Neuro-fuzzy synergism for early detection of critical health condition of a patient

Shubhajit Roy Chowdhury, Arijit Biswas, Rini Chowdhury and Hiranmay Saha

Abstract-- **The recent surge in the application of soft computing techniques for medical diagnosis has motivated the design of fuzzy neural networks that can predict the approaching critical condition of a patient at an early stage. The paper describes the design, training and testing of a fuzzy neural network that is used for predicting the future pathophysiological state of a patient using the past pathophysiological data. . An extended example on the problem of monitoring renal patients using Body Mass Index (B.M.I.), blood glucose, urea, creatinine, systolic and diastolic blood pressure as pathophysiological parameters has been presented in this paper. The system has been tested with height, weight, blood glucose, urea, creatinine, systolic and diastolic blood pressure data of patients where all data other than height have been taken at 10 days interval. Applying the methodology, the chance of attainment of critical renal condition of a patient before the patient actually reaches a critical state has been predicted with confidence.**

***Index Terms*—Criticality, fuzzy neural networks, medical diagnosis, pathophysiological, approximate inference**

I. Introduction

DECISION made by physicians are arbitrary and highly variable (within one physician and between physicians) and often lacking explanation or rationalization [1, 9]. Problems in modern medicine are often very complex, but evidence for the best choice to be made is often lacking. Clinical examples of this phenomenon in diagnosis making are abundant and easy to understand. The body of potentially useful knowledge that is relevant to even a relatively narrow diagnostic area may be too large to make the optimal (diagnostic) decision on the spot. Ironically, modern information technology (especially through the Internet) increases the amount of available knowledge even more, probably further complicating this situation. Moreover, individual patients need individualized decisions, because their characteristics differ from the average [2]. Apparently, individualizing the general results of research may be cumbersome and time consuming, while on the other hand modern medical practice demands efficiency, cost-effectiveness and high technical quality.

Recently soft computing techniques like fuzzy logic and neural networks are gaining considerable importance in the field of automated medical diagnosis. Fuzzy logic is used in situations where approximate values of patient data are to be analyzed using linguistic variables [3, 4]. Similarly neural networks are used in situations where the knowledge about the patient is stored in the form of numerical data sets [5, 6, 7, 8, 10]. Thus an artificial neural network is good enough for autonomous machine learning whereas fuzzy system has a significant potential of reasoning with inexact data and knowledge. A synergism of these two computational intelligence tools can lead to the formation of a hybrid system that is capable of learning from approximate knowledge and also utilize the acquired knowledge for futuristic reasoning [11, 12].

The current work investigates the use of fuzzy neural networks, which is an instance of neuro-fuzzy synergism to predict at an early stage the possible chance of attainment of critical condition of a patient. The proposed system can predict in absence of physician, the future pathophysiological state of a patient using the current and past pathophysiological data of the patient.

II. Functional Architecture of fuzzy neural smart agent based medical diagnostic system

Figure 1 shows the functional architecture of the fuzzy neural smart agent based medical diagnostic system.

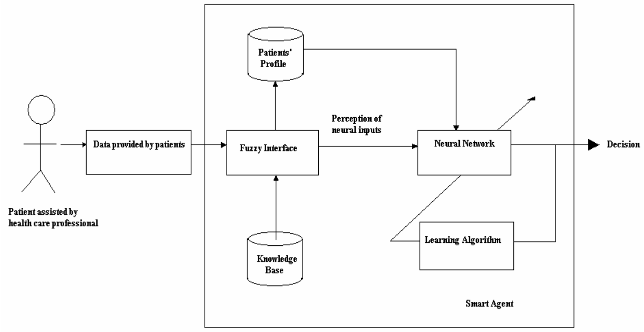

Fig. 1. Functional Architecture of the fuzzy neural smart agent based medical diagnostic system.

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At least two entities, viz. patient and smart agent are required in this concept of smart agent based diagnostic system. The patients are the providers of data under the assistance of health care professionals who need not be physicians. The smart agent is represented by a weakly coupled fuzzy neural system that can predict the future pathophysiological state of a patient in presence of past pathophysiological data. The weakly coupled fuzzy neural network is basically a two unit composite system comprising of a fuzzy system placed before a neural network. The fuzzy interface makes an approximate inference about the current state of the patient from the current patient data being entered into the smart agent. The membership values obtained from the output of the fuzzy interface is supplied to the input of the neural network for making a decision regarding the future pathophysiological state of the patient. The neural network can also be trained at the initial stage using a suitable supervised learning algorithm like the back-propagation algorithm. Once the learning phase of the neural network is over, it will behave as a pre-trained feed-forward neural network.

III. FUZZIFICATION OF PATIENTS' DATA

The fuzzy interface discussed in section 2 performs fuzzification of patient data. Since data from the patient are nothing but physiological measures, they are subjected to noise and uncertainty. The data from the patient such as height or weight data cannot always be trusted as they are subjected to the quality and accuracy of measuring units and the skill of the technician. Moreover, based on a single data, it would be highly uncertain to make an accurate decision about the future physiological state of the patient [13]. So the patient data has been fuzzified with the objective of transformation of periodic measures into likelihoods that the Body Mass Index, blood glucose, urea, creatinine, systolic and diastolic blood pressure of the patient is high, low or moderate.

The present work comprises of analyzing the pathological data of patient and predicting the future physiological state of a patient. From the height in feet and weight in kilograms, the B.M.I. of a patient is computed using the methodology discussed in [14].

Since physicians are more interested in knowing whether the pathological data of patients are high, moderate or low, and also the trend of patient parameters, it would be more useful, to represent the parameters of patients as linguistic variable rather than ordinary variable and use fuzzy logic to build a predictive model, to predict the fuzzy set in which the parameter of a patient is to lie in the next reading of patient data.

The patient data has been fuzzified in a frame of cognition with the objective of transformation of periodic measures into likelihoods that the physiological parameter of the patient is high, low or moderate. For this purpose, triangular fuzzy operators have been used. The membership function has been determined in accordance with the ranges and tolerance limits set up by the World Health Organization. The plot of the membership functions defined above are shown in figure 2.

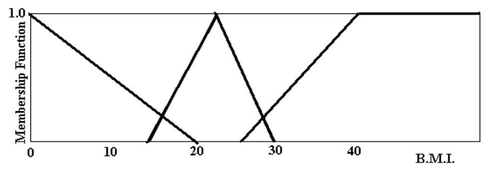

Fig. 2(a)

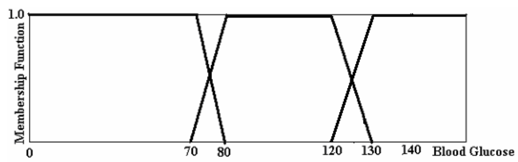

Fig. 2(b)

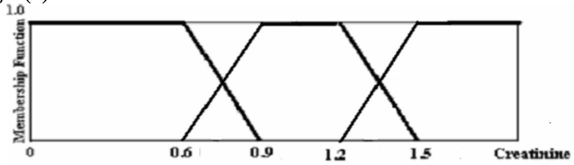

Fig. 2(c)

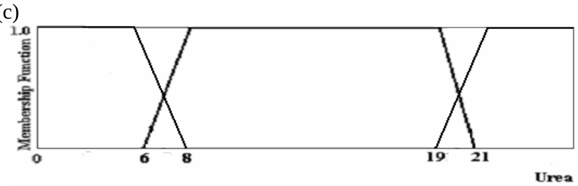

Fig. 2(d)

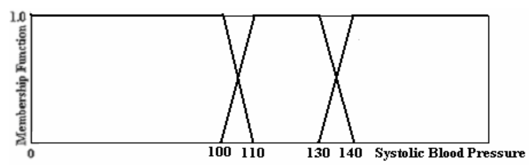

Fig. 2(e)

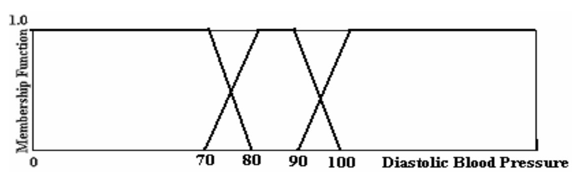

Fig. 2(f)

Fig. 2. Plots of the membership functions:
(a) B.M.I. (b) Glucose (c) Creatinine (d) Urea (e) Systolic Blood Pressure (f) Diastolic Blood Pressure

The figure depicts the cognitive frame used for fuzzy modeling B.M.I., blood glucose, blood urea, blood creatinine, systolic and diastolic blood pressure data of patients. It is obvious that all the low, moderate and high parameter ranges (here modeled as fuzzy sets) of patient falls in the same universe of parameter values.

IV. DESIGN AND TRAINING OF THE FUZZY NEURAL NETWORK

The architecture of the fuzzy neural network is shown in figure 3.

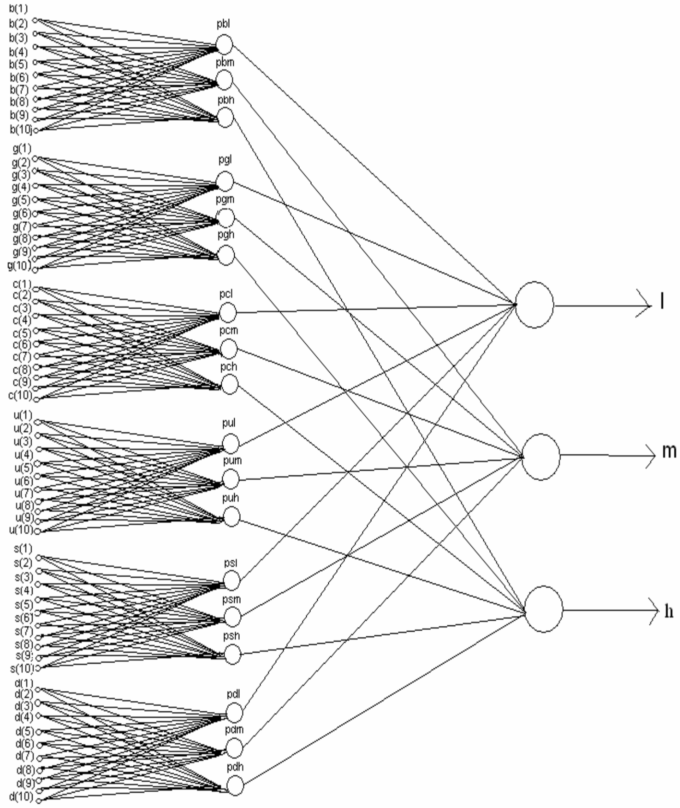

Fig. 3 Design of the fuzzy neural network for diagnosing criticality of patients

The leftmost layer is the input layer which accepts the values of pathophysiological parameters over time and fuzzifies them to generate membership function values which are presented to the hidden layer for calculating the possibilities of the pathophysiological parameters to be low, moderate or high at the next instant of time. The weighted sum of these possibility values from the hidden to the output layer indicates the criticality of the current condition of the patient. The inputs are presented to the input layer in the form of a 60 tuple (b(1), b(2) ……, b(10), g(1), g(2),….. g(10), c(1), c(2),…., c(10), u(1), u(2),….., u(10), s(1), s(2),……, s(10), d(1), d(2), ……, d(10)). Initially only b(1), g(1), c(1), u(1), s(1) and d(1)have non zero values, while others have zero values. At the next instant of time (after 10 days), when a new set of data is entered, b(2), g(2), c(2), u(2), s(2) and d(2) are updated to non-zero values and so on. As new sets of data are entered, the old sets of data are updated. Thus after 10 sets of data collected at 10 days interval are entered, when the 11th set of data are entered, the new set of data goes to b(10), g(10), c(10), u(10), s(10) and d(10) and b(9), g(9), c(9), u(9), s(9) and d(9) are updated with the previous values of b(10), g(10), c(10), u(10), s(10) and d(10) respectively and so on.

The training of the neural network is done with 40 sets of data and testing is done with another 40 sets of data. For training the network, backpropagation learning algorithm is used. The weights of the dendrites between input and hidden layer are shown in table 1.

TABLE I
WEIGHTS OF THE DENDRITES BETWEEN INPUT AND HIDDEN LAYERS

Weight of dendrite	**Value**	**Weight of dendrite**	**Value**	**Weight of dendrite**	**Value**
Wbl(1)	0.9756	Wbm(1)	1.0130	Wbh(1)	1.0338
Wbl(2)	1.9797	Wbm(2)	2.0108	Wbh(2)	2.0281
Wbl(3)	2.9828	Wbm(3)	3.0092	Wbh(3)	3.0238
Wbl(4)	3.9833	Wbm(4)	4.0089	Wbh(4)	4.0231
Wbl(5)	4.9880	Wbm(5)	5.0064	Wbh(5)	5.0166
Wbl(6)	5.9900	Wbm(6)	6.0053	Wbl(6)	6.0138
Wbl(7)	6.9968	Wbm(7)	7.0017	Wbh(7)	7.0045
Wbl(8)	7.9519	Wbm(8)	8.0257	Wbh(8)	8.0666
Wbl(9)	8.9519	Wbm(9)	9.0257	Wbh(9)	9.0666
Wbl(10)	9.9519	Wbm(10)	10.0257	Wbh(10)	10.0666
Wgl(1)	1.0000	Wgm(1)	1.0000	Wgh(1)	1.0000
Wgl(2)	1.9773	Wgm(2)	2.0130	Wgh(2)	2.0335
Wgl(3)	2.9636	Wgm(3)	3.0209	Wgh(3)	3.0537
Wgl(4)	3.9682	Wgm(4)	4.0183	Wgh(4)	4.0469
Wgl(5)	4.9636	Wgm(5)	5.0209	Wgh(5)	5.0537
Wgl(6)	5.9636	Wgm(6)	6.0209	Wgl(6)	6.0537
Wgl(7)	6.9636	Wgm(7)	7.0209	Wgh(7)	7.0537
Wgl(8)	7.9591	Wgm(8)	8.0235	Wgh(8)	8.0604
Wgl(9)	8.9591	Wgm(9)	9.0235	Wgh(9)	9.0604
Wgl(10)	9.9545	Wgm(10)	10.0261	Wgh(10)	10.0671
Wul(1)	1.0000	Wum(1)	1.0000	Wuh(1)	1.0000
Wul(2)	2.0000	Wum(2)	2.0000	Wuh(2)	2.0000
Wul(3)	3.0000	Wum(3)	3.0000	Wuh(3)	3.0000
Wul(4)	3.9951	Wum(4)	4.0021	Wuh(4)	4.0058
Wul(5)	4.9172	Wum(5)	5.0363	Wuh(5)	5.0979
Wul(6)	5.9220	Wum(6)	6.0342	Wul(6)	6.0922
Wul(7)	6.9123	Wum(7)	7.0384	Wuh(7)	7.1037
Wul(8)	7.9074	Wum(8)	8.0406	Wuh(8)	8.1095
Wul(9)	8.9074	Wum(9)	9.0406	Wuh(9)	9.1095
Wul(10)	9.9025	Wum(10)	10.0427	Wuh(10)	10.1152
Wcl(1)	1.0000	Wcm(1)	1.0000	Wch(1)	1.0000
Wcl(2)	2.0000	Wcm(2)	2.0000	Wch(2)	2.0000
Wcl(3)	3.0000	Wcm(3)	3.0000	Wch(3)	3.0000
Wcl(4)	3.9706	Wcm(4)	4.0135	Wch(4)	4.0360
Wcl(5)	4.9405	Wcm(5)	5.0272	Wch(5)	5.0728
Wcl(6)	5.9405	Wcm(6)	6.0272	Wch(6)	6.0728
Wcl(7)	6.9405	Wcm(7)	7.0272	Wch(7)	7.0728
Wcl(8)	7.9405	Wcm(8)	8.0272	Wch(8)	8.0728
Wcl(9)	8.9108	Wcm(9)	9.0408	Wch(9)	9.1091
Wcl(10)	9.9108	Wcm(10)	10.0408	Wch(10)	10.1091
Wsl(1)	1.0000	Wsm(1)	1.0000	Wsh(1)	1.0000
Wsl(2)	1.9928	Wsm(2)	2.0036	Wsh(2)	2.0095
Wsl(3)	2.9856	Wsm(3)	3.0073	Wsh(3)	3.0190
Wsl(4)	3.9569	Wsm(4)	4.0218	Wsh(4)	4.0571
Wsl(5)	4.9498	Wsm(5)	5.0254	Wsh(5)	5.0666
Wsl(6)	5.9426	Wsm(6)	6.0290	Wsl(6)	6.0761
Wsl(7)	6.9354	Wsm(7)	7.0327	Wsh(7)	7.0856
Wsl(8)	7.9282	Wsm(8)	8.0363	Wsh(8)	8.0952
Wsl(9)	8.9282	Wsm(9)	9.0363	Wsh(9)	9.0952
Wsl(10)	9.9282	Wsm(10)	10.0363	Wsh(10)	10.0952
Wdl(1)	1.0000	Wdm(1)	1.0000	Wdh(1)	1.0000
Wdl(2)	2.0000	Wdm(2)	2.0000	Wdh(2)	2.0000
Wdl(3)	3.0000	Wdm(3)	3.0000	Wdh(3)	3.0000
Wdl(4)	3.9654	Wdm(4)	4.0161	Wdh(4)	4.0381
Wdl(5)	4.9480	Wdm(5)	5.0241	Wdh(5)	5.0571
Wdl(6)	5.9307	Wdm(6)	6.0322	Wdl(6)	6.0762
Wdl(7)	6.9307	Wdm(7)	7.0322	Wdh(7)	7.0762
Wdl(8)	7.9394	Wdm(8)	8.0281	Wdh(8)	8.0667
Wdl(9)	8.9134	Wdm(9)	9.0402	Wdh(9)	9.0952
Wdl(10)	9.9134	Wdm(10)	10.0402	Wdh(10)	10.0952

In table 1, wbl(1) refers to the weight of the dendrite from b(1) to pbl and the weights of other dendrites from the input to the hidden layer are also named using the same convention. The weights of the dendrites from the hidden to the output layer are shown in table 2.

TABLE II
WEIGHT OF THE DENDRITES BETWEEN THE HIDDEN AND OUTPUT LAYERS

Weight of dendrite	Value	Weight of dendrite	Value	Weight of dendrite	Value
Wpbl	7.2387	Wpbm	7.2586	Wpbh	7.2145
Wpgl	25.2681	Wpgm	24.9638	Wpgh	25.3231
Wpcl	52.5739	Wpcm	52.4827	Wpch	53.1093
Wpul	38.0776	Wpum	38.9712	Wpuh	38.1984
Wpsl	26.0205	Wpsm	26.5328	Wpsh	26.1839
Wpdl	37.7545	Wpdm	36.8938	Wpdh	37.5788

In the above table, Wpbl refers to the weight of the dendrite from pbl to l and the weights of the other dendrites from the hidden to the output layers are named using the same convention.

TABLE III
RESULT OF A SAMPLE PATIENT OF AGE 42 YEARS
Height of patient : 5.0 ft

Time	Weight	B.M.I.	Glucose	Creatinine	Systolic Blood Pressure	Diastolic Blood Pressure
T1	64.1	27.97	120	1.0	128	87
T2	66.2	28.31	125	1.1	131	88
T3	66.8	28.57	128	1.2	132	90
T4	67.5	28.87	127	1.3	136	94
T5	66.9	28.61	128	1.4	137	96
T6	67.8	29.00	128	1.4	138	98
T7	68.2	29.17	128	1.4	139	98
T8	69.5	29.73	129	1.4	140	97
T9	70.5	30.15	129	1.8	140	100
T10	70.6	30.62	131	2.4	143	101

TABLE IV
RESULTS OF DECISION BEING GIVEN BY THE SMART AGENT

Time	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
AS_B	M	H*	H*	H*	H*	H*	H*	H*	H	H
PNS_B	M	M	M	M	H	H	H	H	H	H
AS_G	M	M	H*	H*	H*	H*	H*	H*	H*	H
PNS_C	M	M	M	H	H	H	H	H	H	H
AS_U	M	M	M	H*	H*	H*	H*	H*	H*	H
PNS_U	M	M	M	M	M	M	H	H	H	H
AS_G	M	M	M	H*	H*	H*	H*	H*	H	H
PNS	M	M	M	M	M	M	H	H	H	H
AS_D	M	M	H*	H*	H*	H*	H*	H*	H	H
PNS_D	M	M	M	M	M	M	H	H	H	H
AS	M	H*	H*	H*	H*	H*	H*	H	H	H
PNS_S	M	M	M	M	M	H	H	H	H	H
C_W	0	0	0	0	0	1	1	1	1	1

V. Results and Discussions

The system has been tested with the data of 40 patients and the results are compared with decisions being given by the medical practitioner. The data of a sample patient of 42 years has been analyzed and shown in the paper. The data of a sample patient of age 42 years and height 5.0 feet is provided in table 3.

Table 4 shows the results of decision being by the smart agent AS refers to the actual pathophysiological state of the patient and PNS refers to the predicted next state. A value M in the AS columns indicate a moderate parameter value of patient, H* indicates the parameter of the patient is high, but falling within the tolerance limits of moderate value and H indicates, the parameter of the patient is strictly high. C_w indicates whether the system indicates a condition of approaching criticality. Although, the developed system gives a crisp decision regarding the future physiological state of the patient, the essence of the system lies in that the system predicts a state of criticality of the patient at time T6, much before the condition of criticality occurs (at time T10). This also elucidates that such type of system when implemented in portable hardware can be deployed in telemedicine environments in rural areas, where the health care professionals often provide support services in absence of the physician.

VI. CONCLUSION

The current work focuses on the application of neuro-fuzzy synergism to detect at an early stage the probable approaching critical condition of a patient. It explains the usage of fuzzy neural networks in medical diagnosis systems and the extended example on the problem of early detection of approaching critical renal condition of patients. For diagnosis purposes, body mass index (B.M.I.), glucose, urea, creatinine, systolic and diastolic blood pressures are considered as pathophysiological parameters. The fuzzy neural network has been suitably trained and tested with real patient data to find out the correspondence with the decision being given by the fuzzy neural network and the actual pathophysiological state of the patient.

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VIII. BIOGRAPHIES

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