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Research Article

Fuzzy Soft System and Arrhythmia Classification

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An arrhythmia is an irregularity with the speed or rhythm of the heartbeat. During an arrhythmia, the heart can beat too fast, too slow, or with an irregular rhythm. Most arrhythmias are harmless, but some can be serious or even life threatening. The present paper deals with the classification scheme of arrhythmia commonly occurring in human beings of Southeast Asian countries. Medical knowledge used in practice has been closely studied for modelling user friendly referral system to sharpen arrhythmia diagnosis by experts and this system is tested with satisfactory factor which is measured with degree of match criterion under the domain of considered inputs and computed output.

1. Introduction

In Charaka and Sushruta Samhitas there is a description of five types of heart disease, namely, Vatika, Paittika, Kaphaj, Tridoshaj, and Krimij that are caused due to Vata, Pitta, Kapha, triple doshas, and worms, respectively. Hridrog Prakarana deals with the treatment for above-mentioned heart diseases. It appears that many kinds of heart related diseases like arrhythmia have been included under Vat-induced inflammation and respiratory disease on the ground of similarity of symptoms. According to Ayurved, when Pran vayu and Saman vayu along with Avlambak kapha get disturbed due to faulty diet (rich in salt, bitter, and pungent), excessive smoking, and prolonged alcohol consumption, the cardiac rhythm may be slow or fast [1]. Although ancient Chinese pulse theory laid the foundation for the study of arrhythmias and clinical electro physiology in the 5th century BC, the most significant breakthrough in the identification and treatment of cardiac arrhythmias first occurred in the 20th century. Hippocrates stated in his Aphorisms (Section II, number 41): those who are subject to frequent and severe fainting attacks without obvious cause die suddenly. This might be the first description of sudden cardiac death [2]. In 1958, Furman and Robinson showed that the heart could be stimulated by connecting an intracardiac catheter to a stimulator. In the late 1960s, a major breakthrough in our understanding of cardiac arrhythmias came when a reliable recording of the electrogram of the Bundle of His and programmed electrical stimulation of the heart became available for clinical use. The background for these developments came from the work of pioneers such as Hecht, Latour, Puech, and Giraud who, in the 1940s to 1950s, showed that intracardiac catheters could be used to record electrical activity inside the heart and to map cardiac activation [3].

There has been extensive work on techniques of classification of arrhythmia based on databases that may not be relevant for present-day clinical diagnostic systems. This is due to limitation in types of arrhythmia considered in them. The present papaer tries to overcome this limitation. Mahmoodabadi, et al. suggested that Neural Networks cannot respond correctly to unpredictable and abrupt changes encountered in patients because of varying shapes of arrhythmias. In contrast, the application of fuzzy tools is firmly tied to human judgment; therefore the study of human behaviour towards a problem is very important to achieve reasonable results [4].

In the field of medicine, Bellman and Zadeh [5] proposed application of fuzzy tools. In 1973, Zadeh [6] introduced a number of procedures to design and develop fuzzy algorithm for the analysis of complex systems and its decision processes.

Zong and Jiang [7] presented a fuzzy reasoning approach for ECG beat rhythm detection and classification. They used linguistic variables to represent beat features and fuzzy conditional statements perform reasoning. De Chazal et al. [8] proposed method for the automatic processing of the electrocardiogram for the classification of heartbeats in which allocation of detected heartbeats to one of the five beat classes recommended by ANSI/AAMI (American National Standards Institute/Association for the Advancement of Medical Instrumentation) EC57:1998 standard, that is, normal beat, ventricular ectopic beat (VEB), supraventricular ectopic beat, fusion of a normal and a VEB, or unknown beat type was manually performed on data obtained from the 44 nonpacemaker recordings of the MIT-BIH arrhythmia database. Yeh et al. [9] proposed fuzzy logic method to analyse ECG signals for determining the heartbeat case which can accurately classify and distinguish both normal heartbeats and abnormal heartbeats; Mahmoodabadi et al. [4] selected ECG features which are compared medically accepted normal cases using the fuzzy classifier, and arrhythmias will be detected accordingly. The inference section of a fuzzy classifier implemented expert designed fuzzy rules. Sadiq and Khan [10] presented an automated approach to beat recognition of four different beat types in ECGs, namely, normal beats, ventricular ectopic beats, supraventricular ectopic beats, and fusion beats with the help of feature vector to differentiate between the different beats containing morphological features and beat intervals for each beat. Recently, in soft computing risk assessment scheme for cardiac analysis and hypertension proposed by P. Srivastava and A. Srivastava [11, 12], the system designed on MATLAB Software gives the person the ratio of the risk and may recommend whether person has to live life normally or with diet or with drug treatment, respectively. Srivastava et al. [13] proposed a soft computing classification criterion to design and develop user friendly diagnostic system for Hepatitis B and the clinical data of the patients and the opinions of medical experts have been utilized to design the diagnostic system. Srivastava et al. [15] proposed soft computing diagnostic system for diabetes that sharpens the diagnostic process as well as guides patients to evolve strategies to control their sugar level. Recently, Srivastava and Sharma [16] proposed a soft computing decision making model to handle real life complex problems related with medical sciences.

2. Materials and Method

The proposed soft computing system is designed by making use of facts related to Sugeno approach of fuzzy inference. The system is applied to real and fresh data collected from hospitals in and around Allahabad district (U.P., India). The categorization of arrhythmia is done by making use of available data and specific features from ECG appropriate to do the classification are decided upon. The input parameters of the system are framed on the basis of ten factors responsible for arrhythmia and output is the type of arrhythmia classification. The accuracy of the inference is obtained by comparing it with the results provided by expert cardiologists.

The algorithm proposed helps us in designing the following information system. There are three steps as in Algorithm 1.

2.1. Input Parameters. The ten input factors are ventricular rate (VR), PR interval (PRI), QRS duration (QRSd), R-R interval, atrial rate (AR), P-P interval (P-P), P-QRS ratio (P : QRS), $RI_2 : RI_1$ ratio, $PI_2 : PI_1$ ratio, and T wave.

(a) Ventricular rate (VR) is categorized in four different fuzzy sets with their membership functions shown in Figure 1 as follows:

(1) slow (S): <40 bpm,

(2) normal (N): 40 to 100 bpm,

(3) high (H): 100 to 150 bpm,

(4) very high (VH): >150 bpm,

$$\begin{gathered}
(1)\ \mu_{\text{Slow}}(x) = \begin{cases} 1 & x \le 55 \\ \dfrac{(60-x)}{5} & 55 < x < 60 \\ 0 & x \ge 60 \end{cases} \\
(2)\ \mu_{\text{Normal}}(x) = \begin{cases} 0, & x \le 55 \text{ or } x \ge 105 \\ \dfrac{(x-55)}{5} & 55 < x < 60 \\ 1, & 60 \le x \le 100 \\ \dfrac{(105-x)}{5} & 100 < x < 105 \end{cases} \\
(3)\ \mu_{\text{High}}(x) = \begin{cases} 0, & x \le 100 \text{ or } x \ge 160 \\ \dfrac{(x-100)}{5} & 100 < x < 105 \\ 1, & 105 \le x \le 155 \\ \dfrac{(160-x)}{5} & 155 < x < 160 \end{cases} \\
(4)\ \mu_{\text{Very High}}(x) = \begin{cases} 0, & x \le 155 \\ \dfrac{(x-155)}{5} & 155 < x < 160 \\ 1, & x \ge 160. \end{cases}
\end{gathered} \tag{1}$$

(b) PR interval (PRI) which represents atrial depolarization is categorized in three different fuzzy sets shown in Figure 2 with their membership functions as follows:

(1) narrow (Na): <120 ms,

(2) normal (N): 120–200 ms,

STEP 1: Algorithm for Fuzzification Mechanism
(1) Input—Fuzzy System with suitable "n" parameters
$A_i, i = 1, 2, \ldots, n$
(2) $i \leftarrow 1$
While $i \leq n$ **do**
  (1) Categorize in n_i fuzzy sets X_j in linguistic variables, $j = 1, 2, \ldots, n_i$
  while $j \leq n_i$ **do**
    (1) Design suitable membership function μ_{X_j}
  end while
end while
STEP 2: Algorithm for Fuzzy Rule Base and Defuzzification Mechanism
(1) Input—"n_i" linguistic variables X_j, $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, n_i$
(2) Input—"m" output parameter Y_k, $k = 1, 2, \ldots, m$
(3) Develop "r" If-Then Fuzzy Rules R_p in consultation with medical experts, $p = 1, 2, \ldots, r$
(4) Input—Fuzzy Rule Base R_p
(5) Input—Values of parameters A_i
(6) $p \leftarrow 1$
while $p \leq r$ **do**
  (1) Calculate firing strength $w_p = \text{AND} A_i$, $i = 1, 2, \ldots, n$
  (2) $Z_p =$ pth rule's consequent fuzzy set.
end while
(7) Final Output of the fuzzy system $Z = \sum_{p=1}^{r} \dfrac{z_p w_p}{w_p}$
(8) Evaluated Diagnosis (ED) = Final output
STEP 3: Algorithm for Satisfactory Factor Mechanism
(1) Input—Evaluated Diagnosis (ED), Observed Diagnosis (OD)
(2) Input—"n" input parameter A_i, $i = 1, 2, \ldots, n$ and output result Z
(3) $i \leftarrow 1$
(4) $\text{DM}_T = 1$
while $i \leq n$ **do**
  (1) Calculate $\text{DM}(A_i) = 2\mu_{A_j} - 1$
  (2) $\text{DM}_T = \text{DM}_T \text{ AND } \text{DM}(A_i)$
end while
(5) Calculate $\text{DM}_O = \text{DM}(Z) = 2\mu_Z - 1$
(6) Evaluate Satisfactory Factor (SF) = $|\text{DM}_T - \text{DM}_O|$

Algorithm 1

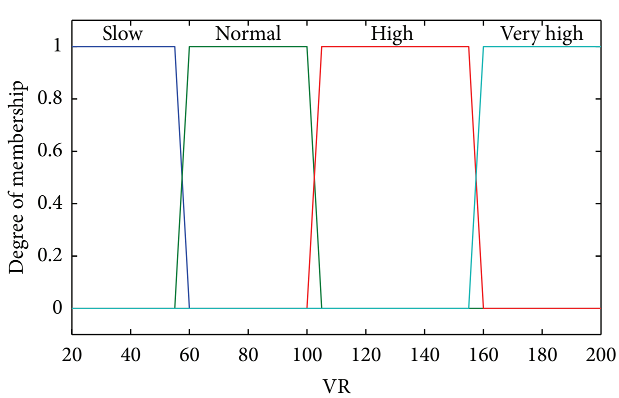

Figure 1: Ventricular rate.

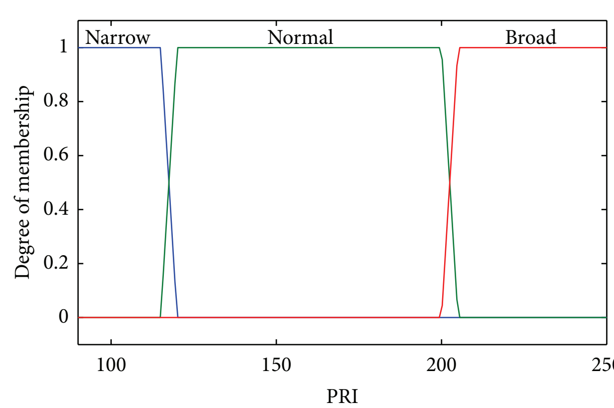

Figure 2: PR interval.

(3) broad (B): >200 ms,

$$\text{(1)}\quad \mu_{\text{Narrow}}(x) = \begin{cases} 1 & x \le 115 \\ \dfrac{(120 - x)}{5} & 115 < x < 120 \\ 0 & x \ge 120 \end{cases}$$

$$\text{(2)}\quad \mu_{\text{Normal}}(x) = \begin{cases} 0 & x \le 115 \text{ or } x \ge 205 \\ \dfrac{(x - 115)}{5} & 115 < x < 120 \\ 1, & 120 \le x \le 200 \\ \dfrac{(205 - x)}{5} & 200 < x < 205 \end{cases} \tag{2}$$

$$\text{(3)}\quad \mu_{\text{Broad}}(x) = \begin{cases} 0, & x \le 200 \\ \dfrac{(x - 200)}{5} & 200 < x < 205 \\ 1, & x \ge 205. \end{cases}$$

(c) QRS duration (QRSd) is categorized in three different fuzzy sets having their membership functions shown in Figure 3 as follows:

(1) narrow (Na): <60 ms,

(2) normal (N): 60–100 ms,

(3) broad (B): >100 ms,

$$\text{(1)}\quad \mu_{\text{Narrow}}(x) = \begin{cases} 1 & x \le 55 \\ \dfrac{(60 - x)}{5} & 55 < x < 60 \\ 0 & x \ge 60 \end{cases}$$

$$\text{(2)}\quad \mu_{\text{Normal}}(x) = \begin{cases} 0 & x \le 55 \text{ or } x \ge 105 \\ \dfrac{(x - 55)}{5} & 55 < x < 60 \\ 1, & 60 \le x \le 100 \\ \dfrac{(105 - x)}{5} & 100 < x < 105 \end{cases} \tag{3}$$

$$\text{(3)}\quad \mu_{\text{Broad}}(x) = \begin{cases} 0, & x \le 100 \\ \dfrac{(x - 100)}{5} & 100 < x < 105 \\ 1, & x \ge 105. \end{cases}$$

(d) R-R interval (RR) is categorized in three different fuzzy sets with their membership functions shown in Figure 4 as follows:

(1) short (S) <0.60 : sec,

(2) normal (N): 0.6–1 sec,

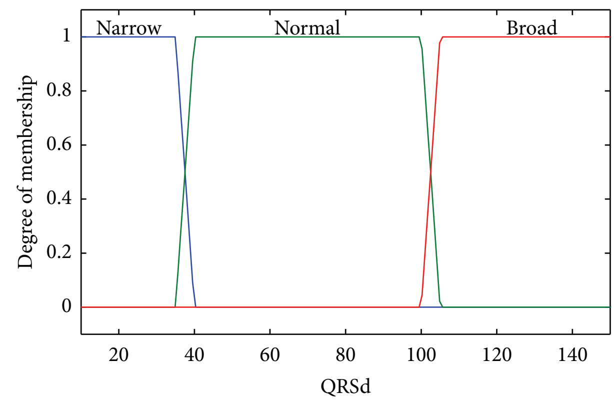

FIGURE 3: QRS duration.

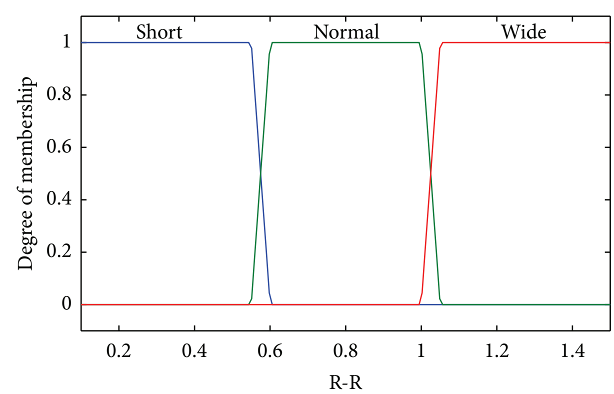

FIGURE 4: R-R interval.

(3) wide (W): >1 sec,

$$\text{(1)}\quad \mu_{\text{Short}}(x) = \begin{cases} 1 & x \le 0.55 \\ \dfrac{(0.6 - x)}{0.05} & 0.55 < x < 0.6 \\ 0 & x \ge 0.6 \end{cases}$$

$$\text{(2)}\quad \mu_{\text{Normal}}(x) = \begin{cases} 0 & x \le 0.55 \text{ or } x \ge 1.05 \\ \dfrac{(x - 0.55)}{0.05} & 0.55 < x < 0.6 \\ 1, & 0.6 \le x \le 1.00 \\ \dfrac{(1.05 - x)}{0.05} & 1.00 < x < 1.05 \end{cases} \tag{4}$$

$$\text{(3)}\quad \mu_{\text{Wide}}(x) = \begin{cases} 0, & x \le 1.00 \\ \dfrac{(x - 1.00)}{0.05} & 1.00 < x < 1.05 \\ 1, & x \ge 1.05. \end{cases}$$

(e) Atrial rate (AR) which is the Atrial rhythm calculated by P waves is categorized in six different fuzzy sets shown in Figure 5 as follows:

(1) slow (S): <60 bpm,

(2) normal (N): 60–100 bpm,

(3) little bit high (LH): 100–150 bpm,

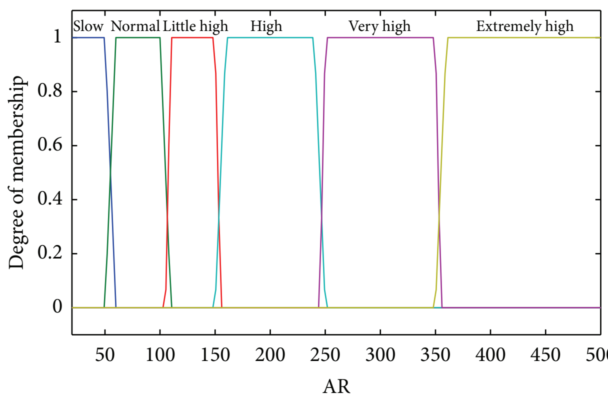

Figure 5: Atrial rate.

(4) high (H): 150–250 bpm,

(5) very high (VH): 250–350 bpm,

(6) extremely high (EH): >350 bpm,

$$\begin{aligned}
&(1)\ \mu_{S}(x)=\begin{cases}1 & x\leq 50\\ \dfrac{(60-x)}{10} & 50<x<60\\ 0 & x\geq 60\end{cases}\\
&(2)\ \mu_{N}(x)=\begin{cases}0 & x\leq 50 \text{ or } x\geq 110\\ \dfrac{(x-50)}{10} & 50<x<60\\ 1, & 60\leq x\leq 100\\ \dfrac{(110-x)}{10} & 100<x<110\end{cases}\\
&(3)\ \mu_{LH}(x)=\begin{cases}0 & x\leq 105 \text{ or } x\geq 155\\ \dfrac{(x-105)}{5} & 105<x<110\\ 1, & 110\leq x\leq 150\\ \dfrac{(155-x)}{5} & 150<x<155\end{cases}\\
&(4)\ \mu_{H}(x)=\begin{cases}0 & x\leq 150 \text{ or } x\geq 250\\ \dfrac{(x-150)}{10} & 150<x<160\\ 1, & 160\leq x\leq 240\\ \dfrac{(250-x)}{10} & 240<x<250\end{cases}\\
&(5)\ \mu_{VH}(x)=\begin{cases}0 & x\leq 245 \text{ or } x\geq 355\\ \dfrac{(x-245)}{5} & 245<x<250\\ 1, & 250\leq x\leq 350\\ \dfrac{(355-x)}{5} & 350<x<355\end{cases}\\
&(6)\ \mu_{EH}(x)=\begin{cases}0, & x\leq 350\\ \dfrac{(x-350)}{5} & 350<x<360\\ 1, & x\geq 360.\end{cases}
\end{aligned}\tag{5}$$

(f) P-P interval (PP) is categorized in three different fuzzy sets with their membership functions shown in Figure 6 as follows:

(1) short (S): <0.60 sec,

(2) normal (N): 0.6–1 sec,

(3) wide (W): >1 sec,

$$\begin{aligned}
&(1)\ \mu_{\text{Short}}(x)=\begin{cases}1 & x\leq 0.55\\ \dfrac{(0.6-x)}{0.05} & 0.55<x<0.6\\ 0 & x\geq 0.6\end{cases}\\
&(2)\ \mu_{\text{Normal}}(x)=\begin{cases}0 & x\leq 0.55 \text{ or } x\geq 1.05\\ \dfrac{(x-0.55)}{0.05} & 0.55<x<0.6\\ 1, & 0.6\leq x\leq 1.00\\ \dfrac{(1.05-x)}{0.05} & 1.00<x<1.05\end{cases}\\
&(3)\ \mu_{\text{Wide}}(x)=\begin{cases}0, & x\leq 1.00\\ \dfrac{(x-1.00)}{0.05} & 1.00<x<1.05\\ 1, & x\geq 1.05.\end{cases}
\end{aligned}\tag{6}$$

(g) P-QRS ratio (P : QRS) shows the ratio of P wave to QRS wave in one cardiac cycle. It is categorized in the following three different fuzzy sets with their membership functions shown in Figure 7:

(1) low (L): <1,

(2) desirable (D): =1,

(3) high (H): >1,

$$\begin{aligned}
&(1)\ \mu_{\text{Low}}(x)=\begin{cases}1 & x\leq -2\\ 1-2\left(\dfrac{x+2}{6}\right)^{2} & -2<x\leq 1\\ 2\left(\dfrac{x-4}{6}\right)^{2} & 1<x\leq 4\\ 0, & 4<x\end{cases}\\
&(2)\ \mu_{\text{High}}(x)=\begin{cases}0 & x\leq -2\\ 2\left(\dfrac{x+2}{6}\right)^{2} & -2<x\leq 1\\ 1-2\left(\dfrac{x-4}{6}\right)^{2} & 1<x\leq 4\\ 1, & 4<x.\end{cases}
\end{aligned}\tag{7}$$

(h) $RI_2 : RI_1$ ratio is the ratio of two successive R-R intervals. It is categorized in the following three fuzzy factors with their membership functions shown in Figure 8:

(1) low (L): <1,

(2) desirable (D): = 1,

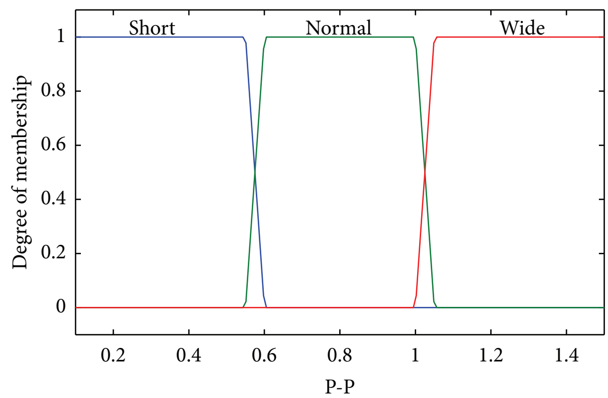

Figure 6: P-P interval.

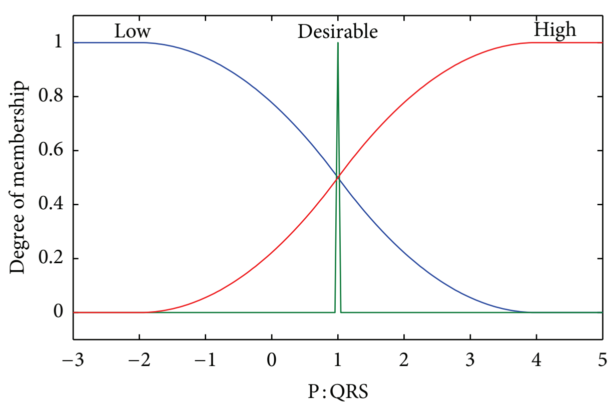

Figure 7: P : QRS ratio.

(3) high (H): >1,

$$\begin{aligned}
&(1)\ \mu_{\text{Low}}(x) = \begin{cases} 1 & x \leq -2 \\ 1 - 2\left(\dfrac{x+2}{6}\right)^2 & -2 < x \leq 1 \\ 2\left(\dfrac{x-4}{6}\right)^2 & 1 < x \leq 4 \\ 0, & 4 < x \end{cases} \\
&(2)\ \mu_{\text{High}}(x) = \begin{cases} 0 & x \leq -2 \\ 2\left(\dfrac{x+2}{6}\right)^2 & -2 < x \leq 1 \\ 1 - 2\left(\dfrac{x-4}{6}\right)^2 & 1 < x \leq 4 \\ 1, & 4 < x. \end{cases}
\end{aligned} \tag{8}$$

(i)$PI_2 : PI_1$ ratio is the ratio of two successive P-P intervals. It is categorized in following three fuzzy factors with their membership functions shown in Figure 9:

(1) low (L): <1,

(2) desirable (D): =1,

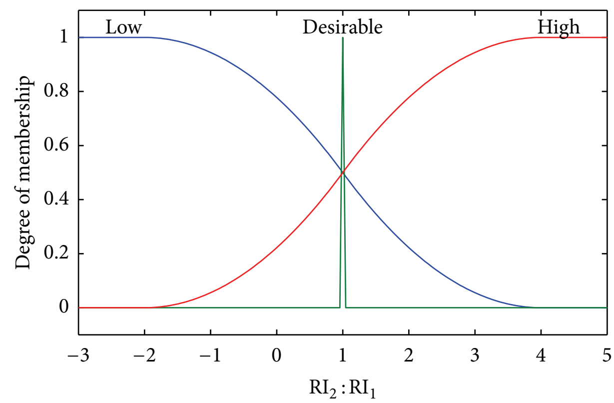

Figure 8: $RI_2 : RI_1$ ratio.

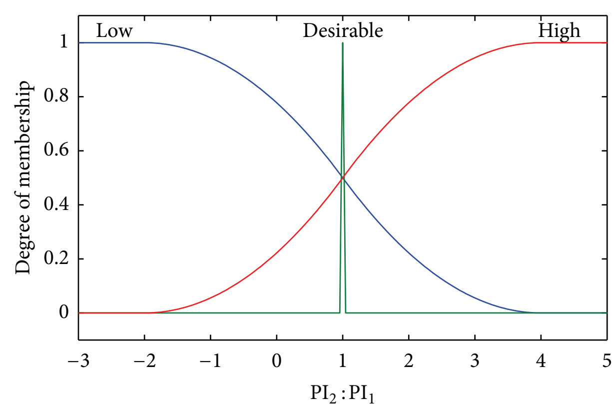

Figure 9: $PI_2 : PI_1$ ratio.

(3) high (H): ¿1,

$$\begin{aligned}
&(1)\ \mu_{\text{Low}}(x) = \begin{cases} 1 & x \leq -2 \\ 1 - 2\left(\dfrac{x+2}{6}\right)^2 & -2 < x \leq 1 \\ 2\left(\dfrac{x-4}{6}\right)^2 & 1 < x \leq 4 \\ 0, & 4 < x \end{cases} \\
&(2)\ \mu_{\text{High}}(x) = \begin{cases} 0 & x \leq -2 \\ 2\left(\dfrac{x+2}{6}\right)^2 & -2 < x \leq 1 \\ 1 - 2\left(\dfrac{x-4}{6}\right)^2 & 1 < x \leq 4 \\ 1, & 4 < x. \end{cases}
\end{aligned} \tag{9}$$

(j) T wave is categorized in three fuzzy sets shown in Figure 10 with their membership functions as follows:

(1) negative (N): <0,

(2) isolated (I): =0,

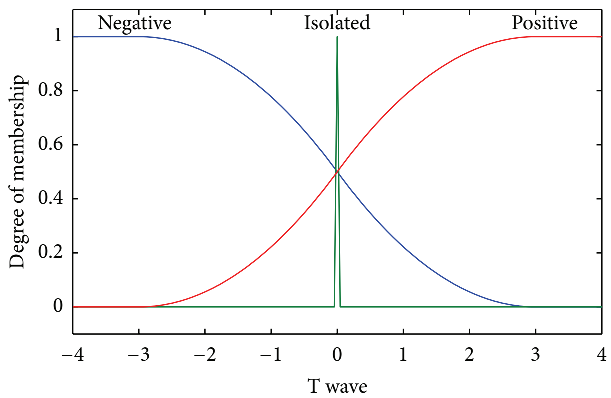

Figure 10: T wave.

(3) positive (P): >0,

$$(1)\ \mu_{\text{Negative}}(x) = \begin{cases} 1 & x \le -3 \\ 1 - 2\left(\dfrac{x+3}{6}\right)^2 & -3 < x \le 0 \\ 2\left(\dfrac{x-3}{6}\right)^2 & 0 < x \le 3 \\ 0, & 3 < x \end{cases}$$

$$(2)\ \mu_{\text{Positive}}(x) = \begin{cases} 0 & x \le -3 \\ 2\left(\dfrac{x+3}{6}\right)^2 & -3 < x \le 0 \\ 1 - 2\left(\dfrac{x-3}{6}\right)^2 & 0 < x \le 3 \\ 1, & 3 < x. \end{cases} \tag{10}$$

2.2. Output Parameter. The abnormalities in rhythm of the heart contribute to a number of arrhythmia of which we have taken thirteen types as outputs for the classification of arrhythmia. These are as follows: Normal (N), Sinus Tachycardia (ST), Atrial Tachycardia (AT), Atrial Flutter (AF), Atrial Fibrillation (AFb), Ventricular Tachycardia (VT), Sinus Bradycardia (SB), First AV Block (1st B), Second AV Block Type 1 (2nd B1), Second AV Block Type 2 (2nd B2), Third AV Block (3rd B), Premature Atrial Contraction (PAC), and Premature Ventricular Contraction (PAC). Spikes are used to represent these outputs as given in Figure 11.

2.3. Fuzzy Inference System. Evaluation of ECG signals for arrhythmia detection consists of the determination of several characteristics of the signal. In order to classify different types of arrhythmia fifty five rules are constructed with the help of medical experts. They are given in Table 1.

The output Z_i, that is, conclusion part of a rule is weighted by the firing strength w_i of the rule which is calculated by using AND operation on each antecedent A_j, where j is the number of inputs used in each rule i as follows:

$$w_i = \text{AND}\left\{A_j\right\}, \quad i = 1, \ldots, 16. \tag{11}$$

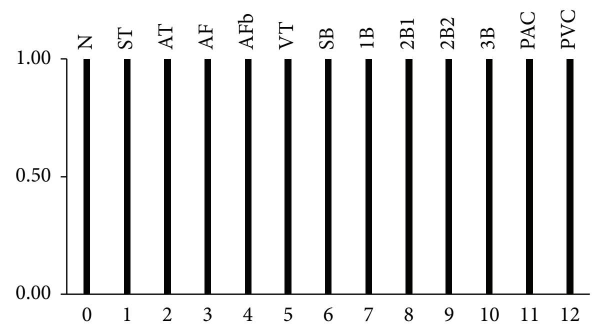

Figure 11: Types of arrhythmia.

This firing strength is further used in finding the final conclusion of the proposed system using the defuzzification of weighted average of all rule outputs Z_i, $i = 1, \ldots, 16$.

The final output of the system is calculated by $\sum_{i=0}^{16}(Z_i w_i / w_i)$.

In order to know to what extent our result is satisfied by given inputs and observed outputs, we make use of Degree of Match algorithm to compute satisfactory factor [17].

Ten cases are discussed below to show the effectiveness of the proposed system.

2.4. Case Study

Case 1. The ECG record of the concerned patient is manually calculated as follows.

VR = 110 bpm, PRI = 90 ms, QRSd = 100 ms, AR = 410 bpm, R-R interval = 0.46 sec, P-P interval = 0.15 sec, P : QRS = 2, $RI_2 : RI_1 = 0.7$, $PI_2 : PI_1 = 0.9$ and T wave is positive.

The membership functions designed for input parameters are used to fuzzify the crisp inputs which are transformed into fuzzy outputs by making use of the constructed fuzzy IF-THEN rules and finally defuzzified by using the weighted average function defined above.

The defuzzification is shown in Figure 12 which shows the output that is, Arrhythmia = 4, which stands for the Atrial Fibrillation (AFb). This diagnosis matches the observed diagnosis by medical experts.

In order to measure satisfactory factor, values of Degree of Match of input parameters are computed and total Degree of Match of inputs DM_T is given below:

$$\begin{aligned} DM_T &= \min\{1, 1, 1, 1, 1, 1, 0.778, 0.595, 0.533, 0.778\} \\ &= 0.533. \end{aligned} \tag{12}$$

Degree of Match of output DM_O is 1; hence our satisfactory factor is $D = |DM_T - DM_O| = |0.533 - 1| = 0.467$ which lies between 0 and 1 and near to zero, that meets level of satisfaction.

Table 1: Rule base.

S. number	VR	PRI	QRSd	AR	P-P	P : QRS	R-R	$RI_2 : RI_1$	$PI_2 : PI_1$	T wave	Arrhythmia
1	Normal	Normal	Normal	Normal	Normal	Desirable	Normal	Desirable	Desirable	Positive	Normal
2	Slow	Normal	Normal	Slow	Wide	Desirable	Wide	Desirable	Desirable	Positive	SB
3	Slow	Broad	Normal	Normal	Normal	Desirable	Wide	Desirable	Desirable	Positive	1B
4	Normal	Broad	Normal	Normal	Normal	Desirable	Normal	Desirable	Desirable	Positive	1B
5	Normal	Broad	Normal	Normal	Normal	High	Normal	High	Desirable	Positive	2B1
6	Normal	Normal	Broad	Normal	Normal	High	Wide	High	Desirable	Positive	2B1
7	Slow	Broad	Normal	Normal	Normal	High	Wide	High	Desirable	Positive	2B1
8	Slow	Normal	Broad	Normal	Normal	High	Wide	High	Desirable	Positive	2B2
9	High	—	Broad	—	—	Low	Short	—	—	—	VT
10	Slow	—	Broad	Normal	Normal	High	Wide	Low	Low	Positive	3B
11	Slow	—	Broad	Normal	Normal	High	Wide	Low	High	Positive	3B
12	Slow	—	Broad	Normal	Normal	High	Wide	High	High	Positive	3B
13	Slow	—	Broad	Normal	Normal	High	Wide	High	Low	Positive	3B
14	Slow	—	Broad	Little high	Short	High	Wide	Low	Low	Positive	3B
15	Slow	—	Broad	Little high	Short	High	Wide	Low	High	Positive	3B
16	Slow	—	Broad	Little high	Short	High	Wide	High	High	Positive	3B
17	Slow	—	Broad	Little high	Short	High	Wide	High	Low	Positive	3B
18	—	Normal	Normal	—	Normal	Desirable	Normal	Low	Low	Positive	PAC
19	—	Normal	Normal	—	Normal	Desirable	Normal	Low	High	Positive	PAC
20	—	Norma	Normal	—	Normal	Desirable	Normal	High	High	Positive	PAC
21	—	Normal	Normal	—	Normal	Desirable	Normal	High	Low	Positive	PAC
22	—	Normal	Normal	—	Wide	Desirable	Wide	Low	Low	Positive	PAC
23	—	Normal	Normal	—	Wide	Desirable	Wide	Low	High	Positive	PAC
24	—	Normal	Normal	—	Wide	Desirable	Wide	High	High	Positive	PAC
25	—	Normal	Normal	—	Wide	Desirable	Wide	High	Low	Positive	PAC
26	—	Normal	Normal	—	Short	Desirable	Short	Low	Low	Positive	PAC
27	—	Normal	Normal	—	Short	Desirable	Short	Low	High	Positive	PAC
28	—	Normal	Normal	—	Short	Desirable	Short	High	High	Positive	PAC
29	—	Normal	Normal	—	Short	Desirable	Short	High	Low	Positive	PAC
30	Very high	—	Normal	Extremely high	—	High	Short	Low	—	Positive	AFb
31	Very high	—	Normal	Extremely high	—	High	Short	High	—	Positive	AFb
32	High	Normal	Normal	Little high	Short	Desirable	Short	Desirable	Desirable	—	ST
33	Very high	Normal	Normal	High	Short	Desirable	Short	Desirable	Desirable	—	ST
34	Very high	Normal	Normal	Very high	Short	Desirable	Short	Desirable	Desirable	—	ST
35	Very high	Normal	Normal	Extremely high	Short	Desirable	Short	Desirable	Desirable	—	ST
36	Very high	Narrow	Normal	High	Short	Desirable	—	—	—	—	AT
37	Very high	Narrow	Normal	Very high	Short	Desirable	—	—	—	—	AT
38	Normal	—	Normal	Very high	Short	High	Normal	Desirable	Desirable	—	AF
39	Normal	—	Normal	Extremely high	Short	High	Normal	Desirable	Desirable	—	AF
40	High	—	Normal	Very high	Short	High	Short	Desirable	Desirable	—	AF
41	High	—	Normal	Extremely high	Short	High	Short	Desirable	Desirable	—	AF

Table 1: Continued.

S. Number	VR	PRI	QRSd	AR	P-P	P : QRS	R-R	$RI_2 : RI_1$	$PI_2 : PI_1$	T wave	Arrhythmia
42	High	—	Normal	Extremely high	—	High	Short	Low	—	—	AFb
43	High	—	Normal	Extremely high	—	High	Short	High	—	—	AFb
44	Very high	—	Normal	Extremely high	—	High	Short	Low	—	—	AFb
45	Very high	—	Normal	Extremely high	—	High	Short	High	—	—	AFb
46	High	—	Broad	—	—	Low	Short	Desirable	—	Negative	VT
47	Very high	—	Broad	—	—	Low	Short	Desirable	—	Negative	VT
48	—	—	Broad	—	—	—	—	Low	Low	Negative	PVC
49	—	—	Broad	—	—	—	—	Low	High	Negative	PVC
50	—	—	Broad	—	—	—	—	High	High	Negative	PVC
51	—	—	Broad	—	—	—	—	High	Low	Negative	PVC
52	High	—	Broad	—	—	Low	Short	Low	—	Negative	VT
53	High	—	Broad	—	—	Low	Short	High	—	Negative	VT
54	Very high	—	Broad	—	—	Low	Short	Low	—	Negative	VT
55	Very high	—	Broad	—	—	Low	Short	High	—	Negative	VT

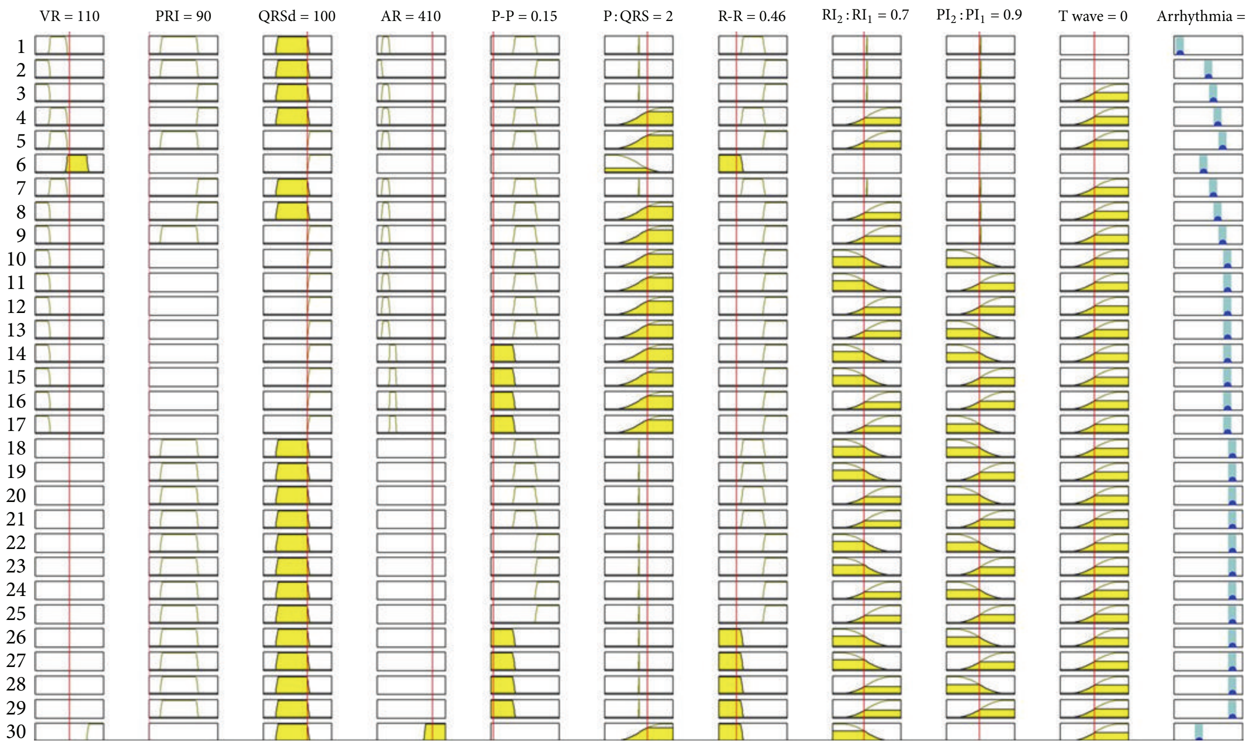

Figure 12: Designed information referral system.

Case 2. The ECG record of the concerned patient is manually calculated as follows.

VR = 114 bpm, PRI = 120 ms, QRSd = 296 ms, AR = 20 bpm, R-R interval = 0.52 sec, P-P interval = 0.5 sec, P : QRS = 0, $RI_2 : RI_1 = 1.2$ $PI_2 : PI_1 = 1$ and T wave is negative.

Implementing these features, the Arrhythmia output is 8.59; that is, heart beat is Second AV Block Type 2 (2nd B2). Here, the observed diagnosis by medical expert is Ventricular Tachycardia (VT).

Values of Degree of Match of input parameters are computed and total Degree of Match of inputs DM_T is given below:

$$\begin{aligned} DM_T &= \min\{1, 1, 1, 1, 1, 1, 0.778, 0.564, 0.5, 0.778\} \\ &= 0.5. \end{aligned} \tag{13}$$

Degree of Match of output DM_O is −1; thus $D = |DM_T - DM_O| = |0.5 - (-1)| = 1.5$ which does not lie between zero and one; therefore level of satisfaction is not good.

Case 3. The ECG record of the patient, as follows.

VR = 40 bpm, PRI = 120 ms, QRSd = 150 ms, AR = 91 bpm, R-R interval = 1.5 sec, P-P interval = 0.66 sec, P : QRS = 1.2, $RI_2 : RI_1 = 1.5$, $PI_2 : PI_1 = 1$, and T wave is positive.

Implementing these features, the Arrhythmia output is 9.77; that is, heart beat is Third AV Block (3B). Here, the observed diagnosis by medical expert is the same, that is, Third AV Block (3B).

Values of Degree of Match of input parameters are computed and total Degree of Match of inputs DM_T is given below:

$$\begin{aligned} DM_T &= \min\{1, 1, 1, 1, 1, 1, 0.564, 0.653, 0.5, 0.778\} \\ &= 0.5. \end{aligned} \tag{14}$$

Degree of Match of output DM_O is −1; thus $D = |DM_T - DM_O| = |0.5 - (-1)| = 1.5$ which does not meet level of satisfaction.

Case 4. The ECG record of the patient is as follows.

VR = 104.89 bpm, PRI = 164 ms, QRSd = 94 ms, AR = 107.14 bpm, R-R interval = 0.572 sec, P-P interval = 0.56 sec, P : QRS = 1, $RI_2 : RI_1 = 1.2$, $PI_2 : PI_1 = 1$, and T wave is positive.

Implementing these features, the Arrhythmia output is 9; that is, heart beat is Second AV Block Type. The evaluated diagnosis is verified by medical expert.

The satisfactory factor is $|DM_T - DM_O| = |0.022 - 1| = 0.978$.

Case 5. The ECG record of the patient is as follows.

VR = 132 bpm, QRSd = 80 ms, R-R interval = 0.457 sec, P : QRS = 1.6, $RI_2 : RI_1 = 1.4$ and T, wave is positive.

Implementing these features, the Arrhythmia output is 1; that is, heart beat is Sinus Tachycardia. The observed diagnosis by medical expert is Atrial Flutter.

The satisfactory factor is $|DM_T - DM_O| = |0.63 + 1| = 1.63$.

Case 6. The ECG record of the patientis as follows.

VR = 57.25 bpm, PRI = 185 ms, QRSd = 73.2 ms, AR = 57.25 bpm, R-R interval = 1.048 sec, P-P interval = 1.048 sec, $P : QRS = 1$, $RI_2 : RI_1 = 1$, $PI_2 : PI_1 = 1$ and T wave is positive.

Implementing these features, the Arrhythmia output is 0; that is, heart beat is Normal. The evaluated diagnosis is verified by medical expert.

The satisfactory factor is $|DM_T - DM_O| = |0.55 - 1| = 0.45$.

Case 7. The ECG record of the patient is as follows.

VR = 61.37 bpm, PRI = 168 ms, QRSd = 68 ms, AR = 61.37 bpm, R-R interval = 0.97 sec, P-P interval = 0.97 sec, $P : QRS = 1$, $RI_2 : RI_1 = 1$, $PI_2 : PI_1 = 1$, and T wave is positive.

Implementing these features, the Arrhythmia output is 0; that is, heart beat is Normal. The evaluated diagnosis is verified by medical expert.

The satisfactory factor is $|DM_T - DM_O| = |0.5 - 1| = 0.5$.

Case 8. The ECG record of the patient is as follows.

VR = 91.3 bpm, PRI = 152 ms, QRSd = 88 ms, AR = 90.2 bpm, R-R interval = 0.66 sec, P-P interval = 0.67 sec, $P : QRS = 1$, $RI_2 : RI_1 = 1$, $PI_2 : PI_1 = 1$, and T wave is positive.

Implementing these features, the Arrhythmia output is 0; that is, heart beat is Normal. The evaluated diagnosis is verified by medical expert.

The satisfactory factor is $|DM_T - DM_O| = |0.5 - 1| = 0.5$.

Case 9. The ECG record of the patient is as follows.

VR = 41.5 bpm, PRI = 150 ms, QRSd = 98 ms, AR = 40 bpm, R-R interval = 1.45 sec, P-P interval = 1.49 sec, $P : QRS = 1$, $RI_2 : RI_1 = 1$, $PI_2 : PI_1 = 1$, and T wave is positive.

Implementing these features, the Arrhythmia output is 6; that is, heart beat is Sinus Bradycardia. The evaluated diagnosis is verified by medical expert.

The satisfactory factor is $|DM_T - DM_O| = |0.6 - 1| = 0.4$.

Case 10. The ECG record of the patient is as follows.

VR = 61.3 bpm, PRI = 134 ms, QRSd = 65 ms, AR = 59 bpm, R-R interval = 0.98 sec, P-P interval = 0.99 sec, $P : QRS = 1$, $RI_2 : RI_1 = 1$, $PI_2 : PI_1 = 1$, and T wave is positive.

Implementing these features, the Arrhythmia output is 6; that is, heart beat is Normal. The evaluated diagnosis is verified by medical expert.

The satisfactory factor is $|DM_T - DM_O| = |0.5 - 1| = 0.5$.

3. Conclusion

The proposed system is capable enough to categorize an ECG waveform into one of the thirteen types of Arrhythmia. The results obtained from the soft system concur with the results provided by experts in 91 out of 105 cases. As available in literature we have observed that classifiers introduced so far cater different types of Arrhythmia, mostly based on databases from western countries. This work is significant as it caters to the most commonly occurring Arrhythmias and provides an easy and reliable tool to apply in real time systems and automation projects, for use in ICU and patient monitoring systems. It can also be used in day-to-day diagnosis of Arrhythmia by implementing the technique in stand-alone systems. Hence the relevance of this work, which is intended to be incorporated into primary care health facilities catering to a wide patient base, helping timely detection and lessening mortality rates.

Conflict of Interests

All authors, Pankaj Srivastava, Neeraja Sharma and C. S. Aparna disclose that there is no conflict of interests. There are also neither financial nor personal relationships with other people or organizations mentioned in this work that could cause any inappropriate influence.

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