Self-Organization Maps for Prediction of Kidney Dysfunction

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Abstract — **This paper presents the prediction of Kidney dysfunction using Self Organization Maps (SOM). Six hundred and sixty three (663) sets of analytical laboratory test 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 SOM model in which the training process is done by SOM. SOM which is a class of unsupervised network is 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 to be equal to 98%, 98% and 97% respectively for this proposed network .We conclude that that the proposed model 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, Urea and Creatinine levels.**

I. Introduction

RENAL failure is a serious medical condition affecting the kidneys. When a person suffers from renal failure, their kidneys are not functioning properly or no longer work at all. 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 side 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.

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.
Neural Networks (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 [4]. Neural networks are tools for multivariate analysis that can be used to estimate disease risk. They are able to model complex nonlinear systems with significant variable interactions. Theoretical work suggests that neural networks may be able to consistently match or exceed the performance of traditional statistical methods [5]. Neural networks 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 was to develop a Kohonen-SOM network as predictor for the kidney dysfunction using a number of different admission laboratory and clinical variables.

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II. SELF ORGANIZATION MAPS THEORY

Kohonen networks or self-organizing feature maps are networks, which consist only of two layers, an input and an output layer. 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. Summarized, one can say that Kohonen networks seek to transpose the similarity of sensorial input signals to the neighborhood of neuron positions.

The proposed ear SOM algorithm 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 neural net 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 $x_i(t)$:

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

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

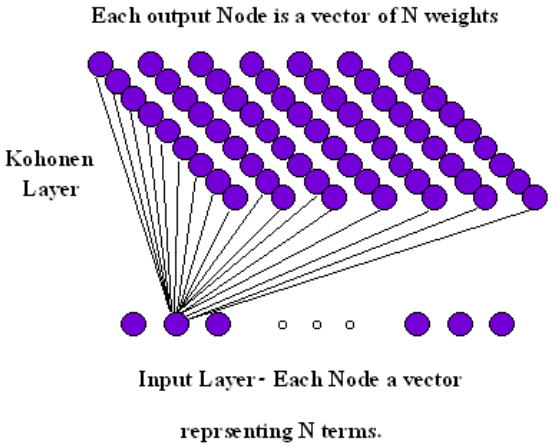

Fig. 1. Kohonen SOM topology

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. PATIENTS AND METHODS

In this work, data were collected from one of the private hospitals 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 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 SOM classifier. Then the SOM will predict whether the kidney will be normal (output of the SOM is 1) or the patient is may have Abnormal Kidney (the output of the SOM is 2).

IV. TRAINING AND TESTING

The network was trained and tested with all 602 cases (450 normal and 152 abnormal cases). These 602 cases are fed to the Kohonen SOM with two neurons.

The Kohonen 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, the network finished the training process. When the training process completed for all of the training data (602 cases), the last weights of the network were saved to be ready for the testing procedure.
The testing process is done for 61 cases (37 normal and 24 abnormal). These 61 cases are fed to the network and their output is recorded for calculation of the sensitivity, specificity and accuracy of prediction.

TABLE 1: Sample of the testing data

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

V. 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 [17]:

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

[SE = 100xTP/ (TP+FN)]

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

[SP = 100xTN/ (TN+FP)]

Accuracy of Prediction: is the prediction rate.

[CP=100x (TP+TN)/ (TN+TP+FN+FP)]

where TP was the number of true positives, TN was the number of true negatives, FN was the number of false negatives, and FP was 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.

In our study, the output 1 indicates normal case. If the output is 2 this means that the patient may have abnormal kidney function.
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 SOM for testing data.

Table 2. The results after training of the network

	No. of cases	*Sensitivity*	*Specificity*	*Accuracy of Prediction*
SOM	61	98%	97%	98%

VI. CONCLUSION

The use of SOM 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 SOM and to predict the kidney failure. The accuracy, sensitivity and Specificity were

calculated to evaluate its effectiveness. We conclude that that the proposed model gives faster and more accurate prediction of Kidney dysfunction and it works as promising neural network technique for predicting of routine kidney dysfunction from the clinical laboratory data.

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