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Adaptive Classification of Impending Human Heart, Kidney and Liver Failures Based on Measurable Blood-Related Parameters Using MIMO HANFA-ART with ACA Algorithms

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Abstract: Heart, kidney and/or liver failure is a life-threatening condition that demands early detection as well as urgent medical attention and diagnosis based on the classification of their respective symptoms. This paper presents the application of multi-input multi-output hybrid adaptive neural-fuzzy algorithm based on adaptive resonant theory (MIMO HANFA-ART) with adaptive clustering algorithm (ACA) for the adaptive classification of the symptoms of impending human heart, kidney and liver failures based on measurable blood-related parameters obtained from hospitals in Akure metropolis of Ondo State, Nigeria. The ACA consist of an adaptive Gustafson and Kessel clustering (AG-KC) algorithm which is initialized by the *K*-means clustering algorithm. The 7 classes are: *(i)* Class 1: heart, *(ii)* Class 2: kidney, *(iii)* Class 3: liver, *(iv)* Class 4: kidney and liver, *(v)* Class 5: heart and liver, *(vi)* Class 6: heart and kidney, and *(vii)* Class 7: heart, kidney and liver. A total of 5888 data set with 16 attributes classified into 7 classes for 368 patients collected from 4 hospitals have been used for this investigation. Comparison of the MIMO HANFA-ART with ACA algorithms with neural-fuzzy classifier trained with the modified error back-propagation with momentum (M-EBPM) algorithm shows the efficiency and superior performance of the MIMO HANFA-ART with ACA algorithms for correct classification and prediction of the symptoms of impending heart, kidney and liver failure. MIMO HANFA-ART with ACA algorithms can be adapted and deployed for real-time online prediction and classification of the symptoms of heart, kidney and liver for early detection and medical attention using advanced biomedical electronics instrumentation techniques and Internet-of-Things (IoT) technologies.

Keywords: Adaptive Clustering Algorithm (ACA), Adaptive Gustafson and Kessel Clustering (AG-KC), *K*-Means Clustering, Adaptive Classification, Blood-Related Parameters, M-EBPM, MIMO HANFA-ART, Neural-Fuzzy Systems

1. Introduction

The heart, kidney and/or liver failure is a life-threatening condition that demands early detection as well as urgent medical attention. The failure of all or any of these three organs can be acute (over days or weeks) or chronic (over months or years). The heart, kidney and liver share one thing in common, namely: the blood from where human state of health can be deduced and/or inferred. For the heart, uncontrolled high blood pressure (hypertension) is a major cause of heart failure even in the absence of a heart attack [1]. On the other hand, while kidney ensures the removal of waste and excess fluid from the blood, kidney failure raises the risk of other cardiovascular problems such as blockage of blood to the heart and congestive heart failure [1]. Apart from the liver's main job of filtering the blood coming from the digestive track before passing it to the rest of the body; the liver also carry out a large number of critical functions including the manufacture of essential proteins and metabolism of fats and carbohydrates, eliminates harmful biochemical waste products, and secretes bile that contains bile acids which aid in the digestion and intestinal absorption of fats and vitamins [1].

Some cancer treatments can affect the function of major organs like the heart, kidneys, liver and lungs [2]. If cancer treatments are combined, such as chemotherapy with immunotherapies or other biological agents, they may be more likely to affect the heart. The effect may be temporary, but sometimes it can be permanent. In such case, the doctor may test the heart function with an electrocardiogram (ECG) or another test(s) before each treatment session [1, 2]. Many drugs are excreted through the kidneys. If a patient have pre-existing kidney damage or impaired kidney function, such a patient may need modified doses of drugs [2]. In such cases, the doctor may order for blood tests to assess kidney function before starting therapy to determine whether a lower dose is needed. Chronic kidney disease (CKD) or chronic renal failure (CRF), as it was historically termed–is a term that encompasses all degrees of decreased kidney function, from damaged–at risk through mild, moderate, and severe chronic kidney failure [1–4]. Furthermore, if the patient has pre-existing liver disease, the patient may need reduced doses of drugs that are metabolized in the liver or excreted into the bile [2]. Some anticancer agents may be toxic to the liver. In this liver cases, the doctor may test the blood periodically to assess the liver function and look for possible damage [1, 2].

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 [5, 6]. 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 area of computational intelligence [7, 8]. 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 [7–11].

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 [12]. 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 type 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 [11, 12]. 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 [13, 14].

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 [1]. 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 multi-input multiple-output (MIMO) hybrid adaptive neural-fuzzy algorithm based adaptive resonant theory (HANFA-ART) with adaptive clustering algorithm (ACA). For performance evaluation and comparisons, the MIMO 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 [1].

2.1.1. The Heart

(i) 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;
(ii) Mean arterial pressure is between 60 mmHg or greater is needed to maintain adequate tissue per fusion; and;
(iii) The blood pressure consist 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.

2.1.2. The Kidney

(i) Packed cell volume/blood cell: *(a)* Male should be between 40–50% and *(b)* Female should be between 35–44%;

(ii) Erythropoetin should be between (4–24 mu/ml)

(iii) 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.

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

2.1.3. The Liver

(i). 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;

(ii). 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.

(iii). Ammonia Level

(a) Adult is between 9.5 – 49 mcg/dl; *(b)* Children are 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). Figure 1 to Figure 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 only 16 of these parameters were available from four different hospitals consulted for this study [1].

3. The MIMO HANFA-ART with ACA Algorithms

3.1. The Takagi-Sugeno Fuzzy Rule-Based Logic: Systems and Models

Generally, fuzzy inference systems (FIS) can be systematically constructed from “pure” input–output data. All methods are based on the optimization of a cost function to minimize the “distance” between the predictions of the FIS and the output data. The main differences among the methods are the initialization and the adjusted parameters.

Table 3. *List of variables and their definitions.*

Variable	Definitions
i	i-th input linguistic variable
j	j-th input-tem node from i-th input linguistic variable
k	Corresponding index of j-th input-term node
m	Number of system inputs
n	Number of system outputs
A	First coded input normalization
B	Second coded input normalization
a	Lower input distribution interval
b	Upper input distribution interval
l	l^{th} rule of Mamdani and Sugeno fuzzy systems
μ	Antecedent term
y	Output variable
y	Output vector
y'	Complement coded output vector
$\overline{\mathrm{y}}$	Mean value of output vector
$\hat{y}$	Predicted node output variable
u	Inputs variable
u	Input vector
u'	2n-dimensional complement coded input vector
$\overline{\mathrm{u}}$	Mean value of complement coded input vector
C	Third coded input normalization
D	Fourth coded input normalization
E	Approximation error vector
N	Normalization strength
P	Fuzzy covariance matrix
S	Set of total parameters
U	Set of rules
W	Regularization factor
Z^T	Number of output variables
c	A cluster point
e	Approximation error variable
f	Fuzzy model
$\overline{f}$	Rule consequences variable
w	T-norm operator on fuzzy-AND operation
$\overline{w}$	Output of normalization strength
v_i	Cluster centers
γ	Membership function fuzziness regulator
κ	Right-flat points of membership functions
ε	Fuzzy model output prediction error
υ	Left-flat points of membership functions
S_1	Set of premise (nonlinear) parameters
S_2	Set of consequence (linear) parameters
$J(U,\theta)$	Cost function to minimize θ
Π	Fuzzy-AND operation
⅂, ⎾, ⎾⏋	Input fuzzification membership functions
u_k	End-point from cluster center
U_k	Cluster point vector
U_c	Cluster sum of squares
$d(v_i,u_k)$	Distance measured from v_i to u_k
$U^{(j)}$	A priori control signal
$U^{(j-1)}$	Posteriori control signal
θ	All adjustable parameters of the fuzzy system
$\in$	Optimization termination quantity
M	Mountain function for AMCC
V	Set of future vectors
Z^R	Number of fuzzy-based rules
Z^N	Number of input variables

The basic FRBL scheme was original proposed by Wang [15]. In this paper, some simple modifications are proposed and these modifications are related to the consequence calculations. In the proposed modifications: the position, the shape and the distribution of the membership functions are choices for the designer rather than being fixed. Further, the rule-based logic is initialized through clustering based on experimentally acquired data and the proposed method finds only the consequences of the rules. The list of the variables and their definition used in this paper are listed in Table 3 while other variables are introduced and defined where used.

Supposed that a sequence of input–output $\{u^i, y^i\}$ for $i = 1, 2, \ldots, n$ data is collected, the inputs $u^i \in V \subset \Re^p$ and the output $y^i \in V \subset \Re^q$. The subset $\wp$ is a portion of the space $\Re^p$ and is defined as $\wp = [a_1, b_1] \times \cdots \times [a_p, b_p]$. The procedure to construct the model is laid out in the following [16, 17]:

1). For each of the p inputs of the system distribute over the interval $[a_i, b_i]$ and n_i membership functions. The shape, position and distribution can be arbitrarily specified. The only condition is that the full interval must be covered and at least two membership functions should be placed on each point of the input domain. However, note that the shape and the distribution affects the smoothness and the accuracy of the approximation.

2). Generate the rules using all possible combinations among the antecedents and the AND-operator (choosing in advance “*min*” or “*product*” operator). The rule l of the rules for Takagi–Sugeno fuzzy systems is:

IF u_1^i is A_1^l AND … AND u_p^i is A_p^l

THEN $y = a_1^l u_1^i + a_2^l u_2^i + \cdots + a_p^l u_p^i + b^l$

3). Calculate the inference of each rule. For rule l of the form.

$$\mu_l(u^i) = \min\left\{\mu_l^1(u_1^i),\ \mu_l^2(u_2^i),\ \ldots,\mu_l^p(u_p^i)\right\} \quad (1)$$

$$\text{or} \quad \mu_l(u^i) = \mu_l^1(u_1^i) \cdot \mu_l^2(u_2^i) \cdot \cdots \cdot \mu_l^p(u_p^i) \quad (2)$$

The general expression for these fuzzy system with L rules for the Takagi–Sugeno fuzzy models is given by

$$f(u^i) = \frac{\sum_{l=1}^{L}\left(a_1^l u_1^i + a_2^l u_2^i + \cdots + a_p^l u_p^i + b^l\right)\mu_l(u^i)}{\sum_{l=1}^{L}\mu_l(u^i)} \quad (3)$$

4). Calculate the consequence parameters. In the Takagi–Sugeno fuzzy model, the parameters to be calculated are

$a_1^l, a_2^l, \ldots, a_p^l$ and b^l for $l = 1, 2, \ldots, L$ such that $f(u^i) \approx y^i$. Using the reasoning applied for the Mamdani fuzzy models, Equation (3) can be written as:

$$f(u^i) = \sum_{l=1}^{L} \left(a_1^l u_1^i + a_2^l u_2^i + \cdots + a_p^l u_p^i + b^l \right) \omega_l(u^i) \quad (4)$$

where $\omega_l(u^i)$ has the form given as follows:

$$\omega_l(u^i) = \frac{\mu_l(u^i)}{\sum_{l=1}^{L} \mu_l(u^i)} = \omega_l^i \quad (5)$$

The n output values can be represented as the vector Y in terms of the inference process as

$$\underbrace{\begin{bmatrix} y^1 \\ y^2 \\ \vdots \\ y^N \end{bmatrix}}_{Y} = \underbrace{\begin{bmatrix} \omega_1^1 u_1^1 & \cdots & \omega_1^1 u_p^1 & \omega_1^1 & \omega_2^1 u_1^1 & \cdots & \omega_L^1 u_p^1 & \omega_L^1 \\ \omega_1^2 u_1^1 & \cdots & \omega_1^2 u_p^1 & \omega_1^2 & \omega_2^2 u_1^1 & \cdots & \omega_L^2 u_p^1 & \omega_L^2 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \omega_1^N u_1^1 & \cdots & \omega_1^N u_p^1 & \omega_1^N & \omega_1^N u_1^1 & \cdots & \omega_L^N u_p^1 & \omega_L^N \end{bmatrix}}_{W} \underbrace{\begin{bmatrix} a_1^1 \\ a_2^1 \\ \vdots \\ a_p^1 \\ b^1 \\ a_1^2 \\ \vdots \\ a_p^L \\ b^L \end{bmatrix}}_{\theta} + \underbrace{\begin{bmatrix} e^1 \\ e^2 \\ \vdots \\ e^n \end{bmatrix}}_{E} \quad (6)$$

In Equations (6), the vector E is the approximation error and the aim is to reduce the norm of this vector as much as possible. Using the quadratic norm to measure the approximation error, we obtain

$$\min_{\theta} \|E\|_2 = \min_{\theta} \|Y - W\theta\|_2 \quad (7)$$

It is a least-squares problem and the consequences can be calculated using least squares. The basic solution to this least-squares problem is

$$\theta = \arg\min_{\theta} \|E\|_2 = \left(W^T W\right)^{-1} Y^T W \quad (8)$$

This solution is applicable as far as the *rank* $(W^T W)$ = *dim* (θ); otherwise other methods must be applied to guarantee a reliable set of consequences for the rules. From the work of Akpan and co-workers, an efficient algorithm called the adaptive recursive least squares (ARLS) has been adapted in this paper for estimating and updating the consequences parameters [18–20].

3.2. The MIMO HANFA–ART with ACA Network Architecture

The MIMO HANFA-ART with ACA network consists of six layers as shown in Figure 1. The proposed network architecture employs two major algorithms for parameters adjustment and learning (i.e. the ARLS and MLMA) and one algorithm for automatic structure learning (i.e. the fuzzy-ART). In the following, we briefly describe the operation of each layer. A descriptive representation of a m-inputs and n-outputs MIMO HANFA-ART with ACA network architecture with 4-fuzzy rules is shown in Figure 1. The code segment that executes the Fuzzy-ART algorithm is adopted (with the necessary modifications) from the well-structured, reliable and tractable Fuzzy-ART [16, 17].

3.3. The Adaptive Clustering Algorithms (ACA)

Until now, the fuzzy sets of the input domains have been placed on their initial positions which is usually equally distributed from the experimental data. Two choices are available for re-positioning these input domains, namely: *1)* the number of membership functions and *2)* their initial distribution. However, 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 U 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 methods based on clustering are considered as data-driven techniques [21–28]. The main idea of these techniques 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) [17, 21–28].

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 the membership functions can be automatically generated such that only the parameters of the clustering algorithms (number of clusters and distance function) can be arbitrarily chosen. According to the type of model to be constructed, the clustering method can be slightly different. In the next few sub-sections, the clustering algorithms as applied to the Mamdani and the Takagi–Sugeno fuzzy models are presented.

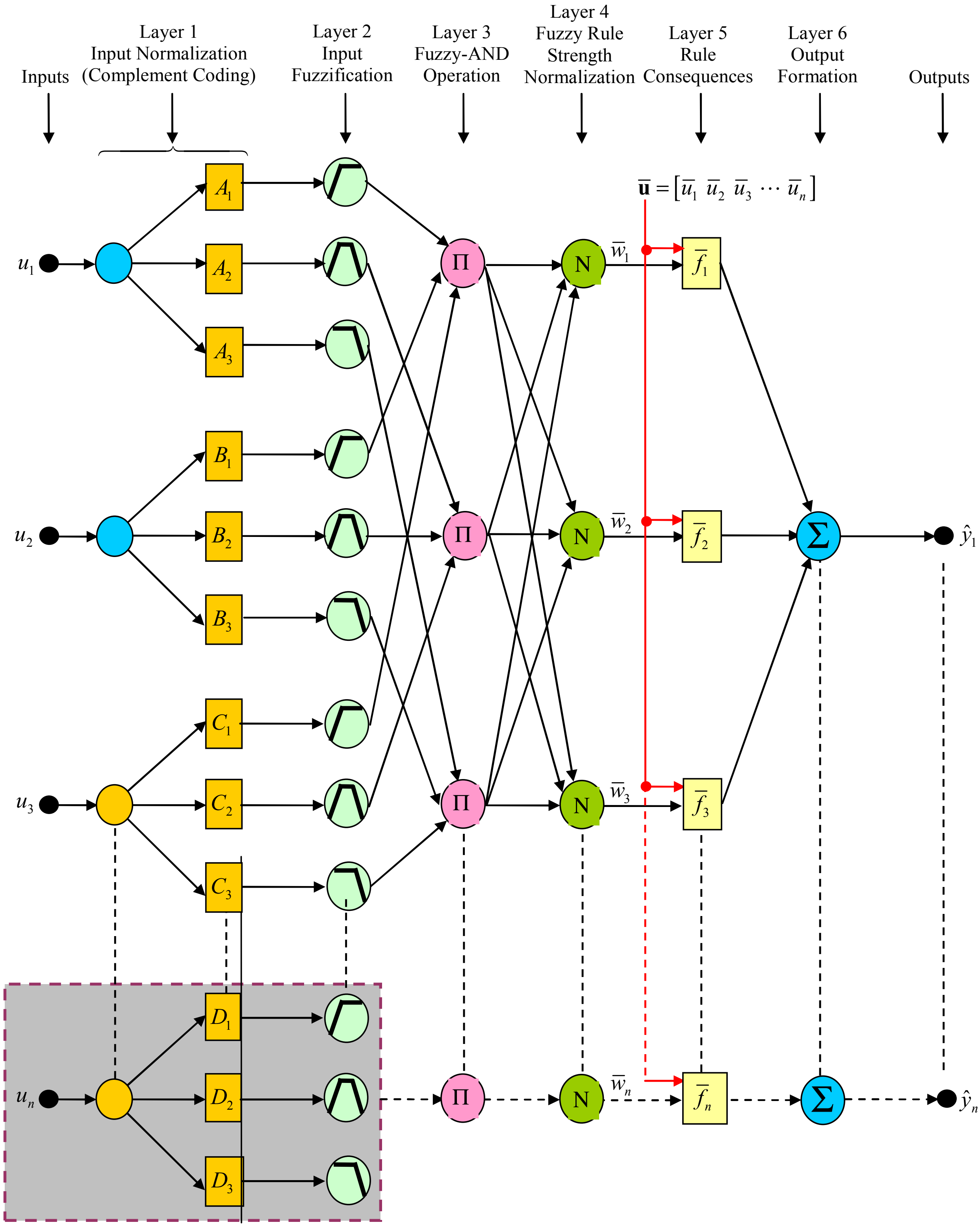


Figure 1. *The HANFA-ART with ACA network architecture [17].*

3.3.1. The K-Means Clustering Algorithms

The hard-partitioning methods are simple and popular, though its results are not always reliable and these algorithms have numerical problems as well [21, 29]. From an $N \in n$ dimensional data set, K-means and K-medoid algorithms allocates each data point to one of c clusters to minimize the within-cluster sum of squares [17, 21]:

$$U_c = \sum_{i=1}^{c} \sum_{k \in A_i} \left\| \mathrm{U}_k - \mathrm{v}_i \right\|_2 \tag{9}$$

where A_i is a set of objects (data points) in the i-th cluster and v_i is the mean for that points over cluster i. Equation (9) denotes actually a distance norm. In K-means clustering v_i is called the cluster prototypes, i.e. *the cluster centers*:

$$v_i = \frac{\sum_{k=1}^{N_i} \mathrm{u}_k}{N_i}, \qquad \mathrm{u}_k \in A_i \tag{10}$$

where N_i is the number of objects in A_i.

However, in K-medoid clustering the cluster centers are the nearest objects to the mean of data in one cluster $V = \{\mathrm{v}_i \in U \mid 1 \le i \le c\}$. The K-means clustering algorithm is used to initialize the data clustering process. This initial clustering by the K-means algorithm sets the initial partitioning of the given data set from the initial distribution.

3.3.2. Adaptive Gustafson and Kessel Clustering (AG-KC) Algorithm

The adaptive Gustafson and Kessel clustering algorithm is based on the minimization of the cost function [17, 25]:

$$\left.\begin{aligned} &\min_{(U,V,A)} \Big\{ J_m(U,V,A;\mathrm{u}) = \\ &\sum_{k=1}^{n} \sum_{i=1}^{c} (\mu_{ik})^m (u_k - v_i)^T A_i (u_k - v_i) \Big\} \end{aligned}\right\} \tag{11}$$

where u is the set of vectors, $u_k \in \Re^p$ 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:

$$M_{fc} = \left\{ \begin{aligned} & U \in \Re^{c \times N} \, \big| \mu_{ik} \in [0,1], \quad \forall i,k; \\ & \sum_{i=1}^{c} \mu_{ik} = 1, \qquad \forall k; \\ & 0 < \sum_{k=1}^{N} \mu_{ik} < N, \qquad \forall i \end{aligned} \right\} \tag{12}$$

The *ith* row of the fuzzy partition matrix contains the membership values of the vectors u 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: $|A_i| = \rho i, \quad \rho > 0$.

Applying the Lagrange multipliers to the above optimization problem of Equation (12) generates the following expression for A_i:

$$A_i = \left[\rho_i \det(P_i) \right]^{1/n} P_i^{-1} \tag{13}$$

where P_i is the fuzzy covariance matrix:

$$P_i = \frac{\sum_{k=1}^{n} (\mu_{ik})^m (u_k - v_i)(u_k - v_i)^T}{\sum_{k=1}^{n} (\mu_{ik})^m} \tag{14}$$

The element of U are calculated as

$$\mu_{ik} = \left[\sum_{j=1}^{c} \left(\frac{(u_k - v_i)^T A_i (u_k - v_i)}{(u_k - v_j)^T A_i (u_k - v_j)} \right)^{\frac{2}{m-1}} \right]^{-1} \quad \forall i,k \tag{15}$$

The prototypes v_i are calculated as

$$v_i = \frac{\sum_{k=1}^{n} (\mu_{ik})^m u_k}{\sum_{k=1}^{n} (\mu_{ik})^m}, \quad \forall i \tag{16}$$

The implementation of the adaptive Gustafson and Kessel clustering (AG-KC) algorithm is summarized as followings.

Given the data set Z with N vectors, select the number of clusters $1<c<N$, the exponent m, the termination tolerance $\varepsilon>0$ 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:

$$\left.\begin{aligned} v_i^{(j)} &= \frac{\sum_{k=1}^{n} \left(\mu_{ik}^{(j-1)}\right)^m x_k}{\sum_{k=1}^{n} (\mu_{ik})^m} \\ &\mathit{for}\ 1 \le i \le c \end{aligned}\right\} \tag{17}$$

3). Step 2: calculate fuzzy partition matrix:

$$P_i^{(j)} = \frac{\sum_{k=1}^{n} \left(\mu_{ik}^{(j-1)}\right)^m \left(x_k - v_i^{(j)}\right)\left(x_k - v_i^{(j)}\right)^T}{\sum_{k=1}^{n} \left(\mu_{ik}^{(j-1)}\right)^m} \tag{18}$$

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

$$\left.\begin{aligned} A_i &= \left[\rho_i \det(P_i) \right]^{1/n} P_i^{-1} \\ &\mathit{for}\ 1 \le i \le c \end{aligned}\right\} \tag{19}$$

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

$$\left.\begin{aligned} \mu_{ik}^{(j)} &= \left[\sum_{l=1}^{c} \left(\frac{\left(x_k - v_i^{(j)}\right)^T A_i^{(j)} \left(x_k - v_i^{(j)}\right)}{\left(x_k - v_l^{(j)}\right)^T A_i^{(j)} \left(x_k - v_l^{(j)}\right)} \right)^{\frac{2}{m-1}} \right]^{-1} \\ & for \quad 1 \le i \le c, 1 \le k \le N \end{aligned}\right\} \tag{20}$$

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

It is important to remark that when the vector u_k is equal to one of the prototypes v_i the Equation (20) 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 *U*.

3.4. The Adjustable Parameters of the HANFA-ART with FRBL 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] and N_i membership functions; the shape, the initial positions and the distribution can be chosen arbitrarily as just discussed in Section 3.3. 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 $\overline{y}^l$ 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

$$J(U,\theta) = \frac{1}{2} \sum_{i=1}^{Z^T} \left(y^i - \hat{y}^i \right)^2 \tag{21}$$

where $\hat{y}^i = f\left(U^i, \theta\right)$ and θ is a vector representing all the "adjustable" parameters (consequences, 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 and non-convex optimization problem. The objective is to obtain an "acceptable" solution and not necessarily "the global minima" of this cost function of Equation (21).

3.5. Training of the MIMO HANFA-ART with ACA Algorithms

Next, how the HANFA-ART with ACA is trained to learn the premise and consequent parameters for the membership functions with the associated rules is considered. There are numbers of possible approaches but the learning algorithm proposed by Jang and co-workers which uses a combination of steepest descent and least squares estimation (LSE) has been widely used with several challenges [30–32]. However, these challenges have been shown to be very complicated but a systematic implementation to overcome these challenges is presented in the remaining of this paper for the MIMO HANFA-ART with ACA.

It can be shown that for the network illustrated in Figure 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 premise (nonlinear) parameters, and S_2 = set of consequent (linear) parameters. Thus, the MIMO HANFA-ART with ACA uses a two-pass learning algorithms:

3.5.1. Forward Pass

Here S_1 is unmodified and S_2 is computed using an adaptive recursive least square (ARLS) algorithm described in [18–20].

3.5.2. Backward Pass

Here S_2 is unmodified and S_1 is computed using a special gradient descent algorithm called the MLMA algorithm described in [18, 19].

3.6. Summary of Algorithm for Takagi–Sugeno Fuzzy Models for the MIMO HANFA-ART with AG-KC Algorithm

The summary of the MIMO HANFA-ART with ACA algorithm for calculating the consequences parameters and to adjust the antecedent parameters appropriately using the Takagi–Sugeno fuzzy model is summarized as follows:

Step 1: Collect the data and construct a set of vectors $Z^N = \{u^i, y^i\}$ where *u* and *y* are the inputs and the output of the function respectively. Observe that it is assumed here that $u^i \in \Re^n$ and $y^i \in \Re$;

Step 2: Search for clusters using the combination of the *K*-means and the AG-KC algorithms;

Step 3: Check for similarities among the clusters. Do 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 appropriate projected membership function using convex membership functions such as triangular, Gaussian, polynomial, trapezoidal, etc. as described in Appendix A, B and C of [17];

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 recursive least squares using the ARLS algorithm; and,

Step 9: Adjust the parameters of the antecedents (if needed) using gradient descent-based MLMA.

3.7. Implementation of the MIMO HANFA-ART with ACA Algorithms

Next, we now consider how the MIMO HANFA-ART with ACA algorithms 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 [30–32] but the hybrid learning algorithms which uses a combination of the MLMA steepest descent-type and ALRS least squares estimation-type algorithms is adapted in this paper [17–19]. However, the implementation of the uses steepest descent and least squares estimation algorithms can get very complicated but a very high detailed description of how the MLMA and the ARLS algorithms operate can be found in [17–20].

It can be shown that for the network described in Figure 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 premise (nonlinear) parameters, and S_2 = set of consequent (linear) parameters. Thus, the MIMO HANFA-ART with ACA algorithms 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 is implemented in this work [17–20].
2) *Backward Pass:* Here S_2 is unmodified and S_1 is computed using a gradient descent algorithm such as the MLMA algorithm is implemented in this work [17–19].

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);
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);
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 MIMO HANFA-ART with AG-KC algorithm is presented, which is a fuzzy inference system (FIS) implemented in the framework of adaptive networks. By using the proposed hybrid learning procedures, the MIMO 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 MIMO HANFA-ART architecture can be adapted to model nonlinear functions, identify nonlinear components on-line in a control system, short-term or long-tem 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 MIMO HANFA-ART with ACA algorithms discussed in Section 3 is 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 Figure 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 Figure 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].

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

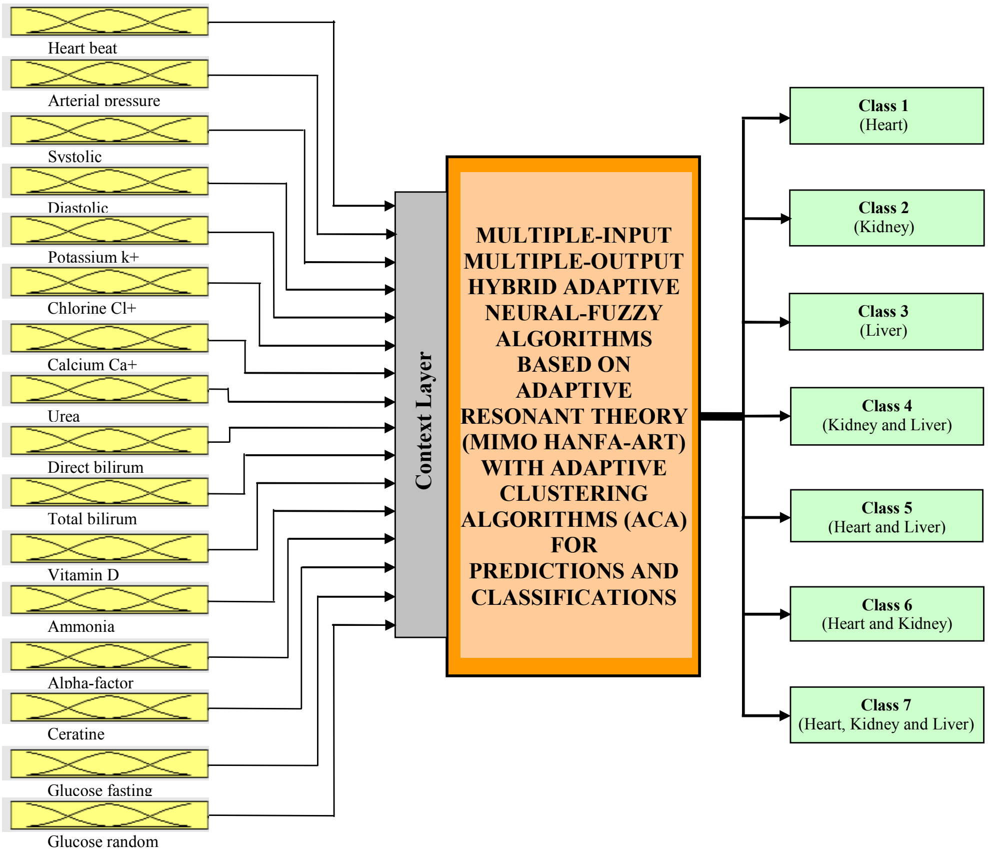


Figure 2. *The architecture for the implementation of the proposed HANFA-ART with clustering algorithm for classification of impending heart, kidney and liver failures.*

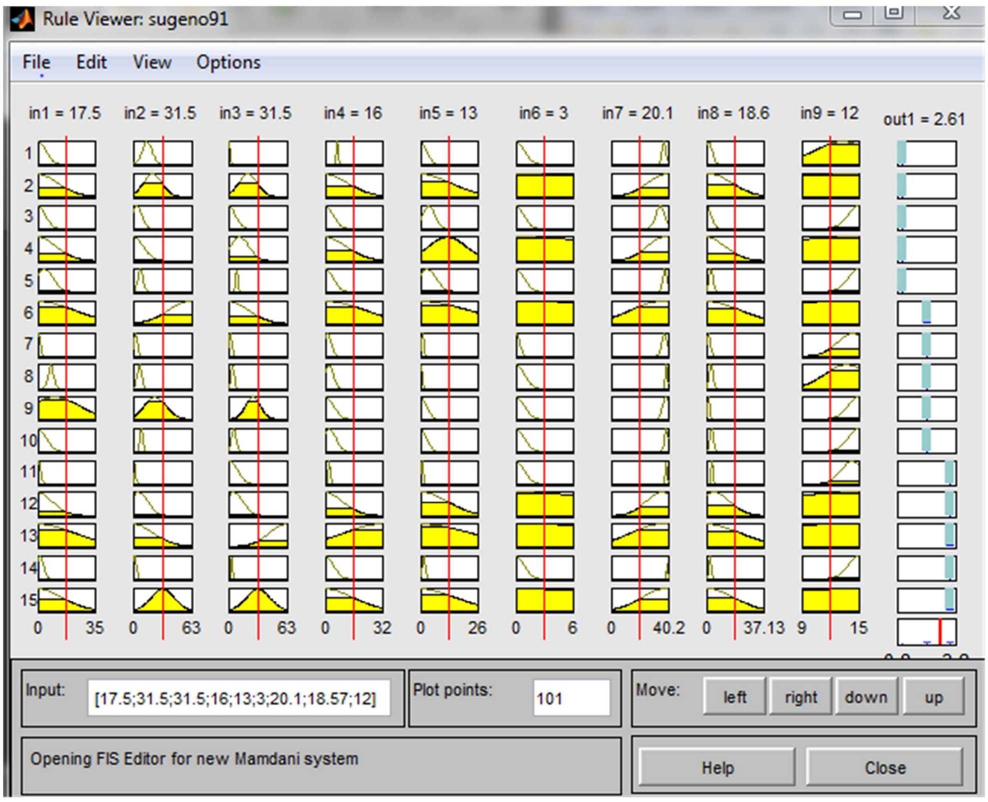


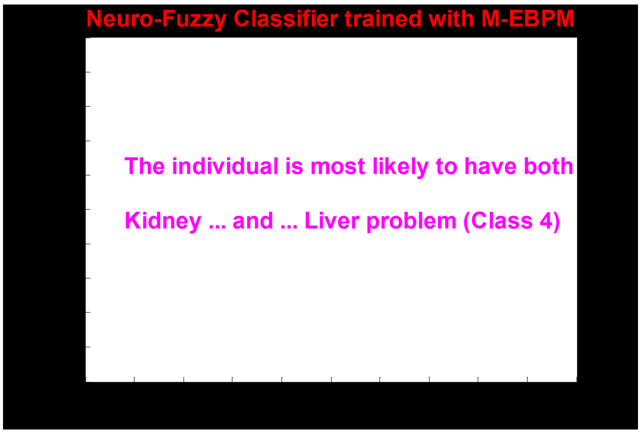
Figure 3. *The classification results of the proposed HANFA-ART with adaptive clustering algorithm for the symptoms of impending heart, kidney and liver failures.*

4.1. Case 1: Impeding Kidney and Liver Related Organs Failure Problems (Class 4)

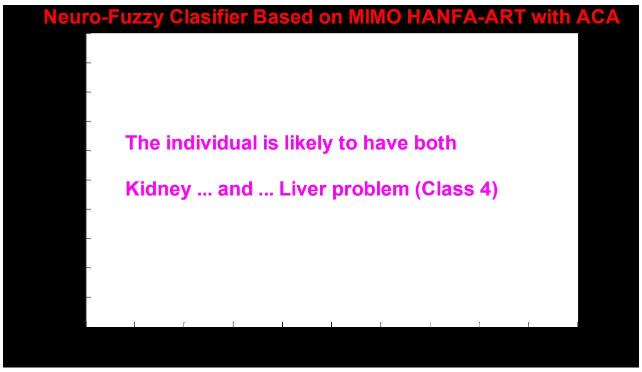
The implementation of the two algorithms (neuro-fuzzy classifier trained with M-EBPM and MIMO HANFA-ART with ACA) for an unknown impending heart, kidney or liver failure is carried out. The randomly selected data is for a patient with symptoms of impending kidney and liver failure problems; and the objective here is to evaluate the ability of the two algorithms to classify the data set into the appropriate category of Class 4. Upon the implementation of the two algorithms, the results of Figure 4(a) and (b) and Table 4 were obtained. The results of Figure 4 show the classification of an impending kidney failure based on (a) Neuro-fuzzy classifier trained with M-EBPM and (b) MIMO HANFA-ART with ACA algorithms.

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

Sampled Individual	Classes	Impending Organ(s) Failure	Neuro-Fuzzy Classifier trained with M-EBPM	Neuro-Fuzzy Classifier trained with MIMO HANFA-ART with ACA
CASE 1 (Kidney and Liver Related Problem)	Class 1	Heart	NAN%	NAN%
	Class 2	Kidney	35.7143%	46.4328%
	Class 3	Liver	NAN%	22.3164%
	Class 4	Kidney and Liver	38.7553%	67.3352%
	Class 5	Heart and Liver	NAN%	NAN%
	Class 6	Heart and Kidney	0.0000%	0.0000%
	Class 7	Heart, Kidney and Liver	NAN%	NAN%



(a)



(b)

Figure 4. *Classification result based on (a) M-EBPM and (b) MIMO HANFA-ART with ACA for sampled Case 1.*

As it can be seen in Figure 4, the neuro-fuzzy classifier trained with M-EBPM and MIMO HANFA-ART with ACA algorithms give correct and acceptable predictions and classifications results as also evident in Table 4. Furthermore, it can be seen in Table 4 based on the results obtained using MIMO HANFA-ART with ACA, the major impending organs with likely failure problems are kidney and liver (Class 4) with 28.7553% and 67.3352% as reported by M-EBPM and MIMO HANFA-ART with ACA algorithms respectively. In addition to the expected probability of the kidney and liver failures, the results of Table 4 also show a higher risk of kidney failure with class accuracies of 35.7143% and 46.4328% by neuro-fuzzy classifier trained with M-EBPM and MIMO HANFA-ART with ACA algorithms respectively classified as Class 2.

The superior performance of the MIMO HANFA-ART with ACA with class accuracy of 22.3164% can be seen in Table 4 compared to NAN% (Not A Number) obtained by neuro-fuzzy classifier trained with M-EBPM. Also, it should be noted that although the 0% seen in Class 6 may mean nothing but it is a value which indicate the absence of a heart related problems which when compared to NAN which is assumed to have no effect nor contribute to the individual's organs failure.

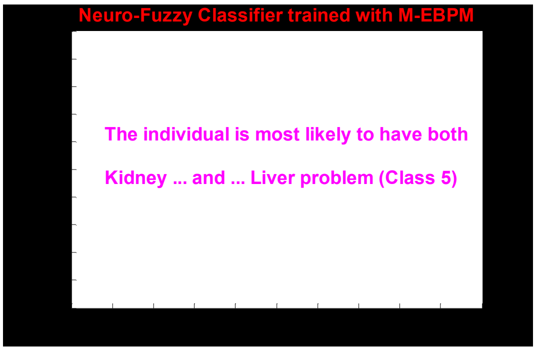
4.2. Case 2: Impeding Heart and Kidney Related Organs Failure Problems (Class 6)

The implementation of the two algorithms (neuro-fuzzy classifier trained with M-EBPM and MIMO HANFA-ART with ACA) for an unknown impending heart, kidney or liver failure is carried out. The randomly selected data is for a patient with symptoms of impending heart and kidney failure problems; and the objective here is to evaluate the ability of the two algorithms to classify the data set into the appropriate category of Class 6. Upon the implementation of the two algorithms, the results of Figure 5(a) and (b) and Table 5 were obtained. The results of Figure 5 show the classification of an impending heart and kidney related organs failure based on (a) Neuro-fuzzy classifier trained with M-EBPM and (b) MIMO

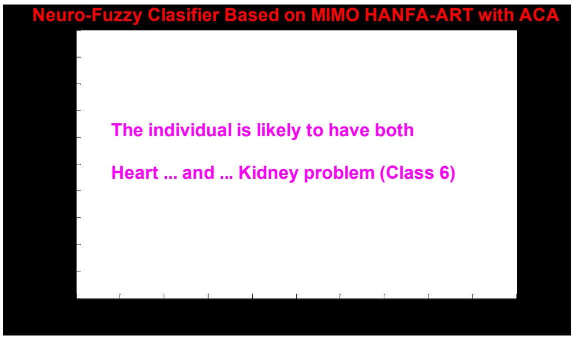
HANFA-ART with ACA algorithms.

As it can be seen in Figure 5 and as evident in Table 5, the MIMO HANFA-ART with ACA algorithms give correct and acceptable predictions and classifications results when compared to the neuro-fuzzy classifier trained with M-EBPM. Furthermore, it can be seen in Table 4 based on the results obtained using MIMO HANFA-ART with ACA, the major impending organs with likely failure problems are the heart and kidney (Class 6) with 53.3333% as reported by the MIMO HANFA-ART with ACA algorithms. In addition to the expected probability of the heart and kidney failures, the results of Table 5 also show a higher risk of the heart failure with class accuracy of 47.3541% followed by kidney with a class accuracy of 28.5714% by MIMO HANFA-ART with ACA classified as Class 6.

From the performance of the two classification algorithms shown in Figure 5, it can be seen that MIMO HANFA-ART with ACA gives the a high expected correct predictions and classifications of heart and kidney organ failures when compared to the neuro-fuzzy classifier trained with M-EBPM. Furthermore, the neuro-fuzzy classifier trained with M-EBPM gives an unexpected incorrect predictions and classifications probabilities of NAN% for both heart as well as heart and kidney failures with a rather combined wrong kidney and liver failure predictions and classifications with class accuracy of 15.8416% of Class 5.



(a)



(b)

Figure 5. *Classification result based on (a) M-EBPM and (b) MIMO HANFA-ART with ACA for sampled Case 2.*

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

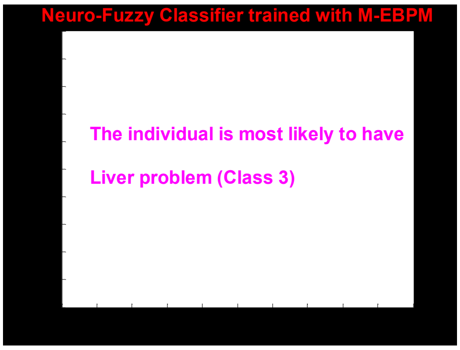
Sampled Individual	Classes	Impending Organ(s) Failure	Neuro-Fuzzy Classifier trained with M-EBPM	Neuro-Fuzzy Classifier trained with MIMO HANFA-ART with ACA
CASE 2 (Heart and Kidney Related Problem)	Class 1	Heart	NAN%	47.3541%
	Class 2	Kidney	NAN%	28.5714%
	Class 3	Liver	8.2125%	NAN%
	Class 4	Kidney and Liver	15.8416%	12.5560%
	Class 5	Heart and Liver	7.6572%	NAN%
	Class 6	Heart and Kidney	NAN%	53.3333%
	Class 7	Heart, Kidney and Liver	0.5234%	NAN%

4.3. Case 3: Impeding Heart, Kidney and Liver Related Organs Failure Problems (Class 7)

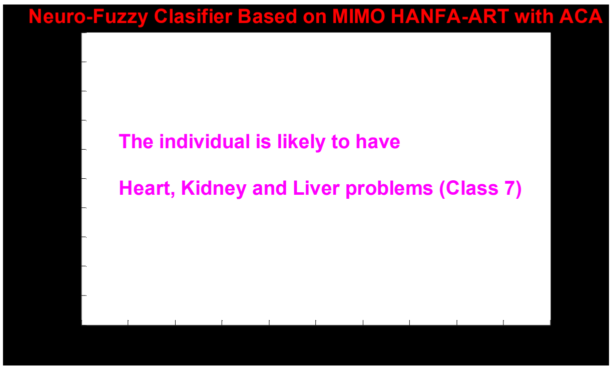
The implementation of the two algorithms (neuro-fuzzy classifier trained with M-EBPM and MIMO HANFA-ART with ACA) for an unknown impending heart, kidney or liver failure is carried out. The randomly selected data is for a patient with symptoms of impending heart, kidney and liver failure problems; and the objective here is to evaluate the ability of the two algorithms to classify the data set into the appropriate category of Class 7. Upon the implementation of the two algorithms, the results of Figure 6(a) and (b) and Table 6 were obtained. The results of Figure 6 show the classification of an impending heart, kidney and liver related organs failure based on (a) Neuro-fuzzy classifier trained with M-EBPM and (b) MIMO HANFA-ART with ACA algorithms.

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

Sampled Individual	Classes	Impending Organ(s) Failure	Neuro-Fuzzy Classifier trained with M-EBPM	Neuro-Fuzzy Classifier trained with MIMO HANFA-ART with ACA
CASE 3 (Heart, Kidney and Liver Related Problem)	Class 1	Heart	NAN%	39.9132%
	Class 2	Kidney	14.4260%	43.6583%
	Class 3	Liver	24.2222%	35.5684%
	Class 4	Kidney and Liver	NAN%	22.1157%
	Class 5	Heart and Liver	NAN%	8.6128%
	Class 6	Heart and Kidney	3.3333%	14.9581%
	Class 7	Heart, Kidney and Liver	NAN%	74.4687%



(a)



(b)

Figure 6. *Classification result based on (a) M-EBPM and (b) MIMO HANFA-ART with ACA for sampled Case 3.*

As it can be seen in Figure 6 and as evident in Table 6, the MIMO HANFA-ART with ACA algorithms give correct and acceptable predictions and classifications results when compared to the neuro-fuzzy classifier trained with M-EBPM. Furthermore, it can be seen in Table 4 based on the results obtained using MIMO HANFA-ART with ACA, the major impending organs with likely failure problems are the heart, kidney and liver (Class 7) with 74.4687% as reported by the MIMO HANFA-ART with ACA algorithms. In addition to the expected probability of the heart, kidney and liver failures, the results of Table 6 also show a high risk of the kidney failure with class accuracy of 47.3541% followed by heart with a class accuracy of 39.9132% and lastly by liver with a class accuracy of 35.5684%by MIMO HANFA-ART with ACA classified as Class 6.

From the performance of the two classification algorithms shown in Figure 5, it can be seen that MIMO HANFA-ART with ACA algorithms demonstrated high predictions and classifications of heart, kidney and liver organ failures when compared to the neuro-fuzzy classifier trained with M-EBPM with poor prediction and classification performances. Furthermore, the neuro-fuzzy classifier trained with M-EBPM gives very poor predictions and classifications probabilities of NAN% for *(i)* heart, *(ii)* kidney and liver, *(iii)* heart and liver, *(iv)* heart, kidney and liver; and a rather low wrong liver failure prediction and classification only with class accuracy of 24.2222%.

4.4. Case 4: Impeding Kidney Related Organ Failure Problem (Class 2)

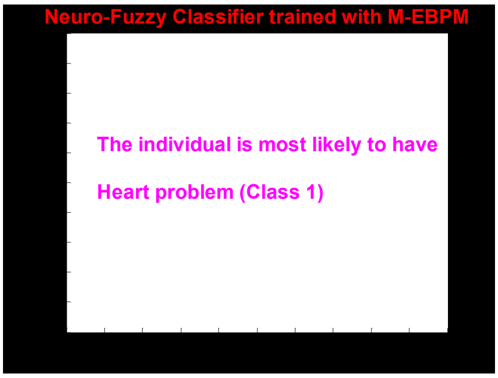
The implementation of the two algorithms (neuro-fuzzy classifier trained with M-EBPM and MIMO HANFA-ART with ACA) for an unknown impending heart, kidney or liver failure is carried out. The randomly selected data is for a patient with symptoms of impending kidney failure problem; and the objective here is to evaluate the ability of the two algorithms to classify the data set into the appropriate category of Class 2. Upon the implementation of the two algorithms, the results of Figure 7(a) and (b) and Table 7 were obtained. The results of Figure 5 show the classification of an impending heart and kidney related organs failure based on (a) Neuro-fuzzy classifier trained with M-EBPM and (b) MIMO HANFA-ART with ACA algorithms.

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

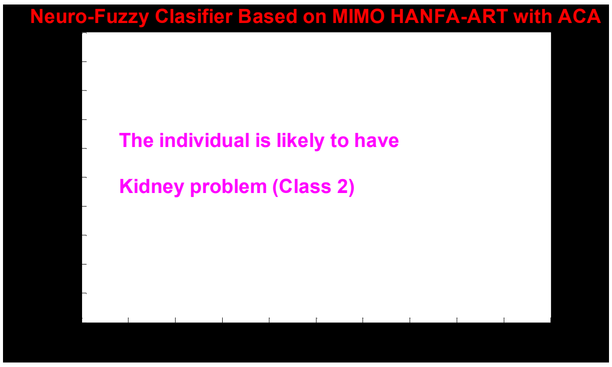
Sampled Individual	Classes	Impending Organ(s) Failure	Neuro-Fuzzy Classifier trained with M-EBPM	Neuro-Fuzzy Classifier trained with MIMO HANFA-ART with ACA
CASE 4 (Hear and Kidney)	Class 1	Heart	22.1157%	NAN%
	Class 2	Kidney	NAN%	69.1268%
	Class 3	Liver	NAN%	NAN%
	Class 4	Kidney and Liver	0.0000%	10.5241%
	Class 5	Heart and Liver	5.3318%	NAN%
	Class 6	Heart and Kidney	NAN%	NAN%
	Class 7	Heart, Kidney and Liver	NAN%	6.1468%

As it can be seen in Figure 7 and as evident in Table 7, the MIMO HANFA-ART with ACA algorithms give correct and acceptable predictions and classifications results when compared to the neuro-fuzzy classifier trained with M-EBPM. Furthermore, it can be seen in Table 7 based on the results obtained using MIMO HANFA-ART with ACA, the major impending organs with likely impending failure problem is the kidney (Class 2) with 69.1268% as reported by the MIMO HANFA-ART with ACA algorithms. In addition to the expected high probability of the impending kidney failure predicted and classified by the MIMO HANFA-ART with ACA, the results of Table 7 also show the impact of the kidney can be felt on *(i)* kidney and liver with class accuracy of 10.5241% and *(ii)* heart, kidney and liver with class accuracy of 6.1468%.

From the performance of the two classification algorithms shown in Figure 7, it can be seen that MIMO HANFA-ART with ACA show excellent predictions and classifications performance of the impending kidney organ failure when compared to the neuro-fuzzy classifier trained with M-EBPM. Furthermore, the neuro-fuzzy classifier trained with M-EBPM gives an unexpected incorrect predictions and classifications of heart with a class accuracy of 22.1157% as the impending organ failure with a rather combined wrong heart and liver failure with a class accuracy of 6.1468%.



(a)



(b)

Figure 7. *Classification result based on (a) M-EBPM and (b) MIMO HANFA-ART with ACA for sampled Case 4.*

5. Summary

5.1. Conclusions

The adaptive prediction and classification of the symptoms of impending human heart, kidney and liver based on blood-related parameters using multiple-input multiple-output hybrid neural-fuzzy algorithm based on adaptive resonant theory (HANFA-ART) with adaptive clustering algorithm (ACA) algorithms has been investigated and accomplished in this study.

Sixteen different attributes that can be used to predict and classify the symptoms of impending heart, kidney and liver failures were classified into seven classes. The adaptive prediction and classification results obtained in this study shows the superior performances of the MIMO HANFA-ART with ACA over the modified error back-propagation with momentum (M-EBPM) algorithm in terms of class accuracies.

The result of this study can facilitate the prediction, classification and diagnosis 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.

Medical practitioners may ask about all substances that a patient might have taken including previous prescriptions, over the-counter drugs, herbal products, nutritional supplements, blood tests as well as other diagnostic procedures are done to identify possible causes of impending heart, kidney and liver failures. On the other hand, the techniques demonstrated in this study together with the MIMO HANFA-ART with ACA algorithms can be adopted in hospitals and medical laboratories for real-time diagnosis of patients for the state of the heart, kidney and liver based on the blood-related parameters listed in this work.

5.2. Future Directions

Medical history of the patients should be incorporated into the fuzzy expert system as this will help in proper decision making process by the MIMO HANFA-ART with ACA algorithms. Hence future works should consider gathering the basic medical information of an individual by means of questionnaire. The acquired information will enhance the effectiveness and more accuracy of the MIMO HANFA-ART with ACA algorithms for the prediction, classification as well as aid the diagnosis of the state of health of the individual.

Further works should provide a friendly graphical user interface (GUI) where someone can monitor or observe his or her health condition by simply providing answers to the questions that may be popped up by the GUI. Furthermore, suggestions or advice for each of the class options to help in the actualization and materialization of the diagnosis of 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 respective levels in the blood-related parameters per test case on an individual.

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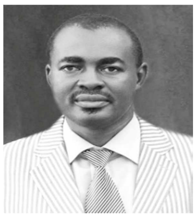

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