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An Adaptive Neurofuzzy Inference System for Improved Diagnosis of Left Ventricular Hypertrophy

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Abstract— The positive impact of the applications of intelligent systems and softcomputing techniques on modern healthcare systems remains significant. This work therefore highlights the role of intelligent systems as a means of improving healthcare provision by designing, optimizing, training and implementing an Adaptive Neurofuzzy Inference System (ANFIS) for improved diagnosis of Left Ventricular Hypertrophy (LVH). The LVH features and the training dataset for the MATLAB-based classification-type ANFIS were extracted from patients' Electrocardiogram (ECG) sheet. The results from the performance analysis of the proposed system showed that the Graphical User Interface (GUI) developed aids medical personnel in making detection and diagnosis of LVH.

Index Terms— Left Ventricular Hypertrophy, ANFIS, diagnosis, Clinical Decision Support Systems.

1 INTRODUCTION

Healthcare is a very important sector in the world. It constantly receives great attention from international bodies and is usually one of the highest beneficiaries of international aids/grants. Healthcare is however currently facing a lot of challenges which include rising costs, large number of deaths due to medical errors, reduced quality. It has therefore become very important to look for ways to arrest the dual problem of rising cost and dwindling quality. One of such ways is a further integration of computing into the provision of healthcare services. Computing and automated systems have a lot of advantages over human processes [1]. Computers store information better, can compute better and can do a large number of repetitive tasks without suffering from fatigue.

The design, development and deployment of satisfactory computerized medical systems are quite challenging tasks. This is as a result of uncertainty in measurements and general natural occurrences. In most Clinical Decision Support Systems (CDSS) and Electronic Medical Records (EMRs) data processing, modeling and programming, fuzzy logic has been considered as an appropriate tool. This preference is due to the ability of fuzzy based systems to inculcate expert knowledge and experience directly without explicit mathematical equations [2],[3].

Two possible ways in which healthcare can be improved include; Electronic Medical Records (EMR), and Clinical Decision Support Systems (CDSS). EMRs make it possible for any attending physician to be able to download patient's history and be better placed to make informed decisions which will reduce the number of deaths arising from adverse drug-drug interaction. It also eliminates the cumbersome task of paper filing which is the current system in place in most hospitals. CDSS on the other hand employs expert knowledge and help physicians predict a patient's illness based on the symptoms displayed by the patient. Studies have already shown that CDSS have been more accurate in diagnosing patient illness than physicians in various tests.

In this work, a CDSS system for the detection and diagnosis of LVH was developed in form of Adaptive Neurofuzzy Inference System. CDSS systems work well, and they, alongside EMRs should be seriously considered as a means of improving healthcare.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

The Adaptive Neuro-fuzzy Inference System (ANFIS) is an inference system implemented on the framework of an adaptive fuzzy-neural network. ANFIS has been shown in different applications [4]-[10] as a robust and powerful approach for modeling nonlinear relationships between a set of input and output data. It combines the explicit knowledge representation of FIS with the pattern learning and classification power of Artificial Neural Networks (ANNs) [6]. Fuzzy systems have been able to expand the scope of logic and reasoning beyond crisp values of 0s and 1s thereby accounting for values which are not absolute 1s or 0s. Additionally, fuzzy logic also enhances flexibility in design, computation and programming through the use of linguistic variables which are more intelligible to the human brain [11]. Generally, in fuzzy logic based applications, generalization is usually achieved through the modification and adaptation of the parameters of membership functions; these are functions which specify the degree of inclusion or exclusion of a particular variable within a sample space. The value of the membership function typically ranges from 0 to 1.

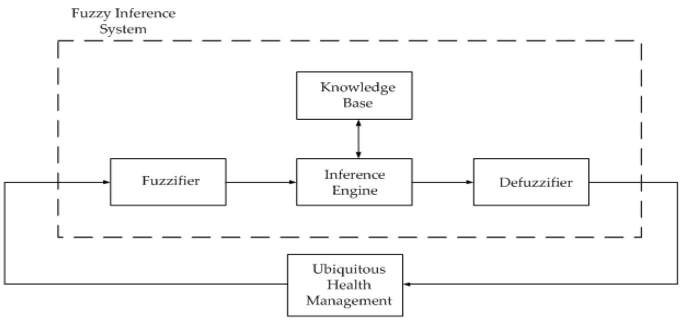

Figure 1. FIS block diagram.

Among many FIS models, the Sugeno fuzzy model is the most widely applied due to its high interpretability, computational and adaptation efficiency.

For a first-order Sugeno fuzzy model, a conventional rule set with two fuzzy if-then rules for example can be expressed as:

$$Rule\ 1\text{:}\ If\ x\ is\ A_1\ and\ y\ is\ B_1, \qquad then\ z_1 = p_1x + q_1y + r_1$$

$$Rule\ 2\text{:}\ If\ x\ is\ A_2\ and\ y\ is\ B_2, \qquad then\ z_2 = p_2x + q_2y + r_2$$

where A_n and B_n are the fuzzy sets in the antecedent, and p_n, q_n, and r_n are the design parameters that are determined during the training process. ANFIS consists of five layers: the fuzzification layer, the rule layer, the normalization layer, the defuzzification layer and the summation layer [12],[13] as shown below:

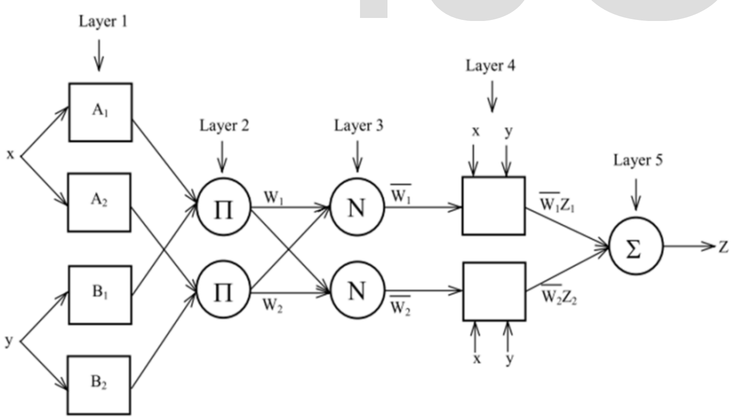

Figure 2. Architecture of ANFIS

Layer 1: Every node in this layer is an adaptive node with a node function.

$$O_i^1 = \mu_{A_i}(x), \ \ i = 1,2$$

$$O_i^1 = \mu_{B_{i-2}}(y), \ \ i = 3,4$$

Where x (or y) represents the input of node i.

Layer 2: Nodes in this layer are fixed nodes labeled Π each, which perform multiplication operation. They multiply the incoming signals and produce the result as their outputs:

$$O_i^2 = \omega_i = \mu_{A_i}(x)\mu_{B_i}(y), \ \ i = 1,2$$

The output of each node in this layer is a measure of the firing strength of a rule.

Layer 3: Every node in this layer is a fixed node labeled N. The i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths:

$$O_i^3 = \overline{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}, \ \ i = 1,2$$

where ω is referred to as the normalized firing strength.

Layer 4: Every node i in this layer is an adaptive node with a linear node function:

$$O_i^4 = \overline{\omega}_i z_i = \overline{\omega}_i(p_ix + q_iy + r_i), \ \ i = 1,2$$

where ω is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer are referred to as the consequent parameters [14].

Layer 5: The single node in this layer is a fixed node labeled Σ, which computes the overall output as the summation of all incoming signals:

$$O_i^5 = \sum_{i=1}^{2} \overline{\omega}_i z_i = \frac{\omega_1 z_1 + \omega_2 z_2}{\omega_1 + \omega_2}$$

It can be seen from the ANFIS architecture that when the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters [15]-[17]:

$$z = (\overline{\omega}_1 x)p_1 + (\overline{\omega}_1 y)q_1 + (\overline{\omega}_1)r_1 + (\overline{\omega}_2 x)p_2 + (\overline{\omega}_2 y)q_2 + (\overline{\omega}_2)r_2$$

ANFIS which combines the advantages of both ANN and fuzzy inference system (FIS) is presently one of the powerful tools used for pattern recognition and system identification having been proven to be capable of creating accurate system models. This approach, as common to several other softcomputing techniques, does not require explicit expertise model equations.

Fuzzy logic approach is based on fuzzy set theory proposed by Bellman and Zadeh [16] which has been very popular in the recent years and is used in various control systems, industrial applications, power plants expert prediction systems, and variety of application in the field of signal processing and consumer products. ANFIS therefore has the advantages portrayed by many fuzzy logic based inference systems. These include accuracy, relatively fast response time, ease of design and application, ability to accurately represent complex and nonlinear systems, as well as the robustness to handle input values that are not exact training datapoints.

LEFT VENTRICULAR HYPERTROPHY (LVH)

Left ventricular hypertrophy (LVH) is a condition in which the muscle wall of the left pumping chamber (ventricle) of the heart becomes thickened (hypertrophy). Other conditions, such as heart attack, valve disease and dilated cardiomyopathy, can cause the heart (or the heart cavity) to get bigger. These are not necessarily classified as LVH.

Causes of LVH

The heart is a muscle. And so, like other muscles, it could thicken if overworked over time. Several health conditions cause the heart to work harder than normal. One of the common causes of LVH is high blood pressure (hypertension). Other identified causes include athletic hypertrophy (a condition related to exercise), valve conditions (occur in case of improper functioning of one or more of the heart valves), hypertrophic cardiomyopathy (HOCM), and congenital heart disease [18].

Symptoms of LVH

The most common symptoms of LVH are:

- Feeling short of breath.
- Chest pain especially after activity.
- Dizziness.
- Fluttering sensation in the chest.

Diagnosis of LVH

Features that are indicative of Left Ventricular Hypertrophy may be first observed on an electrocardiogram (ECG). If the physician detects evidence of LVH in the patient as read from the ECG, the patient will have an echocardiogram in order to reach a conclusive diagnosis. Although an echocardiogram is the most common way to detect and diagnose LVH, the problem of extraction and classification of salient LVH patterns from the ECG signals remains a significant issue, as well as interpretation and diagnosis from the observed features. With this test, the doctor can gather substantial information that is indicative of the measure of the walls of the ventricle. A measurement greater than 1.5 cm is considered enlarged. Patients with athletic hypertrophy may however have a measurement less than 1.5 cm, and the wall returns to normal size after exercising. If the patient does not have any of the typical causes of LVH and has a family history of HOCM, the doctor may determine that the patient has HOCM.

Treatment of LVH

Hypertensive LVH (caused by high blood pressure) is treated by controlling the blood pressure. This is done with lifestyle changes and medications, when necessary. However, the relationship between the use of some medications for hypertension and LVH condition remains a subject of investigation and debate.

Athletic hypertrophy does not particularly require treatment. A patient which exhibits this condition will need to avoid any sustained exercise for a few months as specified by the physician. At the expiration of this period, the patient will have another echocardiogram to monitor the heart's progress.

HOCM is a rare condition that should be followed by a cardiologist with expertise in the area. A patient diagnosed with HOCM, may need medical management or surgery [18].

METHODS

To obtain the results in this work, important features and patterns from ECG waveforms were first extracted which represents the input and output of the ANFIS. The ANFIS was designed and optimized and has eight inputs and one output. These parameters are presented in Table 1. The data for these patterns were then normalized using Min-Max normalization approach [19]. The block diagram of the development process is presented in Figure 3, and the mathematical equations and parameters of the membership functions used are highlighted in Figure 4 and Figure 5. Finally, A MATLAB based Graphical User Interface (GUI) was developed as described in the following section for aiding medical personnel in making more objective and rapid LVH diagnosis.

Table 1: The inputs and the output of the ANFIS system.

ANFIS INPUTS	ANFIS OUTPUT
R-wave in lead 1 and S-wave in lead 3 (mv)	Diagnosis
R-wave in aVL (mV)	
R-wave in aVF (mV)	
S-wave in aVR (mV)	
R-wave in V4, V5 or V6 (mV)	
R-wave in V5 or V6 (mV)	
Largest R and S-wave in precordial leads (mV)	
Increased R-wave peak time (ms)	

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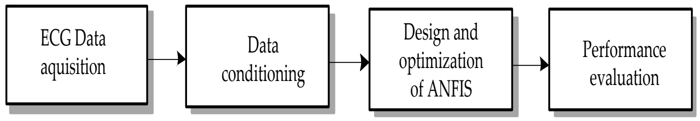

Figure 3: Block diagram of development process.

For the ANFIS, each input has three membership functions. In order to obtain a more effective generalization, the triangular membership function and the Gaussian membership functions were selected. This choice of membership functions was informed by careful observation of the distribution of the input and output data. The relationship between the parameters of the triangular membership function (Figure 4) is shown by Equation (1):

$$f(a,b,c) = \begin{cases} 0 & x \le a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{c-x}{c-b} & b \le x \le c \\ 0 & c \le x \end{cases}$$

While the parameters x, δ and c of the Gaussian membership function (Figure 5) are related by Equation (2)

$$f(x;\delta,c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \qquad (2)$$

These parameters define the shapes of the membership functions which were modified and adapted during ANFIS training to obtain an optimized set of parameters that effectively and accurately modeled the heart condition of the patients. Table 2 shows the descriptions and values of the parameters of the ANFIS.

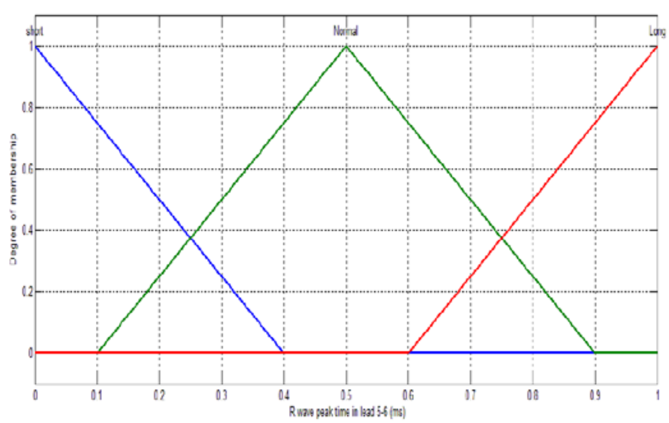

Figure 4: The membership functions for R-wave peaktime in lead 5-6(mV)

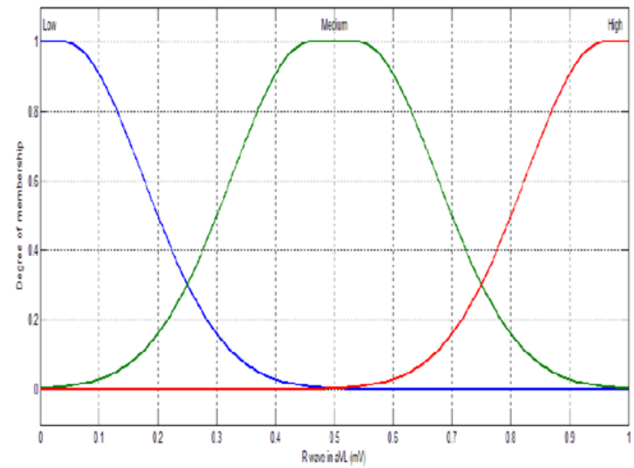

Figure 5: The membership functions for R-wave in aVL

The entire data (made up of 800 data points) were divided into three parts for training, validation, and testing data at a ratio of 70%:15%:15% respectively. This is to ensure that the system is trained with adequate data for good generalization. There are numerous criteria for diagnosing LVH. The most commonly used (and the one used in this work) are the Sokolov-Lyon criteria (S wave depth in V1 + tallest R wave height in V5-V6 > 35 mm). Voltage criteria must be accompanied by non-voltage criteria to be considered diagnostic of LVH.

Voltage Criteria

Limb Leads

R wave in lead I + S wave in lead III > 25 mm
R wave in aVL > 11 mm
R wave in aVF > 20 mm
S wave in aVR > 14 mm

Precordial Leads

R wave in V4, V5 or V6 > 26 mm
R wave in V5 or V6 plus S wave in V1 > 35 mm
Largest R wave plus largest S wave in precordial leads > 45 mm

Non-voltage Criteria

Increased R wave peak time > 50 ms in leads V5 or V6
ST segment depression and T-wave inversion in the left sided leads

Table 2: The parameters of the ANFIS and their corresponding values

ANFIS Parameters	**Description/ Value**
Type of input membership function	Gaussian and triangular
Type of output membership function	Linear
Type of training algorithm	Back propagation optimization
Defuzzification	Centre of gravity
Minimum error tolerance	1×10^{-4}
Maximum epochs	30
Total number of input membership functions	24
Number of output membership functions	1
Total number of rules	75

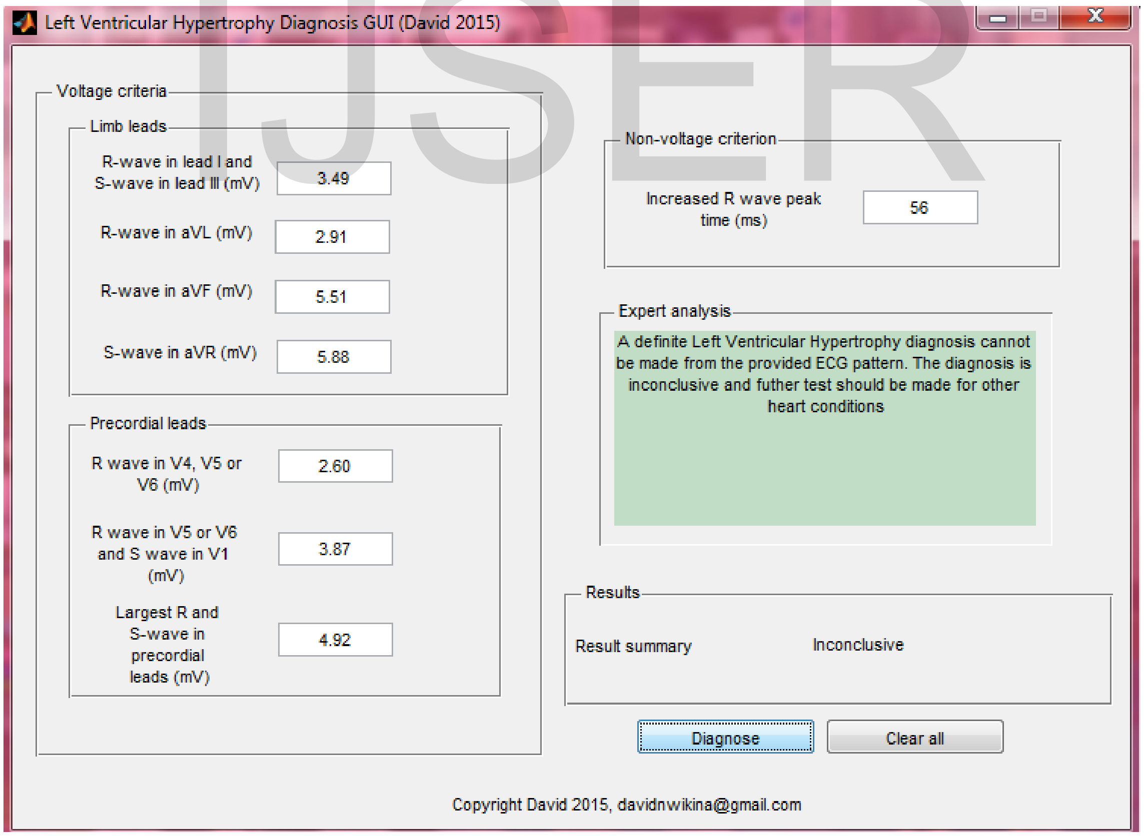

Figure 6: The MATLAB-based GUI for the diagnosis of LVH

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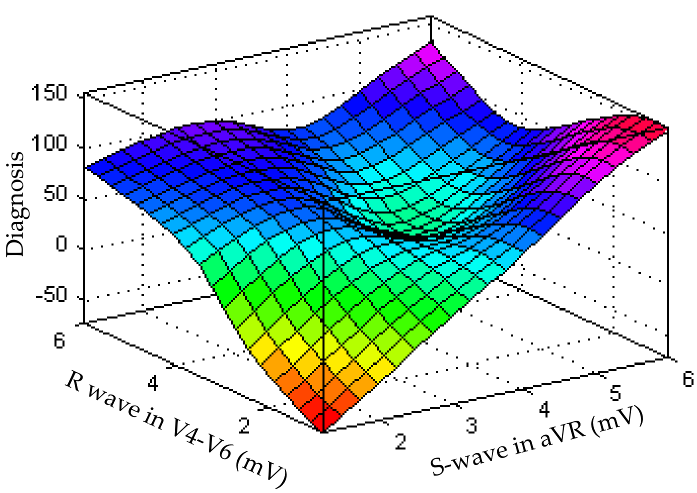
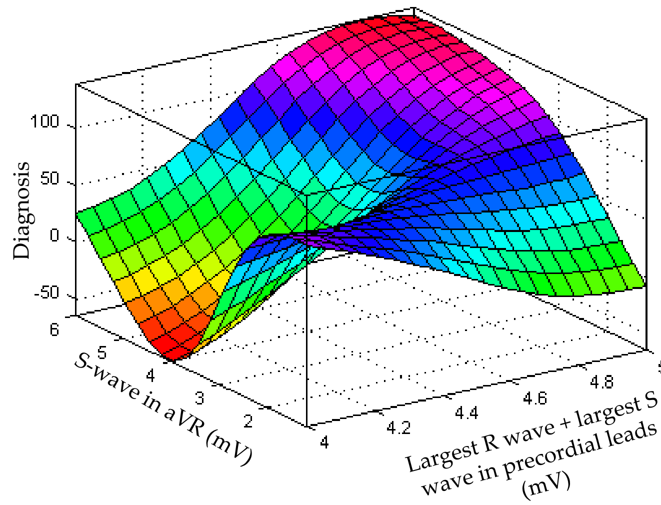
The expert knowledge base which serves as a platform on which the ANFIS adaptation and diagnosis hinges was based on information extracted from the website of Dr Edward Burns, a Physician of Pre-hospital and Retrieval Medicine in Sydney, Australia. The data was converted and normalized into electrical signal equivalents (mV). The ANFIS was fed and trained with the training data and the performance evaluated.

The parameters of each membership function of the ANFIS were modified by repeated training using the backpropagation optimization technique with the minimum epochs of 30 and minimum error tolerance of 1×10^{-4}. After the training and evaluation, resulting rule surface between selected input variables are shown in Figure 7. This shows the observed relationship between the "R-wave in V4-V6 (mV)", the "S-wave in aVR (mV)" and the "Diagnosis" and also between "S-wave in aVR (mV)" and "Largest R-wave + largest S-wave in precordial leads (mV)" and "diagnosis". This 3D representation shows the expected values of one variable relative to a given value of the other. This enables experts and analysts to easily visualize the model and identify the weight or effect of each variable on the eventual diagnosis of LVH.

The graphical user interface makes it possible to input the ECG data and obtain a diagnosis. The GUI was developed using MATLAB software and has 8 entry panels for numerical input. It includes a display panel which advises the physician on the next course of action and also a display box which gives the diagnosis based on the user supplied ECG waveform features. The diagnosis can either be "LVH strongly suspected", "Inconclusive" or "Enter valid ECG data". The GUI also contains a push button that prompts diagnosis and another that clears the entire GUI fields for entry of new data.



(a)



(b)

Figure 7: A 3D representation of the optimized ANFIS rule for selected inputs

After the ANFIS was designed and trained, it was fed with the testing data and its corresponding output was compared with the expected value at each data point. The observed results showed that the ANFIS performed satisfactorily well for the diagnosis of Left Ventricular Hypertrophy. Figure 8 shows the error spectrum of the testing data. The deviation (positive or negative) from the center line indicates the magnitude of the error at each data point. It is evident that there are some spikes which signify error (16), but they are negligible in comparison to the total number of data (800).

The GUI has 8 inputs which are all needed for the system to properly diagnose LVH. These inputs are made up of voltage criteria which are further divided into limb leads and precordial leads, and non-voltage criteria.

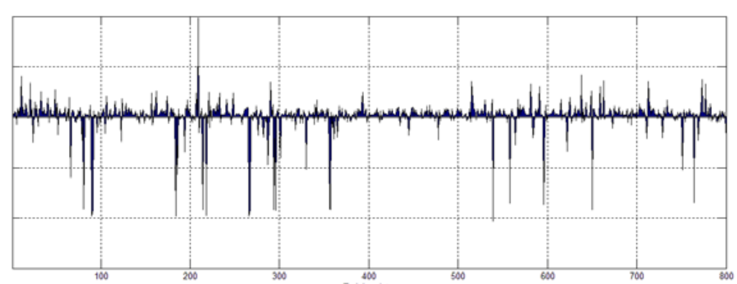


Figure 8: Error spectrum of the testing data.

CONCLUSION

Global healthcare is facing a lot of challenges. These include rising costs, large number of deaths due to medical errors and a dwindling quality. The full implementation of Electronic Medical Records and Clinical Decision Support Systems is a very viable way forward. This work demonstrates the application of a CDSS in the diagnosis of LVH using an ANFIS system. The carefully designed, optimized and trained ANFIS and the corresponding Graphical User Interface was able to accurately classify ECG LVH features using relevant expert knowledge.

In light of this work, it is recommended that countries should be more open to application and implementation of EMRs and CDSS systems in their respective healthcare sectors. This work focused on the detection of LVH in patients‟ ECG using ANFIS as a recognition and classification tool. It is however suggested that similar works can be carried out on other conditions and diseases, and the advantages and flexibility offered by many other softcomputing approaches should be harnessed.

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