Optimal Decision Making Analysis in Categorization of Heart Failure Patient Using Sensitivity Analysis

Bharathi Ramesh Kumar,
Department of Mathematics,
Vel Tech RengarajanDr R.R. Sagunthala R&D Research Institute of Technology, Avadi, Tamil Nadu, India, E.Mail:rameshkumarb@veltech.edu.in
S.Andal
Department of Mathematics, PG & Research Department of Mathematics, Mannar Thirumalai Naicker College, Madurai, Tamil Nadu, India
Email- andalmtnc@gmail.com

R. Lakshmi Narayanan, D.Kanagajothi
Department of Mathematics,
Vel Tech RengarajanDr R.R. Sagunthala R&D Research Institute of Technology, Avadi, Tamil Nadu, India, E.Mail:lakshminarayananr @velltech.edu.in

Abstract- In this paper, we present a decision making analysis in clinical support system (CSS) for the analysis of heart failure (HF) patients, providing various outputs such as an HF severity evaluation, HF-type prediction, as well as a management interface that compares the different patients' follow-ups. The whole system is composed of a part of intelligent core and of an HF special-purpose management tool also providing the function to act as interface for the artificial intelligence training and use. To implement the smart intelligent functions, we adopted a machine learning approach. In this paper, we compare the performance of a neural network (NN), a support vector machine, a system with fuzzy rules genetically produced, and a classification and regression tree and its direct evolution, which is the random forest, in analyzing our database. Best performances in both HF severity evaluation and HF-type prediction functions are obtained by using the random forest algorithm. The management tool allows the cardiologist to populate a "supervised database" suitable for machine learning during his or her regular outpatient consultations. The idea comes from the fact that in literature there are a few databases of this type, and they are not scalable to our case.

Keywords – Heat failure, Data collection, Phase System, Fuzzy genetic Algorithm; SVM Method; Chat Method.

I. INTRODUCTION

This work we present an HF clinical support system (CSS) that, combined with a portable kit for the acquisition of a set of clinical parameters, enables the support to tele monitoring functions. The system provides smart functions using various machine learning techniques that we compared to determine which is the one that better behaves with the data in our database that are typical or the HF field. This system provides many outputs, visible through a management interface tool named HF manager. This tool has a double scope: to manage the patient demographics and the Follow-up checks and to train artificial intelligence (AI) methods using patient data. Once the AI has been sufficiently trained, the tool can be used to display the smart output that the system provides. In this paper, we describe the tool in all its functions and then we show the comparison of the machine learning methods and the choice of the most appropriate method [4]; [5] HF is an alteration of the structure and functionality of heart that results in an inadequate pumping function. Because of this insufficient pumping function, organs and tissues receive an insufficient amount of oxygen for their metabolic needs. The reaction of the organism to the heart insufficient function causes an accumulation of sodium and water in the lungs and tissues. The consequences of this can be summarized in shortened breath, reduced exercise capacity, fatigue, and edema. Patient condition can worsen and lead to acute pulmonary edema and death. The clinical course of the disease consists of a chronic phase in which the patient is stable, often alternating with exacerbations phases that require hospitalization. In some cases, these acute episodes could be avoided by promptly acting on therapy. Being able to predict these de-compensations would be very important for the patient's health. The overall prevalence of HF is increasing because of the population's aging and because of the success in prolonging survival in patients suffering from coronary events [1].[3] has investigated of maximum stress concentrations in a femur bone by photo elastic approach. A systematic review by the Cochrane Collaboration asserts that monitoring scenarios can reduce up to 30% the rehospitalization for HF [2]; [3]. We think that in this scenario, a decision support system that improves HF patients' assistance is necessary, and this is the aim of this study.

Aim of this paper: The main goal of this paper is to provide the final users with the following outputs: HF severity assessment, HF-type prediction, short-term prediction, chronological follow-up comparison, and score-based prognosis: 1) Severity assessment: It is a three level evaluation of actual HF severity (mild; moderate; and severe). 2) Score-based prognosis: It is a risk stratification that pro- vides percentage of mortality according with four literature models that are SHFM [6], EFFECT [7], CHARM [8], and ADHERE [9]. 3) Chronological follow-up comparison: It is a graphic view of parameters of the selected patient in the various dates of follow-up. Follow-ups are displayed as histograms or line charts. 4) HF type: It is a predictive indication of the type of the HF of the patient in terms of the number of acute events that he or she is likely to develop within a year. Acute events are hospitalizations, ambulance calls, or unplanned cardio-logical examinations. Classes for this features are stable, rare exacerbations (2 per year), frequent exacerbations (> 2peryear). 5) Long-term productivity: It is an indication about the possible evolution of the disease in the next follow-up basing on the past trend of follow-ups. The patient may worsen, remain stable, or improve. 6) Short-term productivity: It is an indication of the occurrence of an impending acute episode. By its nature, this type of output requires special training in which the patient is monitored on a daily basis. 7) Therapy guidelines: It is an output that indicates to the doctor if for each patient the "target dose" general principle expressed in the guidelines is applied. In fact, the guidelines [1] for certain classes of drugs such as beta blockers or ACE inhibitors indicate that in the various follow-up it is necessary to increase the dose up to the "maximum dose tolerated by the patient." Once reached this target dose, patients are usually able to continue with- out any problems the beta-blocker therapy. This system output assists the physician and helps him or her to make sure that, during each follow-up, all the actions are carried out to go to the target dose. Outputs 1, 4, 5, and 6 of the above are obtained using machine learning techniques that must be properly trained (details about training of each output are in Section IV). The final users of this system may vary depending on the application scenarios and may be cardiologists or nonspecialist staff. In the last case, the "severity assessment" output is very useful, for example, in a home monitoring scenario in which a nurse periodically goes to the patient's home, performs some measurements and inputs the results using a tablet device. Intelligent core will respond with the severity classification that may also be sent to his general practitioner or to a cardiologist, who will be able to see check his or her patients sorted by severity. More details about the possible scenarios are illustrated in [10]{[12]. B.Supervised Training In this section, we introduce the concept of supervised training, needed in machine learning methods. This training technique consists of providing as input to a machine learning algorithm a series of "examples" of the phenomenon we are ob-serving, together with the desired output. Then, the input of a supervised training process is a series of n pairs of inputs, de- sired output as in Fig. 1. As a result of the training process, we get a reusable model to which, during the use phase, new inputs that the system has never seen during the training phase can be submitted, then providing an output based on how it has learned to behave with inputs similar to the one provided. Remarkably, the learned phenomenon should not necessarily be known; in fact, the system learns from the evidence of the data, and it independently discovers the rules that link the inputs to the desired output. As shown in Fig. 1, in the train phase some input vectors and the respective desired outputs are supplied to the machine. The machine produces the model by organizing its internal parameters. In the use phase, when the user enters as input the vector f15 34 20 62g, the model provides the output (that during the training phase was associated with the input pattern) more similar to the one entered by the user (input f1435 23 64g – output 3).

II HR MANAGER TOOL

The tool's main purpose is to recover parametric data of real patients during outpatient visits suitable for training a machine learning technique. Thus, in agreement with Fig. 1, each follow- up (parametric tab of the patient) must be accompanied by a "desired output," which is nothing more than the evaluation of the HF by the cardiologist. As a secondary goal, the system acts as a special purpose dashboard for the treatment of HF patients, including a master management and many more useful functions related to the disease.

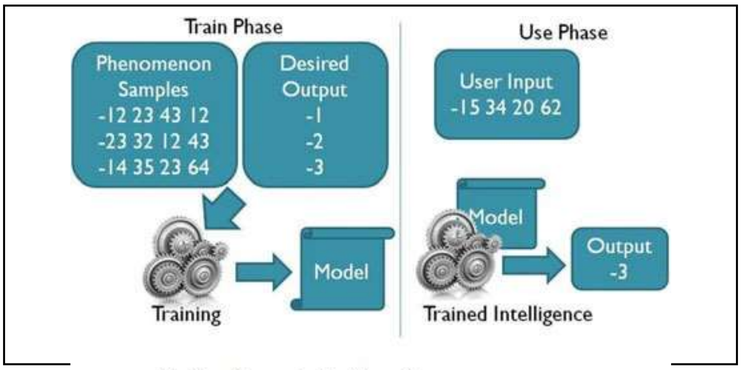

Fig. 1. Supervised training schema

B. Tool Design

This tool has been designed in close cooperation with physicians in order to satisfy practical needs (in terms of both con- tents and usability) that they have during outpatient visits. The requirement of usability aims to reduce as much as possible the system's impact on the outpatient visits workflow. To make sure that the physician can take real and immediate advantage from the use of the tool in cardiology outpatient visits, the tool includes also some practical features such as the modification of diet in renal disease calculation (MDRD), smart therapy module (discovery of drug molecules to prescribe basing on dose, and a tutor that ensures that treatment guidelines are correctly followed), and also some score based models. In this section, we will describe in detail all the tool parts of the tool: parameters acquisition, patient's follow-up displaying, severity assessment (using AI), and smart therapy module, module for asynchronous compiling, score-based prognosis, and enrollment calculation. All these parts are supported by a management module for the patient demographics.

C. Patient Management

Through this section, it is possible to select a patient, if he or she has already included in the database, or add new ones. In addition to standard biographical data, it is possible to insert and then visualize the data related to patient's general practitioner. This interface allows access to the section dedicated to the parameters input, follow-ups display, and calculation of score-based prognosis

D. Enrolment Score

This feature is for the calculation of the risk of rehospitalization according to a custom score. This model requires the input of some physiological parameters such as the brain natriuretic peptide (BNP) and heart's ejection fraction (EF) together with other organizational parameters such as the number of patient hospitalizations for HF or the required complexity of care. The model provides a risk score. If the patient appears to be at high risk of rehospitalization, he or she is suitable to be enrolled into the project and may be useful for the training of the machine.

E. Score-Based Models for Prognosis We included in the tool four prognostic models known in the literature [6]-[9]. Much of the data needed for the models are directly retrieved from the database.

F. Parameters Acquisition

This is section is for use by the cardiologist during the visit. With reference to Fig. 4, we notice that infection I the patient's personal details are shown.

In Section II, the cardiologist can specify whether. the patient is to date classified as table, or if in the past he or she has developed rare or frequent exacerbations; this is useful in training the system to provide the output denominated "HF type." In the part of Fig. 4 labeled

Fig.4 HF type

with the number "3," it is possible to input the patient's parameters. In HF pathology, there are some parameters that need a "frequent update" and others such as the BNP or EF that, in case of a close follow-up, are not to be reentered but are retrieved automatically from previous follow-up records. On this numerical form, there are controls that prevent from entering nonnumeric values or out-of-range numbers. The user can then enter other report parameters related to the ECG (for example, the presence of ICD pacemaker or ventricular tachycardia), the etiology and co morbidities. In case of renal failure as a co morbidity, it is possible to calculate the MDRD by entering race and creatinine value (age and sex are retrieved from the database) using an abbreviated formula [13]. Section IV refers to the module of smart therapy detailed in Section III-H. Section V is dedicated to attributing the status of HF patients in the three provided classes, by the visiting a cardiologist. This will act as "desired output" in the process of supervised training. All various input parameters entered by this acquisition mask will then be associated with these desired outputs that are mild- moderate-severe and improvement stable- worsening, useful for outputs 1 and 5 described earlier in Section II. Using buttons marked with the number 6, it is possible to save the follow- up or analyze it. If the "save" button is pressed, the system will highlight, in red, the possible blank fields before adding the follow-up to the database. When the "analyze" button is clicked, the user is prompted to choose either AI trained with the local database (if it is consistent) or with a default database embedded in the system. The last guarantees the performance showed in Section IV-D.
G. Follow-Ups Display Using this interface, shown in Fig. 5, a user can choose a follow-up of the selected patient (frame 1), view its numerical values (frame 3), and create a summary report of co morbidity, etiology, and treatment (frame 4). It is also possible to have a graphical view of all the patient's follow-ups, with the option whether to display or not some parameters and to select one out of three different types of chart (frame 2). This is the output named "Chronological" follow-up comparison" A follow up can also be analyzed by using AI (5), if it was not processed during the related outpatient visit.

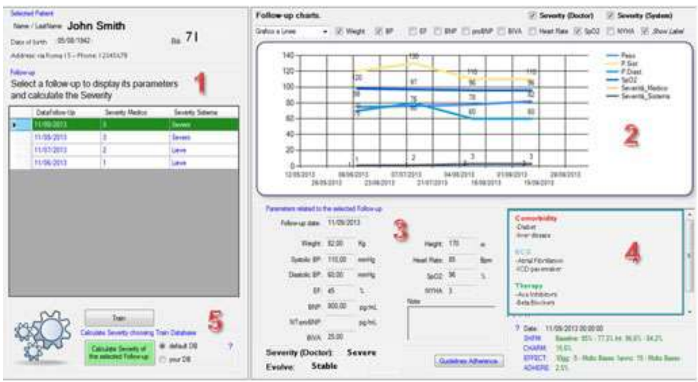

Fig. 5. Graphical view of follow-ups.

H. Smart Therapy Module

1) Smart Molecule Discovering: In the parameters acquisition mask, there is also a part dedicated to therapy management, in which the physician can enter the therapy prescribed to the patient. For some drugs categories (ACE inhibitors, angiotensin receptor blockers, beta blockers, and diuretics) by filling the dose in milligrams, the system, on the basis of preset thresholds, automatically recognizes the active ingredient and highlights if the dose for that drug is considered as high, medium, or low.

2) Therapy Guidelines Module: As explained in Section II, this module helps the cardiologist to make sure that the principle of “Maximum tolerated dose” as required by the guidelines is applied to the patient. In particular, using the information obtained from the present in the form of smart molecule discovery module, for the categories of drugs beta blockers, ACE inhibitors, diuretics, and angiotensin receptor blockers, therapy is categorized as low-medium- high for that patient. Then, the trend in the various follow-up doses of these drugs is displayed as a target. If therapy remains unchanged through several follow-ups without dose increase, an alarm sounds and the cardiologist is asked to assess whether this is desired or not.

I. Asynchronous Doctor/Nurse Compiling From the “clinical practice” of outpatient visits in our case study at the Santa Maria Nuova Hospital, it was found that filling the input forms during the visit was made by a nurse, while the cardiologist performs specialist operations on patients (ultrasound, ECG, etc.). The “desired output” (mild moderate-severe), however, needed to be inserted by the cardiologist, who preferred to insert it at the same time for all patients after finishing all visits. It was therefore necessary to create a special interface that highlighted the patients for whom there were some follow-up with empty fields to be completed (including the “de- sired output”).

3 INTELLIGENT CORE

Using the supervised training method described in Section II- B, and our database, we trained the system to provide the outputs 1 (severity assessment) and 4 (HF type). Until now, we could not set up outputs 5 and 6 that required training, i.e., long- and short-term worsening prediction. In fact, short-term prediction output is currently a work in progress because of the difficulty

TABLE I CLASS DISTRIBUTION

Severity Assessment	Mild	Moderate	Severe
No. Of patients	51	37	48
Type prediction	Stable	Rare	Frequent
No. of patients	110	14	12

in monitoring a patient on a daily basis. Attaining this objective requires monitoring the patient in the days just preceding the acute event. Long-term output instead is not yet ready for use because the standard outpatient follow-up is six months, obtaining an adequate number of follow-ups to train this feature would require three to four years. Outputs 2, 3, and 6 are not properly “smart outputs” since they do not require the intervention of the intelligent core technology but only database operations management. Severity assessment and HF –type and HF –type functions are instead trained retrospectively using our database.

A. Database

The two functions mentioned earlier are trained using 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. The database consists of a total 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: 1 (mild), 2 (moderate), and 3 (severe), which was stored in the database. Moreover, after 12–24 months from the data collection, the status of each patient in terms of HF type was assessed and associated with the correspondent record. Thanks to these target-output assignment operations, performed by a specialist cardiologist, we can perform supervised machine learning. Along with our clinical partners, we chose to use as machine learning input parameters that from literature are more related with HF. Physicians who cooperated with us consider that the following 12 parameters are a good compromise between number and completeness. For a correct diagnosis of the patient, however, the instrumental parameters must be accompanied by medical history parameters. Variables in database that are used as input for the machine learning techniques are the following 12:

1) Anamnestic data: age, gender, and New York Heart Association (NYHA) class.
2) Instrumental data: weight, systolic blood pressure, diastolic blood pressure, EF, BNP, heart rate, ECG parameters (a trial fibrillation true/false, left bundle branch block true/false, and ventricular tachycardia true/false).Table I shows how the classes of severity assessment and type prediction are distributed in database**.**

B. Machine Learning Methods Details We compare five machine learning techniques—a neural net- work (NN), a support vector machine, a fuzzy-genetic expert system

TABLE 11 PARAMETERS THAT WE VARIED TO OBTAIN BEST RESULTS

Method	Investigated Parameter	Machine Learning	Accuracy (%)	STH	Critical
NN	No. of hidden neurons (by automatic cycle)	NN	77.8	7.4	0
SVM	Combination order of the two SVM	SVM	80.3	9.4	3
Fuzzy genetic	No. of fuzzy rules, no. of generation	Fuzzy genetic	69.9	9.9	1
CART	Level of pruning (by automatic cycle)	CART	81.8	8.9	2
Random forest	No. of features (m) to be used for each tree, no. of trees, class cutoff levels	Random forest	83.3	7.5	1

system using Pittsburg approach [14], a classification and regression tree (CART) and a random forest [15]. For each machine learning technique, we have recursively varied internal parameters in order to obtain a good compromise between learning ability and generalization capability. In Table II, the inspected parameters are summarized. Note that SVM is a binary classificatory, so we have to combine two SVM to obtain a three-level. Best performances are obtained by setting the parameters shown in table II as follows: NN: We cyclically trained the NN by varying hidden neurons from 2 to 8. The best configurations are the following: five hidden neurons for HF severity assessment and eight hidden neurons for HF-type prediction. SVM: We tried all the possible permutations of SVM tree, and we obtained the best results with the combination that first detects the non-severe versus severe status, then recognizing the mild and moderate. Fuzzy Genetic: The best results are achieved with a population of 30 individuals, each composed by 45 rules. The algorithm evolves for 600 generations. CART: The system automatically tests the CART with various levels of pruning. Best results in assessing severity are obtained with a prune level = 2. Random Forest: We performed various tests obtaining the best performances with a number of features (m) to be used for each tree equals to 4. Analyzing the out-of-bag (OOB) error period of time (1–2–3 years) and the parametric situation and health of the patient was changed so as to justify the approximation described. Moreover, no significant correlation between repeated measurements was detected. During the cross validation process, we have taken precautions so that follow-ups of the same patient are grouped within the same fold, thus our assumption does not affect the independence of the folds. Since we have to evaluate the performance of a three classes classifier, rather than sensitivity and specificity, we use the multiclass ac- curacy formula shown later, according to the systematic analysis [16] (TP: true positive, TN: true negative, FN: false negative, FP: false positive). Accuracy value of 2000 trees, because above that value the error rate is sufficiently stabilized. We performed several tests, cycling the thresholds for the three classes and establishing the combination, which generated better accuracy, and the resulting cut offs are: stable class, 50; rare class, 20; frequent class, 30. Each tests are made using MATLAB R2010b. Once the best technique has been chosen, we have integrated it in the Microsoft.NET framework to include it in the HFManagertool. Accuracy: In

Table:IV Performance in Type of Prediction

AI Method	Accuracy(%)	SSTH	Critical Errors
NN	84.73	10.9	0
SVM	85.2	11.7	8
Fuzzy Genetic	85.9	11.5	
CART	87.6	11.2	9
Random forest	85.6	11.1	5

addition, we reported for each method the number of “critical errors,” meaning the classification of a severe HF patient as mild and vice versa.

D. Results Tenfold cross-validation results of various machine learning techniques are summarized in Tables III and IV. RF outperformed the other methods for the automatic severity assessment. However, the CART achieved a slightly lower performance than RF but had the advantage to provide an intelligible model. In Fig. 6, the selected CART is shown: the paths from the first node to each terminal one are a graphical representation of a set of “if ... then ...” rules. For instance, if BNP was higher than 95 and EF was lower than 27.5, the subject was classified as a severe CHF cases

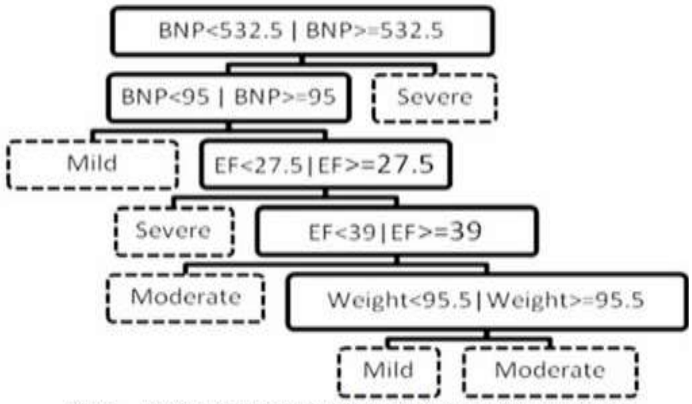

Fig. 6. Decision process of pruned CART in HF severity assessment.

4.1 Choice of AI Output

The relevant outputs were decided along with our clinical partners. In determining the HF severity level, we decided that physicians have to evaluate the patient in his general condition and not just relying on the levels of the best known HF severity markers such as the BNP, EF, or NYHA class that are often conflicting, in patients with complex situations. In this way, we loose a little bit of objectivity but the system will train itself to find a model for assessing general HF condition not just setting simple thresholds on individual parameters.

4.2 Choice of Parameters

In each machine learning method, we varied some parameters in order to contain overtraining and obtained a good generalization capability. Best results are obtained with parameters configuration summarized in Table II, and, in this section, we justified our choices and results. For the NN, we selected five to eight hidden neurons as the best compromise between learning ability and generalization capability; this is conceivable by using a pattern of 12 inputs. The distribution of the three states of HF type, shown in Table I, requires a strong learning ability (there- fore eight hidden neurons) to prevent the system from training itself to always say “stable.” Regarding SVM, the solution of splitting first between “severe” versus “others” class showed the best results. This means that there is a greater separation of parameters from severe state against others. Regarding the CART, in the cross validation process are produced trees with different split levels that use multiple variables up to a maximum of 5, but BNP, EF, and weight are always present as main variables. This confirms that these three variables are the most important in describing the HF severity. Fuzzy-genetic technique is the one which is more affected by having relatively few patients in the database. We consider 45 rules and 600 generations as a good compromise. Adding rules or further evolving the algorithm produces over fitting, while too few rules or generations are not sufficient for correct system training. With the random forest algorithm, we obtained better results with m = 4; as we have 12 inputs, this figure is in line with the literature that states.

4.2 Discussion of results

Random Forest and CART produced good results in severity assessment if compared with other studies that assess HF severity such as [17] that classify HF patients in three groups (78.8%–87.5%–65.6% accuracy to classify healthy–HF prone– HF, respectively). As shown in cross-validation tables, the standard deviation in assessing the severity is very high. This means that there are some lucky folds where accuracy is 92% or 100% and some folds where accuracy is < 50%, except for best models (i.e., random forest and NN). These unlucky folds have a high percentage of “moderate” patients and this fact cause worse results, revealing the difficulty that the system has in classifying patients whose parameters are in a “gray zone.” So the system performance is quite fold-dependent, because the system fails in detecting moderate status. The tests made with the leave one out method confirm these results. We reported results of tenfold cross-validation method because we consider it more appropriate to maintain independence between folds as explained in Section IV-C. Although the random forest is the technique that better combines good accuracy and a few critical errors commit- ted (more information about random forest setting up for HF in [18]), the accuracy is not the only important factor for the performance of a system. In decision support systems of this type, it is important that the decision making process of the machine is humanly understandable. In this aspect, CART is the only one who makes this possible, and since it has accuracy slightly lower than the random forest, we have elected it as winner algorithm of this study. Moreover, the sets of rules of the CART models are clinically consistent, even if CART did not use any medical a priori knowledge [19]. In fact, the expert physicians involved in the project confirmed that the CART selected the most relevant features (see Fig. 6), which they consider for the medical decision making, thus suggesting the proposed algorithm could learn the decision making of an expert physician [1], [20]. About HF-type prediction results are quite distorted because of the high asymmetry between the number of patients with "chronic stable HF" and those with frequent or rare exacerbations, as shown in Table I (unbalanced dataset). Moreover, the dataset consists of clustered data (i.e., repeated measurement of the same subject); for that reason, we adopted the most updated methods to deal with clustered data. In particular, as described in Section IV-C, we adopted a subject based cross- validation approach, which has been shown to result in increased efficiency of the estimation of the misclassification rate [21]. Finally, the adopted data-mining methods, in particular tree-based classifiers, have been shown to achieve satisfactory performance in the analysis of cluster-correlated data [22]. A correct HF prediction would require a more balanced database with a higher number of independent instances (patients).

5 CONCLUSION

In this paper, we present a decision support system to improve assistance for patients affected by HF. The need for this system arises from the ever increasing number of patients suffering from chronic diseases, due to various factors, including the aging of society. In particular, HF is a chronic disease with high prevalence, the management of which can be improved by enabling remote monitoring scenario s. In case of HF to monitor the progress of parameters and perform a timely intervention in therapy may be decisive for the outcome of the patient. The proposed system aims to facilitate monitoring scenarios by automatically providing outputs readable even by noncardiologist physicians and nurses about the severity and type of HF. To provide these outputs, we compare several types of machine learning techniques, finding the CART method as the most adequate to our goal. As well as providing a humanly understandable decision-making process, CART provides a cross-validation multiclass accuracy of 81.8% in severity assessment and 87.6% in type pre- diction. Unfortunately, it is difficult to generalize these findings due to a small sample size.

Acknowledgment

The authors would like to thank Dr. M. Milli for his important and continuous contribution to this paper.

REFERENCES

[1] Adler.W, Brenning.A , Potapov.S, Schmid.M and Lausen.B, (2011) "Ensemble classificationof paired data," Comput. Statist. Data Anal., vol. 55, pp. 1933–1941. 2011.

[2] Alan Oxley.W, (2019), "Simple empirical models of classifying patients form microarray data," Kuwait J. Sci., vol. 46, no. 1, pp. 24-32.

[3] Breiman.L(2001), "Random forests," Mach.Learning, vol. 45, no. 1, pp. 5–32.

[4] Bruce Ralphin Rose.J(2019), " Experimental investigation of maximum stress concentration in a femur bone by photo elastic approach," Kuwait J. Sci., vol.4, no. 4, pp. -74.

[5] Dickstein.K, Cohen-Solal.A, Filippatos.G, McMurray,P. Ponikowski.J.J.V, PooleWilson.P.A, Stromberg.A, Veldhuisen.D.J. Atar.D, Hoes,A.Keren.A.W, Mebazaa.A, Niemine.M, Priori.S.G and Swedberg.K(2008), "ESC guidelines for the diagnosis and treatment of acute and chronic heart failure 2008," Eur. J. Heart Failure, vol. 10, no. 10, pp. 933–989.

[6] Fonarow.G.C, Adams.K.F, Abraham.W.T, Yancy.C.W and Boscardin.W.J,(2005) "Risk stratification for in-hospital mortality in acutely decomensated heart failure: Classification and regression tree analysis," JAMA, vol. 293, no. 5, pp. 572–580.

[7] Guidi.G, Pettenati.M.C, Miniati,R. and Iadanza,E,(2012) "Heart failure analysis dashboard for patient's remote monitoring combining multiple artificial intelligence technologies," in Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., pp. 2210–2213,

[8] Guidi.G, Iadanza.E, Pettenati.M.C, Milli.M, Pavone.F. and Gentili.G.B,(2012) "Heart failure artificial intelligence-based computer aided diagnosis telecare system," in Proc. ICOST (Lecture Notes Comput. Sci.) 7251, pp. 278–281.

[9] Guidi.G, Pettenati.M.C, Miniati,R. and Iadanza.E, (2013), "Random forest for automatic assessment of heart failure severity in a tele monitoring scenario," in Proc. EMBC, 2013, pp. 3230–3233.

[10] Guidi.G, Melillo.P, Pettenati.M.C ,Milli.M and Iadanza.E,(2014),"A system to improve continuity of care in heart failure patients," IFMBE Proc., vol.42, pp. 155–158,

[11] Guidi.G, Melillo.P, Pettenati.M, Milli.M and Iadanza.E,(2014), "Performance assessment of a clinical decision support system for analysis of heart failure," in IFMBE Proc., vol. 41, pp. 1354–1357.

[12] Guidi.G, Pettenati.M.C, Milli.M and Iadanza.E,(2014), "A tool for patient data recovering aimed to machine learning supervised training," in IFMBE Proc., vol. 41, pp. 1899–1902.

[13] Inglis.S.C, Clark.R.A, McAlister.F.A Ball.J, Lewinter.C, Cullington.D and Cleland.J.G,(2009) "Structured telephone support or telemonitoring programmes for patients with chronic heart failure," Cochrane Database Syst. Rev., [Online]. vol. 8, CD007228- CD007228.

[14] Lee.D.S, Austin.P.C, Rouleau.J.L, Liu.P.P and Naimark.D, (2003),"Predicting mortality among patients hospitalized for heart failure derivation and validation of a clinical model (EFFECT)," Hospitals, vol. 290, no. 19, pp.2581–2587.

[15] Levey.A.S, Coresh.J, Balk.E , Kausz.A.T, Levin.A, Steffes.M.W, Hogg.R.J, Perrone.R.D, Lau.J and Eknoyan.E,(2003), "National kidney foundation practice guidelines for chronic kidney disease: Evaluation, classification, and stratification," Ann. Internal Med., vol. 139, no. 2, pp. 137–147.

[16] Levy.W.C, Mozaffarian.D, Linker.D.T, Sutradhar.S.C, Anker.S.D, Cropp.A.B, Anand.I, Maggioni.A, Burton.P, Sullivan.M.D, Pitt.B, Poole-Wilson.P.A, Mann.D.L and Packer.M,(2006),"The Seattle heart fail- ure model: Prediction of survival in heart failure,"Circulation, vol. 113, no. 11, pp. 1424–1433.

[17] Louis.A.A, Turner.T, Gretton.M, Baksh.A and Cleland.J.G.F,(2003), "A systematic review of tele monitoring for the management of heart failure," Eur. J. Heart Failure, vol. 5, pp. 583–590.

[18] Majeed.A, Al-Jawary, J.Al-Zahraa, Abdul Nabi,(2020), " Three iterative methods for solving Jeffery-Hamel flow problem," Kuwait J. Sci., vol. 47, No. 1, pp. 1-13.

[19] Melillo.P, De Luca.N, Bracale.M and Pecchia.L,(2013), "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.

[20] Pocock.S.J, Wang.D, Pfeffer.M.A, Yusuf.S, McMurray.J.J.V, Swedberg.K.B, Ostergren.J, Michelson.E.L, Pieper.K.S and Granger.G.B,(2006), "Predictors B. Granger, "Predictors of mortality and morbidity in patients with chronic heart failure.(CHARM)," Eur. Heart J., vol. 27, no. 1, pp. 65–75,20..

[21] Silver.M.A et al, (2004),"BNP consensus panel 2004: A clinical approach for thediagnostic, prognostic, screening, treatment monitoring, and therapeutic roles of natriuretic peptides in cardiovascular diseases," Congest Heart Fail. vol. 10, no. 5, suppl. 3, pp. 1–10.

[22] Smith.S.F, (1980), "A learning system based on genetic adaptive algorithms," Ph.D. dissertation, Dept. Comput. Sci., Univ. Pittsburgh, Pittsburgh, PA, USA,

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

[24] Yang.G, Ren.Y, Pan.Q. and Ning.G, (2010), "A heart failure diagnosis model based on support vector machine," in Proc. IEEE Int. Conf. Biomed. Eng. Informat., pp. 1105–1108.