ADAPTIVE CLASSIFICATION ALGORITHMS FOR PREDICTING THE SYMPTOMS OF IMPENDING HEART, KIDNEY AND LIVER FAILURES BASED ON MEASURABLE BLOOD-RELATED PARAMETERS

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Abstract: *The major causes of death across the world have been closely link to heart, kidney and liver related diseases. An early prediction and classification of the symptoms of such disease could facilitate the treatment of such disease. Thus, an hybrid adaptive neural-fuzzy algorithm based on adaptive resonant theory (HANFA-ART) with adaptive clustering for classification has been proposed in this paper. The proposed HANFA-ART classification algorithm has been applied to investigate the symptoms of impending heart, kidney and liver failures based on measurable blood-related parameters obtained from hospitals in Akure, Ondo State - Nigeria. A total of 5888 data set with 16 attributes each for 368 patients collected from 4 hospitals have been used for this investigation. Comparison of the proposed HANFA-ART algorithm with neural-fuzzy classifier trained with the modified error back-propagation with momentum (M-EBPM) algorithm shows the efficiency and superior performance of the proposed HANFA-ART algorithm for correct classification and prediction of the symptoms of impending heart, kidney and liver failure.*

Keywords: *Classification Algorithms, HANFA-ART Algorithms, Heart, Kidney, Liver, Measurable Blood-Related Parameters, Neural-Fuzzy systems*

1. INTRODUCTION

The importance of monitoring the human state of health at ease cannot be over emphasized. In an attempt to make correct decision about human state of health, researchers and practitioners are constantly seeking for better decision-making procedures. Due to continuous advancements in industrial and commercial fields, the exchange of information and its associated uncertainty also increases which in-turn raises the complexity of decision-making problems and systems in the form of uncertainty, subjectivity and vagueness. Medical practitioners exhibit variation in decision making because of their approaches to deal with uncertainties and ambiguity in knowledge and information. Diagnostic decisions also depend upon experience, capability and observation of the practitioners. As the complexity of system increases, it is not easy to follow a particular path of diagnosis without any mistake. Hence there is a need for an artificial intelligence and/or expert system approach, capable of making correct decisions on the state of health of an individual based on the input information from an investigator using an inference method.

Medical expert system is a challenging field, requiring the synergy of different scientific areas. The representation of medical knowledge and expertise, the decision making in the presence of uncertainty and imprecision, and the choice and adaptation of a suitable model are some issues that a medical expert system should take into consideration [1, 2]. Uncertainty is traditionally treated in a probabilistic manner; recently, however, methods based on neuro-fuzzy logic have gained special attention. In the medicine area, many expert systems were designed for the diagnosis and treatment of diseases. Fuzzy expert system has found applications in many areas; among these medical engineering has evolved as one of the key application areas of computational intelligence [3, 4]. In the last decade, specifically between 2003 and 2012, a major application area of fuzzy expert system includes diagnosis like local anaesthesia, appendicitis, brain tumor, breast cancer, cardiovascular disease, clinical diagnosis, diabetes, electrocardiogram (ECG) signal evaluation, hypertension diagnosis, liver disorder, lung disease, ovarian cancer, prostate cancer, pulmonary infection, urinary tract infection, prenatal disease detection etc [3–7].

Many new techniques are used for diagnosing the heart, kidney and liver. The diagnosis using machine learning technique is one of the existing techniques which have a transparent diagnostic knowledge. Although, is a challenging field, as it requires combination of various scientific areas. In medical field, the decision making with the presence of uncertainty and imprecision makes some issues for suitable model. So, the methods based on fuzzy rule-based logic (FRBL) are very useful for decision making. Since FRBL is better in handling uncertainties which is associated with natural data [8]. Diagnosis of disease by patients themselves is very popular in the scientific world. People are very busy to visit a doctor hence they can use these types of tool to diagnosis the disease. Machine learning is classified into connectionist learning and symbolic learning. The user can easily understand the rules of symbolic learning techniques and it is considered as a comprehensible technique. The best example for the symbolic technique is rule induction which is extensively used for medical diagnosis [7, 8]. Expert systems such as FRBL and the artificial neural network are an incomprehensible technique and best example for connectionist learning techniques. The connections and information are hidden from the user in this technique. Artificial neural networks have been applied in medical field for various tasks [9, 10].

Artificial neural network (ANN) has been applied to various processes such as pattern recognition and data classification

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in the medical field. It attracts the many researchers and it becomes multi-objective solution to the various problems [11]. ANN working process is based on the neurons in human brain. It is used to find the connection between the given data as input from the user and output data based on the information merged from large number of cases [12]. FRBL is very impressive tool to build intelligent decision-making mechanism for approximate reasoning. FRBL helps to capture the knowledge and diagnosis the correct decision regarding the disease. FRBL presents powerful reasoning methods that can handle uncertainties. FRBL uses mathematical principles to represent knowledge with membership. It is one of the Artificial Intelligence technology tools to handle ambiguity and uncertainties. Traditional logic uses True and False values, FRBL lies between Zero and One to indicate the degree of truth. FRBL is a methodology used to frame words, which helps for computing and reasoning. Computing of words helps to derive rules. Words are modeled based on human sense which plays an important role in decision making. FRBL is an inference morphology that enables human reasoning and applied to knowledge-based system [13]. It plays a very important role in fuzzy set theory which is used in many fields such as Expert System, forecasting, fuzzy control and decision making [13]. To design a fuzzy expert System, we use the concept of fuzzy sets and fuzzy rules.

Among the various combinations of methodologies in soft computing, the one that has highest visibility at this juncture is that of FRBL and neuro-computing (NC), leading to neuro-fuzzy systems (NFS) based on experience. Within fuzzy logic, such systems play a particularly important role in the induction of rules from observations and experience. An effective method developed by Sun and Jang for this purpose is called adaptive neuro-fuzzy inference system (ANFIS) [14]. The nonlinear universal function approximation property of FRBL systems and ANNs qualifies these algorithms to be powerful candidates for identification, prediction and classification of nonlinear dynamical systems.

The ANFIS is a sophisticated hybrid network that belongs to the category of neuro-fuzzy neural networks [15, 16]. It is well-known that there is no sufficient MATLAB program for implementing neuro-fuzzy classifiers due to the complexity and accuracy for sophisticated classification problems [15, 16]. Generally, ANFIS is used as a classifier and it is a function approximator. But, the usage of ANFIS for classifications is unfavorable. For example, there are three classes, and labeled as 1, 2 and 3. The ANFIS outputs are not integer. For that reason, the ANFIS outputs are rounded, and determined the class labels. But, sometimes, ANFIS can give 0 or 4 class labels. These situations are not accepted and as a result ANFIS is not suitable for classification problems except the problems above are addressed with advanced algorithms which one of the focus of this study.

To address the issues mentioned above, a new hybrid adaptive neuro-fuzzy algorithm based on adaptive resonant theory (HANFA-ART) is proposed and presented in this work while the second is a modified version of the so-called error back-propagation with momentum (M-EBPM) algorithm [17–19]. The differences lie in the type of algorithm used to train the ANFIS, MANFIS (multiple ANFIS), CANFIS (co-active ANFIS) [14, 20, 21]. The idea used to develop the HANFA-ART presented in this work is closely follow from the work of Sun and Jang [14]. Rather than using the so-called back-propagation algorithm presented by Guler and Ubeyli [22] or the modified version of the back-propagation algorithm referred to as M-EBPM [18]; the HANFA-ART is developed and trained using the adaptive recursive least squares (ARLS) and modified Levenberg-Marquardt algorithm (MLMA) with an adaptive clustering scheme.

The challenging issue in the present study is the integration of the two proposed training algorithms proposed by Akpan and co-workers [17–19], namely: ARLS and MLMA based on the teacher-forcing method with real-time recurrent network (RTRN) architecture into the CANFIS architecture which uses basic error back-propagation algorithm proposed [22].

Furthermore, different adaptive neuro-fuzzy classifiers have been proposed in this work for data clustering called the adaptive Gustafon–Kessel clustering algorithm. In all data clustering algorithms, the k-means algorithm has been used to initialize the fuzzy rules. For this reason, the number of clusters for each class must be supplied. Also, the Gaussian membership function is only used for fuzzy set descriptions because of its simple derivative expressions. Although, the classifier is based on Jang's neuro-fuzzy classifier described in Guler and Ubeyli [22]; the differences between the existing and the proposed adaptive Gustafon-Kessel schemes are about how the rules, weights and parameters during the optimization are implemented and updated.

The basic CANFIS structure, as listed below according to their computation complexities: *(1)*. Gradient decent only: all parameters are updated by the gradient descent; *(2)*. Gradient decent only and one pass of LSE: the LSE is applied only once at the very beginning to get the initial values of the consequent parameters and then the gradient decent takes over to update all parameters; *(3)*. Gradient decent only and LSE: this is the hybrid learning; *(4)*. Sequential LSE: using extended Kalman filter to update all parameters [22].

These methods update antecedent parameters by using gradient descent or Kalman filtering. These methods have high complexity. In this work, a method which has less complexity and fast convergence is introduced. The fuzzy inference system that we have considered is a model that maps: (1) input characteristics to input membership functions; (2) input membership function to rules; (3) rules to a set of output characteristics; (4) output characteristics to output membership functions; (5) the output membership function to a single-valued output; and/or (6) a decision associated with the output.

Membership functions that have been fixed, and somewhat arbitrarily chosen have been considered in this work. Also, the fuzzy inference engine has been used for modeling systems whose rule structures are essentially predetermined by the particular problem's interpretation of the characteristics of the variables in the model. In general, the shape of the membership functions depends on parameters that can be adjusted to change the shape of the membership function. The parameters can be automatically adjusted by

Table 1: Measurable blood-related heart, kidney and liver parameters

	Heart Parameters	Kidney Parameters	Liver Parameters
1	Pulse rate and rhythm	Packed cell volume/blood cells	Bilirubin and bile salt levels
2	Arterial blood gas such as oxygen (O_2) and carbon IV oxide (CO_2)	Electrolytes (Na^+, K^+, Cl^+, creatinine, urea, uric acid, Ca^{2+}, PO_4)	Protein
3	Arterial pressure and blood pressure	Erythropoietin	Clotting factors (II, V, X) in terms of prothrombin time (PT) and international normalized ratio (INR)
		Vitamin D level	NH_4 or urea, α-feto (alpha-feto) protein, Glucose level

Table 2: Minimum and maximum values of the all the parameters considered for the study

S/N	Measured blood parameters and their units	Minimum value	Maximum value
1.	Heart beats (*number of heat beats per minute*)	65	105
2.	Mean arterial pressure (*mmHg*)	65	115
3.	Systolic blood pressure (*mmHg*)	85	150
4.	Diastolic blood pressure (*mmHg*)	60	110
5.	Packed cell volume (*%*)	33	53
6.	Erythropoietin (*mu/ml*)	4	26
7.	Electrolyte Na^+ (*mol/l*)	118	143
8.	Electrolyte K^+ (*mol/l*)	3	5
9.	Electrolyte Cl^- (*mol/l*)	92	113
10.	Electrolyte Ca^+ (*mol/l*)	2	3
11.	Ceratine (*Umol/l*)	48	133
12.	Glucose fasting (*mol/l*)	2	6
13.	Glucose random (*mol/l*)	4	7
14.	Urea (*mmol/l*)	60	110
15.	Direct bilirubin (*mg/dl*)	0.0027	0.4973
16.	Total bilirubin (direct and indirect) (*mg/dl*)	0.1000	2.2000
17.	Vitamin D level (*mg/ml*)	0	40
18.	Ammonia level (*mcg/dl*)	9	80
19.	Alpha-feto protein (*ng/ml*)	7	500

the algorithms proposed in this work depending on the data describing the problem being model.

In a previous study, the identification of the causes and symptoms of impending heart, kidney and liver failure based on measurable blood-related parameters have been investigated and reported [23]. Thus, this study deals with the classification of symptoms of impending heart, kidney and liver failures based on some measurable blood-related parameters using the proposed hybrid adaptive neural-fuzzy algorithm based adaptive resonant theory (HANFA-ART) with adaptive clustering algorithm (ACA). For performance evaluation and comparisons, the proposed HANFA-ART with ACA is compared with the conventional adaptive neural-fuzzy inference system (ANFIS) trained with M-EBPM.

2. PROBLEM FORMULATION AND EXPERIMENTAL DATA ACQUISITION

2.1. Problem Formulation: Measurable Blood-Related Parameters for Heart, Kidney and Liver

The focus here is to investigate how the symptoms of impending heart, kidney and liver failures could be detected in a given blood sample. Interactions with medical experts and ideas from reviewed literature revealed that some key factors which should be observed in order to suspect, detect or ascertain the symptoms of impending heart, kidney and liver failures based on blood sample from human beings are summarized in Table 1 [23].

1). The Heart:

(1) The pulse is how many times per minute that the artery expands and contracts in response to the heart pulse rate which is also called heartbeat. Normal adult resting heartbeat is between 60 – 100 heartbeats per minute;

(2) Mean arterial pressure is between 60 mmHg or greater is needed to maintain adequate tissue per fusion; and

(3) The blood pressure consists of the systolic which must be less than or equal to 140 mmHg while the diastolic must be less than or equal to 90 mmHg.

2). The Kidney:

(1) Packed cell volume / blood cell: *(a)* Male should be between 40 – 50 % and *(b)* Female should be between 35 – 44 %;
(2) Erythropoetin should be between (4 – 24 mu/ml); and
(3) Electrolytes: *(a)* Na^+ should be between (120 – 140 mol/l); *(b)* K^+ should be between (3 – 5 mol/l); *(c)* Cl^+ should be between (95 – 110 mol/l); *(d)* Ca^+ should be between (2.25 – 2.75 mol/l); *(e)* Creatinine (male and female) should be between (50 – 130 Umol/l); *(f)* Urea should be between (2.0 – 6.0 mmol/l); *(g)* Glucose fasting should be between 3.0 – 5.5 mol/l ; and *(h)* Glucose random should be between 4.4 – 7.0 mol/l.

3). The Liver:

(1) Bilirubin: Normal values of direct (conjugated) bilirubin are from 0.0 – 0.3 mg/dl. Normal values of total bilirubin (direct and indirect) are from 0.3 – 1.9 mg/dl;
(2) Vitamin D Level: The normal range of vitamin D is wide but typically between 20 – 40 mg/ml and in some cases between 50 – 100 mg/ml; and
(3) Ammonia Level: *(a)* Adult is between 9.5 – 49 mcg/dl; *(b)* Children is between 40 – 80 mcg/dl and *(c)* alpha-feto protein: Normal levels are below 10 ng/ml.

2.2. Experimental Data Acquisition of Measurable Blood-Related Parameters for the Heart, Kidney and Liver

A total of 5888 data set based on measurable blood-related parameters with 16 attributes each for 368 patients were collected and collated from 4 different hospitals in Akure, Ondo State, Nigeria (see Acknowledgement for the names of the hospitals). For confidential and security reasons, the bio-data and information for the patients from the where the data were collected have been skipped in this paper. From our comparative study, the 16 attributes of interest that could be acquired from the hospitals contacted which could be used to detect heart, kidney and liver failure are: *(1)* Heart beat per minutes, *(2)* mean arterial pressure (mmHg), *(3)* systolic Bp (mmHg), *(4)* diastolic Bp, *(5)* potassium, *(6)* chlorine, *(7)* calcium, *(8)* creatine (umol/l), *(9)* glucose fasting (mol/l), *(10)*glucose random (mol/l), *(11)* urea (mmol/l), *(12)* direct bilirubin (mg/dl), (13) total bilirubin (mg/dl), (14) Vitamin D (ng/ml), (*15)* ammonia (mcg/dl), and *(16)* alpha-feto (ng/ml). Fig. 1 to Fig. 6 shows the variations of these attributes from the test data collected for 368 patients which are discussed as follows. Furthermore, the minimum and maximum values of the 19 measureable blood-related parameters are listed in Table 2 where on 16 of these parameters were available from four different hospitals consulted in this study [23].

3. HANFA-ART WITH ACA: FORMULATION AND IMPLEMENTATION

3.1. The Adjustable Parameters of the Fuzzy System

This method requires the definition of the number of membership functions and their shape. Normally the *AND* function is fixed to be the "*product*" because an analytical expression for the gradient of the cost function is needed. The initial position of the membership functions is another element that must be chosen. The method proceeds as follows:

(1). For each of the p inputs of the system, distribute over the interval $[a_i, b_i]$, N_i membership functions. The shape, the initial positions and the distribution are user's choices. The membership functions must cover the input interval, and at least two membership functions should be placed on each input domain.
(2). Generate the rule base using all possible combinations among the antecedents and the *AND* operator using "product".
(3). Initialize the value of the consequences using prior knowledge, least squares or recursive least squares.
(4). Optimize the value of the consequences $\bar{y}^l$ and the parameters of the membership functions. The criteria will be to minimize the cost function described in the previous section, but now the optimization will also adjust the membership functions of the antecedents. The cost function can be described as:

$$J = \frac{1}{2}\sum_{i=1}^{N}\left(Y^i - f\left(U^i,\theta\right)\right)^2 \tag{1}$$

Where θ is a vector representing all the "adjustable" parameters (consequences, antecedents and other parameters of the membership functions) of the fuzzy system $f(\cdot,\cdot)$.

The problem will be the minimization of the cost function *J*. This minimization is a nonlinear, non-convex optimization problem. The objective is to obtain an "acceptable" solution and not necessarily "the global minima" of this cost function. Different schemes for optimization can be applied to find this solution. Probably the simplest one will be the gradient descent method. This method consists of an iterative calculation of the parameters oriented to the negative direction of the gradient. The explanation behind this method is that by taking the negative direction of the gradient, the steepest route toward the minimum will be taken. This descent direction does not guarantee convergence of the scheme; for this reason, the α parameter is introduced and it can be modified to improve the convergence rate and properties. Some choices of α are given by Newton and quasi-Newton methods [18, 24, 25]. In this work, an efficient gradient descent algorithm called the MLMA [17, 18] is proposed for estimating and updating the adjustable parameters (i.e. the consequences parameters and the parameters of the membership functions) of the FRBL system.

3.2. Architecture of the Proposed HANFA–ART Model

Unlike conventional ANFIS and CANFIS networks that contain five layers [14–16, 20–28], the proposed HANFA-ART network consists of six layers as shown in Fig. 1. The proposed HANFA-ART is a smarter network because it employs two algorithms for parameter learning (i.e. ARLS and MLMA) and one algorithm for automatic structure learning (i.e. FRBL-ART). In the following, we briefly describe the operation of each layer. A descriptive representation of a 3-input HANFA-ART network with 3-fuzzy rules is shown in Fig. 1. The code segment that executes the Fuzzy-ART algorithm was adopted (with the necessary modifications) from the well-structured, reliable and tractable Fuzzy-ART proposed by Garrett [27].

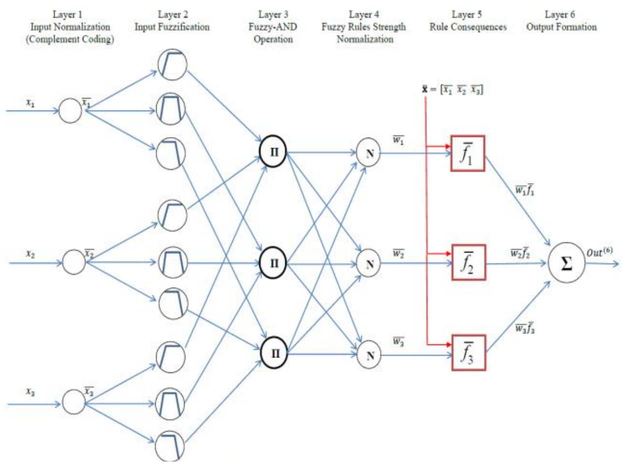


Fig. 1: HANFA-ART network architecture.

Unlike the common and most widely used ANFIS architectures including the one implemented in MATLAB®/Simulink® from The MathWorks [16], the version adopted in this work was first proposed by Lin and Lin [28] and later modified by Garrett [27]. It is called the adaptive neuro-fuzzy inference system based on adaptive resonant theory (ANFIS-ART). For completeness, consistency and simplicity, each of these six layers is described below with their accompanying mathematical descriptions.

a). Layer No.1: Inputs Normalization Layer (Complement Coding)

The ANFIS-ART uses the technique of *complement coding* from fuzzy-ART to normalize the input training data. Complement coding is a normalization process that replaces an *n*-dimensional input vector $\mathbf{x} = [x_1, x_2, \ldots, x_n]$ with its 2*n*-dimensional complement coded form $\mathbf{x'}$ such that:

$$\mathbf{x'} \equiv [\bar{x}_1, 1-\bar{x}_1, \bar{x}_2, 1-\bar{x}_2, \ldots, \bar{x}_n, 1-\bar{x}_n] \quad (2)$$

Where $[\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_n] = \bar{\mathbf{x}} = \mathbf{x}/\|\mathbf{x}\|$. Complement coding helps avoiding the problem of category proliferation when using fuzzy-ART for data clustering. Having this in mind, we can write the input-output function of the first layer as follows:

$$Out_i^{(1)} = \left(\overline{In_i^{(1)}}, 1-\overline{In_i^{(1)}}\right), \qquad i = 1, 2, \ldots, NumInVar \quad (3)$$

(b) Layer No.2: Input Fuzzification Layer

The nodes belonging to this layer are called input-term nodes and each represents a term of an input-linguistic variable and functions as a 1-D membership function. Here we use the following trapezoidal membership function:

$$\left.\begin{aligned} Out_{ij}^{(2)} = 1 - g\left(In_{ij}^{(2)} - \upsilon_{ij}^{(2)}, \gamma\right) - g\left(u_{ij}^{(2)} - In_{ij}^{(2)}, \gamma\right), \\ i = 1, 2, \ldots, NumInVar \end{aligned}\right\} \quad (4)$$

Where $u_{ij}^{(2)}$ and $\upsilon_{ij}^{(2)}$ are, the left-flat and right-flat points of the trapezoidal membership function of the *j*-th input-term node of the *i*-th input linguistic variable. $In_{ij}^{(2)}$ is the input to the *j*-th input-term node from the *i*-th input linguistic variable (i.e. $In_{ij}^{(2)} = Out_i^{(1)}$). Also, the function *g*(.) is defined as:

$$g(s,\gamma) = \begin{cases} 1, & if, \quad s\gamma > 1 \\ s\gamma & if \quad 0 \le s\gamma \le 1 \\ 0 & if \quad s\gamma < 0 \end{cases} \quad (5)$$

The parameter γ regulates the fuzziness of the trapezoidal membership function. More details on how this membership function works on the real *n*-dimensional space combining *n* inputs can be found in [29].

(c) Layer No.3: Fuzzy-AND Operation

Each node in this layer performs a fuzzy-AND operation. Similar to the other ANFIS networks of the library, the *T-norm operator* of the algebraic product was selected. These results make each node's output to be the product of all its inputs:

$$\hat{Y}_{k-j}^{(3)} = w_{k=j} = \prod_{i=1}^{N_{Inputs}} \hat{Y}_{ij}^{(3)}, \quad k(=j) = 1, 2, \ldots, NumInTerms \quad (6)$$

The output of each node in this layer represents the firing strength (or activation value) of the corresponding fuzzy rule. Note that the number of the fuzzy rules equals the number of input term nodes. The latter is common for all the input variables. Therefore, each fuzzy rule may be assigned an index *k* equal to the corresponding index *j* of the input term node, which is common for each input linguistic variable.

(d) Layer No.4: Normalization of Each Rule Firing Strength (Fuzzy Rules Strength Normalization Layer)

The output of the *k*-th node in this layer, is the firing strength of each rule divided by the total sum of the activation values of all the fuzzy rules. This results in the normalization of the activation values of all fuzzy rules:

$$\hat{Y}_k^{(4)} = \overline{w_k} = \frac{\hat{Y}_k^{(3)}}{\sum_{m=1}^{N_{Rules}} \hat{Y}_m^{(3)}}, \qquad k(=j) = 1, 2, \ldots, NumRules \quad (7)$$

(e) Layer No. 5: Rule Consequent Layer

Each node *k* in this layer is accompanied by a set of adjustable parameters $a_{1k}, a_{2k}, \ldots, a_{N_{Inputs}k}, a_{0k}$ and implements the linear function:

$$\left.\begin{aligned} \hat{Y}_k^{(5)} = \overline{w_k}\,\overline{f_k} = \overline{w_k}\left(\begin{aligned} a_{1k}\overline{In_1^{(1)}} + a_{2k}\overline{In_2^{(1)}} + \cdots \\ + a_{N_{Inputs}k}\overline{In_{N_{Inputs}}^{(1)}} + a_{0k} \end{aligned}\right) \\ k(=j) = 1, 2, \ldots, NumRules \end{aligned}\right\} \quad (8)$$

The weight $\overline{w_k}$ is the normalized activation value of the *k*-th rule calculated by aid of (7). Those parameters are called *consequent parameters* or *linear parameters* of the ANFIS system and are regulated by the proposed ARLS algorithm.

(f) Layer No.6: Output Layer

For the multiple-input multiple-output (MIMO) ANFIS-ART considered here this layer consists of one and only node that creates the network's output as the algebraic sum of the node's inputs:

$$Out^{(6)} = \sum_{k=1}^{N_{Rules}} Out_k^{(5)} = \sum_{k=1}^{N_{Rules}} \overline{w_k}\,\overline{f_k} = \frac{\sum_{k=1}^{N_{Rules}} w_k \overline{f_k}}{\sum_{k=1}^{N_{Rules}} w_k} \qquad (9)$$

This is how, typically, the input vector is fed through the network layer by layer to the output.

3.3. Adaptive Clustering Algorithms (ACA)

Until now, the fuzzy sets of the input domains have been placed on their initial positions according to the choice made by the designer (typically equally distributed). Two choices has been made by the designer – the number of membership functions and their initial distribution. The methods based on clustering aim to obtain both parameters at the same time, the number of fuzzy sets needed to make the function approximation and their distribution along the input domains.

Clustering methods are a set of techniques to reduce groups of information X represented as p-dimensional vectors into characteristic sets A_i characterized by feature vectors $v_i \in \Re^p$ and membership functions μ_A. The applications of these techniques include pattern recognition, classification and the two example applications considered in this study to validate the algorithms proposed in this paper for fuzzy classification, modeling, identification and control applications. The methods based on clustering are considered as data-driven methods. The main idea of these methods is to find structures (clusters) among the data according to their distribution in the space of the function and assimilate each cluster as a multidimensional fuzzy set representing a rule. The cluster prototypes can be either a point (to construct Mamdani models) or a hyperplane (to construct Takagi–Sugeno models).

The fuzzy inference system is constructed by means of projecting the clusters into the input space and approximating the projected cluster with a one-dimensional fuzzy set. The advantage of these methods is that they generate automatically the membership functions, leaving as the user's choices only the parameters of the clustering algorithms (number of clusters and distance function). According to the type of model to be constructed the method will be slightly different. In the next subsection, the adaptive Gustafon–Kessel clustering algorithm as applied to the Takagi–Sugeno fuzzy model is presented.

3.3.1. The Gustafson and Kessel Clustering Algorithm

The fuzzy Gustafson and kessel clustering algorithm is based on the minimization of the cost function:

$$\min_{(U,V,A)} \left\{ J_m(U,V,A;X) = \sum_{k=1}^{n}\sum_{i=1}^{c} (\mu_{ik})^m (x_k - v_i)^T A_i (x_k - v_i) \right\}$$

Where X is the set of vectors, $x_k \in \Re^p$ with the information, $V = [v_1, \ldots, v_c]$ is the set of feature vectors, $A = [A_1, \ldots, A_c]$ is a set of c norm-inducing matrices and $U \in M_{fc}$ is the fuzzy partition matrix, defined as an element of the set:

$$M_{fc} = \left\{ \begin{array}{ll} U \in \Re^{c \times N} \,\middle|\, \mu_{ik} \in [0,1], & \forall i,k; \\ \sum_{i=1}^{c} \mu_{ik} = 1, & \forall k; \\ 0 < \sum_{k=1}^{N} \mu_{ik} < N, & \forall i \end{array} \right\} \qquad (10)$$

Table 3: Adaptive Gustafson–Kessel Clustering Algorithm

Given the data set *Z* with *N* vectors, select the number of clusters *1<c<N*, the exponent m, the termination tolerance *ε>0* and the volumes ρ_i of the matrices A_i to calculate the induced norm, and initialize the matrix *U* randomly such that $U^{(0)} \in M_{fc}$.

1). repeat for $j = 1, 2, \ldots$

2). Step 1: calculate the prototypes:

$$\left. \begin{array}{l} v_i^{(j)} = \dfrac{\sum_{k=1}^{n} \left(\mu_{ik}^{(j-1)}\right)^m x_k}{\sum_{k=1}^{n} (\mu_{ik})^m} \\ for \;\; 1 \le i \le c \end{array} \right\} \qquad (11)$$

3). Step 2: calculate fuzzy partition matrix:

$$P_i^{(j)} = \frac{\sum_{k=1}^{n} \left(\mu_{ik}^{(j-1)}\right)^m \left(x_k - v_i^{(j)}\right)\left(x_k - v_i^{(j)}\right)^T}{\sum_{k=1}^{n} \left(\mu_{ik}^{(j-1)}\right)^m} \qquad (12)$$

4). step 3: Calculate the induced-norm matrices:

$$\left. \begin{array}{l} A_i = \left[\rho_i \det(P_i)\right]^{1/n} P_i^{-1} \\ for \;\; 1 \le i \le c \end{array} \right\} \qquad (13)$$

5). step 4: calculate the fuzzy partition matrix:

$$\left. \begin{array}{l} \mu_{ik}^{(j)} = \left[\sum_{l=1}^{c} \left(\dfrac{\left(x_k - v_i^{(j)}\right)^T A_i^{(j)} \left(x_k - v_i^{(j)}\right)}{\left(x_k - v_l^{(j)}\right)^T A_i^{(j)} \left(x_k - v_l^{(j)}\right)} \right)^{\frac{2}{m-1}} \right]^{-1} \\ for \;\;\; 1 \le i \le c, 1 \le k \le N \end{array} \right\} \qquad (14)$$

6). Until $\left\| U^{(j)} - U^{(j-1)} \right\| < \in$

The *ith* row of the fuzzy partition matrix contains the membership values of the vectors x to the A_i fuzzy set. Observe that the cost function can be arbitrarily small by reducing the norm of each A_i. For this reason, a constraint is introduced to preserve the norm of A_i:

$$|A_i| = \rho i \qquad \rho > 0$$

Applying the Lagrange multipliers to the above-mentioned optimization problem generates the following expression for A_i:

$$A_i = \left[\rho_i \det(P_i)\right]^{1/n} P_i^{-1} \qquad (16)$$

where P_i is the fuzzy covariance matrix:

$$P_i = \frac{\sum_{k=1}^{n} (\mu_{ik})^m (x_k - v_i)(x_k - v_i)^T}{\sum_{k=1}^{n} (\mu_{ik})^m} \qquad (17)$$

The elements of U are calculated as:

$$\mu_{ik} = \left[\sum_{j=1}^{c} \left(\frac{(x_k - v_i)^T A_i (x_k - v_i)}{(x_k - v_j)^T A_i (x_k - v_j)} \right)^{\frac{2}{m-1}} \right]^{-1} \quad \forall i,k \tag{18}$$

The prototypes v_i are calculated as:

$$v_i = \frac{\sum_{k=1}^{n} (\mu_{ik})^m x_k}{\sum_{k=1}^{n} (\mu_{ik})^m}, \quad \forall i \tag{19}$$

The implementation of the Gustafson and Kessel algorithm is summarized in Table 3. It is important to remark that when the vector x_k is equal to one of the prototypes v_i the expression (19) becomes singular. For this case the membership value μ_{ik} for this vector is equal to one and zero for all the other entries in the kth row of U. The parameter m is a very important parameter. As $m \to \infty$, the means of the clusters tend to the mean of the set X.

3.4. Takagi–Sugeno Fuzzy Model with Adaptive Gustafon-Kessel Clustering Algorithm for the Classification Problem

Here we summarize the adaptive clustering algorithm incorporating the adaptive recursive least squares (ARLS) and the modified Levenberg-Marquardt algorithm (MLMA) algorithms for calculating the consequences that are not covered by the cluster using ARLS by applying the MLMA to adjust the antecedents appropriately using the Takagi-Sugeno-Kang (TSK) model because of its model-like structure that can be used for classification, control, estimation, and prediction.

The Algorithm for Takagi–Sugeno Models

Step 1: Collect the data and construct a set of vectors $Z^t = \{x^{tT}, y^t\}$ where x^t and y^t are, respectively, the inputs and the output of the function. Observe that here we assume $x^t \in \Re^n$ and $y^t \in \Re$;

Step 2: Search for clusters using the Gustafson–Kessel (G-K) algorithm of Table 3;

Step 3: Check for similarities among the clusters whether two clusters describe a similar hyperplane;

Step 4: Project the membership functions from the partition matrix U into the input space;

Step 5: Approximate the projected membership function using convex membership functions (triangular, Gaussian, polynomial, trapezoidal, etc.);

Step 6: Construct the rules with the projected membership functions;

Step 7: Generate the consequences using the covariance matrices of each cluster;

Step 8: Calculate the consequences that are not covered by the clusters using ARLS recursive least squares estimation-type algorithm [17– 19]; and

Step 9: Adjust the parameters of the antecedents using MLMA gradient-type descent algorithm [17–19].

3.5. Implementation of the Proposed HANFA-ART with Adaptive Clustering Algorithm

Next, we now consider how the HANFA-ART implements the premise and consequent parameters for the membership functions with the associated rules. There are number of possible approaches which uses steepest descent and least squares estimation algorithms [18, 24, 25] but the hybrid learning algorithm proposed in this study which uses a combination of the MLMA steepest descent-type and ALRS least squares estimation-type algorithms [17–19]. However, the implementation of the use steepest descent and least squares estimation algorithms can get very complicated but a very high-level description of how the proposed MLMA and the ARLS algorithms operate can be found in [17–19].

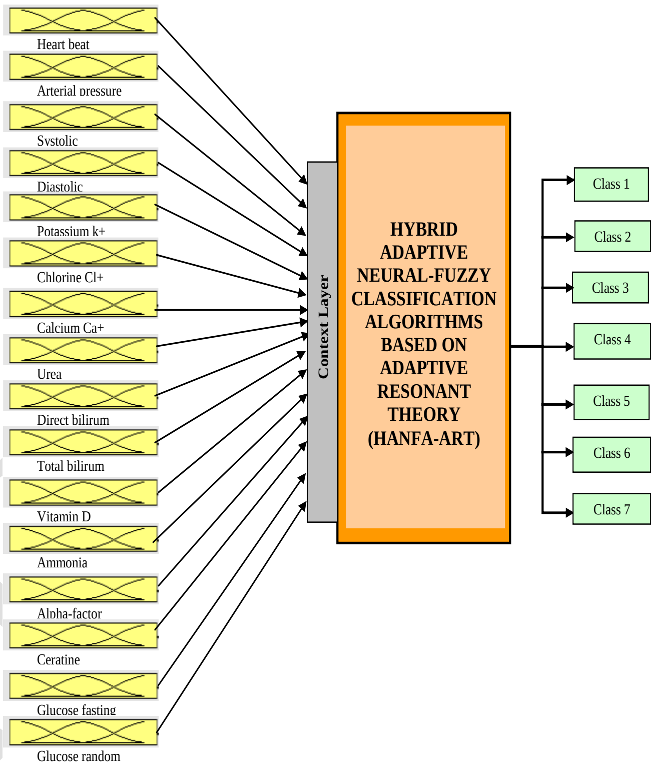


Fig. 2: The architecture for the implementation of the proposed HANFA-ART with clustering algorithm for classification of impending heart, kidney and liver failures.

It can be shown that for the network described in Fig. 1 if the premise parameters are fixed the output is linear in the consequent parameters. Then the total parameters set can be split into three sets: S = set of total parameters, S_1 = set of premises (nonlinear) parameters, and S_2 = set of consequent (linear) parameters. Thus, the proposed HANFA-ART algorithm uses a two-pass learning algorithm:

1). Forward Pass. Here S_1 is unmodified and $S_2$is computed using an adaptive recursive least square (ARLS) algorithm proposed in this work.

2). Backward Pass. Here S_2 is unmodified and S_1 is computed using a gradient descent algorithm such as the MLMA algorithm proposed in this work.

So, the proposed hybrid learning algorithm uses a combination of steepest descent algorithm (i.e. the proposed MLMA) and a recursive least squares algorithm (i.e. the proposed ARLS) to adapt the parameters in the adaptive network. The summary of the process is given below:

(1). The Forward Pass (This propagates the input vector through the network layer by layer as follows):

- *i).* Present the input vector;
- *ii).* Calculate the node outputs layer by layer;
- *iii).* Repeat for all data → A and *y* formed;
- *iv).* Identify parameters in S_2 using least squares algorithm (i.e. the ARLS algorithm); and
- *v).* Compute the error measure for each training pair.

(2). Backward Pass (In this case, the error is sent back through the network in a manner similar to the back propagation but it is implemented here by the proposed efficient MLMA algorithm):

- *i).* Use steepest descent algorithm to update parameters in S_1 (i.e. the proposed MLMA); and
- *ii).* For given fixed values of S_1 the parameters in S_2 found by this approach are guaranteed to be the global optimum

The architecture and learning procedure underlying HANFA-ART is presented, which is a fuzzy inference system (FIS) implemented in the framework of adaptive networks. By using the proposed hybrid learning procedures, the proposed HANFA-ART can construct an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs. In the simulation, the HANFA-ART architecture can be adapted to model nonlinear functions, identify nonlinear components on-line in a control system, short-term or long-term forecast, prediction of a chaotic time series as well as object classification with remarkable results.

4. RESULTS AND DISCUSSIONS

The data collected from various patients from four different hospitals have been discussed in Section 2. Furthermore, the proposed HANFA-ART with adaptive Gustafon-Kessel clustering algorithms which have been developed and discussed in Section 3 will be implemented here and used to investigate and classify the symptoms of impending Heart, Kidney and Liver failure based on the 5888 data set. The architectural design implemented here consists of 16 inputs (attributes) and 7 outputs (classes). The inputs consist of *(1)* Heart beat per minutes; *(2)* Mean arterial pressure (mmHg); *(3)* Systolic Bp (mmHg); *(4)* Diastolic Bp; *(5)* Potassium; *(6)* Chlorine; *(7)* Calcium; *(8)* Creatinine (umol/l); *(9)* Glucose fasting (mol/l); *(10)* Glucose random (mol/l); *(11)* Urea (mmol/l); *(12)* Direct bilirubin (mg/dl); *(13)* Total bilirubin (mg/dl); *(14)* Vitamin D (ng/ml); *(15)* Ammonia (mcg/dl); and (16) Alpha-feto (ng/ml) while the outputs consist of seven classes that defines the likely state of health of the individual depending on the symptoms classified in the blood-related parameter. The seven classes that constitute the outputs are: *(1)* Class 1: Likely Heart Failure; *(2)* Class 2: Likely Kidney Failure; *(3)* Class 3: Likely Liver Failure; *(4)* Class 4: Likely Kidney and Liver Failure; *(5)* Class 5: Likely Heart and Liver Failure; *(6)* Class 6: Likely Heart and Kidney Failure; and *(7)* Class 7: Likely Heart, Kidney and Liver.

The architecture for the implementation of the proposed HANFA-ART with clustering algorithm for classification of impending heart, kidney and liver failures is shown in Fig. 2. The implementation is based on the Sugeno-type fuzzy rule-based logic for fuzzification. The rule viewer for the HANFA-ART implementation is shown in Fig. 3. For performance comparison, two algorithms have been implemented for the current classification problem, namely: the proposed hybrid adaptive neural-fuzzy algorithm based on adaptive resonant theory (HANFA-ART) with adaptive clustering and the M-EBPM [18].

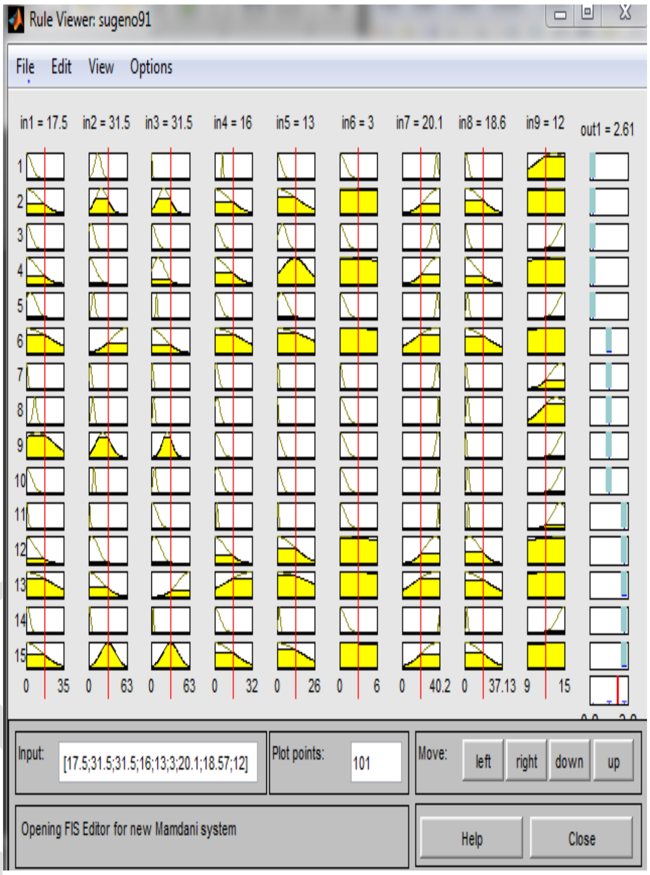


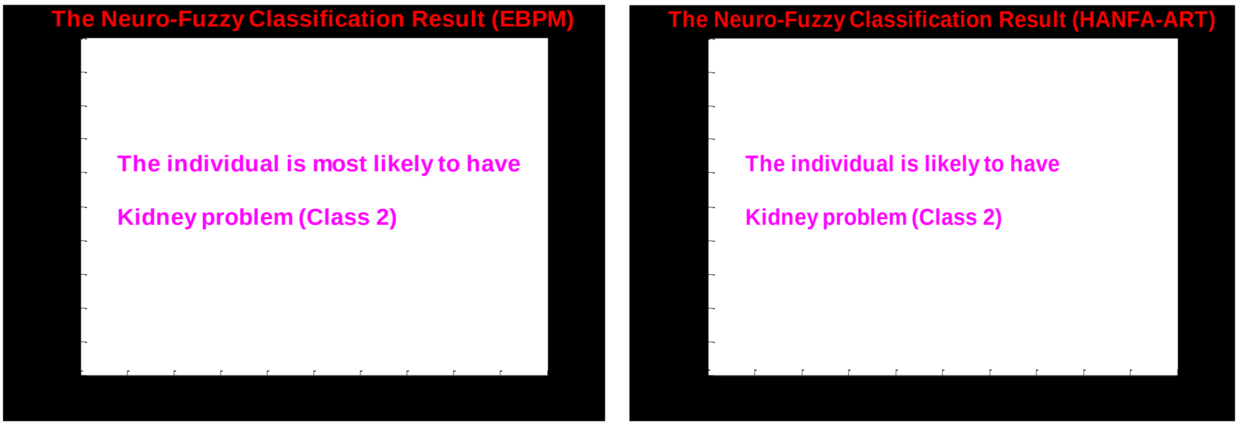
Fig. 3: The classification results of the proposed HANFA-ART with adaptive clustering algorithm for the symptoms of impending heart, kidney and liver failures.

Using these two classification algorithms, the class accuracies of a sampled individual data based on the 16 attributes are computed and expressed in percentage (%).

Case 1: In Case 1, a patient's data selected at random happens to fall into Class 2 who is likely to have kidney problem. The result of a sampled Case 1 is shown in Fig. 4 (a) and (b) for the two algorithms being compared in this work and Table 4 shows the percentage accuracies of each class for both algorithms. From the Figure, both algorithms had the same classification with the HANFA-ART algorithm having the higher percentage conviction.

Case 2: In Case 2, a patient's data selected at random happens to fall into Class 6 who is likely to have both heart and kidney problem. The result of a sampled Case 2 is shown in Fig. 5(a) and (b) for the two algorithms being compared in this work and Table 5 shows the percentage accuracies of each class for both algorithms. From the Figure and Table, the two algorithms had different result of classification but one can see that the percentage of the chances of Class 6 taking effect classified by the HANFA-ART is higher than that of the EBPM algorithm based on that, the result of

HANFA-ART is more valid, as it give more convictions in its decision making process, which is evident in the Table 4.

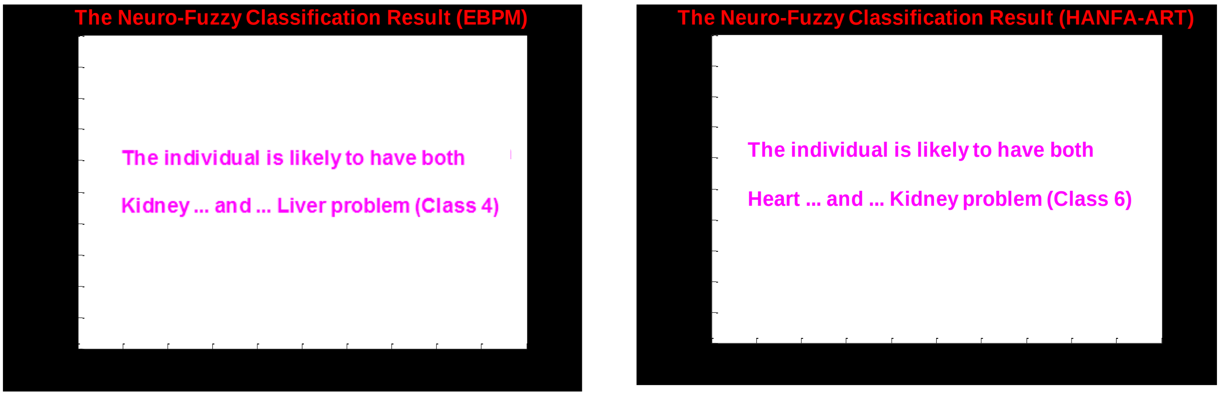


(a) (b)

Fig. 4: Classification result based on (a) EBPM and (b) HANFA-ART for sampled Case 1.

Table 4: Neuro-Fuzzy classification results with class accuracy for Case 1

Sample Individual	**Classes**	**Neuro–Fuzzy Classifier Based on EBPM**	**Neuro–Fuzzy Classifier Based on HANFA-ART**
CASE 1	Class 1	NaN%	NaN%
	Class 2	35.7143%	50%
	Class 3	NaN%	NaN%
	Class 4	30%	47%
	Class 5	NaN%	NaN%
	Class 6	0%	0%
	Class 7	NaN%	NAN%

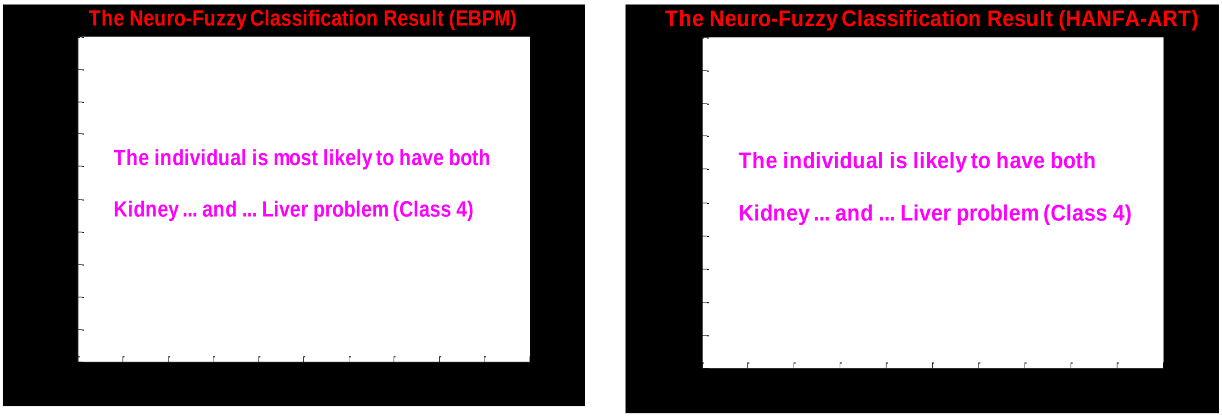


(a) (b)

Fig. 5: Classification result based on (a) EBPM and (b) HANFA-ART for sampled Case 2.

Table 5: Neuro-Fuzzy classification results with class accuracy for Case 2

Sample Individual	**Classes**	**Neuro–Fuzzy Classifier Based on EBPM**	**Neuro–Fuzzy Classifier Based on HANFA-ART**
CASE 2	Class 1	NaN%	10%
	Class 2	14.2857%	28.5714%
	Class 3	10.2667%	NaN%
	Class 4	30%	12.556%
	Class 5	NaN%	NaN%
	Class 6	9.55%	53.3333%
	Class 7	NAN%	NaN%

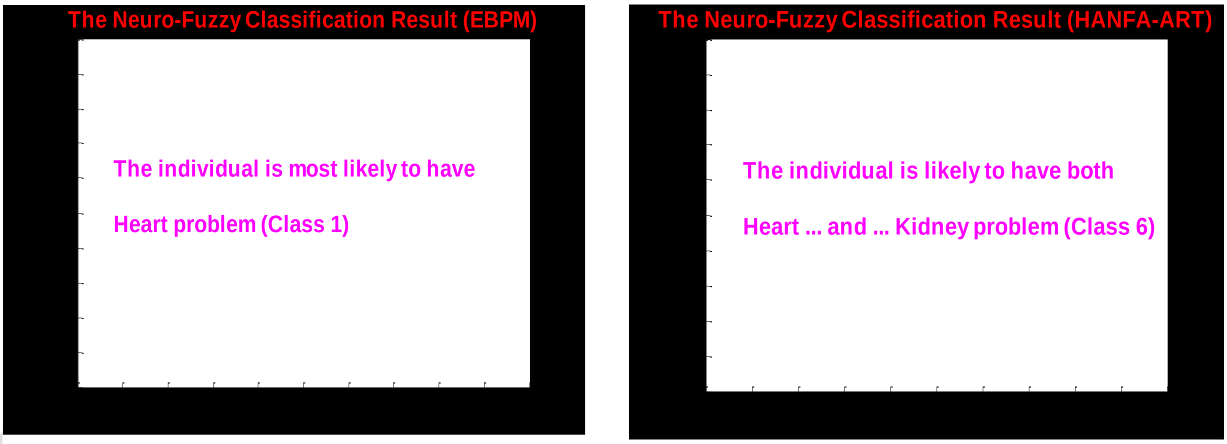


(a) (b)

Fig. 6: Classification result based on (a) EBPM and (b) HANFA-ART for sampled Case 3.

Table 6: Neuro-Fuzzy classification results with class accuracy for Case 3

Sample Individual	Classes	Neuro–Fuzzy Classifier Based on EBPM	Neuro–Fuzzy Classifier Based on HANFA-ART
CASE 3	Class 1	NaN%	NaN%
	Class 2	34.426%	42.8571%
	Class 3	24.22%	34.222%
	Class 4	43.1%	65%
	Class 5	NaN%	NaN%
	Class 6	3.3333%	13.33%
	Class 7	NaN%	NAN%



(a) (b)

Fig. 7: Classification result based on (a) EBPM and (b) HANFA-ART for sampled Case 4.

Table 7: Neuro-Fuzzy classification results with class accuracy for Case 4

Sample Individual	Classes	Neuro–Fuzzy Classifier Based on EBPM	Neuro–Fuzzy Classifier Based on HANFA-ART
CASE 4	Class 1	48.44%	51.4286%
	Class 2	21.4286%	29.2857%
	Class 3	NaN%	NaN%
	Class 4	0%	0%
	Class 5	NaN%	NaN%
	Class 6	13.3333%	66.6667%
	Class 7	NAN%	NaN%

Case 3: In Case 3, a patient's data selected at random happened to fall into Class 4 who is likely to have both kidney and liver problem. The result of a sampled Case 3 is shown in Fig. 6(a) and (b) for the two classification algorithms Table 6 shows the percentage accuracies of each class for both algorithms. Based on the result, both algorithms had the same classification prediction with the HANFA-ART algorithm having the higher percentage accuracy.

Case 4: In Case 4, a patient's data selected at random happened to fall into Class 6 who again is likely to have both heart and kidney problem. Figure 7(a) and (b) shows the result of sampled Case 4 and Table 6 shows the percentage accuracies of each class for both algorithms. From Fig. 7(a) and (b) one can see that the percentage of the chances of Class 6 taking effect classified by the HANFA-ART higher, making it the best classification scheme as it gives more bases for decision making process. This is also evident in Table 7.

5. SUMMARY

5.1 Conclusions

The objective of this work, which are to identify the causes of impending heart, kidney and liver failure based on blood samples; formulate and develop an adaptive classification algorithm (hybrid adaptive neural-fuzzy algorithm based adaptive resonant theory) classify the state of the heart, kidney and liver based on the symptoms identified using the developed algorithm (s) have been achieved.

In this study, 16 different attributes were classified into seven classes. The hybrid adaptive neural-fuzzy algorithm based on adaptive resonant theory (HANFA-ART) with adaptive Gustafon-Kessel clustering algorithm for classification has been developed and its efficiencies over the EBPM has been seen from the simulation results, and hence, can be adopted in hospitals and medical laboratories for real-time diagnosis of patients for the state of their heart, kidney and liver based on their blood samples.

The result of this study can facilitate the diagnosis, classification and prediction of possible symptoms of impending heart, kidney and liver failures based on data obtained from measureable blood-related parameters that medical practitioners normally employ to diagnose the symptoms of impending heart, kidney and liver failures based on the result of physical examination. Blood tests are done to evaluate heart, kidney and liver functions which are usually severely impaired. To check for possible causes, medical practitioners ask about all substances that people have taken, including prescription and over the-counter drugs, herbal products and nutritional supplements, blood tests are also done to identify possible causes.

5.2 Future Directions

Medical history of the patients should be incorporated into the fuzzy expert system; this will help in proper decision-making process by the algorithm. Hence future works should consider gathering the basic medical information as it regards the individual by means of questionnaire. The information when gathered and implemented will enhance the effectiveness of the algorithm for the prediction, classification and control of the state of health of the individual.

Future work should provide a user-friendly graphical interface (GUI) where someone can monitor or observe his or her health condition by simply providing answers to the questions pop up by the interface. Furthermore, suggestions or advice for each of the class options to help prevent the materialization of the diagnosed impending health issues should be included. Future directions should develop technologies that could display the basis for decisions making from the input (symptoms), that is, the algorithm should be able to illustrate why its class 1, class 2, class 3, or class 4, etc as the case may be and should also show the symptoms and their levels in the blood per test case on an individual.

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