International Journal of Engineering Works
ISSN-p: 2521-2419
ISSN-e: 2409-2770
Vol. 5, Issue 11, PP. 232-239, November 2018
https://www.ijew.io/

A Qualitative Overview of Fuzzy Logic in ECG Arrhythmia Classification

Ahmed Farhan[1], Chen Li Wei[2], Md Toukir Ahmed[3]
[1,2,3]College of Information and Communication Engineering, Harbin Engineering University, China
ahmedfarhanzisan77@yahoo.com[1]
Received: 24 October, Revised: 30 October, Accepted: 05 November

Abstract- Achieving elevated efficiency for the classification of the ECG signal is a noteworthy issue in the present world. Electrocardiogram (ECG) is a technique to identify heart diseases. However, the detection of the actual type of heart diseases is indispensable for further treatment. Various techniques have been invented and explored to categorize the heart diseases which are recognized as arrhythmias. This paper aims to investigate the development of various techniques of arrhythmia classification on the basis of fuzzy logic along with an elaborative discussion on accepted techniques. Moreover, a comparative study on their efficiency has been analyzed to emphasize the scope of novel research areas.

***Keywords*—** Arrhythmias, Electrocardiogram, Fuzzy logic, Fuzzy Classifier, Fuzzy Inference System.

I. INTRODUCTION

Preceding researches and studies over decades have resulted in radical development and advancement of many ECG arrhythmia classification techniques for heart disease. Heart is one of the basic organs of the human body which is like a pump made up of muscle tissue. Heart conducts the blood circulation in the human body. Among many heart diseases, some can become severe at times which is why an appropriate diagnosis, detection, and treatment of heart diseases are essential. Electrocardiogram or ECG is a well-recognized technique to detect heart diseases.

A. *ECG Signal*

According to some researchers, four essential processes are required to perform an accurate diagnosis of heart disease and arrive at a quick decision [1]. These include data compression, de-noising, feature extraction, and classification. The heart is monitored by placing sensors at the limb extremities of the subject; Electrocardiogram (ECG) is a documentation of the foundation and the dissemination of the electrical potential in the course of cardiac muscles [2].

Two kinds of information can be extracted from an ECG signal. Firstly it can be determined whether the electrical activity is normal or slow, fast or irregular by measuring the time interval (duration of electrical wave crossing the heart). Secondly, by determining the amount of electrical activity passing through the heart muscle, a cardiologist can find out if parts of the heart are too large or overworked. The frequency range of an ECG signal is 0.05 – 100 Hz and its dynamic range is 1-10 mV [2]. One cardiac cycle in an ECG consists of the P, Q, R, S and T waves [3]. An excellent performance of an ECG investigating scheme depends greatly upon the exact and dependable detection of the QRS complex, along with the T and P waves [2].

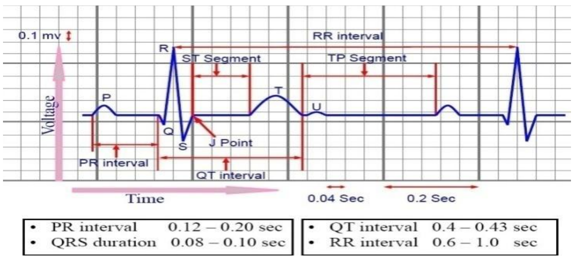

Figure 1 The normal ECG waveform

The P wave lasts about 0.08 seconds and denotes the pumping out of the blood through atrial contraction [3]. The PR interval is calculated from the beginning of the P wave up to the beginning of the Q wave. It symbolizes the length of atrial depolarization. The following portion of the signal is the ‘QRS complex’ which denotes the interval of ventricle depolarization. This part represents the time duration of the contraction to pump out blood to the entire body via the ventricles. Its standard period is from 0.08 – 0.12 seconds. The next rising section is recognized as ‘ST segment’, which points out the time interval from the ending of the contraction of the ventricles to the starting of the remaining period. This segment is crucial in order to identify myocardial infarctions and ischemia [4]. The inactive period of the ventricles is denoted by the T wave which exists for 0.16 seconds [3].

B. *Arrhythmias*

The unusual or unbalanced rhythm of the heart is recognized as an arrhythmia. Sometimes, the heart pumps very promptly and at times it pumps at a snail's pace. Low blood pressure, dizziness, weakness, exhaustion, fainting and palpitations are several signs of arrhythmia. The cause of arrhythmia is because of the deviations or irregularities in the heart rate. Undeniably Arrhythmias are characterized by ECG Signal [5]. The outline of ECG is changed by reason of arrhythmias. The pattern of ECG signals varies differently for a variety of arrhythmias. The early analysis of arrhythmia is indispensable for its treatment. If arrhythmia lasts for a long time, then the heart has a high risk to be damaged eternally [4]. Some notorious kinds of arrhythmias are sinus tachycardia, sinus arrhythmias, sick sinus syndrome, premature atrial contractions, paroxysmal atrial tachycardia, atrial flutter, atrial fibrillation are some of the regular atrial arrhythmias and premature ventricular contractions, ventricular tachycardia, and ventricular fibrillation are some familiar ventricular arrhythmias [4].

II. Literature Review

Appropriate classification of ECG arrhythmias is obligatory to ensure apposite treatment to the patients. Researchers and scientists have explored and invented different types of processes and models to investigate and categorize ECG arrhythmias with the course of time.

A. Classifier

A classifier is a structure where a rule-based algorithm is used as the foundation. The classifiers apply training algorithms as well as training data sets. If the training data set is unavailable, it can be planned from preceding knowledge. Training is required to make the classifier geared up for operation [6]. The classifier follows some rules and they are represented in the shape of 'If condition Then action' [7].

B. Various methods for classification of Arrhythmias

Researchers and scientists have anticipated many procedures to classify ECG arrhythmias. For instance, fuzzy classifier [1], wavelet neural network [8], improved classification performance of Linear Feature Extraction [9], correlation dimension and largest Lyapunov exponent [10], wavelet transform and time intervals methodology [11], multiple signal classification algorithm [12], and efficient formation of morphological wavelet transform features along with the temporal features of the ECG signal [13]. Many investigations have developed numerous methodologies for classifying ECG signals like supporting vector machines for cardiac beat detection [14, 15, 16], Artificial Neural Network (ANN) [17, 18], Fisher Linear Discriminate Analysis (FLDA) technique [19], Hermite functions and self- organized map [20, 21], Heartbeat interval combined with the shape and morphological properties of the ECG parameters [22], multi-lead based on random projection feature [23], analysis by Hilbert transform [24, 25], extreme learning machine [26], logistic model tree [27], Gaussian mixture model [28] etc. There are also some models which are based on the combination and correlation of the methods mentioned above. In some cases, the hybrid and combined methods proved superior result to the individual techniques. In this paper, we have talked elaborately about fuzzy logic and involvement of modern research in ECG arrhythmias detection based on fuzzy logic.

C. Fuzzy Logic

Zadeh was the pioneer of Fuzzy logic. It has multiple values and is parallel to human thoughts. Conventional Boolean and Aristotelian logic handle just absolute values of 0 and 1 along with true or false. On the other hand, fuzzy logic does not work like that. It does not follow a linear function always and deals with the phenomena not having absolute value.

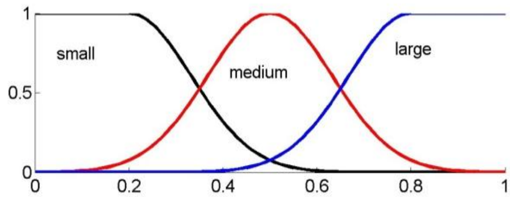

Figure 2 Fuzzy Logic

A conventional set of binary logic considers crisp values while fuzzy sets have fuzzy values with only linguistic variables and can be defined as low, medium and high. The values having fuzzy boundaries can overlap each other [29].

D. Fuzzy Inference System(FIS)

FIS is an outline where fuzzy sets, fuzzy rules, and fuzzy reasoning are the foundations. Fuzzy reasoning is an estimated reasoning. It illustrates the endings from the fuzzy sets and fuzzy rules.

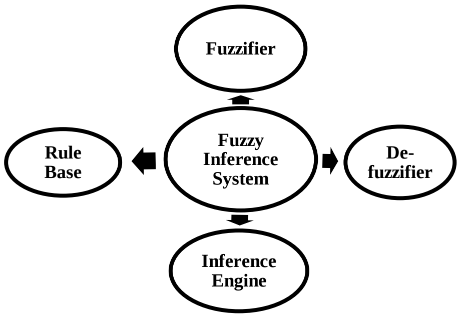

Figure 3 Fuzzy Interface System

It consists of the following four apparatus: fuzzifier, rule base, inference engine, and defuzzifier. Fuzzy sets are formed from the crisp value in fuzzifier along with the formation of fuzzy rules. The inference engine relates the fuzzy rules with the fuzzy sets. The fuzzy output is determined by it and the output is a fuzzy value. In addition to this, the crisp value is found as output by defuzzification process [29].

Fuzzy logic is to some extent beneficial because it is adaptable and cost-effective and it does not require specific and noise-free input. The structure can be designed easily with numerous inputs and outputs because it conducts a rule-based operation. It can model non-linear functions of random complexity and manage those types of non-linear structures whose mathematical models would be complicated [30]. Nevertheless, Fuzzy logic poses exigent difficulties as the membership functions are complicated to a certain extent in nature as well as a collection of too many data for this process becomes a topic of being concerned [29].

E. Applications of fuzzy logic

The purposes of Fuzzy logic to categorize ECG arrhythmias are highlighted in this review paper. This scheme can also be utilized in modulation classifier for non-ideal atmosphere. On the other hand, it becomes quite convoluted when a specific probabilistic process is implied according to the suggestion of researchers [31]. Additionally, Fuzzy 'if-then' rules already have been applied in different image processing applications [32]. In recent days, researchers estimated the performance of a fusion system using Artificial Neural Network (ANN), Gaussian Mixture Model and Fuzzy Rule-base Classifier to make the detection of H1N1 possible [33]. Fuzzy rule-based classification coordination has been executed in case of pattern classification concern. Due to this case, the learning procedure based on error correction and additional learning procedure is obligatory [34]. In order to execute pattern recognition, a small number of schemes have been employed by researchers over years. For instance, Type-2 Fuzzy sets were used for the pattern recognition procedure [35]. Subsequently, Genetic Fuzzy and Neuro-fuzzy classifier were comprehensively investigated and implemented for credit scoring. The Genetic Fuzzy classifier has given a better accuracy in this case [36].

Furthermore, fuzzy classified data and fuzzy classifier were implemented in medical proteomics which is an elementary apparatus for learning the peptide and protein level in medicine and health care [37]. Fuzzy rules have also been implemented in high-resolution multispectral satellite images which are needed to classify urban and suburban regions [38].

III. FUZZY CLASSIFIER FOR ECG ARRHYTHMIAS DETECTION

The fuzzy method is very effectual for clinical analysis. Indeed there are several methods on the basis of fuzzy logic and the combination of fuzzy logic with other logics. Fuzzy classifier implements fuzzy logic or sets in order to classify training data.

A. Simple Fuzzy Classifier

There are basically two foremost function blocks in this classifier. The first one is ECG parameterizer and the next one is Fuzzy Classifier. ECG Parameterizer is comprised of initialization, pre-processing, fuzzification and defuzzification. After these processes, data is sent to the fuzzy classifier for classification purpose where the fuzzy logic and if-then rule is applied [1]:

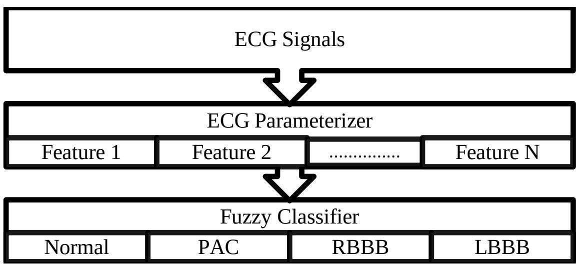

Figure 4 Structure of Fuzzy Classifier [40]

For the classification of ECG arrhythmias using the fuzzy classifier, some ECG patterns and linguistic variables are required, which are tabulated below.

TABLE I. ECG PATTERNS AND LINGUISTIC VARIABLES [40]

ECG features	Medical linguistic variables
Prior-Heart Rate (RR0)	{Short; Normal; Long}
Post-Heart Rate (RR1)	{Short; Normal; Long}
P Wave	{Early; Normal; Disappear}
QRS Complex	{Upward; Downward}
R Wave Amplitude	{High; Normal; Low}
T Wave	{Upward; Downward; Disappear}

It is already mentioned that whole classification begins with the initialization step, where ECG data is read from the database which has already been used. ECG features are revealed in the pre-processing step. Then the crisp values are altered into linguistic or fuzzy variables and after that membership functions are designed in the fuzzification step. The output comes as fuzzy value. Afterward, fuzzy values are defuzzified in order to receive crisp values as output in the defuzzification step [1].

TABLE II. DEFINITION OF THE MEMBERSHIP FUNCTION FOR NORMAL BEAT [40]

Characteristic	Feature	Function Type	Parameter (a)	Parameter (b)
P up-ward	P peak value	S	0.10 mV	0.15 mV
QRS up-ward	R peak Value	S	0.70 mV	0.80 mV
T up-ward	T peak Value	S	0.10 mV	0.15 mV
RR0	Prior-HR	Gaussian	80 bpm	20 bpm
RR1	Post-HR	Gaussian	80 bpm	20 bpm

The tabulated characterization is only relevant to the normal beat. After the completion of the fuzzification step, the incoming aspects are expressed by a membership value [0, 1]. The inference method uses if-then rule. For instance:

IF ("Feature 1" is "Linguistic Variable 1") AND
("Feature 2" is "Linguistic Variable 2") AND
…
("Feature N" is "Linguistic Variable N")
THEN (Name of the Class)

Now, in the case of LBBB, the statements are-
The direction of T wave and the QRS complex is opposite to each other.
Prior Heart Rate RR0 is small.
P wave is disappeared.

So, the LBBB classification can be described as

IF ("T wave is upward") AND
("QRS wave is downward") AND
("P wave is disappeared") AND
("RR0 is small")
THEN (Left Bundle Branch Block)

In this rule, the linguistic values are upward, downward, disappeared and small. The product of the membership grades [0, 1] is considered as the hypothesis. If the product goes beyond the limit, then the beat is considered as LBBB.

B. Adaptive Fuzzy Classifier

Investigations have revealed that an adaptive fuzzy ECG classifier can be used for superior accuracy. This system is in a need of a learning stage in order to optimize the system parameters like threshold values and membership boundaries. The margin values in the membership function are fixed roughly during the learning stage. A predefined rule set is used to categorize a precise beat appropriately. The margin values in the membership function are customized using the noteworthy values of these pre-classified beats. For each record, pre-classification, and self-adaptation take the first 10 minutes in the learning and testing purpose in total time of 30 minutes. The rest 20 minutes is allocated in order to test the updated AFC-ECG [39].

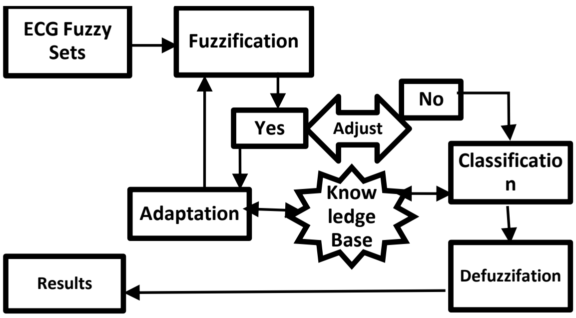

Figure 5 Adaptive Fuzzy ECG Classifier [39]

This process showed excellent performance for classifying ECG signals.

TABLE III. PERFORMANCE COMPARISON OF FUZZY CLASSIFIER AND ADAPTIVE FUZZY ECG CLASSIFIER [39]

Record	MIT-BIH Annotation		Fuzzy Classifier		Adaptive Fuzzy Classifier	
			Result	*Accuracy*	*Result*	*Accuracy*
Sig 106	*Normal*	1507	1208	80.2%	1258	83.5%
	PAC	0	7	-	1	-
	RBBB	0	30	-	27	-
	LBBB	0	0	-	1	-
	Unclassified	0	262	-	220	-

The accuracy of adaptive fuzzy ECG classifier is approximately 88.2% on an average [39], which is about 77.0% in case of usual fuzzy ECG classifier [40].

C. Fuzzy C-means Clustering method (FCM)

Data clustering is used to locate the similarities in data and puts similar data into analogous groups. FCM is a method which deals with data clustering algorithm. In this process, each data point belongs to a cluster to a degree which is specified by a membership grade. The FCM algorithm has four steps. In the beginning, the membership matrix is originated with arbitrary values between 0 and 1. Then c-fuzzy cluster centers are determined and then cost function is computed. The computation should be stopped if it is lower than a certain tolerance value. Also, if its enhancement over the preceding iteration is lower than a certain threshold, then the computation should be brought to an end. In this manner, a new membership matrix is required to be computed and ultimately c-fuzzy cluster centers are calculated once more [41].

TABLE IV. RESULT OF FUZZY CLASSIFIER BASED ON THE FCM CLUSTERING [41]

Type	Sensitivity	Positive Prediction	Accuracy
Normal	99.66%	96.76%	97.41%
LBBB	96.33%	98.29%	
RBBB	98.66%	95.79%	
PB	95.00%	98.95%	

This proposed technique demonstrated an accuracy of 97.41%, which can be considered as an outstanding performance for ECG arrhythmia classification.

R. R. Gharieb, M. Massoud, S. Nady, and M. Moness have established a novel scheme for ECG categorization by adopting linear discriminate analysis (LDA) and minimum distance (MD) in a projected feature space [42]. Continuous wavelet transform of the ECG signal has been applied for the purpose of feature extraction that was followed by Teager-Kiaser Energy (TKE) operator. TKEs were picked appreciably. They were changed to [0, 1] range and were exploited as a feature vector. FCM clustering algorithm was used with the purpose of producing the samples of different categories in the feature space. This method has endowed with 100% accuracy so as to classify PVC and normal beats with MD classifier.

D. Combination of Wavelet Transform and Fuzzy Neural Network for VPC Detection

Another research paper (Shyu et al., 2004) has focused on the combination of Wavelet Transform and Fuzzy Neural Network with the purpose of detecting the ventricular premature contraction (VPC). The information that is used during the detection of QRS duration is reused in this technique as a positive aspect. The QRS duration is taken in scale three and the area under the QRS complex is taken in scale four. These are regarded as the characteristic features. The R wave amplitude also influences the calculation of the characteristic features. The LBBB beats are eradicated here. The accuracy for VPC classification using FNN has been demonstrated to be 99.79% [43].

E. Fuzzy Support Vector Machine

The method FSVM assigns a range of fuzzy membership values which are necessitated to delineate membership functions. For the computation of membership degree, traditional membership functions are employed. The data specific membership functions can also be exploited. In order to allocate the degree of membership, four functions are used which incorporate one class weighing (OCW), Distance to Class Mean (DTCM), Distance to One Class Mean (DTOCM), Cardinality (CAR) and Fuzzy C-Means (FCM). The projected method is applied to the UCI Arrhythmia Database. To facilitate the dimension reduction, four techniques are brought into play which included Principal Component Analysis (PCA), Factor Analysis (FA), Recursive Feature Elimination with Support Vector Machine (RFE-SVM) and Correlation-based Feature Selection (CFS). Researchers have found different accuracies using these membership functions which are tabularized below [44].

TABLE V. ACCURACY COMPARISON [44]

	PCA	FA	RFE-SVM	CFS
MLP	72.86	79.52	79.05	80.48
SVM	78.57	82.62	82.14	81.43
FSVM-DTCM	78.09	80.71	80.48	83.33
FSVM-DTOCM	78.33	80.95	80.71	82.86
FSVM-CAR	77.62	82.14	80.48	81.67
FSVM-FCM	78.33	82.14	81.19	81.90

F. Fuzzy-Genetic Based PCA and ICA

The research paper (Murugan et al, 2010) has highlighted Principal Component Analysis (PCA) and Independent Component Analysis (ICA) techniques for the detection of a different category of arrhythmias. Fuzzy-Genetic based PCA (FGPCA) and Fuzzy-Genetic based ICA (FGICA) are the combination of Fuzzy C-Means (FCM) and Genetic Algorithm (GA) along with PCA and ICA [45]. An accuracy assessment between Fuzzy-Genetic Based PCA and ICA is tabulated in the following:

TABLE VI. COMPARISON OF ACCURACY BETWEEN FUZZY-GENETIC BASED PCA AND ICA [45]

Methods	Accuracy
PCA	86.7%
GPCA	90%
ICA	91%
GICA	93.3%
FGPCA	94.4%
FGICA	94.7%

So, the accuracy of FGPCA is 94.4% and FGICA is 94.7%.

G. Hybrid System by Fuzzy KNN, Multi-layer Perceptron

Another research paper (Ramírez et al., 2010) has recommended an innovative technique where Multi-Layer Perceptron with Gradient Descent, fuzzy K-nearest neighbor and momentum Backpropagation and Multi-Layer Perceptron with Scaled Conjugate Gradient Backpropagation classifiers have been used. At the outset, outputs of these classifiers are figured and then they are merged with Mamdani type fuzzy inference system which established enhanced accuracy. In this paper researchers classified LBBB, RBBB, PVC and Fusion Paced and Normal arrhythmias using this method [46].

TABLE VII. COMPARISON OF ACCURACY BETWEEN THREE CLASSIFIERS WITH THE HYBRID METHOD OF THEIR COMBINATION [46]

Method	Accuracy
First Classifier	95.33%
Second Classifier	96.67%
Third Classifier	97.33%
Hybrid Classifier	98%

H. Pruned fuzzy K-nearest neighbor classifier

Researchers have developed a simple system namely Pruned Fuzzy K-nearest neighbor which is proficient to classify six types of ECG beats of MIT-BIH Arrhythmia database. The accuracy of this technique is quite analogous as typical FKNN although it lessens the computational complication. The calculation time is found near to the ground compared to FKNN. 11 features have been applied in PFKNN. However, through the use of PCA, these features can be diminished to 6 features. The accuracy of FKNN is found to be 97.63% whereas the accuracy of PFKNN is found to be 97.32% with 11 features and 97.31% with 6 features [47].

I. Adaptive neural fuzzy filter method

Another research paper by Golpayegani et al. [48], 2009 has pioneered an Adaptive Neural Fuzzy Filter (ANFF) method for early diagnosis of ECG arrhythmia. ANFF can learn itself according to numerical training data or through proficient knowledge which is extended by the fuzzy if-then rules. This procedure is configured in five layers. Layer-1 nodes are input nodes which represent input variables. Layer-2 and layer-4 nodes are term nodes which act as the membership functions and represent the terms of respective input and output variables.

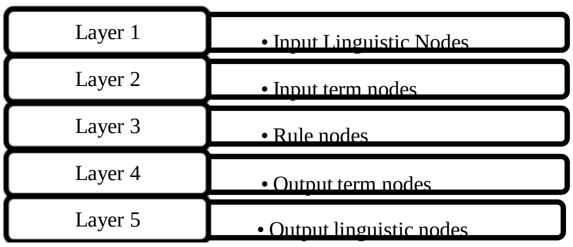

Figure 6 Structure of Adaptive Neural Fuzzy Filter (ANFF) [48].

The layer-3 node is a rule node which specifies the fuzzy logic rule. The linkage between layer-3 and layer-4 function proceed as a connectionist inference engine. Layer-5 nodes act as output nodes which characterize the output variables. In accordance with the research paper, the structure learning step is comprised of three learning processes which include input fuzzy clustering process, output fuzzy clustering process and mapping process [48]. The accuracy of this process has been revealed to be about 97.6%. This method can be considered satisfactorily for classifying ECG beat.

J. Adaptive Neuro-Fuzzy Inference System

Adaptive Neuro-Fuzzy Inference System (ANFIS) was developed with a view of classifying Electrocardiogram (ECG) signals. ICA has been implied to extract features. The feature extraction and Power spectrum with the RR interval serve as the input feature vector and is used as input in the ANFIS classifier. Researchers were capable to classify six types of ECG signals such as normal sinus rhythm (NSR), atrial premature contraction (APC), Ventricular Tachycardia (VT), premature ventricular contraction (PVC), Ventricular Fibrillation (VF) and Supraventricular Tachycardia (SVT) implementing this method. It is indeed the combination of Neural Network Adaptive Capabilities and the Fuzzy Inference System has provided an accuracy of more than 97% [49] and 96% [50].

K. Combination of fuzzy c-means clustering (FCMC) algorithm and neural networks

Another research work introduced FCMCNN which is the combination of fuzzy c-means clustering (FCMC) algorithm and neural networks (NN).

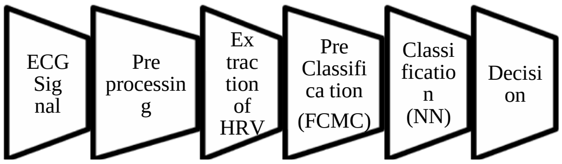

Figure 7 Block diagram of FCMCNN [51]

This combined technique showed the correct classification rate as 99.99% [51].

L. Multi-class MLP ECG classifier using FCM

MLP system has an intrinsic formation. This system is time-consuming and bulky. Researchers have shown the progress of MLP system due to the proficient use of FCM. According to the research findings, the total system proved to be faster and more efficient [52].

M. Type-2 fuzzy clustering neural network

Type-2 fuzzy c-means clustering is applied in order to enhance the performance of neural network. Different types of arrhythmias for instance normal sinus rhythm (N), ventricular tachycardia (VT), sinus arrhythmia (SA), sinus bradycardia (Br), atrial pre-mature contraction (APC), atrial fibrillation (A.Fib), atrial flutter (A.Fl.), paced beat (P), right bundle branch block (RBBB) and left bundle branch block (LBBB) are considered for this technique [53].

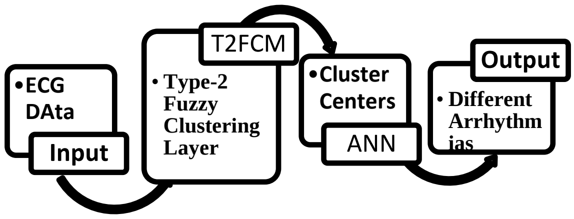

Figure 8 Optimum T2FCNN architecture [53].

The precision of this method is 99.99%. So, this technique is more efficient than other methods [53].

N. Fuzzy Gaussian Neural Network (FGNN)

Some research works have shown FGNN as another technique for heart disease diagnosis. The main stages of this technique include Feature extraction from the QRST zone of ECG signals and Pattern classification for IHD diagnosis using the FGNN. This process has four layer structures. They are layer 1, layer 2, layer 3 and layer 4 [54].

O. Fuzzy Logic Classification (FLCL)method for VT, OVF and DVF detection

In order to classify ECG arrhythmias into ventricular tachycardia (VT), organized ventricular fibrillation (OVF) and disorganized ventricular fibrillation (DVF), FLCL method has been proved as a proficient method [55]. This technique aims to combine ten ECG detectors which have been calculated in both time and frequency domain. With a two-leveled classification, VT has been detected at first with 92.6% accuracy. The inequity between DVF and OVF was perceived with 84.5% accuracy [55].

P. Hybrid model of Wavelet Packet tree and Neuro Fuzzy Network

The research paper [56] has proposed a hybrid model of ANN and Neuro-fuzzy network. This hybrid method has used an algorithm on the basis of wavelet packet tree (WPT) classifier in order to detect QRS complex. By using WPT technique, a set of linear (frequency and time domain) characteristic features have been taken out. A set of non-linear characteristics from the real-time ECG signal have been extracted by exploiting Neuro-fuzzy technique. The hybrid network presents a superior and highly trustworthy error minimization as the result compared with the ANN process.

IV. RESULT COMPARISON OF DIFFERENT METHODS USING FUZZY LOGIC

In this review paper, different methods, their methodologies, and outcomes are compared and analyzed. Some of the methods are very efficient for classifying ECG data. The comparison between the percentages of the accuracy of the methods discussed above is given below in a tabular form.

TABLE VIII. COMPARISON OF ACCURACY BETWEEN DIFFERENT FUZZY LOGIC METHODS

Method	Reference	Accuracy
Simple Fuzzy Classifier	[40]	77%

Adaptive Fuzzy ECG Classifier	[39]	88.2%
Fuzzy c-means clustering method	[41]	97.41%
Fuzzy Genetic based PCA method	[45]	94.4%
Fuzzy Genetic based ICA method	[45]	94.7%
Hybrid Fuzzy KNN, Multi Layer Perceptron	[46]	98%
Standard FKNN	[47]	97.63%
PFKNN (With 11 Features)	[47]	97.32%
PFKNN (With 6 Features)	[47]	97.31%
Adaptive Neural Fuzzy Filter	[48]	97.6%
Adaptive Neuro-Fuzzy Inference System	[49]	More than 97%,
	[50]	More than 96%
FCMCNN	[51]	99.99%
T2FCM	[53]	99.99%
FLCL	[55]	92.6%

ACKNOWLEDGMENT

For the accomplishment of this review paper, we would like to acknowledge the efforts of Rumana Tasnim, the respected faculty member of 'World University of Bangladesh' with appreciation whose support in reviewing the quality of the paper was very significant.

CONCLUSION

This paper has aimed to focus on the succeeding development and historical advancement review on different methods based on fuzzy logic and their accuracy in classifying ECG arrhythmias. Also, efficiency and accuracy evaluation, as well as theoretical basics of these techniques, has been presented in this paper. Many methods have not been combined with fuzzy logic whereas the combination of them with fuzzy logic have been proposed and implemented by researchers as well. Research findings agree that the intelligibly combined fuzzy logic with other methods performed significantly better than the uncombined techniques for classifying ECG arrhythmias. It can be projected that the crucial review and thorough investigation will extend the research scope to an advanced level.

REFERENCE

[1] Channappa Bhyri, Satish T. Hamde, Laxman M. Waghmare, "ECG Acquisition and Analysis System for Diagnosis of Heart Diseases", Sensors & Transducers Journal, Vol. 133, Issue 10, October 2011, pp. 18-29.

[2] B. Anuradha and V.C. Veera Reddy, "Cardiac arrhythmia classification using fuzzy classifiers", Journal of Theoretical and Applied Information Technology, 2008, pp. 353-359.

[3] Introductory Guide to Identifying ECG Irregularities, DailyCareBioMedical Inc.

[4] Miad Faezipour, Adnan Saeed, Suma Chandrika Bulusu, Mehrdad Nourani, Hlaing Minn & Lakshman Tamil, "A Patient-Adaptive Profiling Scheme for ECG Beat Classification," IEEE Transactions On Information Technology In Biomedicine, Vol. 14, No. 5, September 2010, pp. 1153-1165.

[5] Ludmila I. Kuncheva (2008), Scholarpedia, 3(1):2925.

[6] Ryan J. Urbanowicz and Jason H. Moore, "Learning Classifier Systems: A Complete Introduction, Review, and Roadmap", Journal of Artificial Evolution and Applications, Volume 2009, Article ID 736398, 25 pages.

[7] Rahime Ceylan, Yüksel Özbay, "Wavelet Neural Network for Classification of Bundle Branch Blocks", Proceedings of the World Congress on Engineering 2011, Vol. II, WCE 2011, London, U.K., July 6 - 8, 2011, pp. 1003-1007.

[8] R. Acharya, J. S. Suri, J. A. E. Spaan and S. M. Krishnan, "Advances in Cardiac Signal Processing", ISBN-13 978-3-540-36674-4, Springer Berlin Heidelberg New York, 2007, pp. 327-338.

[9] M. Owis, A. Abou-Zied, A. B. Youssef and Y. Kadah, "Robust feature extraction from ECG signals based on nonlinear dynamical modeling", 23rd Annual International Conference IEEE Engineering in Medicine and Biology Society, Vol. 2, 2001, pp. 1585-1588.

[10] O. T. Inan, L. Giovangrandi and G. T. A. Kovacs, "Robust neural network- based classification of premature ventricular contractions using wavelet transform and timing interval features", IEEE Transaction on Biomedical Engineering, Vol. 53, No. 12, 2006, pp. 2507-2515.

[11] A. R. Naghsh-Nilchi and A. R. K. Mohammadi, "Cardiac Arrhythmias Classification Method Based on MUSIC, Morphological Descriptors, and Neural Network", EURASIP Journal on Advances in Signal Processing, Vol. 2008, Article no. 202, 2008.

[12] T. Ince, S. Kiranyaz and M. Gabbouj, "A Generic and Robust System for Automated Patient-specific Classification of Electrocardiogram Signals", IEEE Transactions on Biomedical Engineering, Vol. 56, No. 5, May 2009, pp- 1415-1426

[13] S. S. Mehta and N. S. Lingayat, "Support Vector Machine for Cardiac Beat Detection in Single Lead Electrocardiogram", IAENG, International Journal of Applied Mathematics, 2007, pp. 1630-1635.

[14] Jalal A. Nasiri, Mahmoud Naghibzadeh, H. Sadoghi Yazdi, Bahram Naghibzadeh, "ECG Arrhythmia Classification with Support Vector Machines and Genetic Algorithm", Third UKSim European Symposium on Computer Modeling and Simulation, 2009, pp. 187-192.

[15] Narendra Kohli, Nishchal K. Verma, Abhishek Roy, "SVM Based Methods for Arrhythmia Classification in ECG" International Conference on Computer & Communication Technology, 2010, pp. 486-490.

[16] MiHye Song, Jeon Lee, Sung Pil Cho, KyoungJoung Lee, and Sun Kook Yoo, "Support Vector Machine Based Arrhythmia Classification Using Reduced Features", International Journal of Control, Automation, and Systems, vol. 3, no. 4, December 2005, pp. 571-579.

[17] B. M. Z. Asl and S. K. Setarehdan, "Neural Network Based Arrhythmia Classification Using Heart Rate Variability Signal", Proceedings of the 2nd International Symposium on Biomedical Engineering, Bangkok, Thailand, November 2006, pp.149-162.

[18] B. Anuradha and V. C. V. Reddy, "ANN for classification of cardiac arrhythmias", ARPN Journal of Engineering and Applied Sciences, Vol. 3, No. 3, June 2008.

[19] R. P. W. Duin and M. Loog, "Linear dimensionality reduction via a heteroscedastic extension of lda: the chernoff criterion", IEEE Trans. PAMI, vol. 26, no. 6, June 2004, pp. 732–739.

[20] M. Lagerholm, C. Peterson, G. Braccini, L. Edenbrandt and L. Sörnmo, "Clustering ECG Complexes Using Hermite Functions and Selforganizing Maps", IEEE Transaction on Biomedical Engineering, vol. 47, no. 7, July 2000, pp. 838-848.

[21] Martin Lagerholm, Carsten Peterson, Guido Braccini, Lars Edenbrandt, and Leif Sörnmo, "Clustering ECG Complexes Using Hermite Functions and Self-Organizing Maps", IEEE Transactions On Biomedical Engineering, Vol. 47, NO. 7, JULY 2000, pp. 838-848.

[22] P. de Chazal, M. O'Dwyer and R. B. Reilly, "Automatic Classification of Heartbeats Using ECG Morphology and Heartbeat Interval Features", IEEE Transaction on Biomedical Engineering, Vol. 51, No. 7, July2004, pp. 1196- 1206.

[23] Iva Bogdanova, Francisco Rinc´onand David Atienza, "A Multi-lead ECG Classification Based On Random Projection Features", IEEE, ICASSP 2012, pp. 625-628.

[24] D. Benitez, P. A. Gaydecki, A. Zaidib and A. P. Fitzpatrick, ‘The use of the Hilbert transform in ECG signal analysis’, Computers in Biology and Medicine, 2001, 31, pp. 399-406.

[25] J.C. Nunes, and A. Nait-Ali, ‘Hilbert transform-based ECG modeling’. Biomedical Engineering, 2005, Vol.39, No. 3, pp. 133-137.

[26] S. Karpagachelvi, Dr. M. Arthanari, M. Sivakumar, “Classification of ECG Signals Using Extreme Learning Machine”, Computer and Information Science Vol. 4, No. 1, January 2011, pp. 42-52.

[27] V. Mahesh, A. Kandaswamy, C. Vimal, B. Sathish, “ECG arrhythmia classification based on logistic model tree”, J. Biomedical Science and Engineering 2, 2009, pp. 405-411.

[28] Roshan Joy Martis, Chandan Chakraborty, Ajoy K. Ray, “A two-stage mechanism for registration and classification of ECG using Gaussian mixture model”, Pattern Recognition 42, 2009, pp. 2979 – 2988.

[29] Saniya Siraj Godil, Muhammad Shahzad Shamim, Syed Ather Enam, Uvais Qidwai, “Fuzzy logic: A ‘simple’ solution for complexities in neurosciences?” Surgical Neurology International 2011, Vol-2, Issue-1, page 24.

[30] Raj Kumar Bansal, Ashok Kumar Goel, Manoj Kumar Sharma, “MATLAB and Its Application in Engineering”, Pearson Publication, Fifth Impression, 2012.

[31] Wen Wei and Jerry M. Mendel, “A Fuzzy Logic Method for Modulation Classification in Nonideal Environments”, IEEE Transactions on Fuzzy Systems, Vol. 7, No. 3, June 1999, pp. 333-344.

[32] Tomoharu Nakashima, Gerald Schaefer, Yasuyuki Yokota, Hisao Ishibuchi, “A weighted fuzzy classifier and its application to image processing tasks”, Fuzzy Sets and Systems 158, 2007, pp. 284 – 294.

[33] Reza Boostani, MojtabaRismanchib,Abbas Khosravani, Lida Rashidi, Samaneh Kouchaki, Payam Peymani, Seyed Taghi Heydari, B. Sabayan, K. B. Lankarani, “Presenting a hybrid method in order to predict the2009 pandemic influenza A (H1N1)”, Advanced Computing: An International Journal (ACIJ), Vol.3, No.1, January 2012, pp. 31-43.

[34] Ken Nozaki, Hisao Ishibuchi and Hideo Tanaka, “Adaptive Fuzzy Rule-Based Classification Systems”, IEEE Transactions on Fuzzy Systems, Vol. 4, No. 3, 1996, pp. 238-250.

[35] Jia Zeng and Zhi-Qiang Liu, “Type-2 Fuzzy Sets for Pattern Recognition: The State-of-the-Art”, Journal of Uncertain Systems, Vol.1, No.3, 2007, pp.163-177.

[36] F. Hoffmann, B. Baesens, J. Martens, F. Put and J. Vanthienen, "Comparing a genetic fuzzy and a Neuro-fuzzy classifier for credit scoring", presented at Int. J. Intell. Syst., 2002, pp.1067-1083.

[37] F. M. Schleif, T. Villmann, B. Hammer, “Prototype based Fuzzy Classification in Clinical Proteomics”, *International Journal of Approximate Reasoning*, 2008, 47(1), pp. 4-16.

[38] Aaron K. Shackelfordand Curt H. Davis, “A Hierarchical Fuzzy Classification Approach for High-Resolution Multispectral Data Over Urban Areas”, IEEE Transactions onGeo-science And Remote Sensing, Vol. 41, No. 9, SEPTEMBER 2003, pp. 1920-1932.

[39] Wai Kei Lei, Bing Nan LI, Ming Chui Dong, Mang I. Vai, “AFC-ECG: An Intelligent Fuzzy ECG Classifier”, A. Saad et al. (Eds.): Soft Computing in Industrial Applications, ASC 39, 2007, pp. 189–199.

[40] Yun-Chi Yeh, Wen-June Wang, and Che Wun Chiou, “Heartbeat Case Determination Using Fuzzy Logic Method on ECG Signals”, International Journal of Fuzzy Systems, Vol. 11, No. 4, December 2009, pp. 250-261.

[41] Mohammad Reza Homaeinezhad , Ehsan Tavakkoli, Ali Ghaffari, “Discrete Wavelet-based Fuzzy Network Architecture for ECG Rhythm-Type Recognition: Feature Extraction and Clustering-Oriented Tuning of Fuzzy Inference System”, International Journal of Signal Processing, Image Processing and Pattern Recognition Vol. 4, No. 3, September, 2011, pp. 107-130.

[42] R. R. Gharieb, M. Massoud, S. Nady, M. Moness, “Fuzzy C-Means in Features Space of Teager-Kaiser Energy of Continuous Wavelet Coefficients for Detection of PVC Beats in ECG”, 8th Cairo International Biomedical Engineering Conference (CIBEC) (IEEE Conferences), 2016, pp. 72-75.

[43] Liang-Yu Shyu, Ying-Hsuan Wu, Weichih Hu, “Using Wavelet Transform and Fuzzy Neural Network for VPC Detection From the Holter ECG”, IEEE Transactions on Biomedical Engineering, Vol. 51, No. 7, July 2004, pp. 1269-1273.

[44] N. Özlem Özcan, Fikret Gurgen, “Fuzzy Support Vector Machines for ECG Arrhythmia Detection”, International Conference on Pattern Recognition, 2010, pp. 2973-2976.

[45] S. Murugan & Dr. S. Radhakrishnan, “Improving Ischemic Beat Classification Using Fuzzy-Genetic Based PCA and ICA”, International Journal on Computer Science and Engineering (IJCSE), Vol. 02, No. 05, 2010, pp. 1532-1538.

[46] Eduardo Ramírez, Oscar Castillo, and José Soria, “Hybrid System for Cardiac Arrhythmia Classification with Fuzzy K-Nearest Neighbors and Neural Networks Combined by a Fuzzy Inference System”, P. Melin et al. (Eds.): Soft Comp. for Recogn. Based on Biometrics, SCI 312, 2010, pp. 37–55.

[47] Muhammad Arif, Muhammad Usman Akram, Fayyaz-ul-Afsar Amir Minhas, “Pruned fuzzy K-nearest neighbor classifier for beat classification”, J. Biomedical Science and Engineering, 2010, 3, pp-380-389.

[48] Glayol Nazari Golpayegani & Amir Homayoun Jafari, “A novel approach in ECG beat recognition using adaptive neural fuzzy filter”, J. Biomedical Science and Engineering, 2009, 2, pp. 80-85.

[49] T.M. Nazmy, H. El-Messiry, B. Al-Bokhity, “Adaptive Neuro-Fuzzy Inference System for classification of ECG signals”, The 7th International Conference on Informatics and Systems (INFOS), Date of Conference: 28-30, March 2010, pp. 1-6.

[50] Prarthana B. Sakhare, Rajesh Ghongade, “An Approach for ECG Beats Classification using Adaptive Neuro Fuzzy Inference System”, Annual IEEE India Conference (INDICON), 2015, pp. 1-6

[51] A. Dallali, A. Kachouri and M. Samet, “Fuzzy C-Means Clustering, Neural Network, WT and HRV For Classification of Cardiac Arrhythmia”, ARPN Journal of Engineering and Applied Sciences, Vol. 6, No. 10, October 2011, pp. 112-118.

[52] R. B. Ghongade and A. A. Ghatol, “Optimization of a multi-class MLP ECG classifier using FCM”, Indian Journal of Science and Technology Vol. 3, No. 9, Sep 2010, pp. 1102-1105.

[53] Rahime Ceylan, Yuksel Ozbay, Bekir Karlik, “A novel approach for classification of ECG arrhythmias: Type-2 fuzzy clustering neural network”, Expert Systems with Applications, 30 August 2008, pp. 1-6.

[54] Victor-Emil Neagoe, Iuliana-Florentina Iatan and Sorin Grunwald, “A Neuro-Fuzzy Approach to Classification of ECG Signals for Ischemic Heart Disease Diagnosis”, AMIA Annu Symp Proc. 2003; pp. 494–498.

[55] Nong Weixin, “A novel algorithm for ventricular arrhythmia classification using a fuzzy logic approach,” Australian Physical & Engineering Sciences in Medicine, Vol. 39, No. 4, Dec 2016, pp. 903-912.

[56] S. Mahapatra, D. Mohanta, P. Mohanty, S. K. Nayak, and P. K. Behari, “A Neuro-fuzzy Based Model for Analysis of an ECG Signal Using Wavelet Packet Tree,” Procedia Comput. Sci., vol. 92, pp. 175–180, 2016.

Ahmed Farhan was born in Comilla, Bangladesh on 1st December, 1992. He has received his Bachelor degree in Electrical and Electronic Engineering from Islamic University of Technology, Bangladesh on 2013. At present, he is doing his master in Information and Communication Engineering in Harbin Engineering University, China. He has worked as a Lecturer in the Department of Mechatronics Engineering at World University of Bangladesh, Bangladesh for about 3 years. His research interests are Biomedical Engineering, Image Processing.
E-mail:ahmedfarhanzisan77@yahoo.com