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Comparison of Different Neural Network Approaches for the Prediction of Kidney Dysfunction

Ali Hussian Ali AlTimemy and Fawzi M. Al Naima

***Abstract*—**This paper presents the prediction of kidney dysfunction using different neural network (NN) approaches. Self organization Maps (SOM), Probabilistic Neural Network (PNN) and Multi Layer Perceptron Neural Network (MLPNN) trained with Back Propagation Algorithm (BPA) are used in this study. Six hundred and sixty three sets of analytical laboratory tests have been collected from one of the private clinical laboratories in Baghdad. For each subject, Serum urea and Serum creatinin levels have been analyzed and tested by using clinical laboratory measurements. The collected urea and cretinine levels are then used as inputs to the three NN models in which the training process is done by different neural approaches. SOM which is a class of unsupervised network whereas PNN and BPNN are considered as class of supervised networks. These networks are used as a classifier to predict whether kidney is normal or it will have a dysfunction. The accuracy of prediction, sensitivity and specificity were found for each type of the proposed networks .We conclude that PNN gives faster and more accurate prediction of kidney dysfunction and it works as promising tool for predicting of routine kidney dysfunction from the clinical laboratory data.

***Keywords*—**Kidney Dysfunction, Prediction, SOM, PNN, BPNN, Urea and Creatinine levels.

I. Introduction

RENAL failure is a serious medical condition affecting the kidneys. Renal failure can be a progressive disease or a temporary one depending on the cause and available treatment options [1].

The kidneys are glands that are located in the abdominal region just above the pelvis on either sides of the body. When functioning normally, the kidneys separate and filter excess water and waste from the blood stream. The kidneys are responsible for producing urine, which is used to flush away the toxins. The kidneys also maintain a healthy balance of fluids and electrolytes, or salt compounds, in the body.

A. H. A. Altimemy is with the Department of Biomedical Engineering, Al-Khawarzmi College of Engineering, Baghdad University, Baghdad, Iraq.(phone: 9647808347610; e-mail: aha812003@yahoo.com)

Fawzi M. Al Naima is with the Department of Computer Engineering, College of Engineering, Nahrain University, Baghdad, Iraq. (phone:9647810314812; e-mailo: fawzi_cmc@yahoo.com

In renal failure the kidneys undergo cellular death and are unable to filter wastes, produce urine and maintain fluid balances. This dysfunction causes a buildup of toxins in the body which can affect the blood, brain and heart, as well as other complications. Renal failure is very serious and even deadly if left untreated. There are two types of renal failure: acute and chronic. Acute renal failure occurs suddenly and is usually initiated by underlying causes, for example dehydration, infection, serious injury to the kidney or the chronic use of over the counter pain medications like Tylenol (acetaminophen) or Advil (ibuprofen). Acute renal failure is often reversible with no lasting damage. Chronic renal failure is more serious than acute renal failure because symptoms may not appear until the kidneys are extremely damaged. Chronic renal failure can be caused by other long term diseases, such as diabetes and high blood pressure. Chronic renal failure can worsen over time, especially when the problem has gone undiagnosed and treatment is delayed [2].

Recent changes in health care have motivated attempts to improve measures of illness severity and predict outcomes for several diseases like kidney disease. Adjustments for illness severity may have an important role in evaluating quality of care. Computerized scoring systems may be useful if they have a high prognostic accuracy.

NN derive their power due to their massively parallel structure, and an ability to learn from experience. They can be used for fairly accurate classification of input data into categories, provided they are previously trained to do so. The accuracy of the classification depends on the efficiency of training.

The knowledge gained by the learning experience is stored in the form of connection weights, which are used to make decisions on fresh input [3].

One computer technique under investigation is the Artificial Neural Network (ANN) [4]. They are able to model complex nonlinear systems with significant variable interactions. Theoretical work suggests that NN may be able to consistently match or exceed the performance of traditional statistical methods [5]. NN have been used effectively in several clinical studies, in areas including the evaluation of radiological

studies [6], the diagnosis of acute illness [7], the prediction of intensive- care-unit length of stay [8], the diagnosis of appendicitis [9], the diagnosis of psychiatric disorders [10,11] and the diagnosis of acute pulmonary embolism [12]. In Urology, there is a good example of NN application to diagnose prostate cancer [13].

The purpose of this study is to compare between the performance of three proposed NN predictor for the kidney dysfunction using a number of different admission laboratory and clinical data.

II. SELF ORGANIZATION MAPS

Kohonen networks or self-organizing feature maps are networks, consisting only of two layers, an input and an output layers. The output layer of Kohonen networks can be two-dimensional. The most important difference is that the neurons of the output layer are connected with each other. The arrangement of the output neurons plays an important role. Sensorial input signals, which are presented to the input layer, cause an excitation of the output neurons, which is restricted to a zone of limited extent somewhere in the layer. This excitation behavior comes from the back coupling of the neurons. It is essential to know how the interconnections of the neurons have to be organized in order to optimize the spatial distribution of their excitation behavior over the layer. Neurons with similar tasks can communicate over very short pathways.

The optimization produces topographic maps of the input signals, in which the most important relationships of similarity between the input signals are converted into relationships among the neuron positions. This corresponds to an abstracting capability which suppresses unimportant details and maps the most important features along the map dimension. In summary, one can say that Kohonen networks seek to transpose the similarity of sensorial input signals to the neighborhood of neuron positions.

The proposed algorithm for Kidney Dysfunction is based on the conventional SOM algorithm developed by Kohonen [14] [15]. A sketch of a SOM topology is shown in Fig. 1. The SOM algorithm for classification is summarized below:

1. Initialize input nodes, output nodes, and connection weights: Use the top (most frequently occurring) N terms as the input vector and create a two-dimensional map (grid) of M output nodes. Initialize weights w_{ij} from N input nodes to M output nodes to small random values.
2. Present each set in order: Describe each set as an input vector of N coordinates.
3. Compute distance to all nodes: Compute Euclidean distance d_j between the input vector and each output node j:

$$d_j = \sum_{i=0}^{N-1} (x_i(t) - w_{ij}(t))^2 \qquad (1)$$

where $x_i(t)$ can be 1 or 0 depending on the presence of i-th term in the document presented at time t. Here, w_{ij} is the vector representing position of the map node j in the document vector space. From a NN perspective, it can also be interpreted as the weight from input node i to the output node j.

4. Select winning node j^* and update weights to node j^* and its neighbors: Select winning node j^*, which produces minimum d_j. Update weights to nodes j^* and its neighbors to reduce the distances between them and the input vector $x_i(t)$:

$$w_{ij}(t+1) = w_{ij}(t) + \eta(t)(x_i(t+1) - w_{ij}(t)) \qquad (2)$$

Where $\eta(t)$ is the learning parameter. After such updates, nodes in the neighborhood of j^* become more similar to the input vector $x_i(t)$. Here, $\eta(t)$ is an error-adjusting coefficient ($0 < \eta(t) < 1$) that decreases over time.

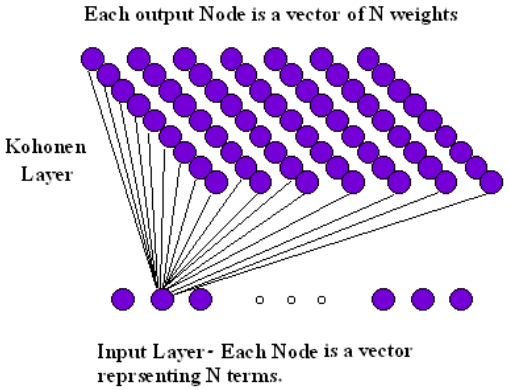

Fig. 1 Kohonen SOM topology

Kohonen's SOM or a feature map [16] provides us with classification rules. SOM combines competitive learning with dimensionality reduction by smoothing clusters with respect to an a priori grid. With SOM, clustering is generated by having several units compete for (training) data. The unit whose weight vector is closest to the data becomes the winner so as to move even closer to the input data, the weights of the winner are adjusted as well as those of the nearest neighbors. This is called Winner Takes All (WTA) approach. SOM assumes some topology among the input data. The organization is said to form a SOM map because similar inputs are expected to put closer position with each other.

III. PROBABILISTIC NEURAL NETWORK

PNN which is a class of radial basis function (RBF) network is useful for automatic pattern recognition, nonlinear mapping and estimation of probabilities of class membership and likelihood ratios. It is a direct [17] continuation of the work on Bayes classifiers in [18] which it is interpreted as a function that approximates the probability density of the underlying example distribution. The PNN consists of nodes with four

layers namely input, pattern, summation and output layers as shown in Fig. 2. The input layer consists of merely distribution units that give similar values to the entire pattern layer.

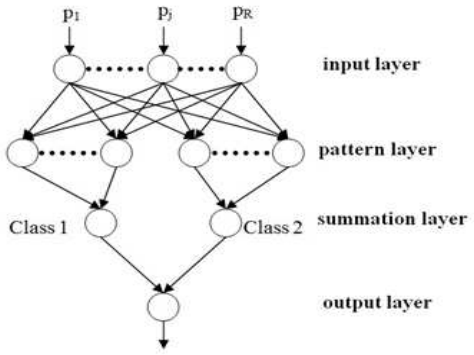

Fig. 2 PNN Architecture

For this work, RBF is used as the activation function in the pattern layer. Fig. 3 shows the pattern layer of the PNN.

The ||dist|| box shown in Fig. 3 subtracts the input weights, $IW_{1,1}$, from the input vector, p, and sums the squares of the differences to find the Euclidean distance. The differences indicate how close the input is to the vectors of the training set. These elements are multiplied element by element, with the bias, b, using the dot product (.*) function and sent to the radial basis transfer function. The output a is given as,

$$a = radbas\ (\ \|IW_{1,1} - p\ \|b) \tag{3}$$

where *radbas* is the radial basis activation function.

The training algorithm used to train the RBF is the orthogonal least squares method which provides a systematic approach to the selection of RBF centers [19, 20]. The summation layer shown in Fig.2 simply sums the inputs from the pattern layer which correspond to the category from which the training patterns are selected as either class 1 or class 2.

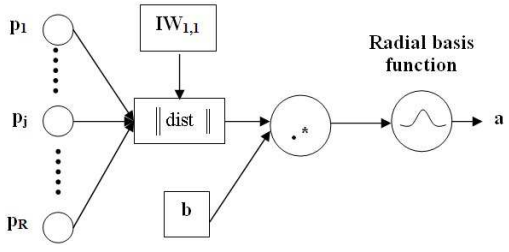

Fig. 3 PNN pattern layer

Finally, the output layer of the PNN is a binary neuron that produces the classification decision. As for this work, the classification is either class 1 for stable cases or class 2 for unstable cases.

Performance of the developed PNN can be found by calculating the Error (E_n) between the Desired Output (DO_n) and the Actual Output (AO_n) as follows:

$$E_n = \left|\ DO_n - AO_n\ \right| \tag{4}$$

where, n is the test data number. The desired output is the known output data used for testing the NN. Meanwhile, the actual output (AO) is the output obtained from testing on the trained network. The percentage mean error, ME (%), can be obtained as:

$$ME\,(\%) = \sum_{n=1}^{N} \frac{E_n}{N} \times 100 \tag{5}$$

where N is the total number of test data. The general architecture for the proposed PNN system of prediction of kidney dysfunction is shown in Fig. 4.

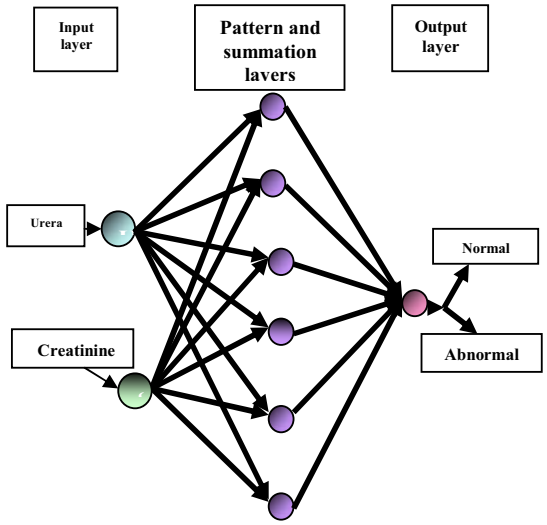

Fig. 4 Architecture of Kidney PNN predictor

IV. Multi Layer Perceptron NN

Feed forward neural networks have a wide application field. This type of network has been used successfully in many fields. Neurons are stored and interconnected in the form of feed forward NN. Feed forward NN is composed of three layers: input, hidden, and output layers. The input vectors are obtained by being applied as [x_1, x_2, . . . , x_n] to the input layer of the neural network, and output vectors are obtained by being applied as [y_1, y_2, . . . , y_n] to the output network of the neural network.

The weight coefficient of each vector connection between the input, hidden, and output layers is computed according to

the effect of each operation element on other elements. A function such as sigmoid or hyperbolic tangent (tanh) could be chosen as a function of transfer, which is used to determine the outputs according to the neuron inputs. Tanh transfer function output may be between −1 and +1. The outputs of the neurons in the output layers are computed in the same way.

There may only be one hidden layer in the feed forward NN or there may be several hidden layers. Each neuron having the total weights of each neuron in the preceding layer sends inputs to each neuron in the next layer. Activation of each neuron is controlled by threshold function.

One of the most important points that should be done during the learning in the ANN is the adjusting of the learning coefficients. The learning coefficient is a fixed number, which may be chosen between 0.01 and 10. The learning behavior of the ANN may be violated due to high weights. To prevent this, the learning coefficient should be lower. On the other hand, lower learning rate slows down the learning. Thus for the momentum learning technique, the step size and the momentum coefficient should be set in accordance with the learning of the network.

In the learning of the network, multilayer perceptron (MLP), which is a successful learning algorithm, is used. MLP, which is back propagation algorithm, computes the error at the output of the network and sets weights of neurons again.

This operation is spread out to the layers and the error in the output is reduced. It is possible to determine which inputs affect the output and how much they affect the output while the neural network learns the obtained data. This can be found by comparing the weights of the inputs applied to the neural network relatively. After the learning is completed successfully, the classification performance is determined by applying test data to the neural network. If the performance values meet the desired criteria at the end of the test, the structure of the neural network is completed. In this stage, the output prediction can be made by applying different data to the NN. The back propagation feed forward NN is shown in fig. 5. Before the learning, lower and random values were selected for weight coefficients [21].

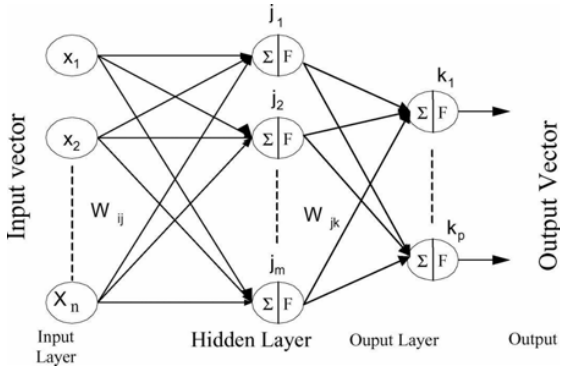

Fig. 5 Feed forward back propagation neural network architecture.

V. BACK PROPAGATION ALGORITHM

Different network topologies with powerful learning strategies to solve nonlinear problems have been reported. For the present application, back propagation with momentum is used to train the feed forward neural network. The output units (yk units) have weights and the hidden units have weights. During the training phase, each output neuron compares its computed activation yk with its target value dk to determine the associated error E for the pattern with that neuron.

The ANN weights and biases are adjusted to minimize the least-square error. The minimization problem is solved by the gradient technique. This is achieved by BP of the error. When using momentum, the net is proceeding not in the direction of the gradient, but in the direction of a combination of the current gradient and the previous direction of weight correction. Convergence is sometimes faster if a momentum term is added to the weight update formula [22].

The summary of the BPA applied in the present work can be described as

1. Initialization Assuming no prior information is available, the synaptic weights and thresholds are picked to be of random value.
2. Presentations of the training examples The network is presented with an epoch of training examples. For each example in the set, ordered in some fashion, the sequence of forward and backward computations described under points 3 and 4 are performed.
3. Forward computation
4. Backward computation
5. Iteration The forward and backward computations under points 3 and 4 are iterated by presenting new epochs of training examples to the network to reach the stopping criteria.

The BPA is a supervised learning algorithm, which aims at reducing the overall system error to a minimum. The connection weights are randomly assigned at the beginning and progressively modified to reduce the overall mean square system error. The weight updating starts with the output layer, and progresses backwards. The weight update aims at maximizing the rate of error reduction, and hence, it is termed as 'gradient descent' algorithm. It is desirable that the training data set be large in size, and also uniformly spread throughout the class domains. In the absence of a large training data set, the available data may be used iteratively, until the error function is reduced to an optimum level. For quick and effective training, data are fed from all classes in a routine sequence, so that the right message about the class boundaries is communicated to the ANN [23,24].

VI. PATIENTS AND METHODS USED

In this work, data were collected from one of the private clinical laboratory in Baghdad from January-2008 to May-

2008. Urea and Creatinine levels for 663 subjects have been analyzed by clinical laboratory methods. The total amount of cases for all subjects have been divided into two groups, one for training (602 cases) and the other for testing of the algorithm (61 cases).

MATLAB software package version 7 is used to implement the software for the current work. A typical sample of the testing data for thirty seven cases is shown in Table-1. The Urea and Creatinine levels were used as an input to the three NN. Then NN will predict whether the kidney will be normal or the patient is may have Abnormal Kidney.

VII. TRAINING AND TESTING

The three networks were trained with all 602 cases (450 normal and 152 abnormal cases). These 602 cases are fed to the Kohonen SOM with two neurons. When the training process is completed for all of the training data (602 cases), the last weights of the network were saved to be ready for the testing procedure. Learning rate is set to 0.01, the output of the network was 1 for the class normal and 2 for the class abnormal. After 100 epochs and training time of 70 sec., the network finished the training process.

PNN is developed for predicting of kidney dysfunction in which the PNN classifies '1' for normal cases and '2' for abnormal cases. The architecture of the PNN is such that it has 2 input neurons, the hidden layer neurons equal the number of training data which is 6 and with a single output neuron.

For MLPNN, The architecture of the MLPNN is such that it has 2 input neurons representing the 2 input features, one hidden layer with 5 neurons of sigmoid transfer function and a single output neuron. The output of NN was 1 for normal and -1 for abnormal case. The mean squared error is used as a goal for training the NN which is set at 0.001. The training algorithm used for this network is BPA. The performance goal was met at 280 epochs after a training time of 168 sec.

The testing process is done for 61 cases (37 normal and 24 abnormal). These 61 cases are fed to the three networks and their output is recorded for calculation of the sensitivity, specificity and accuracy of prediction.

NN derive their power due to their massively parallel structure, and an ability to learn from experience. They can be used for fairly accurate classification of input data into categories, provided they are previously trained to do so. The accuracy of the classification depends on the efficiency of training. The knowledge gained by the learning experience is stored in the form of connection weights, which are used to make decisions on fresh input.

VIII. RESULTS AND DISCUSSION

The performance of the algorithm was evaluated by computing the percentages of Sensitivity (*SE*), Specificity (*SP*) and Accuracy of Prediction (*AP*), the respective definitions are as follows [25,26]:

Sensitivity: is the fraction of real events that are correctly detected among all real events.

$$SE = \frac{TP}{(TP + FN)} \times 100 \quad (6)$$

Specificity: is the fraction of nonevents that has been correctly rejected.

$$SP = \frac{TN}{(TN + FP)} \times 100 \quad (7)$$

Accuracy of Prediction: is the prediction rate.

$$CP = \frac{(TP + TN)}{(TN + TP + FN + FP)} \times 100 \quad (8)$$

where *TP* is the number of true positives, *TN* is the number of true negatives, *FN* is the number of false negatives, and *FP* is the number of false positives. Since it is interesting to estimate the performance of predictors based on the prediction of normal and abnormal kidney , the true positives (*TP*), false positives (*FP*), true negatives (*TN*), and false negatives (*FN*) are defined appropriately as shown below:

FP: Predicts normal as abnormal.
TP: Predicts abnormal as abnormal.
FN: Predicts abnormal as normal.
TN: Predicts normal as normal.

Sensitivity, specificity and accuracy of prediction have been calculated according to the above formals for all of the testing data (61 cases). Table 2 shows the resulted *SE, SP* and *CP* for testing data of the three networks.

9. CONCLUSION

The use of NN has been proposed for prediction of kidney dysfunction by means of classifying the kidney into either normal or abnormal kidney. Urea and Creatinine levels were first measured in the clinical laboratory. These data were carried out to generate training data for the three NN and to predict the kidney failure. The accuracy, sensitivity and Specificity were calculated for the proposed networks to evaluate its effectiveness.

For the supervised NN, PNN gives better accuracy, sensitivity and specificity compared with MLPNN as well as lower time of running the algorithm.

For the unsupervised training, SOM gives good result compared to the supervised networks (PNN and MLPNN). In conclusion, the proposed PNN model gives faster and more accurate prediction of Kidney dysfunction than SOM and MLPNN. It works as promising neural network technique for predicting of routine kidney dysfunction from the clinical laboratory data.

TABLE I
UNITS FOR MAGNETIC PROPERTIES

No	Urea(mg/100ml)	Cretin.(mg/100ml)	Diagnosis
1	35	0.8	Normal
2	34	0.8	Normal
3	57	1.4	Abnormal
4	65	1.4	Abnormal
5	38	0.9	Normal
6	34	0.8	Normal
7	53	1.3	Abnormal
8	38	0.9	Abnormal
9	185	4.6	Abnormal
10	43	1.1	Normal
11	36	0.8	Normal
12	48	1.1	Normal
13	48	1.2	Normal
14	47	1.1	Normal
15	142	3.7	Abnormal
16	27	0.8	Abnormal
17	32	0.8	Normal
18	39	0.9	Abnormal
19	39	0.9	Normal
20	36	0.9	Normal
21	50	1.2	Normal
22	39	0.8	Normal
23	38	0.9	Abnormal
24	39	0.9	Normal
25	45	1.1	Normal
26	39	0.9	Normal
27	50	1.2	Normal
28	44	1.1	Normal
29	32	0.8	Normal
30	72	1.9	Abnormal
31	39	0.9	Normal
32	32	0.8	Normal
33	46	1.2	Normal
34	38	0.9	Normal
35	147	3.9	Abnormal
36	39	0.9	Normal
37	50	1.2	Normal

TABLE II
UNITS FOR MAGNETIC PROPERTIES

	No. of cases	*SE*	*SP*	*AP*
SOM	61	98%	97%	98%
PNN	61	98%	99%	99%
MLPNN	61	95%	94%	95%

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Ali Hussian Ali Al Timemy was born in Baghdad in 1981, Iraq. He is assistant lecturer in Biomedical Engineering Department, Al-Khawarzmi College of Engineering of University of Baghdad, Iraq since 2006. He received B.Sc. and M.Sc. degrees in Medical Engineering from Nahrain University in 2003 and 2006, respectively. Now he is pursuing PhD study in School of Computing, Communications & Electronics, Faculty of Technology, University of Plymouth, UK. He has published over 10 papers in national and international conferences. His research interests are in artificial intelligence in medicine, pattern recognition, neural network for biomedical applications and biomedical signal processing. He is a member of IEEE.

Fawzi Mohammed Munir Al-Naima (M'03) was born in Mosul, Iraq in 1948. He received both B.Sc. (First Class Honors), and Ph.D degrees in Electrical Engineering from the University of Newcastle upon Tyne, UK in 1971 and 1976 respectively.

He worked as a Lecturer and Associate Professor in Al-Rasheed College of Engineering, Baghdad, Iraq from 1977 to 1989. He has been with the College of Engineering, Nahrain University, Baghdad, Iraq since 1989. He served as Head of Department of Electronics and Communication Engineering from 1992 to 2000, and Head of Department of Computer Engineering from 2000 to 2003, and then a Dean of the College of Engineering from 2003 to 2007 in the same university. He spent one Sabbatical year in Aleppo University, Syria from Oct 2006 to Sept 2007. Also, he worked as a Foreign Faculty Professor in the University of Engineering and Technology UET Taxila, Pakistan from Oct 2007 to Sept 2008.

Professor Al-Naima published more than 70 research papers in national and international journals and conferences. He is also the co-author of two chapters in two books published in 2002 and 2007 by international science publishers. His main research interests include computer aided design of large circuits, design of active filters, analog and digital signal processing and medical signal processing. Professor Al-Naima has been a Life Fellow Member of the IETE, India since 1999.