Comparative study between Fuzzy Inference System, Adaptive Neuro-Fuzzy Inference System and Neural Network for Healthcare Monitoring

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***Abstract*—this paper compares three supervised machine learning algorithms for healthcare monitoring. The first step of the presented work is the collection of vital signs information data that are utilized for training a Fuzzy Inference System (FIS), an Adaptive Neuro-Fuzzy Inference System (ANFIS) and a Neural Network (NN). Then, the trained algorithms are used to predict the Health Status (HS) of patients. Extended comparison results are demonstrated which indicate that the classifiers could be utilized as a basis for HS assessment.**

***Keywords*—healthcare monitoring, health status, vital signs, FIS, ANFIS, NN**

I. Introduction

Prolonged life expectancy along with the increasing complexity of medicine and health services raises health costs worldwide dramatically. Advancements in ubiquitous computing applications in combination with the use of intelligent sensor networks may provide effective and decisive contribution. To keep pace with the growing amounts of complex data, smart hospital systems are a commandment of the future [1]. In such a system smart medical assistants support doctors to manage their floods of data and patients to facilitate an appropriate treatment and wellness. Efficient healthcare in hospitals as well as efficient patient flow can reduce waiting times and the duration of hospital stays, reduce errors, increase revenues, improve organization and scheduling processes and boost patient and employee satisfaction.

Effective emergency response by identifying high-risk patients with the hope of taking timely preventive measures is a matter of utmost importance for the improvement and the reliability of every health system. Rapid and serious deterioration of patients in hospitals is often accompanied by deterioration of their vital signs. Studies indicate that evidence of clinical deterioration can be identified prior to the occurrence of serious adverse events such as death, cardiac arrest, or intensive care admission [2]. The need for a mechanism by which hospitals are able to recognize patients at risk of catastrophic deterioration is therefore very critical and imperative. To serve this purpose we developed and compared three classifiers which utilize patients' vital signs readings, heart rate (HR), respiratory rate (RR) and systolic blood pressure (SBP), process and analyses them to predict patients' HS.

II. Related work

There are several references in the literature applying machine learning algorithms in the field of healthcare.

A wireless body area network that uses a FIS which can determine the condition of a person by employing sensors to monitor vital signs is proposed in [3]. Another FIS approach for healthcare services which determine abnormal conditions of a patient based on processing his vital signs is presented in [4].

In [5] an ANFIS is applied as vital signs monitor that processes and analyses the data acquired from measuring instruments to determine the health condition of an individual as well as in [6] is presented a real time patient monitoring system based on ANFIS.

NNs have been used to identify associations between certain chronic diseases and behavioral habits in the context of preventive healthcare [7] as well as to provide individualized embedded decision/diagnosis support for remote health monitoring of people at risk [8].

III. Implementation

With the purpose of taking timely preventive measures by identifying patients in critical health conditions we developed and compared three dominant machine learning algorithms,

namely FIS, ANFIS and ANN, which use and process patients' vital signs (HR, RR, SBP) to predict their HS.

A. Data

The vital signs data of patients are pumped from PhysioNet's Massachusetts General Hospital / Marquette Foundation (MGH / MF) Waveform Database [9]. The information that are used by the Database are electrocardiogram (ECG), RR (breaths per minute), BSP (mmHg) and AGE for each patient. The HR (beats per minute) is calculated by processing the ECG signal and extracting its features. The vital signs (HR, RR, SBP, AGE) are given as input parameters to the classifiers which predict the HS as output. The value of HS depends on whether the vital signs are on their physiological scales or not, as shown in Table I, and it is characterized by three class labels: *critical*, *bad*, *good*. *Critical* HS declares that the patient is at risk situation and needs urgent medical care, *bad* HS states that the patient needs medical treatment but not urgent and *good* HS means that the patient is in physiological state.

TABLE I
NORMAL RANGES OF VITAL SIGNS

AGE range	HR range	RR range	SBP range
newborn	100-160	30-50	75-100
0-5 months	90-150	25-40	75-100
6-12 months	80-140	20-30	75-100
1-5 years	80-130	20-30	80-110
6-10 years	70-110	15-30	85-120
11-14 years	60-105	12-20	85-120
15-20 years	60-100	12-30	95-140
adults	50-80	16-20	120

B. Classification Strategy

We focused on a performance comparison between three well established and popular techniques of supervised learning algorithms. The cornerstone of every machine learning classification approach are the data that feed and train the classifiers. However, medical data present very low availability for the researchers. The MGH / MF Waveform Database offer a dataset that consists of 500 instances.

The classifiers' performance have been evaluated from the study of the respective confusion matrices derived from the experiments along with the *accuracy* metric which is the percentage of the correctly predicted class labels (*critical*, *bad*, *good*) over all the predictions, $Acc = \frac{correctly\_predicted\_instances}{total\_instances}$. *Accuracy* metric indicates the ability of classifier to identify the class labels. Further, we compute *recall* and *precision* metrics for each class label so to analyze the individual performance on class labels. For a given class label X, *recall* is defined as $rec = \frac{correctly\_predicted\_X}{actual\_X\_instances}$ indicating the identification rate of a class X and *precision* is defined as $prec = \frac{correctly\_predicted\_X}{predicted\_X\_instances}$ indicating the percentage of the correct predictions as X over all the predictions as X [10].

MATLAB Toolbox from MathWorks is used as the development tool to implement and test the proposed classifiers.

1) FIS: The FIS is a knowledge-based system that consists of a fuzzifier, a knowledge base, fuzzy inference engine and defuzzifier. The fuzzifier converts input data (crisp values) into fuzzy variables. The knowledge base consists of a database and rule base. The rule base contains the set of fuzzy if-then rules. The database defines the membership functions of the fuzzy sets. The fuzzy inference engine (decision making unit) maps the input space into output space based on the set of fuzzy rules. The defuzzifier converts the processed fuzzy variables back into crisp values.

In the system implemented here, the mamdani FIS is used [11]. The input membership functions are HR, RR, SPB, AGE and the output membership function is the HS as shown in Fig. 1. The FIS implements 63 if-then rules which are synthesized based on the knowledge that exists for human vital signs and their age-appropriate physiological scales according to Table I. The knowledge is extracted from experts (medical doctors in the context of this work).

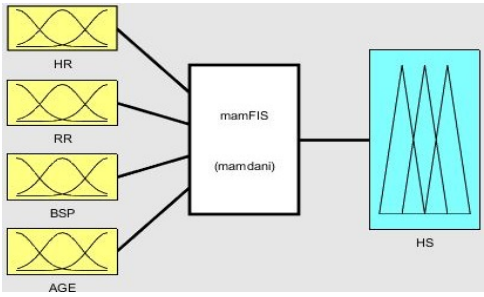

Fig. 1. Input and Output Membership Functions of FIS

2) ANFIS: ANFIS is a technique that uses Fuzzy Logic (FL) to transform given inputs into a desired output with the help of highly interconnected NN processing elements and information connections, which are weighted to map the numerical inputs into an output. ANFIS combines the benefits of the two machine learning techniques (FL and NN) into a single technique [12]. An ANFIS works by applying NN learning methods to tune the parameters of a FIS.

The ANFIS system was trained according to the following methodology in Matlab. The data were divided into two separate sets: the training dataset and the testing dataset. The training dataset was used to train the ANFIS, whereas the testing dataset was used to verify the accuracy and the effectiveness of the trained ANFIS model. The optimal ANFIS model setting was selected based on the minimum training and testing error values for number of epochs. The ANFIS system

was structured by selecting four inputs namely: HR, RR, BSP and AGE having 3,3,3,3 membership functions respectively and one output as HS. The generated FIS structure contains 81 fuzzy rules. The ANFIS model structure is as shown in the Fig. 2. The four inputs each having the membership functions are represented. With the help of these membership functions the rules are constructed and accordingly an output is generated.

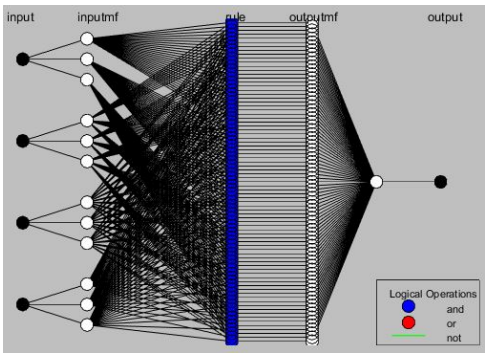

Fig. 2. ANFIS model structure

3) NN: A NN consists of a series of processing elements called neurons that are interlinked to form a network. Each link has a weight associated with it. A NN consists of an input layer, one or more hidden layers, and the output layer. The neurons in the input layer receive stimulus from outside the network, the neurons in the hidden layer receive stimulus from the interconnected neurons and pass on the output to other neurons within the network and the neurons in the output layer receive the stimulus from the linked neurons and pass on the output externally. Different neural network structures arise based on combinations of neurons and layers [13].

In this work the NN consists of an input layer, one hidden layer and an output layer as shown in Fig. 3. The number of neurons at the input layer is guided by the number of independent variables, while the number of neurons at the output layer correlates with the number of values that need to be predicted. Unlike the input and output layers, there are no widely accepted rules for determining the optimal number of hidden layers. The optimal configuration is most often derived by trial and error approach.

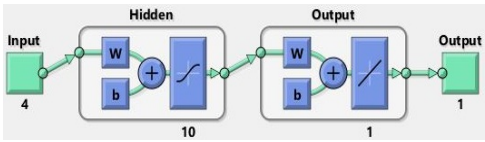

Fig. 3. NN model structure

The NN is initially fed an array of input-output values. It is then trained to assign appropriate weights for the connections and calculate the outputs. These training iterations are repeated until the network learns to adjust the weights and arrives at predictions that show a minimal difference with the actual values. We experimented with different partition rates (%) of the dataset for training, testing and validation rates to come up with the best performance of the NN system.

IV. Experimental Results

The confusion matrices for the FIS, ANFIS and NN classifiers are depicted in Table II, Table III and Table IV respectively.

TABLE II
Confusion Matrix of FIS

Classified as:	critical (pred.)	bad	good	total
critical (actual)	**307**	19	2	328
bad	19	**96**	10	125
good	2	12	**33**	47
total	328	127	45	**500**
Performance metrics	rec=94% prec=94%	rec=77% prec=76%	rec=70% prec=73%	**Acc=87%**

To give an example of how the calculations were made, for the class label *bad* of FIS classifier *recall* is the number of correctly predicted bad instances (96) divided by the total number of bad instances in the dataset (125), $rec = \frac{96}{125} = 77\%$ and *precision* is the number of correctly predicted bad instances (96) divided by the total number of predicted bad instances (127), $rec = \frac{96}{127} = 76\%$. The *accuracy* of the classifier is the number of correctly predicted class labels (307+96+33) divided by all predictions/instances (500), $Acc = \frac{436}{500} = 87\%$.

TABLE III
Confusion Matrix of ANFIS

Classified as:	critical (pred.)	bad	good	total
critical (actual)	**271**	53	4	328
bad	10	**102**	13	125
good	3	3	**41**	47
total	284	158	58	**500**
Performance metrics	rec=83% prec=95%	rec=82% prec=65%	rec=87% prec=71%	**Acc=83%**

TABLE IV
Confusion Matrix of NN

Classified as:	critical (pred.)	bad	good	total
critical (actual)	**256**	71	1	328
bad	10	**112**	3	125
good	1	22	**24**	47
total	267	205	28	**500**
Performance metrics	rec=78% prec=96%	rec=90% prec=55%	rec=51% prec=86%	**Acc=78%**

We observe that we get a classification *accuracy* 87% for the FIS classifier while ANFIS reaches 83% and NN 78%. From a more thorough study of the confusion matrices we observe how the unbalanced training dataset is highlighted on the classification metrics for each class of HS. The FIS identifies the *critical* class with 94% success rate, the ANFIS with 83% and the NN with 78% (respective *recall* metrics), exceeding both their average hit rate (*accuracy*). However, poor performance is observed in the identification of *good* HS. This is obviously attributed to the training dataset, since the instances of class *good* are the 9.4% of all instances. The performance on the identification on each particular class would be increased and more balanced if the distribution of classes in the training dataset was also balanced.

The three classifiers achieved satisfactory results but they present potentials for further improvement. This improvement could be achieved from the enhancement of the dataset so the classifiers can be trained more specifically and accomplish even more sufficiently results.

V. FUTURE WORK

Future work is about to monitor the patients' HS in Emergency Departments (EDs) of hospitals on a continuous and real time basis with the development of an unobtrusive and robust wearable healthcare monitoring system. The goal is to improve and automate the Triage process for priority and sorting of medical incidents in EDs [14]. To realize this goal a wearable device integrated with bio-sensors monitor patients' vital signs and feed the classifier with the acquired bio-signals to estimate the patient's HS, achieving a dynamic evaluation of the incidents while waiting in ED as well as when entering a clinic or the Intensive Care Unit (ICU). At the same time, the continuous bio-signal recording from the wearable device in conjunction with the decision support system will provide real time alerts to medical staff on the progress of patients' HS, while the network infrastructure which will be developed will be able to detect the location of incidents during their stay in ED. In this way, administrative coordination between individual hospital departments is strengthened.

VI. CONCLUSION

In this paper, three well-known machine learning algorithms, namely FIS, ANFIS and NN were used for the prediction of patients' HS. The algorithms were assessed for their performance and the results have shown that the three techniques can deliver sufficient *accuracy*. The best classification *accuracy* was achieved by the FIS with 87%, followed by the ANFIS with 83% while the NN reached the 78% which was the worst performance. It is obvious that fuzzy rule-based (FIS, ANFIS) algorithms are more efficient in HS assessment. A clear advantage of the fuzzy approach is based on the fact that fuzzy diagnosis resembles human decision-making. One disadvantage of the system is the high dependency of its response on the amount of available information which derives from human experts in the rule database. However, the ANFIS approach can successfully solve the problem of incompleteness in the fuzzy rule database with the automatic generation of the fuzzy rules from the training dataset that it is fed with. That requires an ideal and unbiased dataset. As a consequence, when the available amount of information is high, both FIS and ANFIS response is useful and suitable in healthcare assessment.

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