an apt intrusion in therapy might be conclusive for the outcome of the patient. The proposed MDSS systems objective is to enable monitoring situations by automatically yielding results understandable even by non-specialist of cardiology physicians and non-technical staff, about the criticality and type of HF prediction. For providing these outcomes we compared various types of Machine Learning algorithms and concluded that the CART method outperforms well for reaching the goal. For making a physically understandable decision-making procedure, CART produces an accuracy level of 80.8% in criticality assessment calculation and 86.5% accuracy in HF type prediction. Overall CART is considered as the best algorithm among the compared machine learning algorithms.

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