



An Effective Internet of Things based Assessment of ANN and ANFIS algorithms for Cardiac Arrhythmia

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Abstract

Reducing the influence of significant noise signal components on the obtained raw ECG signal is essential for precise identification of cardiac arrhythmias (CA), which frequently present as irregularities in heart rate or rhythm. Preprocessing is used to remove noise signals and baseline drift from the ECG wave that is recorded using the internet of things (IoT). After that, the denoised signal is subjected to dimensionality reduction and feature extraction. In order to determine whether classification method is more effective in detecting cardiac arrhythmias, this study compares two methods: an adaptive neuro-fuzzy inference system and artificial feed-forward neural networks trained with the back-propagation learning algorithm. An Adaptive Neuro Fuzzy Inference System analyses ICA features obtained by non-parametric power spectral estimates, and an Artificial Neural Network (ANN) classifier uses the ECG signal's morphological and statistical aspects to identify patterns. The creation of artificial feed-forward neural networks provides a rich framework for studying the Back Propagation Algorithm. Sensitivity, specificity, accuracy, and positive predictiveivity are some of the performance characteristics that are thoroughly examined. An overall accuracy of 97.79%, sensitivity of 99.82%, specificity of 99.68%, and positive predictivity of 98.58% were seen in the results of the Artificial Neural Feed Forward Network (ANFFN). The Adaptive Neuro Fuzzy Inference System (ANFIS) outperforms these metrics with an astounding overall accuracy of 99.62%, specificity of 98.63%, and positive predictivity of 99.46%. With a classification accuracy of 99.82%, ANFIS demonstrates to be the most effective classifier for identifying cardiac arrhythmias.

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1. Introduction

The electrical activity of the heart's coronary arteries is detected by an electrocardiogram (ECG) that is transmitted through the skin. Cardiology diagnosis, monitoring, and prognosis are greatly impacted by it. Depending on the intended use, the ECG signal can be evaluated using either a single- or

multiple-channel approach [1]. In a typical modern clinical ECG, 12 separate leads (channels) are recorded from the patient's skin while they are at rest. Arrhythmia evaluations often involve recording or monitoring just one or two ECG leads in order to look for potentially fatal changes in heart rhythm. The P wave, QRS complex, T wave, and U wave make up the ECG signal tracing of a normal cardiac cycle (heartbeat), with the U wave being obscured by the T wave and the preceding P wave in about 50–75% of ECGs [2]. Baseline of the ECG signal (the linear horizontal segments) is determined by summing the interval between the end of the P wave and the beginning of the next QRS complex (i.e. the PR segment) and the beginning of the T wave. Figure 1 depicts the typical ECG waveform and its defining features [3].

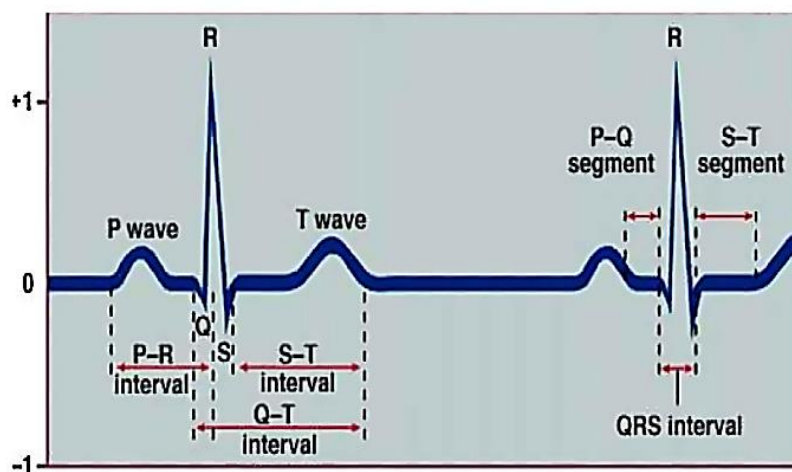


Figure 1: Different ECG signal Segments.

The baseline, signifying the phase of the cardiac cycle where no ionic currents flow toward the negative or positive ends of the ECG leads in a healthy heart, closely resembles the isoelectric line [4]. Conversely, in a diseased heart, damage currents occurring during the TP and PR intervals, when the ventricles are at rest, may alter the baseline. In instances such as cardiac ischemia, the baseline might be lowered, while in myocardial infarction, it could be raised compared to the isoelectric line. During these intervals, as the ventricles are fully depolarized, the ST segment typically maintains proximity to the isoelectric line on an electrocardiogram [5].

Notably, ECG recordings often omit the depiction of the isoelectric line. Consequently, a low baseline may misleadingly suggest ST segment elevation, while a high baseline may create the illusion of ST segment depression [6]. The study of an electrocardiogram rhythm can be performed quickly and painlessly by monitoring. The patient is made to adhere to a small number of leads, and the ECG machine checks each and every heartbeat [7]. Understanding ECG requires familiarity with the signal generated by the leads used to verify the heart's electrical activity. The ECG pattern verifies the signal of each heartbeat. We can tell what kind of cardiac arrhythmias, if any, are occurring by looking for certain characteristics [8]. Due to differences in the P, QRS complex, and T wave parts of the signal, this approach is able to analyze a wide variety of arrhythmias. The breadth and height of the wave are used to determine the degree of difference in the cardiac signal [9].

Diseases affecting the heart and vascular system (the capillaries, arteries, and veins) are often referred to as cardio vascular disease (CVD) or heart disease. About 17 million lives are lost annually due to cardiovascular disease. Heart attacks, faulty heart valves, strokes, and arrhythmia disorders are the leading causes of cardiovascular disease [10]. It is difficult job to categorize ECG features into the various heart disorders. Therefore, it is necessary to determine the ECG's signature outline in order to complete the classification process. ECG and the characteristics of the PQRST wave are used to analyze regular heartbeats by measuring their area, amplitude, and duration [11]. If an ECG monitoring system is unable to reliably detect an ECG irregularity, the patient risks losing the opportunity for therapy.

A single input layer, three hidden layers, and a single output layer are proposed for use in this Artificial Neural Feed Forward Network. There are 12 neurons in the input layer with a tan-sigmoid transfer function; 5, 5, 5, 10, 10, 10, 10 and 20 neurons in the hidden layer, each with a different transfer function [12]. This neural network system performs QRS detection, preprocessing, dimensionality

reduction using principal component analysis (PCA), feature extraction using independent component analysis (ICA) that is constructed using principal component analysis sensitivity analysis (PSD estimation), and finally feeds the extracted features into a neural classifier [13].

The subsequent sections of this paper are organized as follows: Part 2 provides a concise overview of the related work, while Section 3 discussed the research question, section 4 and section 5 discussed the motivation and objectives of the research work. Section 6 delves into the methodology and theoretical underpinnings of the employed methods. Section 7 is dedicated to presenting the simulation results and conducting a thorough analysis. The concluding segment of this research paper, titled "Key Findings," succinctly summarizes the paramount results garnered from the study in the section 8.

2. Related Work

In the context of signal denoising, certain novel approaches based on global and local transforms have recently gained traction. First, the signal is transformed into a domain where filtering can be performed. An inverse transform is then used to get the original, noise-free signal [14].

By properly tailoring the basic functions used for decorrelation and the transform domain filters created to fit the morphology of the ECG signal, these methods have the potential to be highly effective tools for ECG signal denoising. Preprocessing methods such as filtering and wavelet transform decomposition can be used to clean up an ECG signal that has been contaminated by noise [15].

Many different ECG analysis methods make use of signal preprocessing techniques that involve various forms of filtering. Filtering the ECG is situational and should be done only if there is still uncertainty about the data. Several studies have focused on decreasing background noise in the ECG reading [16]. Band pass filters have the potential to eliminate most sources of interference with ECG readings; nevertheless, their lack of optimal performance is discouraging. But the nature of the disturbances in the ECG data will determine the filtering technique used. Real-time heart monitoring systems have filtering as a key design feature [17].

The 50Hz frequency of standard electrical power lines is a substantial contributor to noise in ECG readings. Extra genus low-frequency activity in the ECG known as baseline wander (BW) can muddy the signal and throw off clinical interpretation. The ST-T segment of the electrocardiogram is evaluated relative to the isoelectric line [18]. Because of the presence of BW, the isoelectric line is not as clearly defined, rendering ST analysis unreliable. Noise from sweat, breathing, bodily movement, or faulty electrode contact are all potential causes of BW [19].

As a rule, its spectral content is lower than 1Hz, but during particularly severe exercise, it may include frequencies above that range. The most common methods for removing BW are linear filtering and polynomial fitting. To protect the ECG's clinical significance while simultaneously removing as much BW as feasible, linear filtering necessitates the development of an LTI high pass filter with cut off. The lowest frequency component in the ECG is 0.67Hz, which is based on the lowest heart rate, which is roughly 40 beats per minute during bradycardia [20]. As a result, we have settled on a cutoff frequency of roughly 0.5 Hz. However, the ringing effect (Gibbs phenomenon) in the ECG that results from applying a high pass filter for BW removal complicates ST interpretation [21].

Neuro-Fuzzy methods for the recognition and classification of cardiac rhythms from an electrocardiogram (ECG) waveform concept have been the subject of substantial research. The innovative approach to heart-beat detection is used. If you're having problems classifying ECG signals based on their morphology, this project is the answer [22]. It combines the methods of recognizing and classifying ECG patterns using a modified neuro-fuzzy TSK network, as well as characterizing the QRS complex of an ECG using Hermite polynomials and employing the coefficients of Hermite kernel enlargement due to the presence of features in the system [23].

Combining the strengths of neural networks with those of fuzzy set theory yields "Neuro-Fuzzy" approaches that are well-suited to dealing with a wide variety of data types, resolving conflicts through teamwork and information sharing, learning on their own, organizing and tuning themselves with little in the way of prior knowledge, emulating human decision-making processes, computing quickly through the use of fuzzy-number operations, and so on [24-26].

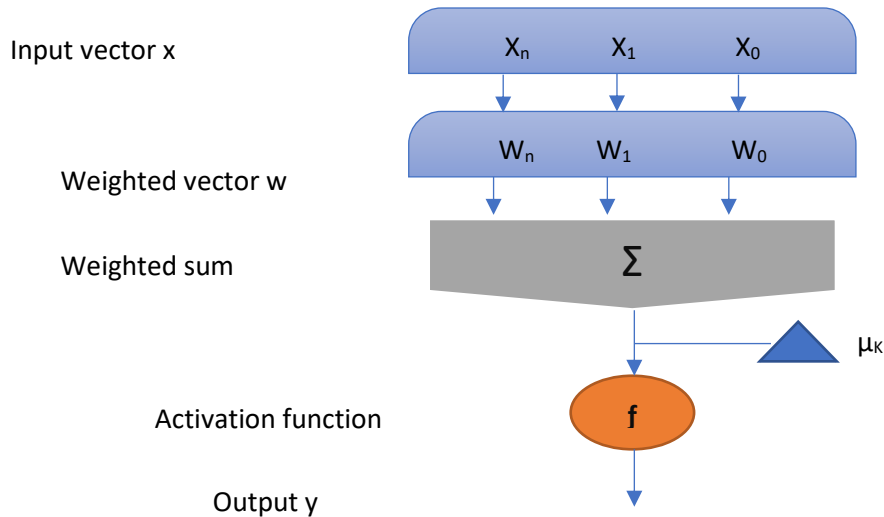


Figure 2: Neuron Construction.

Researchers for the detection of cardiac arrhythmias within ECG alarms have proposed a system based on a Bayesian ANN (ANN) classifier [27]. It is compared to other classifiers like Naive Bayes, selection trees, logistic regression, and RBF networks to determine how well it does in this endeavor. To select the optimal classifier, a paired t-test is used for comparison [28]. The machine is tested in an international setting that is modeled after noisy ECG statistics.

In order to extract the QRS complex using the spatial velocity method, the authors offer windowing strategies. The derived features can then be used to identify heart irregularities [29]. The final step is to apply the decision-making rules based on the ECG wave properties used to diagnose LBBB and RBBB, resulting in a highly optimized result in terms of accuracy [30].

3. The research Questions

- How does the classification accuracy of ANFFN compare to ANFIS in the context of cardiac arrhythmia diagnosis?
- What are the specific strengths of ANFFN and ANFIS in handling diverse patterns of cardiac arrhythmias?

4. The Motivation of the Research Work

The motivation for selecting ANFFN and ANFIS lies in their proven efficacy for cardiac arrhythmia classification. ANFFN's neural network capabilities and ANFIS's adaptive fuzzy inference system offer complementary strengths, enhancing accuracy in diverse arrhythmia patterns.

5. The Objective of the Research Work

- The objective in opting for ANFFN and ANFIS is to leverage their respective strengths in neural network and adaptive fuzzy inference for precise cardiac arrhythmia classification, ensuring robust and accurate diagnostic outcomes.
- Classification of cardiac arrhythmias necessitates the use of ANN, specifically an Artificial Neural Feed Forward Network based on a Back Propagation method, and an Adaptive Neuro Fuzzy Inference System.

6. The Proposed Work

The primary goal of this research paper is to classify cardiac arrhythmias with high accuracy by comparing the performance of Artificial Feed Forward Neural Networks trained with the Back Propagation Learning algorithm and an Adaptive Neuro Fuzzy Inference System. In order to realize classifiers, ANNs have become increasingly popular because of their increased ability to handle nonlinear discriminating across classes and their ability to accept partial input patterns. Although many real-time applications of ANNs are proposed for ECG analysis, a well-organized commercial plan of ANN applications as an ECG analyzer is not possible due to an incomplete, non-systematic,

and parametric comparison with different existing traditional methodologies which are currently implemented in analyzers of ECG signal.

An ANN is a computational model that mimics biological brain networks or human cognitive processes. Moreover, it is modeled as a processor mode of element, with several key performance characteristics that are shared with biological NNs. The following are examples of representations of neural network properties: What we call "architecture" is actually just the arrangement of connections between individual neurons. The training or learning algorithm is the one responsible for assigning values to each link. The activation has been successful at last.

1. *Melody Note Sequence:*

$$M = (m_1, m_2, \dots, m_n) \quad (1)$$

Where, m_i is the i^{th} note in the sequence. Using ANN,

$$P(M) = i = 1nP(m_i m_1, m_2, \dots, m_{i1}) \quad (2)$$

may be used to generate melodies.

2. Using a neural network model, HarmonyRefine enhances musical compositions by enhancing harmony and chord progressions.

3. Chord progression formula is

$$C = (c_1, c_2, \dots, c_j) \quad (3)$$

where c_j is the j^{th} chord in the progression. Harmonic amplification using deep learning:

$$H(C) = j = 1kH(c_j) \quad (4)$$

AudioWaveGAN is a tool that uses GANs to synthesis high-quality audio waveforms.

4. Audio Waveform:

$$A(t) = A_0 \sin(2\pi ft + \phi) \quad (5)$$

Represents an audio waveform, where A_0 is the amplitude, f is the frequency, t is time, and ϕ is the phase.

5. In GAN, the discriminator (D) is subtracted from the generator (G) to calculate the loss function (LD):

$$LD = E[\log D(A(t))]E[\log(1D(G(z)))] \quad (6)$$

6. Power output degradation due to generator use:

$$LG = E[\log(1D(G(z)))] \quad (7)$$

7. Boosting Creative Capacity

$$CE = N_{total}N_{new}100 \quad (8)$$

Where N_{total} is the total number of melodies in the dataset, and N_{new} is the number of freshly created melodies or compositions.

8. Enhancing the Audio's Quality

$$\text{Sound Quality Index (SQI)} = \text{Original Sound Quality Score (Soriginal)} - \text{Enhanced Sound Quality Score (Senhanced)} \times 100 \quad (9)$$

9. Effectiveness of Computation The efficiency of the training process is defined as:

$$CEff = T_{train}N_{gen} \quad (10)$$

Where N_{gen} is the rate at which new melodies are produced. The number of realistically evaluated created melodies, N_{real} , is calculated as follows:

$$R = N_{total}N_{real} * 100 \tag{11}$$

Where N_{real} is the number of freshly created melodies, and N_{total} is the total number of notes in the score.

The use of MelodyNet, HarmonyRefine, and AudioWaveGAN with mathematical modeling will allow us to fully grasp the ways in which neural networks improve music composition and sound quality. Their efficacy and prospective influence on the music business may be measured using the quantitative assessment metrics.

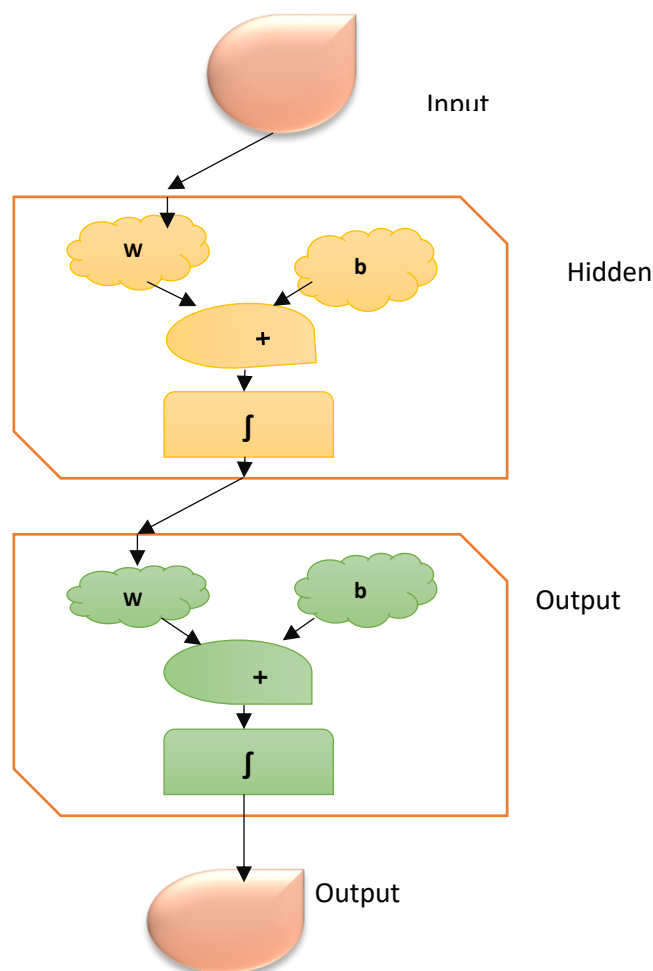


Figure 3: neural network (fitting function) training tool.

A linear neuron output layer is often the next step after a hidden layer(s) of sigmoid neurons in a Feed Forward Neural Network. The network is able to learn non-linear correlations between input and output vectors because of the neuron's multi-layer structure and non-linear transfer characteristics function. Non-linear regression techniques often make use of the linear output layer to solve their problems. If the network output must be limited to values between 0 and 1, the sigmoid transfer function must be used. If the network is being used to solve the pattern recognition problem (with which network the choice is being made), this will be the case. For multilayer networks, the number of layers specifies the superscript on the weight matrix. Prior to training the feed forward network, the weights and biases must be setup. The network could be trained after the bias and weights have been setup.

The ANFIS is modeled as a system in which inputs are mapped using a set of Membership Functions (MFs) and associated parameters, and outputs are mapped using a set of Membership Functions (MFs) and related parameters. The initial design of the rules and membership functions for a fuzzy inference system is based on human knowledge and experience in the area of target system modeling. When describing the input-output behavior of a complex system, fuzzy rules (if-then) and membership functions can be refined using ANFIS. The process of neural network training can be used to generate

a fuzzy set of rules that approximates the desired set of data as its dataset, allowing for the establishment of practical membership functions even in the absence of human expertise.

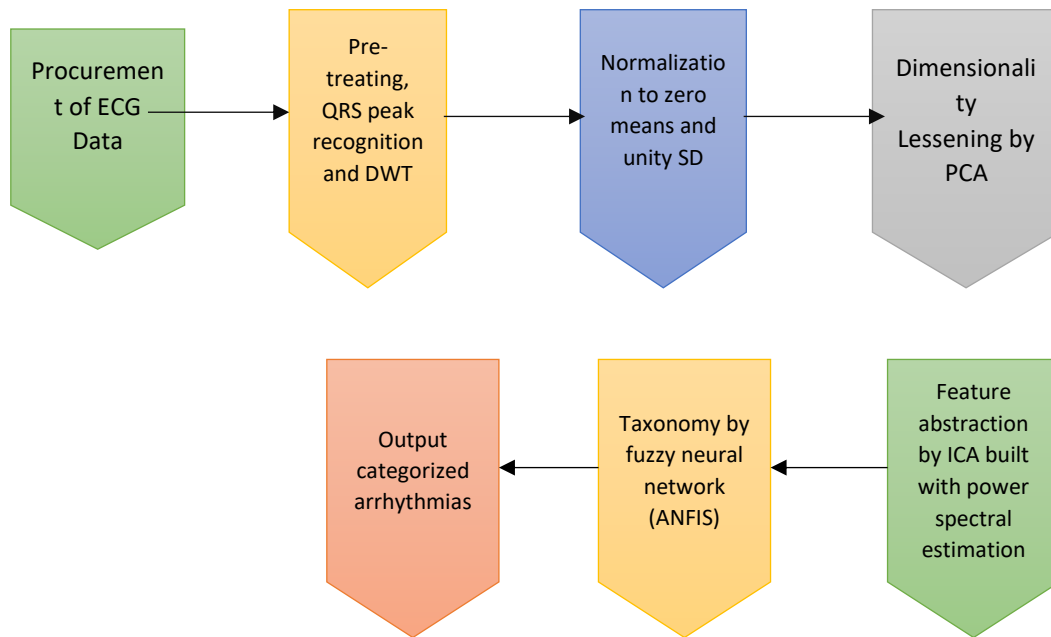


Figure 4: Flow diagrams of the ANFIS classifier

To tune rule-based fuzzy systems, an ANFIS decides how best to use a Fuzzy Inference System (FIS) in conjunction with neural networks. Because of its low computational cost, Sugeno ANFIS has been selected as the preferred method. And it reacts best to mathematical analysis, adaptive methods, linear methods, optimization strategies, and linear methods. The Sugeno ANFIS type has a linear function at the end and a fuzzy proposition at the beginning of the fuzzy rule. Selecting the ECG data records from the MIT-BIH arrhythmia database kicks off the program. During the preliminary phase of classification, ANFIS is used to perform preprocessing, QRS detection, normalization, dimensionality reduction, and feature extraction. Since ANFIS only produces a single output, the process of creating the output feature vector has begun. A unique heart rhythm is being assigned to each index of the output vector. Assigning the value "1" to the Normal Sinus Rhythm (NSR) and "0" to the other 6 types of heart rhythms is an example. A matrix is generated based on the input data's characteristics and linked to the vector of results. For each cardiac rhythm type, the input training data (55%) is being split into three subsets: 10% for checking, 35% for testing. For the purposes of testing and training, random heartbeats were selected from the MIT-BIH arrhythmia database.

6. Result and Discussion

The ANFIS and ANFFN classifier's efficacy is measured by its Sensitivity (Se), Specificity (Sp), Positive Predictivity (Pp), and Accurateness (Ac). The definition of heat beat in terms of TP, FP, TN, and FN is incorporated into all four of these calculations. Let's call the classification of heartbeats TP, for true positive. Let's call the heart rate classification's real negative TN. Let's call the misidentification of a heartbeat the false positive, or FP. Let's call the error in identifying a heartbeat a false negative (FN). Let's call the number of heartbeats being used as training data N. These parameters are defined below.

A. Accurateness

It is a standard method for allocating numerical values to the outcomes of tests. An improved level of accuracy denotes a system that operates more effectively.

$$\text{Accurateness} = \frac{TN+TP}{\text{Total data Sample}} \times 100 \quad (12)$$

B. Specificity

The absence of inappropriate data classification was the defining characteristic of specificity. Another name for it is the True Negative Rate, which is abbreviated as TNR. The recall of the currently employed method is shown in contrast to other ways that are typically used in Figure 5.

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100 \quad (13)$$

C. Sensitivity

The sensitivity of the current technique can be conceptualized as the degree to which the model correctly categorizes the test data inside one of its categories. The question that was attempted to be answered by it was, "How many true positives were successfully detected?" There is also a term for it called True Positive Rate.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \times 100 \quad (14)$$

D. Positive Predictivity

The positive predictivity is defined as

$$\text{Positive Predictivity} = \frac{TP}{TP+FP} \times 100 \quad (15)$$

Table 1: Performance Assessment of ANFFN with ANFIS based on Different Evaluation Parameters.

S. No.	Ten-fold Cross Validation	Sensitivity (%)		Specificity (%)	
		ANFFN	ANFIS	ANFFN	ANFIS
1	2	99.85	98.56	98.58	99.73
2	4	99.79	98.64	98.62	99.78
3	6	99.91	98.72	98.64	99.81
4	8	99.89	98.59	98.65	99.79
5	10	99.95	98.67	98.67	99.85

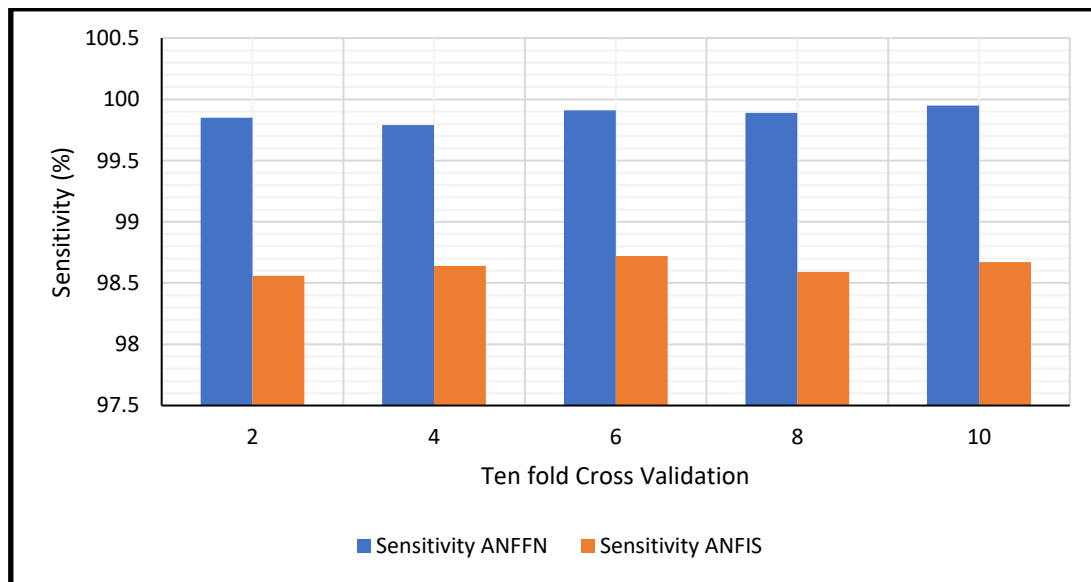


Figure 5: Assessment of ANFFN with ANFIS algorithm based on Sensitivity.

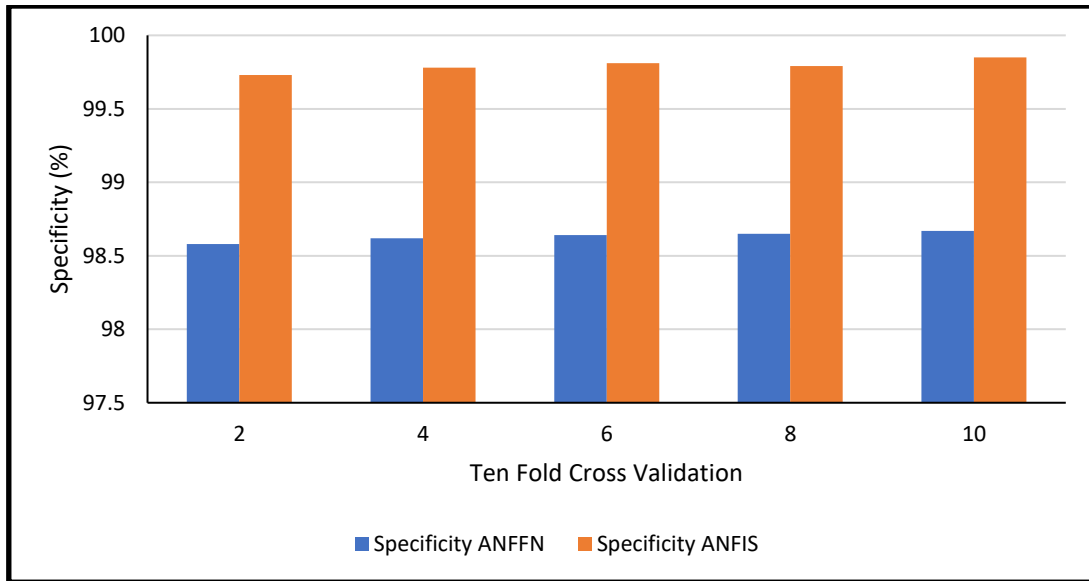


Figure 6: Assessment of ANFFN with ANFIS algorithm based on Specificity.

Sensitivity results for various classifier folds employing independent components are shown in Figure 5. The results suggest that the Feed Forward Neural Network classifier has the highest sensitivity across all 10 folds. The specificity results for the independent component folds are shown in Figure 6. From this, we may conclude that the ANFIS classifier outperforms the ANFFN classifier over all 10 folds thanks to its superior specificity.

Table 2: Performance Assessment of ANFFN with ANFIS based on Different Evaluation Parameters

S. No.	Ten-fold Cross Validation	Accurateness		Positive Predictivity	
		ANFFN	ANFIS	ANFFN	ANFIS
1	2	97.52	99.62	98.25	99.28
2	4	97.58	99.65	98.43	99.36
3	6	97.62	99.71	98.61	99.45
4	8	97.48	99.69	98.72	99.52
5	10	97.61	99.74	98.83	99.67

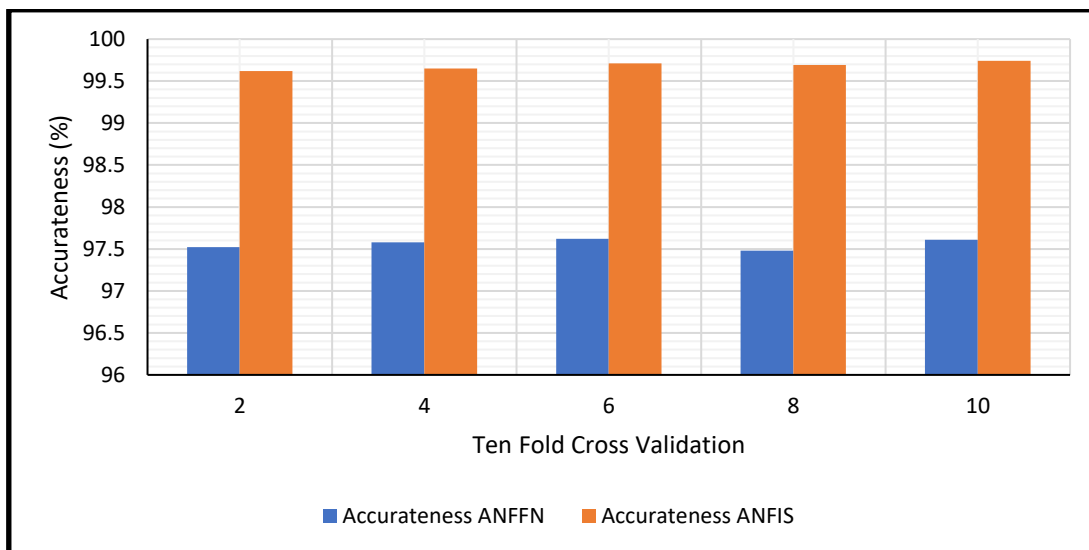


Figure 7: Assessment of ANFFN with ANFIS algorithm based on Accurateness.

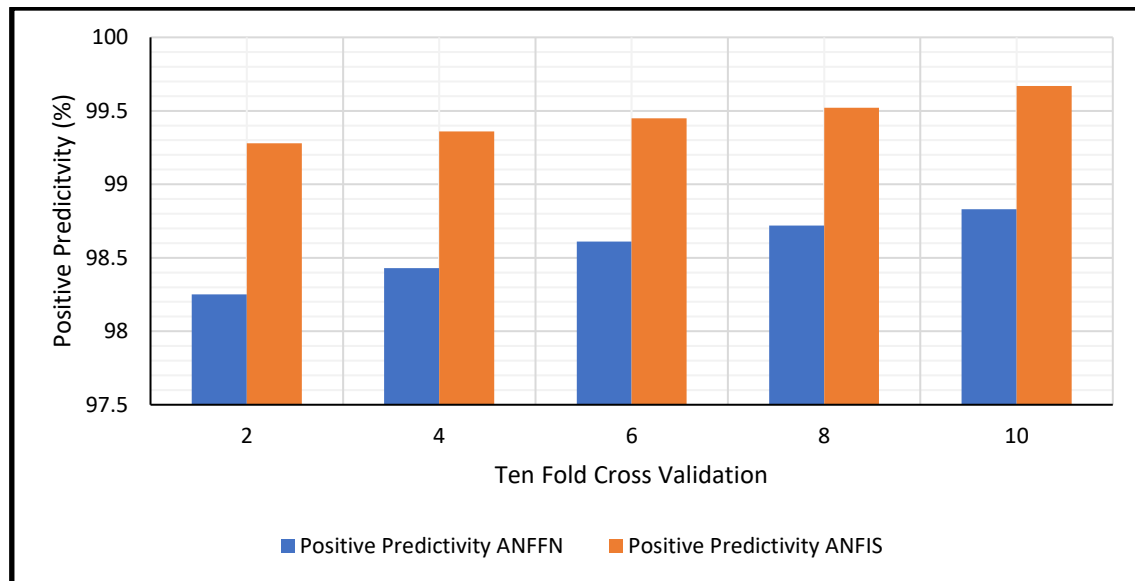


Figure 8: Assessment of ANFFN with ANFIS algorithm based on Positive Predictivity.

The calculation of performance measures for the entire classification process is shown in Figure 6. for compared to ANFFN classifiers, ANFIS is shown to have a far higher average accuracy of 99.63 percent for identifying cardiac arrhythmias. Positive predictivity findings for the independent component folds of several classifiers are shown in Figure 7. It can be deduced that the ANFIS classifier has better performance than the ANFFN classifier over all 10 folds, as measured by positive predictivity. Accuracy in classification was measured using the independent components and the results are shown in Figure 6. It can be deduced that the ANFIS classifier is more accurate than the ANFFN classifier over all 10 folds.

6. Conclusion

This study involves a comparative analysis of two methodologies for cardiac arrhythmia classification: an artificial neural feed-forward network (ANFFN) employing the backpropagation algorithm and an adaptive neuro-fuzzy inference system (ANFIS). Morphological and statistical features of the ECG signal are input into an ANN classifier for pattern recognition, and ANFIS processes ICA features obtained through non-parametric power spectral estimation. The utilization of the Back Propagation Algorithm and ANFIS in the evolution of artificial feed-forward neural networks is explored. Simulation results of ANFIS and ANFFN are examined, incorporating sensitivity, specificity, positive predictive value, and accuracy percentage analyses. ANFFN exhibits a sensitivity of 99.82%, specificity of 99.68%, and positive predictivity of 98.58%, averaging an overall accuracy of 97.79%. In contrast, ANFIS demonstrates a sensitivity of 98.42%, specificity of 98.63%, and positive predictivity of 99.46%, resulting in a remarkable average accuracy of 99.62%. Comparative analysis reveals that ANFIS outperforms ANFFN with the highest classification accuracy of 99.82% in detecting cardiac arrhythmias. This research elucidates the effectiveness of these methodologies, providing insights into their strengths and contributions to enhancing diagnostic precision in cardiac arrhythmia classification.

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Conflicts of Interest:

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